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Use of Business Intelligence in Management Accounting

An application of the Technology Acceptance Model on the use of dashboards with financial data in decision-making practices in management accounting

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Master thesis in Business Analytics

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Abstract

The purpose of this thesis is to explore the acceptance and use of business intelligence (BI) solutions in decision making in management accounting (MA). To do so we have sought to answer the following research question:

How can the use of BI solutions in MA facilitate data-driven decision making?

During the last decade, due to the staggering technological growth, there has been a lot of research on both BI and MA. However, the research on BI solutions and their impact on MA is limited. We aim to contribute with insights into this cross-disciplinary field by identifying which elements are important to consider when using financial data as decision making support, and by this facilitate for data-driven decision making in MA, using BI solutions. To do this we conducted a survey, directed at decision makers in a large Norwegian company. The survey is mostly quantitative, with questions based on the TAM framework, while also having embedded qualitative components. Subsequently the analysis is based on both quantitative and qualitative data gathered from the respondents to our survey.

When answering our main research question, we find three main findings which have important implications for our case company. We find that compatibility (C) is the factor shown to be the most important for the acceptance and use of BI solutions, which implies that the specific needs which make up the compatibility need to be mapped out and taken into account. Secondly, we find that the information presented in the dashboard needs to be uncomplicated and tell a story about the data, so that it can be used as efficient decision support. Lastly, we find that it is important to have a continuous development of the users' knowledge and skills, so that they are kept at an adequate level in accordance with the solutions used. Subsequently it is highly important that there is a valid reason for implementing new technological solutions, to avoid implementing for the sake of implementing it. Our research finds that for a dashboard solution to be a good decision support for basing decisions on these aspects need to be both considered and acted on.

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1. Introduction

1.1. Background

In 2017, *The Economist* published a report titled *The world's most valuable resource is no longer oil, but data* (The Economist, 2017). This highlights an important point: data is gaining more and more importance and value. The field of data and data analysis, as we know it today, has increasingly gained interest and importance across a wide range of fields since around the 1960s (Friendly, 2008), and has become more and more important for organizations as the world has become increasingly technological. In addition, the amount of data available for an organization, and the changes that data and analytics brings to an industry, is increasing at a staggering pace (Davenport, Guszcza, Smith, & Stiller, 2019; McKinsey, 2019). Following these developments, technology, data and analytics is gaining importance on the corporate agendas and are seen as a transforming force in organizations (Columbus, 2015; PwC, 2018).

In addition, the use of data, and especially financial data in an accounting context, is crucial for decision making in organizations (Brynjolfsson, Hitt, & Kim, 2011; Friedman, 1970). This has increased the need for emerging technologies and in an age of collaboration between humans and machines, advantages are gained by designing systems which utilize this collaboration to improve the speed and quality of reporting and decision making (CGMA, 2016; Davenport et al., 2019). These developments and the need to shorten the time lag between data acquisition and decision making have resulted in the emergence of business intelligence (BI) and analytics solutions (Chaudhuri, Dayal, & Narasayya, 2011). Given that management accounting (MA) is the primary support for control and decision making in an organization, organizations can get substantial benefits from utilizing BI solutions to generate insights used for decision support (CGMA, 2016; Davenport et al., 2019; Deloitte, 2019; Elbashir, Collier, Sutton, Davern, & Leech, 2013; McKinsey, 2019).

However, not every organization is exploiting the opportunities and solutions available and many are struggling with the overwhelming volume of data and how to consistently embed data processing, analysis and evidence-based reasoning into valuable insights in their decision-making practices (Davenport et al., 2019; PwC, 2018). It is decades since technologies like big data and analytics became available, and the constant change in this field makes it hard to keep up, meaning that most companies are responding with single and ad hoc actions and are lacking long-term initiatives that makes them mature and sustainable when it comes to BI (Davenport et al., 2019; McKinsey, 2019). In fact, a study found that 62% of large companies still rely on spreadsheets as a BI solution (Deloitte, 2019). This states the fact that there is a gap between todays' situation and the potential situation when it comes to the acceptance and actual use of BI solutions for decision making (Rikhardsson & Yigitbasioglu, 2018). There is a potential for a better utilization of financial data by using both the emerging and existing solutions in this digital age. To further reinforce both the importance and possible challenges, BI solutions is said to be one of the fastest growing enterprise software and 70% of the survey respondents in Deloitte`s survey anticipate that the importance of utilizing BI will increase over the next three years (Columbus, 2015; Davenport et al., 2019).

The fast pace of digital growth and the indisputable need for managing businesses as an economic entity have opened up for interesting research in the fields of both MA and BI. Nielsen (2016) states that BI represents an interesting new field that MA can benefit from. Additionally, according to surveys within the field of MA, BI is gaining importance, and there is an increasing occurrence of these types of solutions in this field (ACCA, 2009; CIMA, 2011). However, based on a review of the literature in top accounting and information system journals, the current research of BI solutions and the actual implications of this on MA is very limited and there is yet much to gain from looking further into this link (Nielsen, 2018; Rikhardsson & Yigitbasioglu, 2018). By looking into the acceptance and use of BI solutions in MA, and describe which factors that affects this, we want to bring valuable insights as to which implications this could have for the users and the companies. This is our focus in this thesis, where we aim to conduct a cross-disciplinary research, including both the field of MA and Information Systems (IS).

1.2. Research Question

We aim to explore the acceptance and use of BI solutions in MA decision- making practices as this is an interesting research topic. By MA we refer to management accounting activities, such as financial reporting and decision making, and not the specific role of the management accountant. Furthermore, we aim to identify which elements that are important to consider when using financial data as decision making support and by this facilitate for data-driven decision making, using BI solutions. We understand "facilitate" as describing the act of making a process easier and subsequently helping to produce more beneficial output. Our main research question is:

How can the use of BI solutions in MA facilitate data-driven decision making?

To answer this research question, we firstly need to establish which factors that affects a user's interaction with BI solutions as decision support. Further, we aim to identify the current needs for such BI solutions and analyze how they coincide with existing system features and user characteristics. In doing so, we seek to answer the following sub questions.

- *i.* *Which factors affects the acceptance and use of BI, such as dashboards, as a decision supporting solution in MA?*
- *ii.* *How do the current needs for BI solutions match the present user characteristics and system features?*

With our first research question we seek to investigate factors that may be important for a user when interacting with a dashboard as a decision supporting solution, and this is answered in chapter 6.2.1. With our second research question we aim to find out what the current needs for a BI solution are, and if these match the present features of the solutions used and the characteristics of the users. The second research question is answered in chapter 6.2.2. By doing so, we answer our main research question on how BI solutions can facilitate for using financial data for data-driven decision making. Our main research question is answered in chapter 6.2.3.

1.3. Methodology

We aim to answer our main research question by conducting a mixed research method with an abductive approach to theory development, as we combine deductive and inductive approaches throughout the different phases of our research. To collect the necessary data, we conducted a survey with both open and closed question, which gives the opportunity for both qualitative and quantitative analyses of the data. To structure our data collection and analyses we use the technology acceptance model (TAM) as a framework by developing hypotheses and constructs based on existing research. This will enable us to test the variables and relationships, as well as providing insights on how the BI solutions and visualization of financial data can facilitate for data-driven decision making. Consequently, the first stages of our research will be deductive by nature, with a descriptive design. By analyzing the closed-ended questions by using TAM as a framework, we aim to establish which factors that affect the acceptance and use, as well as providing pointers to needs and demands of the users. Furthermore, as cross-disciplinary research between MA and IS are limited, we will in the last phases of our research include an inductive approach with an exploratory design. This will involve a qualitative method to analyze the more unstructured and open questions in the survey. This will provide further insight into how the needs for BI solutions are matched with system features and user characteristics. By conducting a mixed research survey design with an abductive approach in this thesis we manage to expand and strengthen our conclusions.

Based on the insights we gained when reviewing relevant literature and theories (see e.g. Chaudhuri et al., 2011; Davenport et al., 2019; Rikhardsson & Yigitbasioglu, 2018), we found that the use of BI solutions is closely connected to storage and processing of data. Subsequently, we needed to identify a company with a large quantity of data to be able to conduct a thorough research. With this as a demand, we found Equinor being an interesting company to analyze, as they are very ERP-heavy with lots of data available that is not fully utilized. In addition, they are already partially engaging in BI and data visualization, with varying degree of acceptance and use of such solutions.

1.4. Relevance

By conducting this research, we aim to find out how BI solutions can facilitate for using financial data and visualize it in a way that can be beneficial as decision support. One output we want to achieve, as a central step towards the facilitation of data-driven decision making, is to define some demands for what the decision makers want and need in visualizations of financial data. This is based on the fact that in current literature there has been a focus on descriptive research on the links between factors affecting the acceptance and use of BI solutions (Dilla, Janvrin, & Raschke, 2010; Işik, Jones, & Sidorova, 2013; Yigitbasioglu & Velcu, 2012), but not much research on the user's wants and needs, and which implications this brings. By mapping out the acceptance and actual use of BI solutions and matching this with specific system features, we want to contribute with insights on how data-driven decision making can be facilitated by the use of BI solutions and highlight important aspects for the acceptance and utilization of this. By doing this research and conducting these analyses we set out to facilitate for decision makers to use BI as a decision supporting solution.

This thesis will also contribute in an area where we have found some missing research and we will therefore add valuable knowledge when it comes to the subject of use of BI solutions in the practice of decision making in MA. A lot of literature and research exist on both BI solutions and MA, but there is a lack of research done on the combination of these two (Rikhardsson & Yigitbasioglu, 2018). We aim to investigate the current needs to BI solutions and if this matches the user characteristics and system features. This perspective is based on the importance of knowing the users wants and needs, before implementing new technology such as BI solutions

As mentioned, the topic of this research is a prevailing case for Equinor which alone makes this research very valuable to conduct. For the use of BI in this company there exists differing views on what is the optimal solution, and how this should be utilized. We have also been informed that this has led to differences in both acceptance and use of BI solutions, in MA, among the employees. Furthermore, the use of emerging technologies such as BI is a subject most companies face, and by conducting this research we will contribute with knowledge, not just for Equinor, but also for other companies facing similar challenges. This study can be relevant for other companies with the following similar features to Equinor: ERP-heavy industrial companies that operates within different assets. This will typically be companies within, for example, oil and gas, energy, chemical industry, forestry and aqua culture. Further, we acknowledge cultural differences, and our findings will therefore be most relevant for Nordic-based companies, as both Equinor and the respondents are mainly Norwegian or Norway-based.

1.5. Outline

In chapter 1 we presented our research question, and relevance of this research. Further, in chapter 2, we will describe our theoretical foundation, while chapter 3 is a presentation of our theoretical framework. Chapter 4 is an explanation of our methodological choices, while chapter 5 is the analysis of the collected data from our survey. In chapter 6 we discuss on our findings, and answer our research question, while a short conclusion is provided in chapter 7.

2. Theoretical Foundation

In our research questions we ask, "*How can the use of BI solutions in MA facilitate data-driven decision making?"* To be able to answer this we need to review existing literature on the different components of the research question. We will present some theoretical foundation for the following topics in chapter 2.1 to 2.3: Data and MA, decision making and use of BI in MA.

To form our literature foundation, we mainly utilized Google Scholar and Scopus to find relevant articles. Our main focus was to gather articles from journals with a high ranking in the Academic Journal Guide to assure reliable sources for our theoretic foundation. Our main key words when searching for literature includes: "MA", "decision making", "BI","IS" and "solutions".

2.1. Data and MA

In chapter 2.1 we will define and explain the terms MA and data. As for data, this will mainly be defined, and we will delimit our definition and focus of it for this thesis. MA as a term will be defined, along with a brief explanation of recent development in this field. The main goal of this chapter is to give brief explanations and definitions of these terms, as they make up important components of our following elaborations.

2.1.1. Definition of Data

The origin of data can be traced back to the ancient Greek times (Bruno, 1999), but the meaning of the word has slightly changed over time. As of today, data is, in the Oxford English Dictionary, defined as "Facts and statistics collected together for reference or analysis" ("Data," n.d.). The field of data and data analysis, as we know it today has increasingly gained interest and importance across a wide range of fields since the 1960s (Friendly, 2008), and has become more and more important for organizations to utilize as the world has become increasingly technological (CGMA, 2016; Davenport et al., 2019).

As data is such a wide topic, we are limiting it to concern the area of financial data in this thesis. Financial data contains information or sets of information related to the financial health of a business. This data is crucial for decision making in businesses, as it early became common understanding in the field of economics that the main goal of a business is to maximize profits for its owners (Friedman, 1970). Subsequently, having financial data as a foundation is a crucial part of decision making in MA, with the main goal of maximizing profits and creating value.

2.1.2. Definition of MA

During the last decades several definitions of MA has been proposed (CGMA, n.d.; National Association of Accountants, 1981). In this thesis we have adopted the definition from the Institute of Management Accountants (IMA, 2008, p. 1), which as of 2008 was consisting of: "(…) partnering in management decision making, devising planning and performance management systems, and providing expertise in financial reporting and control to assist management in the formulation and implementation of an organization's strategy.". The reasoning for adopting this definition is that it incorporates the components in the field of MA that we will cover in this thesis, which is mainly providing insights in financial reporting and decision making.

It should be emphasized that a part of the literature on MA talk of the *management accountant* and the role of the management accountant as a profession, as well as management control, cost accounting and resource management. In this thesis the focus will be on MA as a holistic process. We will therefore not focus on the changing role of the management accountant, but rather the change in the processes of financial reporting and decision making in MA. A definition of decision making in MA will be presented in chapter 2.2.2.

2.1.3. Development of MA

A series of research have confirmed that MA is a practice which continuously goes through extensive change, and this has made it a highly popular research area (Chanegrih, 2008; Gärtner, Feldbauer-Durstmöller, & Duller, 2013; Waweru & Uliana, 2008). The main trend is that MA has moved from an orientation of compliance and transaction, to have a more central role in strategic business planning (IMA, 2008). By this it is implied that MA now is becoming more and more a strategic business partner in terms of facilitating performance management, planning, internal control, financial reporting etc. (Burns & Vaivio, 2001; Gärtner et al., 2013; IMA, 2008; Quattrone, 2016).

Several researchers have focused on how the adoption of enterprise resource planning (ERP) systems (or integrated information systems) affect MA tasks and techniques (Chapman & Kihn, 2009; Cooper & Kaplan, 1998). These systems have with no doubt increased the efficiency of collecting and reporting accounting data, and it has also shifted the conceptual design of MA in an organization. ERP systems are considered one of the most important drivers of change in the field of MA, as the tasks of summarizing, analyzing and reporting has largely become integrated into the ERP systems (Gärtner et al., 2013). Subsequently, the field of MA is expanding further into the organization (IMA, 2008). In figure 1, both the previous and emerging conceptual design of MA is displayed.

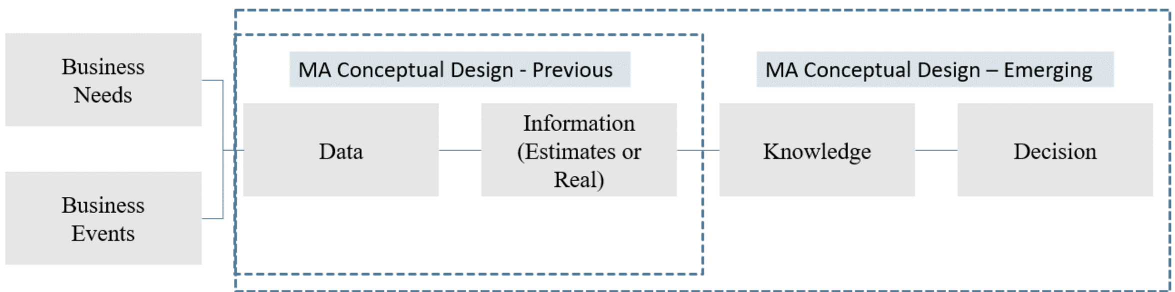

Figure 1- Previous and emerging conceptual design of management accounting (MA). Adapted from "Statements on Management Accounting. Definition of Management Accounting," by IMA, 2008.

As MA gets more influenced by technology (both ERP and BI), and the conceptual design is changing, MA is getting more engaged in the actual process of decision making (Moorthy, Voon, Samsuri, Gopalan, & Yew, 2012). The reason for this is that MA, as a holistic process, has transformed from information providing to "business partner" (Gärtner et al., 2013), as shown in figure 1. The concept of decision making will be introduced in the next chapter.

2.2. Decision Making

In this chapter the term decision making will be presented. The term will first be defined and explained, before we will present some literature concerning both MA and decision making in combination.

2.2.1. Definition and Components

According to Jones et al. (2003, p. 33) decision making is defined as the following:

> Decision making is the process of identifying alternative courses of action and selecting an appropriate alternative in a given decision situation. This definition presents two important parts:
>
> 1. *Identifying alternative courses of action* means that an ideal solution may not exist or might not be identifiable.
> 2. *Selecting an appropriate alternative* implies that there may be a number of appropriate alternatives and that inappropriate alternatives are to be evaluated and rejected. Thus, judgment is fundamental to decision making.
>
> Choice is implicit in our definition of decision making. We may not like the alternatives available to us, but we are seldom left without choices.

This thesis will lean on this definition when using the term decision making during our thesis.

2.2.2. Decision Making in MA

The topic of decision making, like data, stretches over many fields of study. Within economics, and large parts of social science, it has traditionally been stated that decision making is an intentional consequential action, meaning that whatever decision is taken is the rational choice which yields the highest expected value (Jarrow, Maksimovic, & Ziemba, 1995; March, 1991). March (1991) further emphasizes that this is a simple rational-choice model, which does capture some truth, but also lacks some parameters that might affect decisions, including limited rationality. The mentioned literature, along with other literature on decision making, has traditionally been quite general, with limited focus on specific types of decisions within organizations (Jarrow et al., 1995; March, 1987, 1991). However, as the field of MA has been changing rapidly during the past couple of decades, there has been more focus on decision making within the field of MA (Chanegrih, 2008; IMA, 2008; Rikhardsson & Yigitbasioglu, 2018).

To discuss decision making in MA it is important to first establish who actually takes decisions in a MA context, and what the common basic goal assumption is. The typical decision maker in a MA context is often a combination of someone holding both an analytical role and a consulting role, to a broad range of areas in an organization (Elbashir, Collier, & Sutton, 2011). As for the goal assumption, the main objectives for a company might vary, and be multiple, such as maximizing profits, maximizing sales or ROI. According to Goosen (2008), MA as a holistic process does not require such a specific type of goal, but the common denominator here is that the end goal for both MA and decision making in general is to create value.

As of today, numbers and data are turned into simple inputs to decision making, where a decision maker receives already packaged data to base decisions on. This implies that the exercise of judgment in decision making starts at a later point in the process than before, and that the whole process of manufacturing of the data, which can provide a lot of insight, is held outside of the action of decision making (Quattrone, 2016). As this is evident today, the aspects of limited rationality in the decision maker becomes even more important. According to March (1987) the idea of limited rationality is that not everything can be known, and when making decisions one bases this on incomplete information, the existing alternatives and their known consequences. As we know that limited rationality is a complication for decision making in organizations, the focus has moved more towards making logical decisions, based on the available information, rather than assuming that every decision is fully rational (Quattrone, 2016). Bettering the available information for a decision maker can therefore be key to creating value when making decisions.

As data, data science and BI has evolved, decision making in MA has also been incorporated into this field, to become known as data-driven decision making (DDD). DDD refers to the practice of, instead of solely basing decisions on intuition, basing decisions on analysis of data. It is important to note that DDD is not an all-or-nothing approach, but that it can be, and usually is, combined with intuition, knowledge and experience (Provost & Fawcett, 2013). The two definitions, of decision making and DDD, do not contradict, but rather build on each other. As we will focus on data-driven decision making, we will lean on a combination of these two definitions, and when referring to decision making this will incorporate DDD in our thesis. Data-driven decision making is becoming a more popular field of research (Doya & Shadlen, 2012; Provost & Fawcett, 2013), and literature concerning this term in combination with MA will be discussed in the next chapter.

The benefits of DDD in MA have during the past years been widely demonstrated (Provost & Fawcett, 2013), and a study from MIT and Penn's Wharton School demonstrates the impact of DDD on MA well. A study was conducted on how data-driven decision making affects a firm's performance. It was then statistically shown that the more the firm engaged in DDD, the more productive it is. DDD was also found being correlated with higher return on assets and equity, higher market value and better asset utilization (Brynjolfsson et al., 2011). This study, among others, then implies that using data-driven decision making in MA tends to create value for companies. On the other hand, some studies have challenged this view on the emerge of DDD and the increasing amount of available data. E.g. Quattrone (2016) argue that the digital revolution will augment uncertainty, due to overwhelming amounts of data and increased distance to the origin of the source. Therefore, to utilize the possibilities the digital revolution and DDD can give, it is important to give attention to the changes it causes and how to best adopt to these (Quattrone, 2016).

2.3. Use of BI in MA

In chapter 2.3 we present the term BI and literature elaborating on this subject in combination with the MA field. We will define the term BI and present existing challenges with BI in MA. Furthermore, existing research on this subject and the identified research gaps will be presented.

2.3.1. Definition of BI

The umbrella term BI is often described as being a combination of the terms data, decision making and technology (CGMA, 2016; Chaudhuri et al., 2011; H. Chen, Chiang, & Storey, 2012). In this thesis we will adopt the definition from Rikhardsson and Yigitbasioglu (2018, p. 38) where BI is defined as "a technology and a process for analyzing data and presenting actionable information to help organizational decision makers make better decisions". The term BI cover a range of technology and methodologies that enable organizations to collect data, prepare it for analysis, create reports, dashboards and visualizations to make the information available to an end-user with the aim generate knowledge, understanding and learning (CGMA, 2016; Rikhardsson & Yigitbasioglu, 2018). In this way BI solutions can support evidence-based decision making and performance management in an organization (CGMA, 2016). BI solutions in an organization encompasses four basic technological elements. These are (1) Infrastructure (e.g., cloud-based infrastructure relational or non-SQL databases); (2) Data management (e.g., integration of internal and external data); (3) Data analyses (e.g., statistical techniques and artificial intelligence); and (4) Information Delivery (e.g., dashboards) (Rikhardsson & Yigitbasioglu, 2018). In this thesis we will focus on the link between the last two, data analyses and information delivery, and mainly concentrate the research on solutions meant for visualization of data, i.e. dashboard solutions.

2.3.2. Challenges with BI

The use and utilization of BI solutions to present data and results in a satisfying way to support decision making, is still an remaining challenge (CGMA, 2016). Several researchers have found that the biggest threats for a satisfying utilization of BI solutions is different levels of expertise, data silos, cognitive load and bias (CGMA, 2016; H. Chen et al., 2012; Tversky & Kahneman, 1974). In general, people in an organization are differing in comfortability with using different sets of systems and solutions due to varying knowledge and skills (CGMA, 2016; H. Chen et al., 2012). This leads to different ways of interpreting data and might hamper the insights of analyses presented in unfamiliar solutions and settings. Also, different roles in an organization will have different expertise of the data itself, which also can influence the utilization of a BI solution (H. Chen et al., 2012). Data silos can also be a threat against BI solutions, and this is very applicable for many organizations, which usually have data stored in departmental silos. This hinder proper exploitation and sharing of data between different departments and business lines. Furthermore, research on bias in BI is also particularly relevant. Bias is a pattern of deviation in judgement that occurs by the user's personal assumptions and cognitive filters that shape their decision-making process in particular situations. This can lead to decisions containing perceptual distortion, inaccurate judgment and illogical interpretation (Tversky & Kahneman, 1974).

2.3.3. Research Categorization and Gaps

In this section we will present the relevant research, which we have categorized into four different categories based on their research topics: (1) Importance of research within these fields, (2) the impact of fit between user characteristics, system features and the task, (3) user characteristics and (4) the impact BI solutions have on MA tasks.

Based on the literature review, one of the overall themes in the current research within the fields of IS and MA is focused on the importance of utilizing BI in MA. The use of BI solutions for data analysis and decision support to facilitate for value creation in an organization has gained more attraction from executives over the last years and is now high on the corporate agenda of many organizations (Columbus, 2015; PwC, 2018). This is supported by the fact that given that MA is a decision-supporting activity, several researchers have found an link between BI, MA and value for an organization (Bronzo et al., 2013; Elbashir, Collier, & Davern, 2008; Elbashir et al., 2013), which promotes the importance of integrating BI solutions into MA processes. The developments and interests in this field are also reflected in professional accounting bodies' agendas where the potential for studying BI solutions and their implications for MA and decision making is highly motivated, but the current understanding and literature is yet limited (Rikhardsson & Yigitbasioglu, 2018).

The second theme found in BI and MA research is concerned with the impact of fit between user characteristics, system features and the task. The aim of this theme and linked studies is to investigate how to optimize the presentation of data in terms of features like visualization, interactivity and system feedback, all to support decision making. The focus of the studies was mainly on the format of the information, that is in tabular or graphical format, the level of opportunity for interaction and the type of feedback in the system. Many of the studies also draw on cognitive fit theory, where they conclude that the quality of decision making improves when the presentation format, the task and the user's knowledge all fit together (Dilla et al., 2010; Yigitbasioglu & Velcu, 2012).

In addition, some studies have found that in the absence of one of these three elements, system features, user's characteristics and the task, the use of drill down paths can result in suboptimal decisions and the level of interactivity can lead to an change in calibration (Peng, Viator, & Buchheit, 2007; Tang, Hess, Valacich, & Sweeney, 2011). In terms of interactivity, other studies have found opposing results, where Locke, Lowe, Lyner and Monroe (2015) find no value in presentation format interactivity, and Chen and Koufaris (2015) found that the degree of interactivity is a factor that determine the overconfidence of the user. A higher degree of choices presented by the system and level of interactivity is also features that may introduce bias and suboptimal decision making, by increasing the user's overconfidence and risky behavior (C. W. Chen & Koufaris, 2015). On the other hand, the flexibility and adaptability of the BI solution is shown as an important system feature because of the different, and possibly conflicting, requirements of different user (Işik et al., 2013; Kowalczyk & Buxmann, 2015).

Another theme in the research is concentrated around the user characteristics, and how this affects the acceptance and use of BI solutions. Some studies have indicated that a user's decision-making practice is affected by their cognitive abilities (Dilla et al., 2010; Yigitbasioglu & Velcu, 2012) and that the presentation of information affects an user's judgement and decision making different depending on task-specific knowledge and experience (Dilla, Janvrin, & Jeffrey, 2013). In addition, studies have investigated how a user's expertise, satisfaction and the technical problems encountered affect the acceptance and use of a BI solution and the decision quality (Deng & Chi, 2012; Hou, 2012; Z. Lee, Wagner, & Shin, 2008). Lee et al. (2008) find that users with different levels of expertise perceive and use a BI solution differently, but are unsure how this affect decision quality. Level of expertise affect if the users perceive the solution as being restrictive or not, where it is different how the users use the system features and functions. However, it is task expertise, not decision support solution expertise, that are shown to have the largest effect on the decision quality (Z. Lee et al., 2008). User acceptance and use frequency and duration is also shown to have positive relation to the user satisfaction with the BI solution. Furthermore, this also affects the user performance of BI solution in terms of efficiency and effectiveness in the decision-making practice in MA (DeLone & McLean, 2003; Hou, 2012). User acceptance is an interesting factor to further investigate, especially for BI solutions, which tends to be rich in different features and functionalities. However, in this cross-disciplinary field it is still limited research on the actual user acceptance of specific BI solutions used in MA.

The last theme in BI in MA research is the impact of BI on the performance of MA tasks. The aim of these studies has been to investigate the value of BI through focusing on the link between BI and MA tasks (Bronzo et al., 2013; Elbashir et al., 2008, 2011, 2013; Vukšić, Bach, & Popovič, 2013). BI-solutions are shown to be used in MA as a tool to provide performance information to decision makers for support (Vukšić et al., 2013) and through this affect business processes, management control and organizational performance (Elbashir et al., 2008, 2011). However, to fully utilize the opportunities of using BI in MA it is important to match the user's needs and capabilities, with the features of the BI solution (Vukšić et al., 2013). This relates to and strengthen the findings of a correlation between decision making quality, and the fit between the system features, the task and the user characteristics (Dilla et al., 2010; Yigitbasioglu & Velcu, 2012). This represents one of the most prevailing challenges a company may face when implementing and utilizing a BI solution for decision support in MA.

In addition to the themes identified in our literature review, the new reality in BI have also opened for end-users to have direct access to data and the ability to apply analytical and visualization solutions to support in decision making (Işik et al., 2013). For an organization, this poses new challenges regarding the overall strategy and structure, and the implementation of data-driven decision making in organizations have raised some tensions (Rikhardsson & Yigitbasioglu, 2018). This consist of challenges between flexibility and stability of data sources and solutions, challenges involving complexity and understandability of data sources and solutions, and challenges between broad and focused scope of the analyses. Further research on how to balance problems within standardization, flexibility, complexity, interactivity and focus scope of the data sources and BI solutions will add valuable insights in the research field of BI in MA.

Based on the emphasize current research have on the user characteristics, and the fit between this and system features and the task, it is clear that different features of the BI solution and the user have implications of how a dashboard should be designed to get the most value from using BI in MA. However, there are still many areas to explore further. In MA there is a lack of knowledge and empirical evidence about the extent of actual use of visualization solutions and their effectiveness. In addition, it is valuable to look further into required features of a BI solution for use in MA for different users and tasks. Users may have different requirements for the features, depending on the specific task, and further research highlighting this is necessary. In addition, as research have shown that different features of a BI solutions may affect the user's cognitive load and bias it is important to increase the understanding of the decision-making process itself, the nature of the tasks, and the user requirements for a BI solution.

2.4. Summary of Theoretical Foundation

Chapter 2 provides the definitions of data, MA, decision making and BI. We have also presented relevant literature and existing research in the fields of MA and information systems. Based on the reviewed literature we have presented some interesting areas that are missing further research. Many of the reviewed studies are conceptual and does not prove empirical research on the use of BI solutions for data-driven decision making in MA. The general conclusion is that there is a lack of cross-disciplinary research that focus on the application of BI solutions in the field of MA. Given the possible impact BI solutions is predicted to have on decision making in an organization, there is a lot of potential for research in this field. We have identified some research gaps especially within how different features of the BI solution and different user characteristics influence the use and acceptance of different solutions in organizations.

3. Theoretical Framework of TAM

In this part we will explain the theoretical framework of the Technology Acceptance Model (TAM) which we use as our framework for our data collection and analysis. We found this theory suitable for our thesis because it aims to examine what affects actual use with the variable behavioral intention to use, which is highly dependent on the user's satisfaction. In addition, the model's flexibility allows for adopting external variables that further aim to explain the acceptance and use, and this is relevant for us as our case contexts require multiple explaining variables. Furthermore, in the IS field, TAM is a highly verified model with a reputation of high predictive power and is generally considered one of the most influential theoretical frameworks for describing an user's acceptance and use of technological innovations (Y. Lee, Kozar, & Larsen, 2003). The theory is extensively used by researchers in a range of situations with different control variables (Davis, Bagozzi, & Warshaw, 1989; Giovanis, Binioris, & Polychronopoulos, 2012; Taylor & Todd, 1995; Venkatesh & Morris, 2000; Wang, Wang, Lin, & Tang, 2003).

In chapter 3.1 we will go through the contents of TAM, with an explanation of the different variables of the model. Further, chapter 3.2 will go through the different modifications that have been applied to TAM over time, which again will be used as the grounds for our research model. We will present our research model in chapter 3.3, before we explain the different constructs we have included and present our hypotheses in chapter 3.4. In chapter 3.5. we address the possible limitations with TAM.

3.1. The Technology Acceptance Model

Over the last decades a main concern has been the adoption and use of information technologies in the workplace. As mentioned, significant developments in technologies and solutions has been made, but there has been a continuing problem of underutilized systems. Research in this area has been of high priority and over the last decade significant progress has been made (Venkatesh & Davis, 2000). In particular, the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989) has gained significant theoretical and empirical support. TAM has been found to consistently explain a substantial percentage of variance in information technology usage intentions and behavior, and is favorable over alternatives like Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) (Venkatesh & Davis, 2000). As of TRA, TAM is an adoption of this, especially meant to explain behaviors related to solutions within IS (Davis et al., 1989). Moreover, studies have found that TAM has a slightly empirical advantage over TPB, in addition being a simpler and a more powerful theoretical framework for research on acceptance and use of a technology (Y. Lee et al., 2003)

TAM can explain user behavior across a range of technologies and populations. The model is helpful both for prediction and explanations, which makes the researchers able to identify if a system is acceptable or not, and accompany this with the appropriate actions (Davis et al., 1989). TAM hypothesize that an individual's acceptance behaviors to a system is explained by two principal beliefs: Perceived usefulness (PU) and perceived ease of use (PEOU). These constructs is based on research that have found that people tend to adapt their use based on "(…) the extent they believe it will help them perform their job better and to what degree they believe that the system is too hard to use and that the performance benefits of usage are outweighed by the effort" (Davis, 1989, p. 320). TAM also states that perceived usefulness is influenced by perceived ease of use, because, other thing being equal, the less effortless the system is to use, the more useful it can be to increase job performance (Davis, 1989).

TAM theorize that actual usage of a system is determined by the user's behavioral intention to use (BIU), where BIU is determined by PU and the person's attitude toward using the system (ATU). These relationships imply that people form behavioral intentions to actual use, and to which they believe will increase their job performance. According to the model, ATU is determined by PU and PEOU. This is adapted from TRA where attitudes toward a behavior are influenced by relevant beliefs.

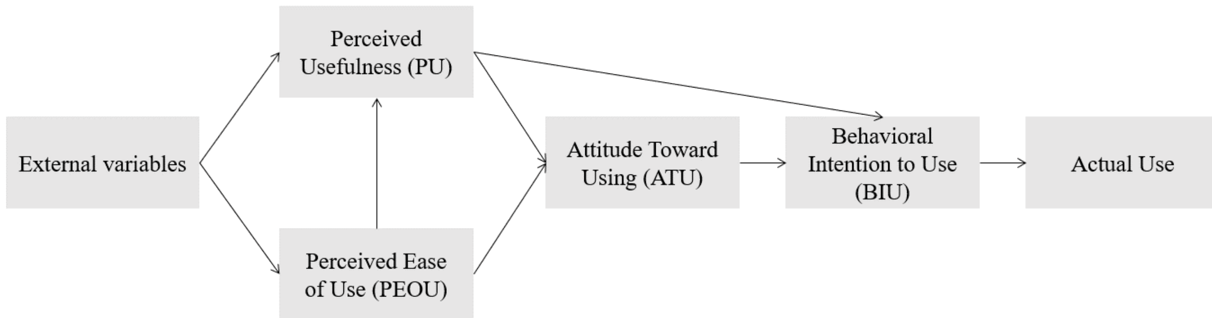

Figure 2- TAM. Adapted from "A Model of the Antecedents of Perceived Ease of Use: Development and Test" by F. Davis and V. Venkatesh, 1989, Decision Sciences, 27, p.451-481

In addition, TAM has theorized both PU and PEOU to be affected by various external variables. An overview over the complete model is seen in figure 2. Davis et al. (1989, p. 988) define these as factors that "(…) provide the bridge between the internal beliefs, attitudes and intentions represented in TAM and the various individual differences, situational constraints and managerially controllable interventions impinging on behavior". External variables can for example be user characteristics and system features. From the introduction of TAM in 1989 and up until 2007, over 70 different external variables has been proposed by different researchers (Yousafzai, Foxall, & Pallister, 2007).

3.2. Modifications of TAM

In this section we will explain the different modifications that have been applied to TAM over time, which we will use further to develop our research model.

The different elements and constructs in the model have, as mentioned, been through extensive verification and validation by several studies. We have looked further into some studies that we mean are relevant for our thesis, as these have all used the framework on research on a comparable technology, but in different contexts with a focus on multiple external variables (e.g. Giovanis et al., 2012; Venkatesh & Davis, 2000; Wang et al., 2003). The studies have in common that they all have used the theoretical framework to explain acceptance and use of a technology in the IS field. The findings and learnings from these studies have impacted our design of the research model and its constructs.

Early on, the construct of ATU was found to have only a partial, or none, mediating effect on BIU (Davis et al., 1989; Taylor & Todd, 1995). This is strengthened by the fact that some studies have found that both PU and PEOU have a direct effect on BIU (Giovanis et al., 2012; Venkatesh & Davis, 2000).

Through the linkages and definitions in TAM, the model taps into the instrumental outcomes a user associates with the use of a technology (Davis, 1989). In 2000, Venkatesh and Davis presented research on an extended model, TAM2, which included additional key determinants to TAM's construct. The motivation for this was to better understand how different effects of the determinants changed when user experience increases over time. TAM2 incorporates additional theoretical constructs covering cognitive instrumental processes. Meaning that people form their perceived usefulness by comparing the systems capabilities with their needs in the job. One key component of this matching process is job relevance, which is defined as "(…) an individual's perception regarding the degree to which the target system is applicable to his or her job" (Venkatesh & Davis, 2000, p. 191). Further, building on other models in technology acceptance and earlier research on TAM, Karahanna, Agarwal and Angst (2006), provided a comprehensive definition of a compatibility construct. By doing this they could hypothesize a casual linkage between compatibility beliefs and perceived usefulness and perceived ease of use. They described the content of this constructs as, compatibility with preferred work style, existing work practices, prior experience and values (Karahanna et al., 2006).

Several empirical studies have also found that computer self-efficacy as a construct have significant effects on a user's acceptance of a system through perceived usefulness and perceived ease of use (Taylor & Todd, 1995; Venkatesh, 2000; Venkatesh & Morris, 2000; Wang et al., 2003). Computer self-efficacy is an interesting construct for capturing some of the differing variables on an individual level, as this can be manipulated and adapted through training and promotion approaches. Computer self-efficacy is also found to have a strong connection with age (Giovanis et al., 2012). Older individuals may find new technologies interesting, but the understanding can be limited as they feel it is not easy for them. The limited experience of older individuals may therefore lead to self-efficacy concerns about the system (Bandura, 1997), which makes them perceive a system as less compatible with their existing way of living and working and less useful both in the short and long term (Giovanis et al., 2012).

3.3. Research Model

In this section we will explain our research model, built on the original TAM explained in 3.1, and the modifications explained in chapter 3.2. Our primary goal in this thesis is to use TAM to examine user acceptance of a particular system and find which factors that influence the actual use the most. To do this we will examine the relationships in the research model through the hypotheses, working from the external variables and forward to the actual use.

The constructs and hypotheses presented in chapter 3.4 are the basis for our research model, as seen in figure 3. This is based on the original TAM from Davis (1989) and Davis et al. (1989) and relevant modifications based on presented research.

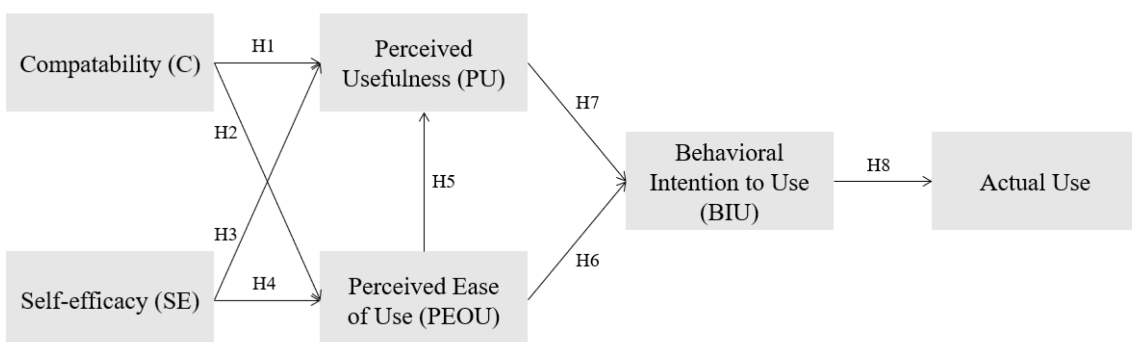

Figure 3- Research model, based on TAM and extensions.

3.4. Constructs

In this section we will explain the constructs of our research model, presented in chapter 3.3. These constructs will be explained one by one in separate subchapters, with their respective hypotheses.

As seen in our research model, each of the constructs is related to each other, where compatibility and self-efficacy are independent variables, and perceived usefulness, perceived ease of use and behavioral intention to use are dependent variables. In this section we will give a further explanation of each construct and the relationships, where we will start with the independent variables and continue with the dependent variables.

3.4.1. Compatibility

Building on the research by Karahanna et al. (2006) on the comprehensive compatibility construct, and the fact that studies have found such a construct being significant (Hameed, Counsell, & Swift, 2012), we have incorporated this construct in our model. They define the conceptual idea of compatibility as the "perceived cognitive distance between an innovation and precursor methods for accomplishing tasks" (Karahanna et al., 2006, p. 784). As mentioned, this construct consists of four dimensions which has the following explanations:

> (1) compatibility with existing work practices, measuring the extent to which a technology "fits" with a user's current work process; (2) compatibility with preferred work style, capturing the possibility offered by the technology of being consistent with a desired work style; (3) compatibility with prior experience, reflecting a fit between the target technology and a variety of users' past encounters with technology; and (4) compatibility with values, epitomizing the match between the possibilities offered by the technology and the user's dominant value system. (Karahanna et al., 2006, p. 787)

Building on this definition, it is hypothesized that higher compatibility beliefs will have a positive effect on the user's acceptance of a system, through the constructs of perceived usefulness and perceived ease of use.

> *H1: Compatibility will have a positive effect with perceived usefulness*
> *H2: Compatibility will have a positive effect on perceived ease of use*

3.4.2. Self-efficacy

According to TAM, self-efficacy is a basic mechanism and a strong determinant to how PEOU influence a person's attitudes and behaviors (Davis et al., 1989; Venkatesh & Davis, 1996). The original model has incorporated this mechanism into the construct of PEOU. However, we have adopted this as a separate construct to capture some external user characteristics. We found this construct particular relevant for our research due to the strong link between self-efficacy and age.

Self-efficacy is defined as "(…) judgments of how well one can execute courses of action required to deal with prospective situations" (Bandura, 1982, p. 122). Several empirical studies have found self-efficacy as a strong determinant of a user's acceptance of a system (Hameed et al., 2012; Venkatesh & Morris, 2000; Wang et al., 2003). Thus, it is hypothesized that a higher self-efficacy, will lead to a higher acceptance of and intention to use a system, through perceived usefulness and perceived ease of use.

H3: Self-efficacy will have a positive effect on perceived usefulness
H4: Self-efficacy will have a positive effect on perceived ease of use

3.4.3. Perceived Ease of Use

Davis (1989) define perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort". This definition is based on Radner and Rothschild (1975) statement that effort is a limited resource that must be allocated to a person's various activities. Perceived ease of use as a effort-oriented construct have been widely studied and been found to be a central belief to explain an user's acceptance behavior (Venkatesh & Davis, 2000). Thus, it is hypothesized that the greater perceived ease of use of the system, the more useful it is perceived, and the higher the acceptance of the user.

H5: Perceived ease of use will have a positive effect on perceived usefulness
H6: Perceived ease of use will have a positive effect on behavioral intention to use

3.4.4. Perceived Usefulness

Davis (1989) define perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance". Perceived usefulness has over several empirical studies been found to have consistent significant effect on the behavioral intention to use, with a standardized regression coefficient generally around 0.6 (Venkatesh & Davis, 2000). Thus, it is hypothesized that the higher perceived usefulness, the higher the behavioral intention to use are.

H7: Perceived usefulness will have a positive effect on behavioral intention to use

3.4.5. Behavioral Intention to Use

We have adapted behavioral intention (BIU) as a construct based on evidences of strong linkages between both PU and PEOU to BIU. BIU captures the strength of a user's intention to use a system and the feelings the user have about performing the targeted behavior (Davis et al., 1989). Using BIU as a construct let us measure the user's likelihood to engage in using the targeted system and it is found that a user's performance of a specified behavior is determined by the user's behavioral intention to perform the behavior (Davis et al., 1989; Taylor & Todd, 1995). Thus, it is hypothesized that the higher the behavioral intentions to use, the higher is the user's actual usage.

H8: Behavioral intention to use will have a positive effect on actual use

3.5. Limitations with TAM

Even if TAM is a highly verified theoretical framework for research on technology acceptance and use within the IS field, it has also received criticism on some elements. In this section we will present some of the prevailing limitations.

One of the most reported limitations of TAM is deterioration of generalizability due to examination of one solution used for one task, with a homogenous group of respondents at a single point of time (Y. Lee et al., 2003). Considering that a user's perception, beliefs and intentions usually change over time, some studies emphasize the importance of measuring at several points in time (Y. Lee et al., 2003; Yousafzai et al., 2007). However, in practice, such choices are influenced by the nature of the research and the prevailing limitations.

Further, several analyses of the use of TAM points out that the most widely used method for data collection for TAM is self-reporting of use rather than measuring actual use (Y. Lee et al., 2003; Yousafzai et al., 2007). Such measures is subjective and have some disadvantages, such as reporting bias, inaccurate estimation and common-method bias, compared to objective measures (Yousafzai et al., 2007). However, some research have also suggested that self-reported usage have a high correlation with actual usage (e.g. Taylor & Todd, 1995). When using subjective measures on acceptance and use, attention should therefore be focused on establishing a thorough understanding of the context and accurate development of the measurement items used to avoid biases in self-reported measures.

4. Research Methodology

In chapter 4 we present and discuss our methodological choices for how we have answered our research question in this thesis. Methodological choices refers to the informed choices regarding philosophy, approach, design and data collection that fits best with the respective research (Saunders, Lewis, & Thornhill, 2019).

This chapter consist of eight sections. In section 4.1 we will introduce the research philosophy, while 4.2. explains the approach to theory development. Section 4.3. regards the research design, and includes four subsections explaining our choice of purpose, approach, strategy and time horizon. In section 4.4. the data collection of both primary and secondary data is explained in separate subsections, while chapter 4.5. describes the process of the data analysis. The research quality is described in chapter 4.6., which is divided into the two subsections: validity and reliability. The research ethics are explained in section 4.7, while a summary of our methodological choices is presented in chapter 4.8, to give a more emphasized overview of the research methodology we have chosen.

4.1. Research philosophy

According to Saunders, Lewis and Thornhill (2019, p. 130), *Research philosophy* "refers to a system of beliefs and assumptions about the development of knowledge". This is to say that in the process of research, one will automatically make a series of assumptions, which again will shape the interpretation of the research question, the method and the findings. The choice of research philosophy will underpin the entire research, and consequently, it is important being aware of the choice of philosophy (Saunders et al., 2019).

The different research philosophies can be placed on a spectrum, with interpretivism on one side, and positivism on the other. Pragmatism can be placed anywhere on this spectrum, with the possibility of containing several different positions (Alasuutari, Bickman, & Brannen, 2008). We find pragmatism being the most fitting philosophy for our thesis, as research conducted with pragmatism starts with a problem, and in addition to the theoretical contribution the aim is to contribute practical solutions which can help future practice concerning such problems (Saunders et al., 2019). As a result, pragmatists use the method, or methods, that can generate the most relevant data for the problem in question, and it is not uncommon that mixed methods are used.

Our first research question *Which factors affects the acceptance and use of BI, such as dashboards, as a decision supporting solution in MA?* leans more towards the positivism side of the spectrum, as it seeks to identify observable factors using aspects of a scientific method. The second research question *How do the current needs for BI solutions match the present user characteristics and system features?* will be more fully pragmatic, with interpretivism tendencies, as this seeks to solve a problem and have an emphasis on practical outcomes, while also including focus on narratives from the open-ended questions. As the last research question is the one with most emphasis in the thesis as a whole, we find pragmatism being the most fitting research philosophy for us.

4.2. Approach to Theory Development

This section will explain our approach to theory development. There are traditionally two contrasting approaches to this: inductive and deductive. The first explains an approach where one starts with data and turns this into theory. The latter is the opposite, moving from theory and hypotheses to data (Johannessen, Christoffersen, & Tufte, 2011). The abductive approach is an alternative to these approaches, where one can move more back and forth more freely between theory and data. With the abductive approach one is collecting data for exploration of themes and patterns to modify existing theory, or generate new one (Saunders et al., 2019).

The research approach selected for our thesis is abduction, as we combine using deductive and inductive approaches throughout the different phases of our research. For the most part, our research proceeds through four phases: (1) deducting and formulating hypotheses from existing literature, (2) testing the hypotheses, (3) analyzing the results and (4) modifying the theory if necessary (Saunders et al., 2019). The first three stages of the research process will be deductive by nature, but as the research in the cross-disciplinary field of BI and MA is limited, to our knowledge, we will use the collected data to generate insights on the topic in the fourth stage, and this implies an inductive approach. According to the definition of abductive approach by Saunders et.al (2019, p. 153), this means that an abductive approach is fitting for our thesis.

4.3. Research Design

The research design is the broad plan of how the researcher undertakes the entire process of answering the research questions (Saunders et al., 2019). In subsection 4.3.1 we will explain our purpose of research design, while subsection 4.3.2 will consider the research approach. The research strategy is described in 4.3.3, and the time horizon is explained in 4.3.4.

4.3.1. Purpose of Research Design

The purpose of research design can be classified as exploratory, descriptive, explanatory, evaluative or a combination of either of these (Saunders et al., 2019). In short, exploratory studies have a focus on clarifying and understanding a problem or phenomenon by asking open questions. Descriptive studies on the other hand, have a focus on *what, who, where* questions or descriptions to gain insight to an accurate profile of a situation or event (Raţă, 2014; Saunders et al., 2019). As we have opted for an abductive research approach, it is natural that our purpose of research design will be a combination of descriptive and exploratory.

Our first research question *Which factors affects the acceptance and use of BI, such as dashboards, as a decision supporting solution in MA?* seeks to gain an accurate profile of the factors affecting a dependent variable, which in nature implies a descriptive purpose. However, our second research question *How do the current needs for BI solutions match the present user characteristics and system features?* seeks to gain insight into the needs of the users and establish if this matches the current features and characteristics. The second research question is more exploratory in nature.

4.3.2. Research Approach

According to Creswell (2014, p. 3) research approaches are defined as: “plans and procedures for research that span the steps from broad assumptions to detailed methods of data collection, analysis and interpretation”. The research approach can be classified as either qualitative, quantitative or mixed, where they can be placed on a continuum (Creswell, 2014). As we have chosen a combined purpose for research design, it is also natural that we will opt for a mixed method for our research approach. This is again coinciding with our choice of research philosophy, where a pragmatist philosophy is commonly used with a mixed research approach (Saunders et al., 2019).

Within mixed methods there are numerous different approaches, but the common denominator with these approaches is that the combination of quantitative and qualitative approaches provides a more profound and complete understanding of the research problem in question (Creswell, 2014). The quantitative component in our research is the main body of our survey, which mainly consists of testing variables and relationships. However, we have also included, in the same survey, some open-ended questions to gain even more insight into the problem in question. These open-ended questions will play the role of the qualitative component in our research. As we are collecting both quantitative and qualitative data in the same survey, and subsequently at the same time, we find our study to comply with a concurrent embedded design. Our main argument for using this approach is that we are in need of both the accurate insights gained from the numerical data from the survey, and the more personal reflections of the open-ended questions to answer our research question.

4.3.3. Research Strategy

The choice of research strategy explains how a researcher intend to answer the research question and should be guided by the nature of this, in addition to the research philosophy, approach and purpose, as well as practical considerations as time and resources (Creswell, 2014). Our previously made choices in methodology coincide well with a choice of survey as a research strategy. Initially we opted for a mixed strategy including both survey and interviews. Due to restrictions in time and resources, both on our part, and the respondents, we found it more appropriate to use a survey and aim to incorporate the aspects of interviews by including open-ended question. Consequently this choice makes for a mixed research method, and it also incorporates the pragmatist view of accepting that multiple realities might be present (Saunders et al., 2019).

Survey research is usually recommended when using a research model with clearly defined independent and dependent variables with expected relationships to be tested against the observations of the phenomenon. In addition, in research on acceptance and use of a technology at the user level, survey has been a widely used strategy and is shown being appropriate for the purpose of such research (Choudrie & Dwivedi, 2005; Rikhardsson & Yigitbasioglu, 2018).

Using survey as a strategy is a convenient choice due to practical considerations such as time and resources, because it let us reach the necessary respondents in an effective and inexpensive manner. In addition, a self-administered survey allows the respondents to answer anonymously and at their own convenience, which is shown being less likely to contaminate or falsify the respondent's answer, and increase the response rate (Saunders et al., 2019).

4.3.4. Time Horizon

The time horizon of a research is either longitudinal or cross-sectional (Saunders et al., 2019). For this thesis, the research is conducted as a cross-sectional survey. This is affected by the natural time constraint inherent to writing a master thesis. A cross-sectional survey studies a phenomenon and give data from a population at a given point in time (Saunders et al., 2019). Further, for testing variables and the relationship between them using a survey study, cross-sectional data is appropriate.

As the concept of BI is quite new and unexplored, the use of such solutions is in constant change and there are rapid developments in the relevant technologies. Accordingly, conducting a longitudinal study would be interesting to explore the phenomena over a longer time period. For future research on this cross-disciplinary field it would therefore gain valuable insights to conduct a longitudinal study that aim to explore how acceptance and use of BI solutions evolve over time.

4.4. Data Collection

This section will describe the process of data collection. Data collection is either done by collecting primary or secondary data. The data collection is influenced by our choices regarding research design. Subsection 4.4.1 regards our primary data, and will be further divided into several parts, where 4.4.1.1. will regard the respondents, 4.4.1.2. explains the TAM constructs and 4.4.1.3. will explain additional items in the questionnaire. Subsection 4.4.2. briefly explains relevant secondary data.

4.4.1. Primary Data: Questionnaire

We have used a questionnaire to collect our primary data. A questionnaire is defined as a "general term to include all methods of data collection in which each person is asked to respond to the same set of questions in a predetermined order"(Saunders et al., 2019, p. 503). By our choice of survey strategy, we found it convenient to use a questionnaire, as this enables us to analyze the variables in our research model and describe the relationships between them. Furthermore, it is a good method for gathering data about a user's attitudes, behaviors, values and experiences with a phenomenon such as BI solutions.

To answer our research question, we see it advantageous to use a semi-structured questionnaire, with both adapted and self-developed questions. To allow for using TAM as a framework, we have used adapted close-ended questions with a seven-point Likert-scale. All items using the Likert scale was formulated positively. The values used were (1) strongly disagree, (2) Disagree, (3) Slightly disagree, (4) Neutral, (5) Slightly agree, (6) Agree and (7) Strongly agree. Additionally, we have included some list and category questions. Such questions are designed with some predefined response categories and are convenient for collecting factual data about the respondents (Saunders et al., 2019).

Further, to be able to elaborate on the findings from our research model using TAM and other close-ended question included in the questionnaire, we find it beneficial to include open-ended question that let the respondents comment on the different elements. The inclusion of these questions is based on the nature of our research question and the fact that there is yet limited research on the cross-disciplinary field of MA and IS, which makes it difficult to validate that our close-ended questions capture all relevant information. These questions also allow for a more detailed picture of the phenomena.

The questionnaire is conducted in Microsoft Forms as a self-completed questionnaire. This is a free online program, and employees in Equinor are familiar with using this tool. The respondents were notified to expect a questionnaire beforehand and the questionnaire was distributed by e-mail by a contact person in the company.

4.4.1.1. Respondents

Since our focus in this thesis is on the use of BI solutions for decision support in MA functions, our target population is decision makers in a company that is responsible for taking highly-influential decisions. For this study our target population is Equinor and similar companies, based on size, nature of operations and features.

The choice of sample is influenced by our aspiration to target people that can provide us with deep insights to the theme. In addition to this, restrictions concerning both time and resources are present. As we include both close-ended and open-ended questions in our survey to obtain more insight, we subsequently limited the possibility of distributing the survey to a vast number of respondents. The reason for this being that the analysis of open-ended questions requires more time and resources to analyze, as they need to be analyzed separately. For us this became a weighting between more respondents, and what we considered deeper insight, where we opted for the latter. As we mapped out that the target population seem to have many similarities, we therefore wanted to focus on a smaller sample in one single company, while still retaining the possibility of applying this to other companies.

To identify relevant respondents in Equinor we were helped by a contact person in the company. The decision makers in Equinor that base their decisions mainly on financial data is typical the production and platform managers. Due to limitations of the thesis, our aim was to select respondents who were adequately suited to answer our research question and focus on these. This is a form of non-probability, convenience sampling based on certain criteria, which is a practical sampling method for reaching out to respondents with an adequate volume of information available (Johannessen et al., 2011). Our sample of respondents consisted of 19 employees in DPN in Equinor, which were chosen based on their responsibilities and relevance to our research topic.

Table 1- Data collection and response rate

	Sent out	Completed surveys	Response rate
Initial survey invitation	19	10	52,63 %
Reminder 1	9	5	55,55 %
Reminder 2	4	1	25 %
Total		16	84,21 %

An invitation to participate in the survey was sent to all 19 employees in our sample. The survey was administered in the period of 21st of October to 8th of November 2019. In total, 16 responded to the survey, which gives a total response rate of 84,21 %. Two follow-ups were sent out during the data collection period to further encourage participation, at 1st and 7th of November. Evidently, as shown in table 1, the reminder had a substantial effect on the response rate.

4.4.1.2. TAM Constructs and Items

In order to explore the variables from our research model and the relationships, we used items adapted from existing academic research. Each of the constructs presented in chapter 3.4. represents variables that cannot be observed and measured directly and therefore needs to be operationalized. To operationalize implicate "the translation of concepts into tangible indicators of their existence" (Saunders et al., 2019, p. 677). Thus, we have translated these constructs into meaningful and measurable items, as shown in chapter 5.2.2, table 6, by leveraging existing scales, to ensure consistency with previous research.

Regarding perceived usefulness (PU), perceived ease of use (PEOU) and behavioral intention to use (BIU), all have measurements items that are recommended and/or validated in IS acceptance and use. We have used items validated by, among others, Davis (1989), Venkatesh (2000), Venkatesh & Davis (1996, 2000) and further made some adjustments to ensure appropriacy with this study. Concerning compatibility (C), the items used are adapted from validated measurements items by Karahanna et al. (2006) and Taylor & Todd (1995). Further, for self-efficacy (SE) we have also used items based on Karahanna et al. (2006), in addition to Venkatesh & Davis (1996) and Wang et al. (2003). Items measuring C and SE have also minor adjustments to fit the context of this study. We have also included some self-constructed items for some of the constructs to further cover all interesting aspects of the variables in this context, based on feedback, adjustment iterations and conversations with relevant people.

Furthermore, for all constructs we included an open-ended question at the end of the page, where the respondents were able to freely comment on the topic and questions included. This was to ensure that all valuable information and thoughts that the respondents may have, was captured in the survey.

4.4.1.3. Additional Items

In addition to the specific items for measuring the constructs in our research model, we added some additional close-ended questions. The first page of the survey contains general questions to collect factual data about the respondents, as age, gender, education, position in the company and seniority. Such data is valuable to explore how attitudes and behaviors differ, and to check representativeness of the sample (Saunders et al., 2019). To further establish an understanding of todays' situation and what solutions and system the respondents use, we included some close-ended category questions regarding which solutions they use and how often. These questions are shown in table 2 and aim at establishing the actual use and can be a measurement for this variable in our research model.

Table 2- Questions regarding todays' use of solutions

Question	**Answer categories**
Which BI-tools do you currently use on a regular basis when treating financial data? (Several options possible)	Power BI, Excel, Dashboard in MIS (from SAP), Other
How often do you actively use these BI- tools in the practice of decision-making?	Several times a day, Once a day, Several times a week, Once a week, Several times a month, Once a month, More rarely

In addition, we also added some close-ended question regarding other needs and demands the respondents may have concerning the acceptance and use of BI-solutions. These questions were based on conversations with our contact person in the company, as well as interesting topics found during our literature review. For most of them we adapted the 7-point Likert scale and for one we used a category question, as seen in table 3.

Table 3- Additional questions

Question	Answer categories
I would like to be able to customize the dashboard and its contents myself. I prefer interactive dashboards. I would like to use standardized dashboards. I am dependent on real-time data in my decision-making. Using dashboards facilitates an increased level of collaboration.	7-Point Likert Scale
Which "levels" of data would you like to have access to, to make well-based decisions?	Asset level, Area level, Country level, Company level

4.4.2. Secondary Data

In addition to our collected primary data, we used some secondary data sources such as preparatory conversations, company reports and existing surveys. These documents are used as a guide when developing our questionnaire, in addition to establishing a better knowledge about the broader context of this study. The insights we gained about the phenomena and organizational context beforehand was valuable for preparatory work and when formulating our questions. It also added understanding during our analyses, provided sources for comparison of findings and made us able to place our findings from the survey in a wider context.

4.5. Data Analysis

This thesis has followed a concurrent embedded mixed method with an abductive approach. Consequently, for our data analysis we use both quantitative and qualitative analysis. The majority of our data is quantitative, and this is the leading analyze technique. We will structure our analysis by starting with our research model, then including and analyzing all open-ended questions, before lastly including the additional close-ended questions.

The process of quantitative analysis of data consist of three phases: Preparing data, data entry and checking, and selecting appropriate format for explore and present data. For quantitative analysis, data recorded using numerical codes are the most appropriate, as this enables for quicker and better analyses. All close-ended question should therefore be numerical coded. Further, when the data is ready for analysis it is important that the data layout and format match the analysis software, data is saved and backed-up and data is checked for errors and if any found, corrected. Using Microsoft forms as a questionnaire software provides us with automated data input and the possibility for analyzing data within the survey tool, as well as downloading the data as a excel-file for external analysis.

In the quantitative analysis, we will start with descriptive statistics to explore and highlight the main trends and results from the questionnaire. Further, to analyze the constructs and relationships in our research model, we will conduct an exploratory factor analysis. This is conducted to verify which items in the questionnaire actually measure what they intend to measure. Subsequently, a data reduction is done to reduce our data set into distinct variables, based on which measurement items explain which construct. Further, to test our hypotheses, we will conduct a correlation analysis to discover which variables are connected to each other and if the relationships are statistically significant.

In addition, to elaborate further on the findings from the quantitative analysis, we analyze our open-ended question. For analyzing qualitative data, it is appropriate with a process that include summarizing and categorizing in order to group the data into different themes. For our qualitative analyses we have used the data display and analysis approach which consist of data condensation by discovering categories in the data and displaying and drawing conclusions based on these. Even if our questionnaire was conducted in Norwegian, we opt for not translating the answers in whole, but just the relevant parts of it and the corresponding categories. We opted for doing so as the important parts of the answers for our purpose are the essence of them, not the specific wording.

4.6. Research Quality

To make sure the questionnaire was conducted in a proper way and ensure quality in our research, we have considered several different requirements and factors as presented in Saunders et al. (2019) and Johannessen et al. (2011). This section is divided into two subsections, where 4.6.1. will discuss the validity of the research, and 4.6.2. will discuss the reliability. For survey studies and questionnaires, the validity and reliability of the research study depend, to a large extent, on the design and structure of the survey and questions (Saunders et al., 2019).

4.6.1. Validity

"Validity refers to the appropriateness of the measures used, accuracy of the analysis of the results and generalizability of the findings" (Saunders et al., 2019, p. 214). Internal validity is the ability of the study to measure what the researcher intend to measure (Saunders et al., 2019). The survey was conducted in Norwegian, as formulating a questionnaire in the respondent's main language is favorable to ensure measurement validity (Brancato et al., 2004). The questionnaire was developed over several iterations, with feedback and adjustments, which mainly consisted of re-phrasing and re-wording. These iterations also served as a pre-study, and ensured the internal face validity of the survey, which refers to whether "the questionnaire appears to make sense" (Saunders et al., 2019, p. 541).

Concerning the design of the survey, there are several factors and trade-offs to consider regarding potential source of bias and threats to internal validity. For the grouping of items, we mainly focused this around the different constructs in the research model and avoided a mixing of these. General questions concerning age, gender, position, etc., were grouped together at the beginning, and additional questions beyond the constructs were grouped together at the end of the survey. The different question categories and constructs are placed on different pages to avoid survey fatigue related to long surveys. In addition, a trade-off is done between number of items per construct and total length of the survey. The survey is therefore limited to a completion time of around 10 minutes.

Furthermore, the design and format of the questions can be a threat to validity (Saunders et al., 2019). The measurement items used, when applicable, is based on validated scales from relevant research work, with some adjustment to fit the research context (see subsection 4.4.1.2.). To further ensure validity, all formulations are held as simple as possible to avoid confusion. For the close-ended questions, we have used only positive manner questions to simplify the questionnaire and prevent confusion with reverse-worded questions. Furthermore, to avoid various understandings of the terms used, we presented a definition and explanation of these, as seen in appendix 1.

External validity involves to what extent the results from the study can be generalized or transferred to other situations outside our studied situation (Johannessen et al., 2011). In empirical research and survey studies, the sample size should be sufficiently large enough to be representative for the target population. In this thesis we have a rather small sample, which indicate that it could be difficult to generalize. However, as we seek to identify general learnings from a particular case company and use these to contribute with knowledge beyond this setting, our sample should be viewed as one “typical” case that enables us to study the phenomena of BI in MA. Due to similarities in companies and the decision makers, we argue that our findings would be applicable to a group of companies with similarities in size, operations and features.

Furthermore, online surveys are often plagued by low response rates, and the respondent’s motivation to participate and respond accurately is a primary concern of questionnaires and a threat to the representativeness of the sample (Saunders et al., 2019). To avoid this, we included a cover letter that aimed to motivate the respondents, as seen in appendix 1. The letter explained the focus of the study and why their participation was requested, as well as how the response would be treated. In addition to stating the importance of their attendance for this master thesis, we highlighted how it could be useful for the company.

4.6.2. Reliability

The reliability refers to the consistency and the replicability attained in the study. A study has a high degree of reliability if the findings are consistent at different times and under different conditions (Saunders et al., 2019)

A factor that affects the reliability is consistency in the results, meaning to what degree that items measuring the same constructs correlates or not. One way to test if the study is internal consistent is the Cronbach's Alpha. This value is an estimated score between 0 and 1 showing the percentage of variance related to a set of items that are combined to measure a particular construct. Values above .7 is generally sufficient and one can conclude that the construct gives an acceptable explanation (Saunders et al., 2019). We will further explain our test for Cronbach's Alpha in chapter 5.3.3 and 5.3.5. Furthermore, as we have used a set of items for measuring the same construct, this ensures reliability by serving as "check questions".

4.7. Research Ethics

Research ethics refers to the standards of behavior that instruct the conduct of research concerning the rights of the people involved in the research, or those affected by it. Ethical concerns emerge during most phases of the research. This research has been conducted in compliance with NHH ethical research guidelines, and these are used, in addition to a set of ethical principles as described by Saunders et al. (2019), as guidance during our research work.

The reliability and quality of the study depends partially on the integrity and objectivity of the study and the researchers. This include the accuracy of the study, as well as an openly and truthful conduct throughout the study (Saunders et al., 2019). Following ethical principles, we have acted in a way that avoids deception, dishonesty, misrepresentation and partiality in both our conduct and presentations of data and findings. We have embraced a transparency in our thesis by presenting those assumptions and limitations that we are aware of, as well as including correct references to the sources of information used.

Further, even though our questionnaire initially was mandatory to complete, we have not forced any of the respondents to answer and they could at any time withdraw from the survey. To ensure privacy of those taking part, the data was collected and analyzed confidentially and with anonymity for the respondents. There is no matching key between data collection and identification of the respondents. The survey was therefore of no subject to notification to NSD (Norsk Senter for Forskningsdata).

4.8. Summary of Methodological Choices

Table 4 summarizes our methodological choices for this thesis.

Table 4- Summary of methodological choices

Dimension	**Methodological choice**
Research philosophy	Pragmatism
Approach to theory development	Abduction
Purpose of research design	Combined – Exploratory and descriptive
Research approach	Mixed – Concurrent embedded design
Research strategy	Survey
Time horizon	Cross-sectional
Data collection	Questionnaire
Data analysis	Quantitative- Correlation analysis Qualitative- Data display and analysis

5. Results

In chapter 5 we will present the results from the survey, and analysis of these results. In chapter 5.1 we will first present the case description, before we provide some descriptive statistics of the findings in chapter 5.2. We will then present the factor analysis and corresponding assumptions and reliability and validity assessments in chapter 5.3. In chapter 5.4 we will carry out a correlation analysis. Further, chapter 5.5. cover the qualitative analysis of the open-ended question, before we in chapter 5.6 analyze the addition items in the survey using descriptive statistics.

5.1. Case Description

Equinor is an international energy company with more than 20,000 employees. Equinor is the leading operator on the Norwegian continental shelf and they are engaged in development, production and exploration of oil, gas, wind and solar power. They are also a major supplier of natural gas, which includes activities such as processing, refining and trading. The company is present in more than 30 different countries and is headquartered in Stavanger, Norway. The company is partially owned by the Norwegian State, which have an ownership percentage of 67%. The company was founded in 1972 under the name Den Norske Stats Oljeselskap AS – Statoil, but as of 2018 the name was changed to Equinor (Equinor, 2018a).

Their activities are organized in eight different support divisions, as seen in figure 4, which shows the organizational chart for the management in Equinor (Equinor, 2018b). Geographically they operate in North and South America, Africa, Asia, Europe and Oceania, and Norway (Equinor, 2018a).

The support division we will be focusing on in our research is the DPN division. DPN is in charge of efficient and safe operations on the Norwegian continental shelf, including extracting crude oil, natural gas and natural gas liquid, and is made up of the following business clusters: Operations North, Operations West, Operations South and Operational Technology & Support (Equinor, 2018b). The organizational structure of DPN is shown in figure 5.

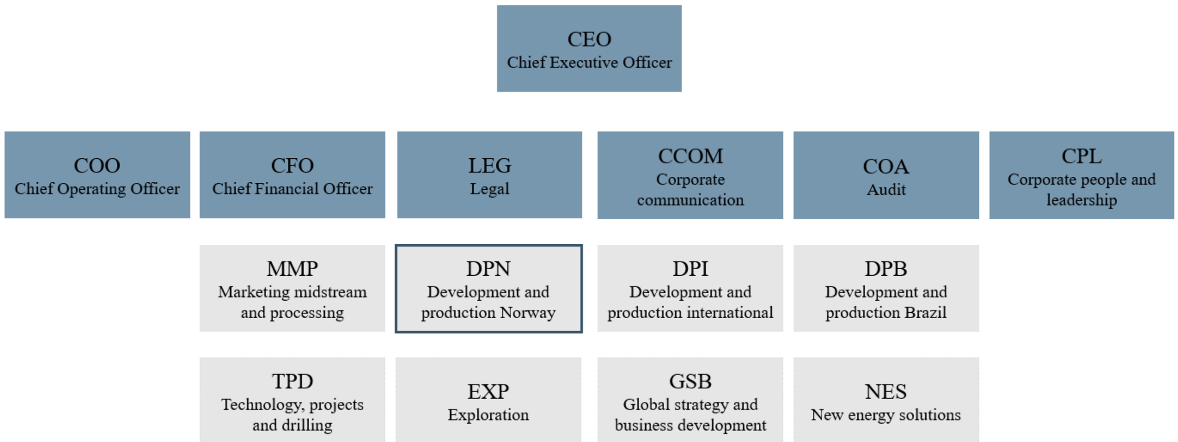

Figure 4 - Divisions Equinor. Adapted from "Organization", by Equinor, 2018 (https://www.equinor.com/en/about-us/organisation.html)

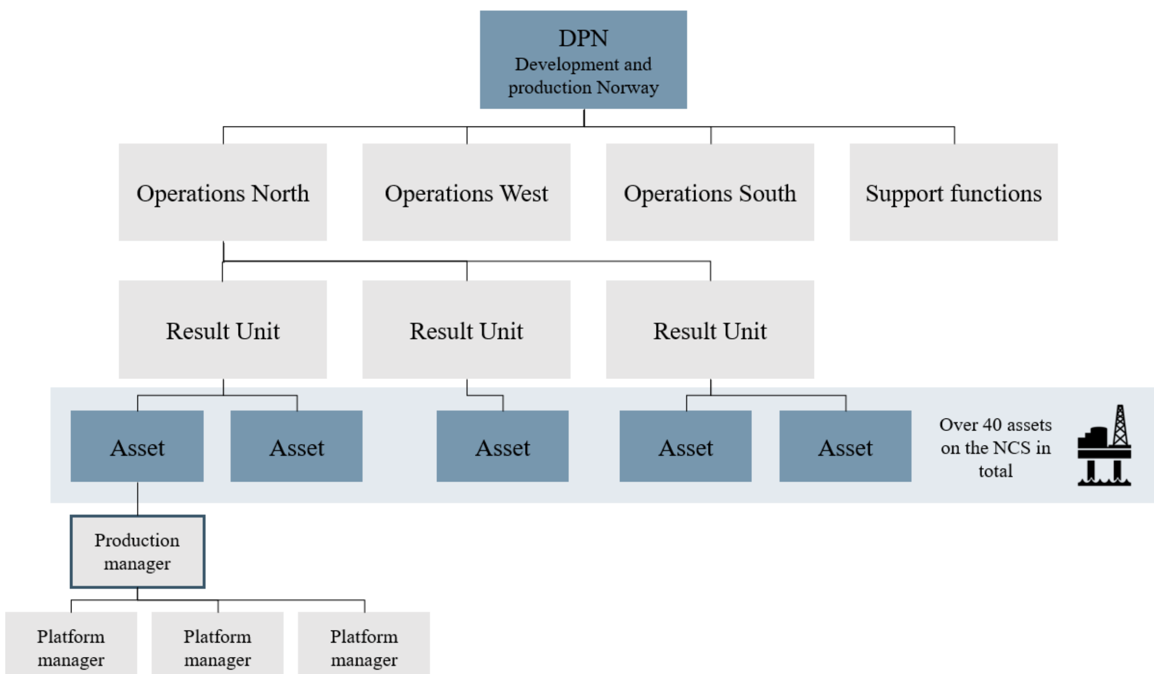

Figure 5- Organizational structure DPN Equinor

The structure shown in figure 5 is somewhat stylized, as Equinor operates with a matrix type of structure. However, as we do not find it relevant to go further into this, the structure shown here is explanatory for understanding how the DPN division works, and where our respondents belong in the division. As mentioned earlier, Equinor chose who the survey should be distributed to. The respondents are either production managers or managers of support functions, where the latter is typically product managers responsible for delivering products to the different assets. The common denominator for the respondents is that they are employees that are responsible for taking highly influential decisions on, or regarding, the asset level in the company.

5.2. Quantitative Analysis

In this section we will conduct and elaborate on our quantitative analysis. 5.2.1. will regard our data screening and descriptive statistics. The factor analysis will be described in 5.2.2, while 5.2.3. will discuss the correlation analysis.

5.2.1. Data Screening and Descriptive Statistics

In this section we will shortly present the data screening of our data in subsection 5.2.1.1, before we go through some descriptive statistics of the dataset in 5.2.1.2.

5.2.1.1. Data Screening

As data quality might be an issue when conducting an online survey, a thorough data screening is usually recommended. The reason for doing this is to ensure that the data is valid for further analysis, including applicability, reliability and validity of the data. The general goal with data screening is to remove respondents with insufficient responses or who are outside of the target population. In our case all the respondents are inside the target population, as Equinor were the ones who decided who should receive and respond to the survey. As for missing data, we had one respondent missing one Likert-question on compatibility, more specifically question C2. As this can be considered a random missing value, we opt for to removing this respondent. This choice is also justified by the fact that this respondent generally responds around the average, so that removing him from the data set don't change the outcomes. This means that we had N=15 complete survey responses. All these 15 responses were therefore taken to further analysis. The case of possible outliers did also not yield any need for removing any observations in our case and will therefore not be discussed any further. It is worth mentioning that N=15 is a small sample, and that we need to take this into account in our analysis.

5.2.1.2. Descriptive Statistics

The first section of our survey consists of questions regarding background information. The results from these questions are summarized in table 5. From this we see that the vast majority of the respondents are between 40-59 years old, male, have a master's degree in either economics or engineering and have worked in Equinor for 10-19 years. In addition to this we get the affirmation that the respondents are in positions known to make decisions, hence they are decision makers and inside the target population.

Table 5- Sample characteristics

	% Full Sample (N=15)
Age	
30-39	6.67 %
40-49	60.00 %
50-59	26.67 %
60-69	6.67 %
Gender	
Male	93.33 %
Female	6.67 %
Education level	
Bachelor	6.67 %
Master	93.33 %
Field of study	
Engineering	66.66 %
Economics	33.33 %
Current position?	
Production managers	60.00 %
Managers of support functions	40.00 %
Seniority	
0-9	6.67 %
10-19	66.67 %
20-29	13.33 %
30-39	13.33 %

In table 6 some descriptive statistics of the measurement items of TAM are shown. To make the comprehension of these statistics easier we have opted for including the measurement items with their respective questions in table 7 for reference. We see that the upper part of the scale is most frequently used, and the minimum response value is 2, which is only utilized in six of the 27 questions. The mean is also above 4 (neutral) for all questions, which indicates that the data is top-heavy. The columns for kurtosis and skewness show the distribution characteristics for the different measurement items. Kurtosis measures if the data is heavy- or light-tailed, and skewness measures the lack of symmetry in the data. High values for kurtosis indicate heavy tails, and therefore more outliers, whereas high skewness values indicate skewed data (Mardia, 1970).We observe that some of the items have relatively high values for skewness and kurtosis, which implies that there might be a problem with normality. This is especially relevant to measurement items PEOU2, BIU3 and SE9, and we will investigate the normality further in chapter 5.2.2.1. Furthermore, for the standard deviation, the items meant to measure the same construct have quite similar values. However, there are some differences from construct to construct. We see that for the items in PEOU and C, most items have values above 1, but for the other constructs, most items have values below 1. This implies that the respondents use a broader range of the scale on PEOU and C.

Table 6- Descriptives measurement items

	Min	Max	Mean	Std. deviation	Skewness	Kurtosis	N
Perceived Usefulness							
PU1	5	7	6.00	0.76	0.00	-1.37	15
PU2	3	7	5.67	0.98	-1.08	1.25	15
PU3	5	7	5.87	0.64	0.08	-0.79	15
PU4	5	7	5.93	0.80	0.10	-1.53	15
PU5	4	7	5.80	0.94	-0.60	-0.62	15
Perceived Ease of Use							
PEOU1	4	7	5.80	0.86	-0.27	-0.78	15
PEOU2	2	7	5.80	1.21	-1.92	3.77	15
PEOU3	2	7	5.27	1.33	-0.79	-0.03	15
PEOU4	2	7	4.73	1.79	-0.39	-1.43	15
PEOU5	2	6	4.47	1.36	-0.66	-1.02	15
Behavioral Intention to use							
BIU1	6	7	6.40	0.51	0.37	-1.98	15
BIU2	5	7	6.40	0.63	-0.44	-0.95	15
BIU3	4	7	6.20	0.77	-1.17	1.72	15
Compatibility							
C1	2	6	4.80	1.26	-0.84	-0.57	15
C2	4	7	5.07	1.03	0.61	-0.89	15
C3	3	7	5.13	1.19	-0.24	-0.68	15
C4	3	7	5.33	0.98	-0.64	0.07	15
C5	3	7	4.93	1.03	0.12	-0.71	15
Self-efficacy							
SE1	2	6	4.33	1.23	-0.39	-1.30	15
SE2	3	7	5.47	0.99	-0.94	0.33	15
SE3	4	7	5.53	0.99	0.12	-1.23	15
SE4	4	7	5.80	0.86	-0.27	-0.78	15
SE5	4	7	5.47	0.92	0.09	-1.01	15
SE6	4	7	5.07	0.80	0.68	0.17	15
SE7	5	7	6.00	0.53	0.00	0.27	15
SE8	4	7	5.93	0.80	-0.68	0.17	15
SE9	4	7	6.20	0.77	-1.17	1.72	15

Table 7- TAM measurement items

Construct	Item	
Perceived Usefulness (PU)	PU1	Using dashboards of financial data would improve my performance in decision-making and enhance my ability to make well-based decisions.
	PU2	Using dashboards of financial data would enable me to make decisions mo quickly.
	PU3	Using dashboards of financial data would enable me to make decisions mo easily.
	PU4	Using dashboards of financial data is useful for me to make well-based decisions.
	PU5	Using dashboards of financial data would make me better informed in the practice of decision-making.
Perceived Ease of Use (PEOU)	PEOU1	Learning to use dashboards is easy.
	PEOU2	Using dashboards is easy.
	PEOU3	Interacting with a dashboard is clear and understandable.
	PEOU4	Interacting with a dashboard does not require a lot of my mental effort.
	PEOU5	Finding the information I need to make well-based decisions in dashboards easy.
Behavioral intention to use (BIU)	BIU1	Assuming I had access to dashboards, I intend to use it.
	BIU2	Assuming I had access to dashboards, I intend to actively use the provided information
	BIU3	Assuming I had access to dashboards, I intend to actively use it in my decision-making practices.
Compatibility (C)	C1	Using the current versions of the dashboards solutions is compatible with n decision-making practice.
	C2	Using other available dashboard solutions fits well with the way I would lil to engage in decision-making.
	C3	Using dashboards as a solution is compatible with the data captured in my company.
	C4	Using dashboards is compatible with my company's IT infrastructure.
	C5	Using dashboards is compatible with the other systems and solutions I use.
Self-efficacy (SE)	SE1	I have access to sufficient and relevant data to make well-based decisions
	SE2	Assuming access to sufficient data, I feel confident finding the information need in dashboards.
	SE3	It is easy for me to become skillful at using dashboards.
	SE4	I have the necessary skills for using a dashboard tool.
	SE5	I have enough background information about the visualized data to utilize i for well-based decision-making.
	SE6	When making decisions based on data-driven information, I am confident t I understand the underlying assumptions the data is based on.
	SE7	In decision making I use my general knowledge and experience.
	SE8	In decision making I use my prior knowledge and experience with the spec data.
	SE9	My knowledge and experience are valuable for my decision making.

In addition to the background- and TAM-questions, the respondents were asked two questions regarding todays use of BI-tools. From the figures 6 and 7 we see that Power BI and dashboards in MIS are most utilized, closely followed by excel. Only four respondents answered that they utilized other solutions, which included BW, Spotfire, PDP and Sigma (company specific software). From the next question we see that there is an equal distribution between respondents that utilize such solutions once a month, once a week and several times a week. Only 6% and 13% use it once a day or several times a day respectively.

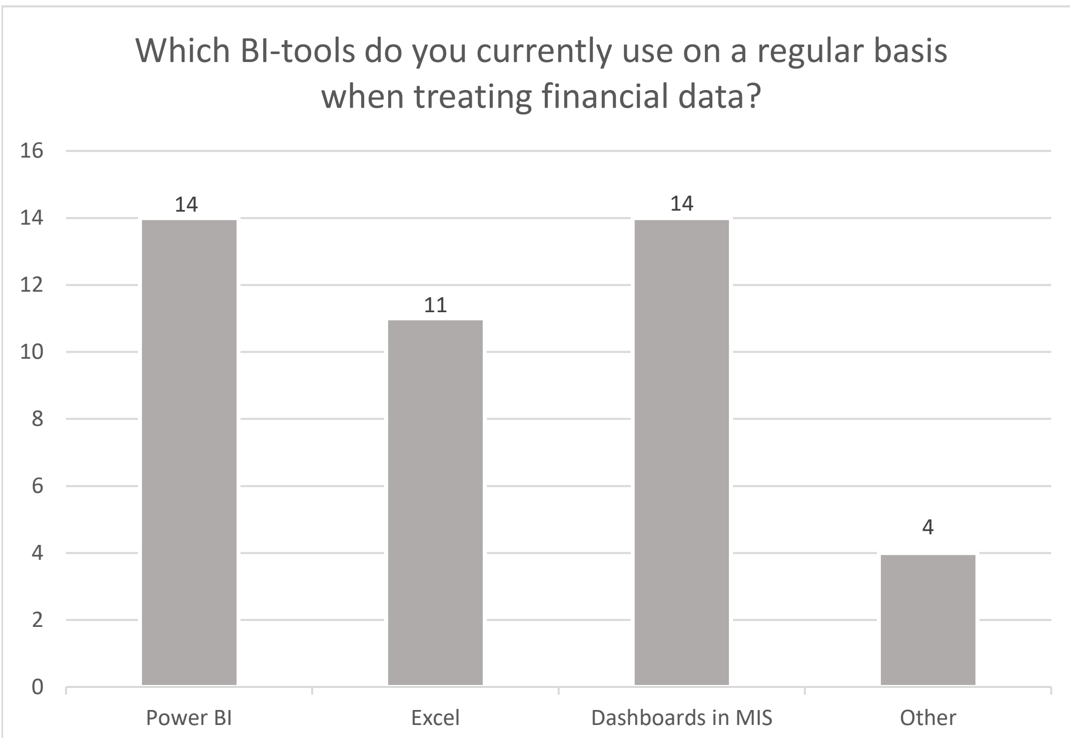

Figure 6- Todays use of BI tools (1)

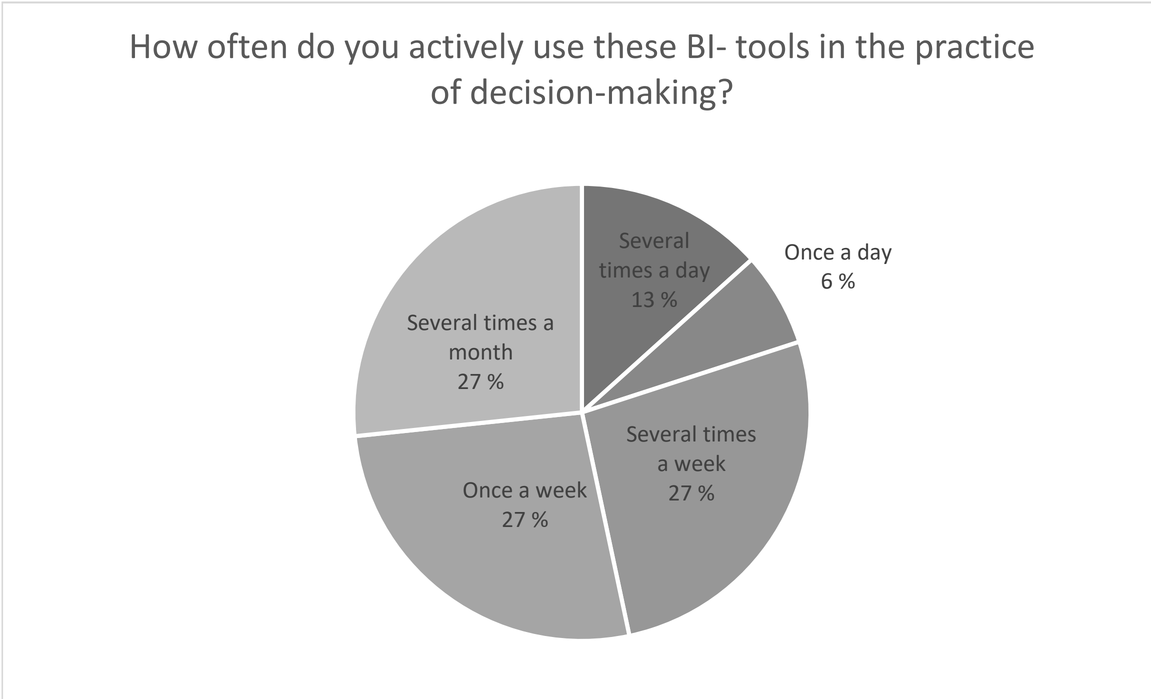

Figure 7- Todays use of BI tools (2)

5.2.2. Factor Analysis

Before testing the hypotheses and assessing the relationships between different constructs, it is necessary to check if the measurement items included in our survey actually measure the intended construct. This section will describe the factor analysis technique we have used to assess the relationships between our items and the constructs they are intended for. In section 5.2.2.1, 5.2.2.2. and 5.2.2.3 we discuss the assumptions for factor analysis, conduct a preliminary analysis and an initial reliability assessment. In section 5.2.2.4 the factor analysis is presented, and the assessment of reliability and validity is considered in 5.2.2.5.

The measurement items represent the variables that can be measured directly, defined as observable variables, and the constructs represents variables that cannot be measured directly, but implicitly from observable variables, defined as latent variable (Field, Miles, & Field, 2012). A measurement model, figure 8, represent the relationships between the measurement items and the construct they are intended to measure. The rationale behind having multiple measurement items for one construct is that the combined answer to multiple observable items provide a better representation of the complexity of one construct (Field et al., 2012)

For this research, our measurement items and constructs are based on an extended version of TAM. Consequently, we have a priori established the number of factors and hypotheses. However, since our research model is specific for our context, we cannot be certain about the appropriateness about the hypothesized relationships between the different variables, and we cannot rely on that a measurement item (observable variable) only load one construct (latent variable). Subsequently, we will conduct an exploratory factor analysis in this thesis, which allows for items to load any identified factor in the analysis and let us further explore our data set (Field et al., 2012). This is aligned with the exploratory nature of the research and the research context. Furthermore, there are several factors that justify this choice: the empirical support is mainly adopted from research on different technologies, as well as the items being translated from English to Norwegian.

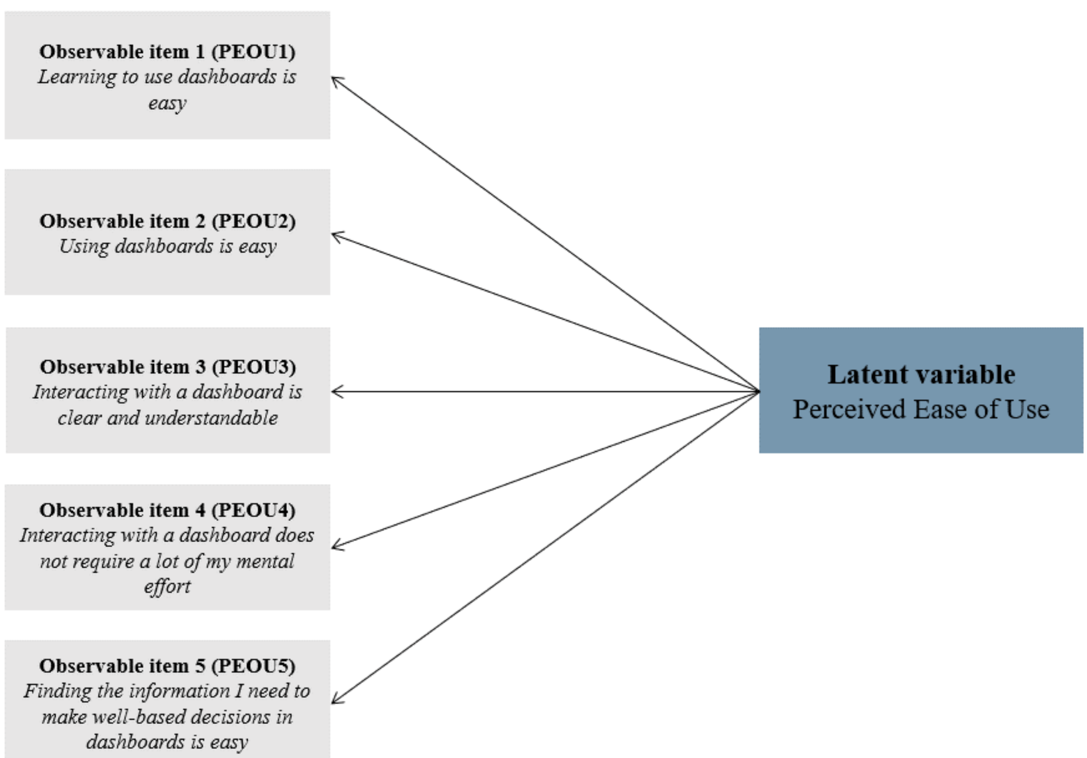

Figure 8- Measurement model for the latent construct Perceived Ease of Use

5.2.2.1. Assumptions for Factor Analysis

The first assumption we need to consider is the sample size. As for the correlation coefficients, these seem to fluctuate much more in small samples and the reliability of the analysis is therefore dependent on the sample size. Typically, it is recommended to have at least 10-15 respondents per variable. However, it is also found that the most important elements for establishing reliability in factor analysis is the absolute sample size and magnitude of the factor loading, as well as communalities (Field et al., 2012). Given the small sample size in this research, attention is given to these elements throughout the analysis.

When conducting an exploratory factor analysis, it is favorable that the variables are normally distributed, as normality may enhance the solution (Tabachnick & Fidell, 2013). Both visual and statistical methods can be used to assess the normality of a variable. Visually, histograms and normal probability plots are methods for assessing normality. Statistical methods include calculation of the skewness and kurtosis values for the variables, and the Shapiro-Wilk test.

As mentioned in section 5.2.1.1., the values for skewness and kurtosis indicate that especially three variables, PEOU2, BIU3, SE9, have values that indicates deviation from normality. To further investigate normality, we have firstly inspected the distribution plots, where deviations were observed. Furthermore, the Shapiro-Wilk test resulted in significant levels ($p < 0.05$) for all items except five. These findings indicate a problem with normality in several of our items, but while normality is recommended when conducting a factor analysis, it is not required and will not degrade the solution (Tabachnick & Fidell, 2013). Furthermore, the use of Likert-Scale and a small sample size affects the normality of the items, and we will not further problematize this assumption in this part of the analysis.

5.2.2.2. Preliminary Analysis

Before conducting the factor analysis, we verified whether out data set was suitable for a factor analysis by checking the correlation matrix, testing the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test of Sphericity. These tests consider an important element when conducting factor analysis: the correlations of the variables. The correlations are important elements to investigate to ensure high correlation between items that are meant to measure the same construct (Field et al., 2012). In this thesis we use the bivariate correlations and calculate the Pearson correlation coefficient. Essentially, there are two potential problems: (1) correlations close to zero, and (2) very high correlations (>.8) (Tabachnick & Fidell, 2013).

Bartlett's Test of Sphericity, which checks whether the population matrix is significant different from an identity matrix (Field et al., 2012), was significant for all scales ($p < 0.001$). The value of Bartlett's test indicate that our dataset is suitable for factor analysis (see appendix 2.1). However, moving forward to KMO, some problems arise. The KMO test relies on a positive definite matrix and the test cannot be computed without it (Field et al., 2012). In our case the data set seem to have too many variables for only a few cases of data. This makes our correlation matrix slightly unstable and it is not possible to test the KMO. Further investigation shows that some items have very low and high correlation, which implies that our data set may not be fitting for factor analysis. One solution is to limit the number of items prior to the factor analysis. However, we opt for taking several elements into consideration before removing items. We will therefore move forward to the factor analysis with all items in our data set.

5.2.2.3. Initial Reliability Assessment

To test initial scale reliability in our measurement items we have calculated Cronbach's Alpha for all our constructs. This measure tests for internal consistency and is extensively used for responses across a subgroup. This fits well with examine consistency in multiple items that are meant for testing the same construct (Saunders et al., 2019). Values of Cronbach's Alpha ranges from 0 and 1, where values above .7 generally are considered acceptable and indicate that the items combined in one construct are internally consistent in their measurement (Field et al., 2012).

When calculating Cronbach's Alpha, all constructs except BIU yield values above .7, as seen appendix 2.2. Further, Field et al. (2012) recommends removing items that cause a significant improvement in overall reliability in the construct. As seen in appendix 2.2, dropping item BIU3 would lead to a substantial improvement in reliability for BIU. However, the value of Cronbach's alpha correlates with the number of items, where an increase in the number of values on the scale lead to an increase in Cronbach's alpha (Field et al., 2012). Consequently, we decide to keep all measurement items in our scale, and rather take these findings into account in our factor analysis.

5.2.2.4. Exploratory Factor Analysis

For the exploratory factor analysis, we set the initial number of factors as five, given the assumed number of factors in our research model. Firstly, we conducted an analysis on all initial 27 measurement items. The results for these initial communalities and factor loadings are presented in appendix 2.4. The aim of a factor analysis is to reduce the dataset "(…) by explaining the maximum amount of common variance in a correlation matrix using the smallest number of explanatory constructs" (Field et al., 2012, p. 751). Consequently, we have further investigated which items that seems to group together by looking into the correlation matrix (see appendix 2.3), the initial factor loadings and communalities (see appendix 2.4) and further iterated the factor analysis based on the findings.

Communalities represent the common variance that is present in an item, and values above 0.5 are generally acceptable. For the factor loadings, a value above 0.3 is usually considered important. However, the significance of the loadings is dependent on the sample size, and with a smaller sample size, higher loadings should be emphasized. For correlations between items meant to measure the same construct, a lower limit of .3 is generally recommended. (Field et al., 2012)

Given that our constructs are not independent, we use an oblique rotation, which is the preferred method when having interrelated factors (Field et al., 2012). Based on the findings in the preliminary analysis, initial reliability assessment, communalities and factor loadings, we decided to cut out the following items from our data set: BIU3 due to reliability, high correlations with items in other constructs and low factor loading, SE1, SE7, SE9 due to low correlations with other items in the same factor and low factor loadings, PEOU4 due to low factor loadings and C4 due to similar, and low, factor loadings on all five factors.

The eigenvalues, which represents how much variance the factors explains (Field et al., 2012), of the factors are also considered, where Kaiser (as cited in Field et al., 2012) recommends retaining all factors with values above 1. All of the five factors have values above 1, which means that the factors represent a substantial amount of variation (Field et al., 2012) and it is appropriate to keep all five factors. In addition, given the fit of the model of .97, five factors are sufficient in this analysis.

The final factor analysis was run with the remaining 21 items and the initial number of five factors. Bartlett's test of sphericity is now significant for all constructs and for the KMO we obtain a value of 0.724. A simple factor structure was achieved in the final analysis after oblique rotation, where each item loaded highly on only one of the five factors. The pattern matrix for the final factor analysis is shown in table 8. The factor loadings indicate that factor one represents perceived ease of use (PEOU), factor two self-efficacy (SE), factor three perceived usefulness (PU), factor four behavioral intention to use (BIU) and factor five compatibility (C). Furthermore, the percentage of variance accounted for by each factor is: (PEOU) 35,6 %, (SE) 19,8 %, (PU) 13,4 %, (BIU) 8,4 % and (C) 6,5 %. To conclude, the final factor analysis explained 83,7 % of the cumulative variance. This indicates that random error is minimized and the included measures accounts for a substantial part of the variance.

Table 8- Pattern matrix, communalities and Cronbach's Alpha

	PEOU	**SE**	**PU**	**BIU**	**C**	**Communalities**
Cronbach's Alpha	.851	.918	.908	.878	.751	
PEOU1	0.77					0.80
PEOU2	0.81					0.78
PEOU3	0.75					1.00
PEOU5	0.47					0.56
SE2		0.86				0.88
SE3		0.79				0.98
SE4		0.53				0.68
SE5		0.92				0.89
SE6		0.90				0.91
SE8		0.55				0.81
PU1			0.85			0.82
PU2			0.81			0.71
PU3			0.58			0.67
PU4			0.82			0.77
PU5			0.91			0.94
BIU1				0.92		0.92
BIU2				0.80		0.73
C1					0.66	0.66
C2					0.77	0.87
C3					0.54	0.62
C5					0.52	0.51

5.2.2.5. Assessment of Reliability and Validity

Regarding reliability, which is concerned with the consistency between measurement items in the same construct, this was checked by calculating Cronbach's Alpha. As seen in table 7, the values are above the recommended lower limit of .7 for all constructs. In addition, we examined the values for r.drop, which checks an items correlation with the scale total if it was not included in the scale total (Field et al., 2012). None of the items have values below a recommended lower limit of .3, which means that the items correlate well with the scale total. Thus, reliability is established.

For assessing the validity of the factor structure, two measures are used: convergent validity and discriminant validity. Convergent validity concerns to which degree the measurement items within the same construct are correlated. When investigating the correlation matrix, all correlations between items in the same construct are mostly high. Further, discriminant validity is concerned with the extent to which the factors are uncorrelated and distinct, where the rule is that the items should relate more to its own factor than to another factor. Given the overall higher correlations between items measuring the same constructs, both convergent and discriminant validity is sustained.

5.2.3. Correlation Analysis

As our sample size is rather small, we see it expedient to focus on the correlations in our factors, rather than conducting a regression analysis. The reason for this is that a small sample size affects the precision of the predictions. We will start by presenting the final hypotheses to be tested in section 5.2.3.1. Further, in section 5.2.3.2. we conduct a data reduction on our data set. Lastly, section 5.2.3.3. contains the correlation analysis and testing of significant relationships between the variables.

5.2.3.1. Final Hypotheses

Since the factor analysis confirmed that a number of five factors were satisfying in our research model, all initial hypotheses are maintained for further analysis of the relationships between the variables. The final hypotheses are seen in table 9.

Table 9- Final hypotheses

Hypotheses
H1: Compatibility will have a positive effect with perceived usefulness
H2: Compatibility will have a positive effect on perceived ease of use
H3: Self-efficacy will have a positive effect on perceived usefulness
H4: Self-efficacy will have a positive effect on perceived ease of use
H5: Perceived ease of use will have a positive effect on perceived usefulness
H6: Perceived ease of use will have a positive effect on behavioral intention to use
H7: Perceived usefulness will have a positive effect on behavioral intention to use
H8: Behavioral intention to use will have a positive effect on actual use

5.2.3.2. Data Reduction and Descriptive Statistics

After conducting factor analysis and testing the validity and reliability, the next step is to carry out a data reduction. At this stage we assemble the measurement items into five variables representing the five different constructs in our model. By doing this we can present descriptive statistics on variable level, shown in table 10. The variables represent the average values of those items that make up the same construct. In addition, we now establish a factor for the variable actual use (AU) as this is the variable we ultimately want to measure in our research model. This factor is based on questions in the survey regarding which BI solutions they use today and how often.

Table 10- Descriptive statistics variables

	Min	Max	Mean	Std. deviation	Skewness	Kurtosis	N
Perceived Usefulness (PU)	4.60	7.00	5.85	0.71	0.00	-1.04	15
Perceived Ease of Use (PEOU)	2.50	6.25	5.33	1.00	-1.37	1.55	15
Behavioral Intention to use (BIU)	5.50	7.00	6.40	0.54	0.05	-1.75	15
Compatibility (C)	3.75	6.50	4.98	0.86	0.37	-1.23	15
Self-efficacy (SE)	4.00	7.00	5.54	0.75	-0.22	-0.28	15
Actual Use (AU)	4.88	7.00	5.59	0.50	1.25	1.69	15

As for the descriptive statistics on item level, skewness and kurtosis are important measures for checking normal distribution on variable level. Investigating these values indicate a problem with normality in some of the variables, especially PEOU and AU. To investigate normality in our variables, we conducted a Shapiro-Wilk test. The test indicate violation against normality in the variables PEOU, BIU and AU. Given that normality is not established in all our variables, this need to be considered in the correlation analysis. Furthermore, when examining the min, max and mean for the variables, we see that BIU have the highest values, implying that the average respondent has high intentions to use BI solutions such as dashboards. Furthermore, the values for PU and SE shows that the minimal value are quite high, which means that the average respondent is high on the scale when it comes to their perception of these variables.

Moreover, PEOU and C are the variables that vary the most across the scale, reflected in the highest values for deviation. These two variables also have the lowest values for the mean. Since we are looking at which factors affect acceptance and use of BI solutions, we are interested in the variables that may contain the most variation and, in that way, affect the variables BIU and AU. Given this, it is interesting to look further into the variables PEOU and C, as these are the two that may have the highest potential to affect BIU and AU.

5.2.3.3. Correlation Analysis

For our hypothesis testing we will start by verifying if the relationships between the variables are considered significant by looking at the correlations. Based on the correlations, we could have concluded the hypotheses as supported or not in this part of the analysis. However, as we want more substance in our hypothesis testing and gain more practical implications, we will conduct a further analysis on addition items and open-ended questions before deciding upon whether we keep or reject the hypotheses. This is covered in chapter 5.3 and 5.4.

As mentioned, we are looking at the bivariate correlations and are using the Pearson's correlation coefficient for the calculation. Having interval data is the only requirement for the Pearson's correlation coefficient being an accurate measure of the relationship between two variables. However, as the sample size is quite small, normality is not established in all our items and this is a requirement for statistically significant correlations. Consequently, we have bootstrapped the correlation calculations. Bootstrapping the correlations considers non-normalized variables and by doing so and assessing the confidence interval and p-values we can determine if the correlations are statistically significant or not (Field et al., 2012).

As seen in table 11, the highest correlation is between compatibility (C) and perceived ease of use (PEOU). This correlation is significant, and the bootstrap prove a positive relationship between these two variables. This is also one of the assumed relationships in our model which means we can validate this link in our research model. As seen in the descriptive statistics, these two variables were also the ones with the largest variation in our data set.

Furthermore, the correlation between PU and PEOU is also high and significant. In our research model, it is hypothesized that a higher PEOU lead to an increase in PU. Also, both PU and PEOU have significantly correlation with BIU. However, only the correlation between BIU and PEOU is significant and can be proven positive in the bootstrap. The highest correlation to our dependent variable AU is with BIU and this is significant. This substantiates the relationship between these two variables in our research model.

For the independent variables, C and SE, these have both lowest correlations with BIU. This is expected, as the other variables, PU and PEOU, are mediating between these. However, C and SE have a rather high correlation between each other, and even though this cannot be proven significant, it is interesting because this is not a hypothesized relationship in our research model.

Table 11- Variable correlation matrix

	PU	PEOU	BIU	C	SE	AU
PU	1					
PEOU	**.439***	1				
BIU	**.330**	**.444***	1			
C	.324	**.593****	.304	1		
SE	.178	.242	.127	**.337**	1	
AU	.024	.088	**.366***	.288	.277	1
* p < .05, ** p < .01						

Furthermore, the square of the correlation coefficients gives a measure called the coefficient of determination, which is defined as "(…) a measure of the amount of the of variability in one variable that is shared by the other" (Field et al., 2012, p. 222). This is a useful measure of the substantive importance of an effect, but it should with carefulness be used to infer causal relationship. Even though it can explain how much one factor share variability with another, this does not necessarily mean that the one factor is causing this variation.

Table 12- Variable coefficients of determination matrix

	PU	PEOU	BIU	C	SE	AU
PU	1					
PEOU	.193	1				
BIU	.109	**.197**	1			
C	.105	**.352**	.092	1		
SE	.032	.059	.016	.114	1	
AU	.001	.008	**.134**	.083	.077	1

The matrix of coefficients of determination is shown in table 12. Since AU is the dependent variable we ultimately aim to say something about, emphasis is on the variables that can explain most of the variance in this. As seen in the matrix, BIU is the variable that shares the most variance with AU. Further, BIU shares the most variance with PEOU, which again shares the most variance with C. Consequently, this chain of links contains the variables that share the most variance with each other and ends up in our final dependent variable, AU. Further in our analysis, attention will be given to these variables and the relationships between them, as these relationships are also proven significant in our bootstrapped correlation coefficients. An overview over the significantly proven relationships are shown in figure 9 with the corresponding correlation coefficients.

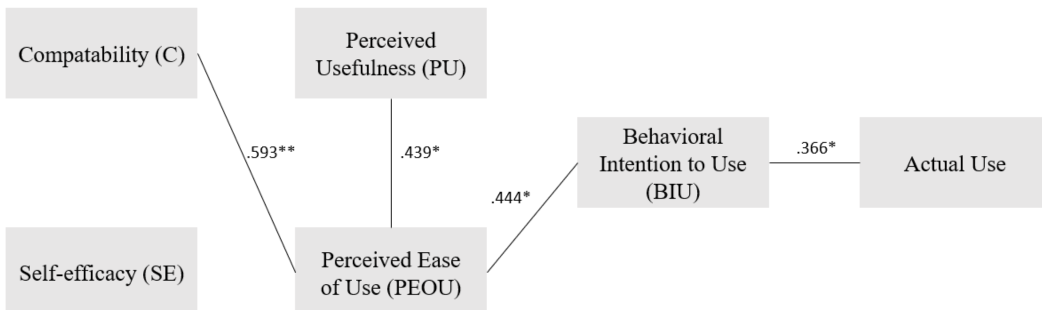

Figure 9- Significant relationships in research model

5.3. Additional Items Analysis

In this chapter we will explore the additional questions asked in the survey, regarding demands for BI tools.

Following question SE1, about if they feel like they have access to sufficient amount of relevant data to make well based decision, we asked a follow-up question if they answered either ‘strongly disagree’, ‘disagree’ or ‘slightly disagree’. As seen in figure 10, most respondents meant that the data they have access to is too complicated to make well-based decisions on. Further, how the visualization of the information is made and presented affects how well they feel it enhance their ability to make well- based decisions. In addition, an issue with permission and access to the right data seem to be one reason, if the data even exists.

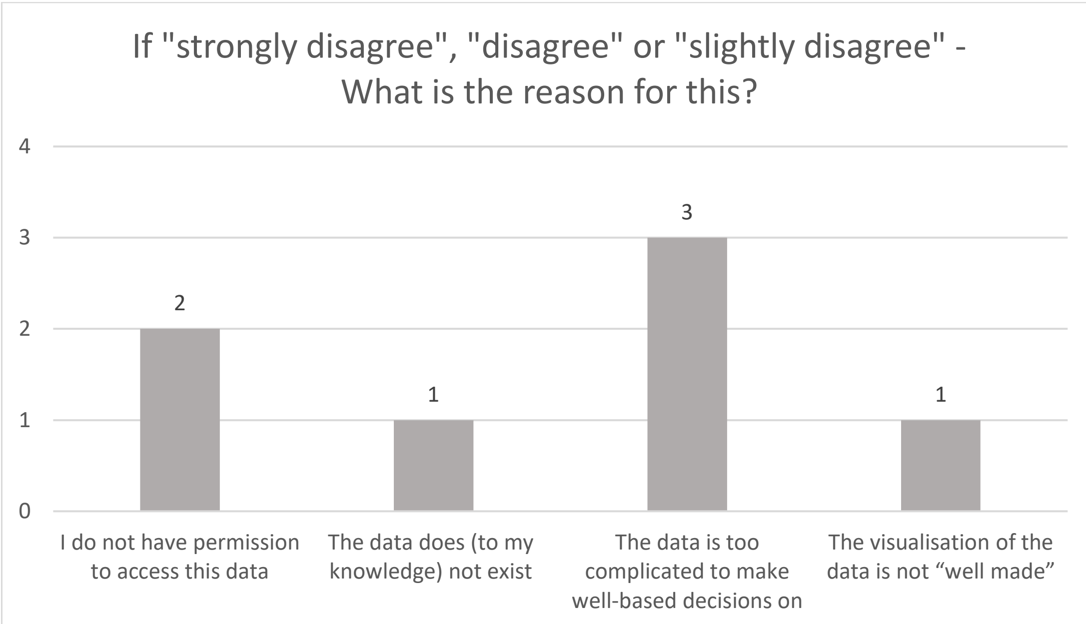

Figure 10- Additional question SE1

In addition, a category question was asked on which type of data they would like to have access to to enhance their ability to make well based decision. As figure 11 shows, the respondents have the most need for data that contains information about their own asset. Further, for area level, country level and company level, the need for data decreases respectively. This shows that the decision makers are mainly taking decision that is concerned with their asset of interest, however there is also a demand for data on different levels and possibly across units as well.

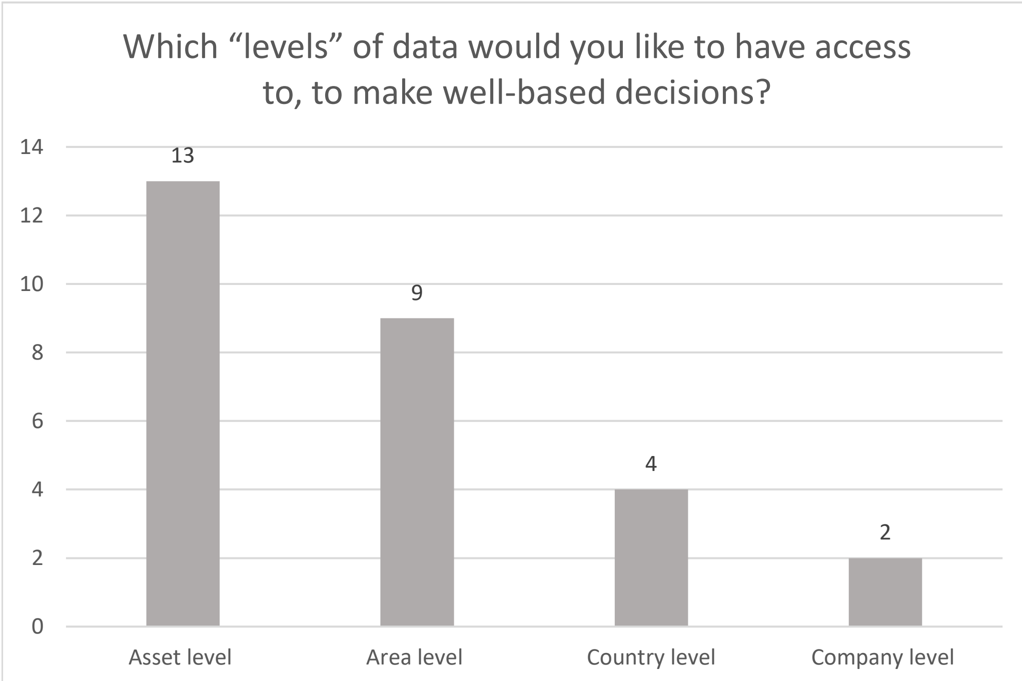

Figure 11- Additional question data levels

The last part of our questionnaire contained question regarding other different demands the users may have to a BI solution that was beyond what the questions concerning the constructs in the research model covered. The answers in this section is shown in figure 12. The respondents are quite high on the scale and agree on the fact that they would like to customize the dashboard and its contents themselves and that interactive dashboards are preferable. Most of the respondents also agree that the use of dashboards may increase the level of collaboration. The questions that the respondent agreed the least upon was number two, concerning standardized dashboards. Together with the open-ended responses, the findings will be discussed further in chapter 6.

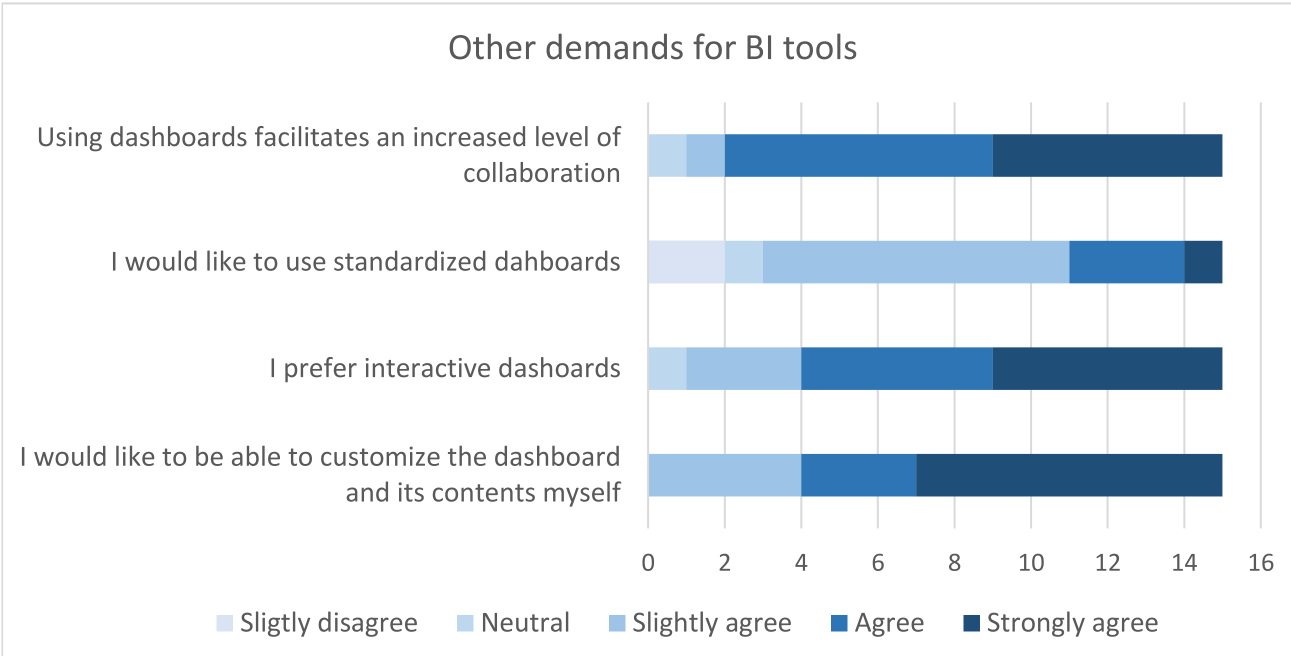

Figure 12- Additional questions general demands

5.4. Qualitative Analysis

In this section we will analyze the qualitative parts of the survey, which refers to the responses to the open-ended questions, as seen in appendix 3. As mentioned in subsection 4.5 we are utilizing the data display and analysis approach for analyzing the open-ended questions from the survey. This approach consists of three steps: (1) Data condensation, (2) data display and (3) drawing and verifying conclusions (Miles, 2014). These three steps will be addressed in respectively sections 5.4.1, 5.4.2 and 5.4.3.

5.4.1. Data Condensation

For the data condensation the goal is to summarize and simplify the data, so that we more easily can selectively focus on the important parts of the responses for our analysis (Miles, 2014). We have removed irrelevant responses with no connection to the theme in question, and further categorized the text answers into several categories. The open-ended questions were asked in each of the five sections containing close-ended questions about the constructs in the research model. However, as they could write whatever they wanted we have categorized the text answers based on the topic of their responses. By doing so we ended up with four different groups of responses. These categories were first named category 1-4, but when conducting further analysis of the responses it became evident that the different categories coincided surprisingly well with important aspects from the literature review and quantitative analysis.

Consequently, the categories were re-named into the following: (1) System features, (2) User characteristics, (3) Importance of fit, (4) Data infrastructure. System features contains elements such as the format of the dashboard, level of interactivity and what type of information they need. User characteristics consists of elements as level of expertise, experience and ownership of the dashboard solution. The importance of fit contains answers that has emphasized this, and in what way this is important for them. The last category, data infrastructure, concerns factors such as type of data, data access, data silos and data quality.

5.4.2. Data Display

Based on the conducted data condensation, we have displayed the qualitative data in a table. The table shows our four categories, where each category contains the main element from the answers on the open-ended question. The data display is showed in table 13.

Table 13- Data display open-ended questions

System features	**User characteristics**
Needs for system features: - Estimates, forecast, changes, milestones - A comprehensive view, not just parts of information - Possibility for drill down - Interactive dashboard - Display of assumptions made and active filters - Status against a KPI	- Good insights and understanding of own-built dashboard - Less ownership and need for dashboard built by others - Competence and complete understanding of company needs are important, especially when building dashboards - Drill down can be difficult to use and understand if it is not used often
Importance of fit	**Data infrastructure**
- Behavioral intention to use is dependent on quality and purpose of the dashboard - Dashboard is useful, but dependent on type of, and format of, information - The size of the decision determines the quality of the decision made - Dashboard should support the decision made by the user - In decision making, the use of today's dashboards is limited	- Occasionally mismatch in data from different solutions, this is unnecessary - Dashboard is often based on and broken down on distinct units. This is not always relevant, especially for decisions made across units - Dashboard demands quality data, both in relevance and potential error sources - Drill down is important for accessing the underlying data to understand what is displayed in the dashboard

5.4.3. Drawing and Verifying Conclusions

Supplementary to the categories used to sort the responses, the importance of, and need for, BI solutions such as dashboards is widely expressed in the open-ended questions. This is stated as fundamental component of many of the responses, and due to this we have opted for not using this as a respective category, but rather interpret it as a core opinion of the respondents. Consequently, it is clear that the respondents see the value in using dashboards, but to fully take advantage of the value it may bring, the needs for system features, and fit between that and the user characteristics, must be met.

As for the first category and the answers regarding system features, these mostly consists of different needs the respondents have to the dashboard solutions. The level of interactivity through use of drill down features and possibilities to adapt the dashboard themselves are important needs that are highlighted. In addition, several respondents want the data to be visualized against targets and KPIs, and that the trend in the data is clearly shown. This is to make it simpler for the users to quickly see in which direction the data are moving. Furthermore, a complete overview of the data, and not just parts of information, are also needed to make well-based estimates and forecasts. This is also related to the data infrastructure, as it may be difficult to provide a comprehensive view if data across different units are necessary. Lastly, information about the assumptions that are made on the data and display of the filters applied are important system features to ensure giving the user a complete impression of the information illustrated in the dashboard.

The second category, the answers regarding user characteristics, shows that they generally have good expertise and knowledge in using dashboards. However, this is stronger for an individual's own built dashboards than for dashboards that are built by others and given to them as decision support. If they use dashboards that is built by, and administrated by others, it may be more difficult to use different functions in the dashboard, e.g. drill downs, as they are not familiar with the functionalities. In this case, experience with that specific dashboard will enhance the use of such system functionalities. Furthermore, when building and using dashboards, knowledge about the context and needs of the company is important to obtain a satisfying dashboard that meet the demands of the users.

For the third category regarding the importance of fit, this is highlighted in several of the answers. Their view on the usefulness and value of dashboard is connected to how good the fit is between the specific system features, their own characteristics and the task and context at hand. The respondents emphasize that these are important factors, and it is also stated that as a decision support the current dashboard solutions may not be sufficient, which implies that the fit is not optimal today. Furthermore, their intention to use dashboards as a part of their decision-making process is dependent on the quality of the dashboard and the contained information, and that they have easily access to the data they need. They emphasize the fact that use of dashboards is a decision supporting activity that should enhance the decision made by the user. This means that dashboards should provide information and illustrations that make it easier for the decision maker, and not just contain a range of information that the user themselves must examine and analyze.

For the last category, data infrastructure, this contains different aspects. Firstly, the match between data extracted from sources as SAP, which is an ERP-system, and data showed in the dashboard need to be correct. If not, the usefulness of the dashboard minimizes. Furthermore, data stored in data silos can be a challenge for decision makers working across different units, as data access can be limited. In this case, they are dependent on finding and comparing data across different units to make a well-based decision. Also, the functionality of drill downs in a dashboard is important for decision makers to understand what the underlying data is and by that enhance the understanding of the context. Lastly, the usefulness and value of a dashboard is dependent on the data quality, which should be a concern of the company and the owners of the dashboards.

5.5. Summary of Analysis

To finish the analysis, we will in this section conclude on which hypotheses are supported or not. The decision of supporting or not supporting the hypotheses will be based on the quantitative analysis, however the extended explanation of why will mostly be drawn from the qualitative analysis. Subsequently, in this section we will summarize the findings from both analyses and give a short explanation of the hypotheses that are supported, and why they are verified. The hypotheses are shown in table 14.

Table 14- Hypothesis testing

Hypotheses	
H1: Compatibility will have a positive effect with perceived usefulness	*Not supported*
H2: Compatibility will have a positive effect on perceived ease of use	***Supported*****
H3: Self-efficacy will have a positive effect on perceived usefulness	*Not supported*
H4: Self-efficacy will have a positive effect on perceived ease of use	*Not supported*
H5: Perceived ease of use will have a positive effect on perceived usefulness	***Supported****
H6: Perceived ease of use will have a positive effect on behavioral intention to use	***Supported****
H7: Perceived usefulness will have a positive effect on behavioral intention to use	*Not supported*
H8: Behavioral intention to use will have a positive effect on actual use	***Supported****

* $p < .05$, ** $p < .01$

For H2, the variable compatibility (C) is shown to have a significant relationship with perceived ease of use (PEOU). This is explained further in the open-ended questions, where the importance of the fit between system features, the task and user characteristics were emphasized, consequently the importance of C. Regarding system features, the respondents had some different needs for what the BI solutions must satisfy, e.g. interactivity and drill downs. Furthermore, regarding user characteristics, they generally have a high self-efficacy, which means they do not doubt themselves and their abilities to use BI solutions in a satisfying way. Consequently, how easy they think it is to use a dashboard depends on the compatibility variable and if their different needs for system features are attained.

Second, for H5, how useful they perceive the dashboard is mostly dependent on how easy they think it is to use it. In the quantitative analysis, the relationship between perceived usefulness (PU) and PEOU was established as significant. Furthermore, as pointed out in the qualitative analysis of the open questions, they have stated that they regard dashboards as useful for decision support.

Further, for H6, the respondent's behavioral intention to use (BIU) dashboards as a part of their decision making is significant correlated with their PEOU, where a better fit for the respondents, and by that an easier solution to use, increases their intention to use the dashboard. The respondent's BIU can also be explained by their acceptance of the solution, where acceptance is considered as a measure of a user's perception of both how useful and how easy to use a solution is. From both the quantitative analysis, and emphasized by the open-ended questions, their BIU is therefore highly affected by their PEOU of the solution.

Lastly, for H8, and the relationship between BIU and actual use (AU), this is shown to be significant in the quantitative analysis. However, as AU is based on a few self-reported answers in the quantitative data and is something we do not have extensive answers on in the qualitative data, it is difficult to further verify and explain this relationship. As for AU, this will be an element of our discussion on our main research question, where we will further elaborate on this relationship.

6. Discussion

In this chapter we will discuss on our findings from the analysis in light of the literature reviewed and theoretical framework. Firstly, in 6.1. we will answer our main research question, by discussing our two sub-research questions. In this section we will present our findings and relevant literature, as well as discussing similarities, differences and what consequences this might have. In chapter 6.2. we will further discuss the implications of our findings, before we give a brief summary of the discussion in chapter 6.3. Limitations to our thesis will be discussed in section 6.4.

6.1. Answering the Research Question

Our main research question is: *How can the use of BI solutions in MA facilitate data-driven decision making?* To answer this, we have sought to investigate two sub-questions, respectively: *Which factors affects the acceptance and use of BI, such as dashboards, as a decision supporting solution in MA?* and *How do the current needs for BI solutions match the present user characteristics and system features?* The two research questions will be answered in sections 6.1.1 and 6.1.2.

6.1.1. First Research Question

First, we examined the question: *Which factors affects the acceptance and use of BI, such as dashboards, as a decision supporting solution in MA?* This question can be answered by investigating the findings from our quantitative analysis, using TAM as a framework for examining our research model. As our research model was intended to investigate both acceptance and use of BI solutions, it is worth mentioning that during the research, actual use (AU) was found as a difficult measure for us to establish. We based the initial measure on self-reported answers, but as we consider this as inadequate for establishing a reliable measure for AU, we will focus on the factor behavioral intention to use (BIU) and by definition assume that this gives a reliable measure for both the acceptance and use.

The quantitative analysis, with the factor analysis and correlation analysis respectively, showed that the factors that shared the most variance with behavioral intention to use (BIU), was perceived ease of use (PEOU) and further compatibility (C). This was established as a significant link with the highest correlations and shared variance. Hence, as we want to find out what affects the acceptance, which is stated by Davis (1989) that is measured by BIU, these two factors, PEOU and C, seem to have the most influence on acceptance and use in our findings. As PEOU is a factor measuring the user's perception of the solution (Davis, 1989), we see factor C as a more tangible and achievable variable to be affected, and therefore the factor that is most beneficial for Equinor to focus on and put efforts in. Based on this, for our case company we state that C of a BI solution seems to affect the user's acceptance of the current dashboard solutions the most.

The variable C is, as previously mentioned, defined by Karahanna et al. (2006) as a variable consistent of dimensions concerning the fit between the technological solution and a user's current work practices, work style, experience and values. Furthermore, they describe that the user's perceived usefulness (PU), which is further affected by PEOU, of a technological solution is dependent on this fit as they describe it. Additionally, as discussed in our qualitative analysis, we found this, being the fit, as an element that is extensively mentioned by the respondents as being important for recognizing the solution as both useful and easy for them to use. Furthermore, researchers like Dilla et al. (2010) and Yigitbasioglu and Velcu (2012) are also centered around the importance of a fit between the system features, user characteristics and the task and context at hand. They argue that this affects the user's actual use of a solution and the quality of the output. For Equinor we find the factor C as containing the elements in the definition of the fit presented by Dilla et al. (2010) and Yigitbasioglu and Velcu (2012). This means that for affecting the user acceptance of the dashboard solutions, the company needs to focus on attaining the fit between the current system features, user characteristics and the actual needs, which again is a result of the task and context at hand. We find this as a fundamental element in how Equinor can facilitate for data-driven decision making in MA.

6.1.2. Second Research Question

Second, we asked: *How do the current needs for BI solutions match the present user characteristics and system features?* To answer the second research question, we firstly need to identify what the current needs for BI are. This is elaborated on in section 6.1.2.1. Secondly, we want to figure out if these needs actually meet the current user characteristics and system features. To do so, the user characteristics and system features need to be elaborated. This will be discussed in section 6.1.2.2., while section 6.1.2.3. will regard the actual matching between the respective elements.

6.1.2.1. Current Needs for BI Solutions

Following the first research question, where compatibility was established as an important factor that affects the acceptance of a BI solution, the answer to the second research question is closely connected to this. As the factor C concerns the fit between system features, user characteristics and task specifics, the user's needs for BI solutions are mainly centered around their needs for system features that attain this fit. Findings from both the quantitative analysis and qualitative analysis highlighted several different needs from the respondents. We have further categorized these into two categories: (1) needs for system features and (2) needs for data infrastructure. These two categories will be discussed respectively further in this section.

Starting with their needs for system features, we will firstly focus on the *functional system features*, which describe what the dashboard can do. Yigitbasioglu & Velcu (2012) found that common needs for functional system features in dashboards include: presentation format type (graphs vs. tables), flexibility, possibility for drill-downs and format selection. The needs emphasized by our respondents coincide well with these general findings, as both flexibility, which includes interactivity and filtering, and the possibility for drill downs were highly emphasized by our respondents in both the close-ended and open-ended question. They indicate that with a more interactive interaction with the dashboard they are able to further dive into the data and presented information. The inclusion of drill downs as a functionality will satisfy their needs for different information for different tasks and decisions, which is also emphasized by the respondents. As the stated needs coincide well with the generalized needs to functional system features in dashboards, it is necessary for Equinor to take these into consideration and focus on them. It is evident that these needs are important to build the foundation of a good use of BI in MA, both for Equinor, but also more generally for companies, as the same needs are stated in relevant literature (Yigitbasioglu & Velcu, 2012).

Further, we will focus on the findings of needs for *visual system features*, which is how the data is visualized. According to Yigitbasioglu & Velcu (2012) the following were found to be common needs for visual system features in dashboards: single page, good use of colors and use of gridlines. These common needs are quite detailed, whereas our respondents mostly emphasize that the dashboard should be easy to understand, having a much more general approach to such needs, saying that the visual presentations should be intuitive to comprehend. The reason for this general approach might be that there is limited knowledge and experience on the actual process of building a dashboard among our respondents, and hence limited knowledge on the possibilities for visual system features. This implies that for Equinor it will be advantageous to focus on informing about which possibilities are present, so that more specific needs might be addressed.

Additionally, a need that might touch on both *visual- and functional system features* is the respondents stated need for targets and trends. This can e.g. be measuring data against a KPI, to endorse the same perception of the data, and if the values portrayed are desirable or not. Such equal view on the data, and a clear perception of targets and trends presented and visualized are stated by the respondents as important to increase both the ease of use, and also their usefulness of the dashboard. The wish for specified targets and trends is not mentioned as one of the common needs in the reviewed literature (Yigitbasioglu & Velcu, 2012). A reason for this might be that the emphasis in their research is on largely generalizing needs and features of dashboards across many different industries, whereas our focus is much more specified. In addition to this it is natural that KPI is a part of our findings, as Equinor are very KPI-driven in their daily operations. The need for targets and trends is quite broad, and can be interpreted and met, almost purely visual or purely functional, or anything in-between. Therefore, it is very important for Equinor to go further into this to figure out what the desired use of this particular need is. This is to ensure that the need does not get handled in a far too simple or far too complicated way, meaning that they need to identify the proper level of interactivity when including targets and trends.

According to CGMA (2016) and Rikhardsson & Yigitbasioglu (2018) BI, and subsequently dashboards, aim to present information to an end-user with the goal of generating knowledge, understanding and learning. Further emphasized by CGMA (2016), dashboards can therefore support evidence-based decision making in an organization. Knowing from our findings that Equinor have both clearly stated *functional system features* and less specified needs to *visual system features* for dashboards, this will have implications for them if they want to ensure that dashboards are used efficiently and in accordance with the desired purpose. To do so it is important for Equinor to both take the clearly stated needs of the relevant users into account, and further map out specific needs where these are not clearly stated.

For our findings regarding the second category of needs for system features, needs for data infrastructure, the needs stated by the respondents are mainly centered around a fast and easy access to sufficient and relevant data and information. They state in the open-ended questions that to enhance their performance in the decision-making practice, the data and information they need should be easy for them to both find, and use. Data access and quality is also emphasized by several other researchers, where e.g. Yigitbasioglu and Velcu (2012) states that in lack of this, it may hinder the acceptance and use of the dashboard. Davenport et al. (2019) have an even clearer statement about the value of a satisfying data infrastructure, which is that if there is no data, there is no insights, and having problems with data access is something that often hinders the utilization of BI. Our findings indicated that all relevant data is not available or existent for the users in our case company today. This shows that data access and quality are found to be important elements in our research, but it appears to not be properly established in Equinor. Consequently, it would be beneficial for the company to map out all needs for data access and further asses data quality to ensure that the users have easy access to sufficient and relevant data.

In addition, the respondents highlight a need for surpassing *data silos* when taking decisions that affects different units. Data silos is found by CGMA (2016) as one of the biggest threats for a satisfying utilization of BI solutions, as it hinders proper exploitation and sharing of data between different departments and business lines. A siloed approach to BI and data is also found by Davenport et al. (2019) as a prevailing issue for many companies today, and as damaging for success. As Equinor is a company with data mainly stored in departmental silos, this is therefore a threat for proper utilization of the current dashboard solutions. Furthermore, considering our findings, if cross unit data and analysis is made possible, we think that this could also bring an increase in cross unit collaboration. This is similar to the findings of Yigitbasiouglu and Velcu (2012), who furthermore state that collaboration within the BI solutions may increase decision making quality.

Further, Isik et al. (2013) points out that the new reality in BI have opened for end-users to have direct access to data and the ability to apply analytical solutions and visualizations directly on the data to support in decision making. This can open for an increased flexibility for the users, which on one hand can be beneficial. However, for an organization, Rikhardsson and Yigitbasioglu (2018) raise a point that the new digital era brings new challenges regarding the overall strategy and structure, and that the implementation of data-driven decision making is shown to generate tensions in some organizations. As we have found that our respondents have some issues with the current data infrastructure, e.g. a mismatch between the data presented and the data stored in the data sources, this finding promote the need for establishing an overall strategy and structure when it comes to data infrastructure and management in Equinor. The respondents further express that the mentioned mismatch is an unnecessary problem that should not be present in any of the solutions used, which further implies that the current data infrastructure hinder the acceptance and use of the current dashboards.

6.1.2.2. Current User Characteristics and System Features

Furthermore, to answer the second research question we also need to establish some truth about the present user characteristics and system features.

Regarding the user characteristics, the quantitative analysis showed that the respondents have a high self-efficacy (SE), which implies that the respondents are technically competent people and have the necessary skills and competence to use the current dashboard solutions. In the qualitative analysis they also highlighted that they think dashboards are easy to use. Given that over 90 % of the respondents in our sample are older than 40 years, this finding is contradictory to the findings of Giovanis et al. (2012) that found that older individuals often perceive new technologies as harder to use and have higher concerns regarding SE, due to limited experience. However, this is further explained as being correlated with technological experience, and this is an element that is emphasized by our respondent who state that they are more comfortable with using dashboards they are familiar with. This indicate that in general, our respondents are technological competent and comfortable with using the current dashboards, but the utilization of the solution and its features is dependent on the familiarity with the specific solutions.

Yigitbasioglu and Velcu (2012) highlight the importance of the user element in the fit, as they describe the mental processes of the users as the connecting link between the visual presentation in a dashboard and the task at hand. They further state that a user's decision-making process is highly affected by the cognitive abilities of the users. This corresponds with the findings from Dilla et al. (2013) who found that a user's judgement and decision making differ dependent on their task- and solution-specific knowledge and expertise. Even if our findings show that the current knowledge and expertise of the respondents hold a satisfying level, we can't state anything about if this holds for dashboards different than the current solutions used. Given the literature's emphasis on the importance of the user's cognitive abilities, this will be an important element for Equinor to have in mind moving forward if the dashboard solutions continue to develop.

The respondents in our sample are users with different tasks at hand, which further implies that have different needs to the dashboards. Consequently, it will differ how the fit is attained for different users, based on if the features in that solution match their needs. This is also acknowledged by Isik et al. (2013) and Kowalczyk and Buxmann (2015), who states that users have different, and possibly conflicting, needs for system features and that this affects how the fit is achieved for different users. This implies that for a broader group of people, a given solution with a specific set of features may not match the needs from all users. For Equinor, this brings a question of a balance between the number of solutions and number of features included. They need to meet the needs from different users in the best possible way, without having a too complex number and mix of solutions.

Moving on to the current system features of the solutions, this is something that we cannot with certainty say much about, as the solutions used by our respondents are many and highly different. Consequently, we do not have a thorough picture of all the solutions used by our respondents today, and exactly which features these contain. However, it is not crucial for us to settle the current system features, as we have enough grounds to make the necessary assumptions and base the discussion on that. Therefore, we can move on to answering if there exists a matching between the user's needs, current user characteristics and current system features, without a detailed description of the current system features.

6.1.2.3. *Matching*

We will now answer if our findings support a matching between the respondents needs, their characteristics and the current system features, before we further discuss which implications this may have for the use of BI for decision support in MA.

As the respondents emphasize a quite high number of different needs in a dashboard solution in their open-ended responses, in addition to stating that several of the current dashboards do not serve the desired purpose, we assume that all these needs are not met in the current dashboards. This is further substantiated by the quantitative data, where the respondents on average have rated question C2 higher than C1. These questions regard whether they see the current dashboard solutions (C1) or other dashboard solutions (C2) as compatible with their decision-making practice. In addition, as we have found that the current needs are highly influenced by their task and context at hand, we assume that the system features in current dashboards are not adequate for a satisfying decision support.

For the matching of the user characteristics, this seem to be satisfying for the current system features of the solutions, as most respondents report a high level of PU and SE, which indicate a high level of expertise and knowledge in using the current solutions. However, given the findings that the current system features do not meet the user's current needs, there may also be a gap between their needs and the current user characteristics. This is an important link to consider moving forward, because if the current user characteristics do not match the users' actual needs for system features, the future dashboards containing such features may change the requirements to the users' technical skills and expertise.

To conclude, even if there exist several different solutions today, generally, for a given user there does not exist one single dashboard solution with a specific set of features that meet all needs of this user. The answer to the second research question: *How do the current needs for BI solutions match the present user characteristics and system features?* is illustrated in figure 13.

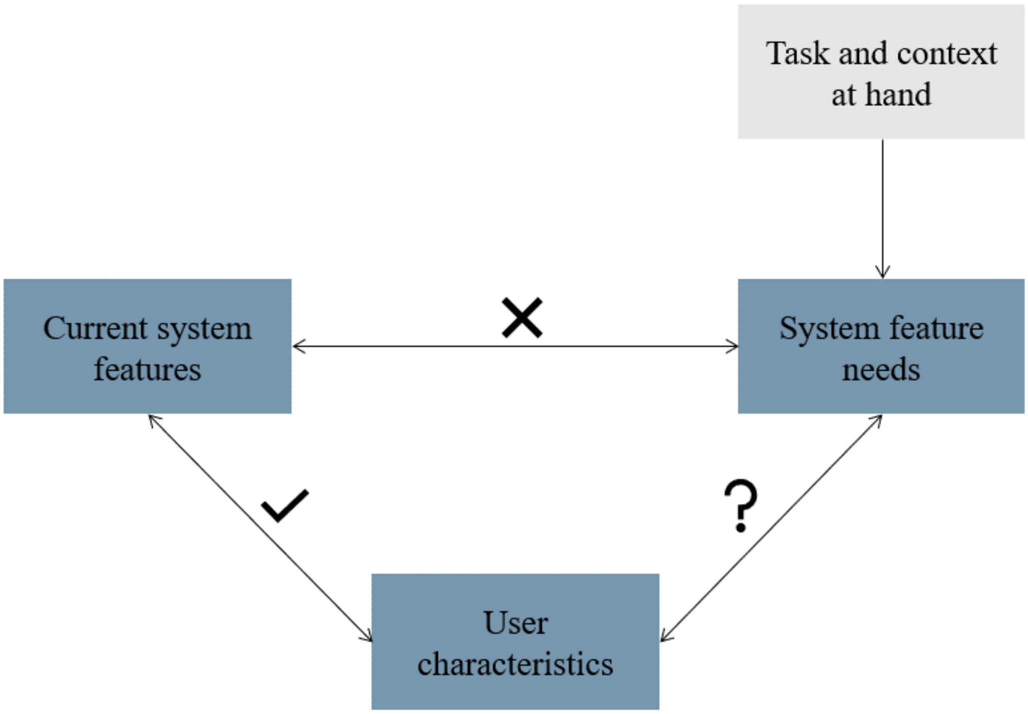

Figure 13- Answer to second research question

6.2. Implications of our Findings

The main finding in our research is that the fit is not attained for the current solutions used by our respondents, due to a missing match in current system features and the users' system features needs. Further there is a questionable fit between the current user characteristics and system feature needs, and by that the task and context at hand. As compatibility (C) is found to be the most important factor that affects a user's acceptance and use of a BI solution such as dashboards, this may have several implications, which we will now discuss further. These implications for Equinor will be discussed in light of relevant literature. The two main focuses of the implications are centered around implications due to missing match between current system features and system feature needs, which is presented in section 6.2.1, and implications due to a questionable fit between current user characteristics and system feature needs, which is presented in section 6.2.2.

6.2.1. Implications- Features and Needs

Firstly, we will discuss the implications due to a missing match between the current system features and the user's system features needs.

For the developments in MA, Gärtner et al. (2013) states that MA, as a holistic process, has transformed from information providing to "business partner". For the decision making in MA, this has also evolved over time. As of today, Quattrone (2016) implies that the exercise of judgment in decision making starts at a later point in the process than before, and that the whole process of manufacturing of the data is held outside of the action of decision making. Furthermore, given that Equinor is assumed to be a fast-paced company, our respondents are therefore assumed to have a dynamic and hectic workday and it is highly important that the information presented in a dashboard supports the user to make an effective and well-informed decision. This is also in accordance with the definition of decision making, presented by Jones et al. (2003), where it is highlighted that judgement is fundamental to decision making, as there most likely are a number of both appropriate and inappropriate alternatives to choose from. To ensure that the appropriate alternatives are chosen, Equinor has to make sure that the information presented is relevant and actually acts a decision support.

In one of the close-ended question, several of the respondents stated that they did not have access to sufficient and relevant data, as the current dashboard solutions contained and presented data that are too complicated to make well- based decisions on. It is also stated that the visualizations are not well-made. Moreover, given the present time-pressured decision-making process, it is also important to have in mind that large amounts of data and information may be overwhelming for the user. Based on our findings, the dashboard should present information that tells the user a story about the data that is easy to understand, which simplifies the user's interpretation of the information and removes the necessity of extensive analysis done by the user. Presenting data with stories and pictures are also found by CGMA (2016) as optimal to achieve the best understanding for different users, and further decrease subjective biases and errors in the interpretation of the data.

Subsequently, our findings support the fact that, given that the exercise of judgement has moved to a smaller time horizon later in the process, combined with a dynamic and hectic workday of our respondents, it is highly important that the information presented in a dashboard supports the user to make an effective and well-informed decision. For the dashboards used in Equinor today, this do not seem to provide a satisfying decision support solution.

Furthermore, given our findings of a time-pressured decision-making process, the concept of rationality is important. On the one hand, Jarrow et al. (1995) states that decision making is an intentional consequential action, meaning that whatever decision is taken is the rational choice which yields the highest expected value. On the other hand, March (1987, 1991) emphasizes that this is a simple rational-choice model, and brings the concept of limited rationality which is that not everything can be known, and when making decisions one bases this on incomplete information, the existing alternatives and their known consequences. Quattrone (2016) further discusses this view, where he states that limited rationality is a complication for decision making in organizations today and the focus has moved more towards making logical decisions, based on the available information, rather than assuming that every decision is fully rational.

Following the presented findings and developments, decision making in MA has become more data-driven, where decisions are based on analysis of data, rather than solely on intuition. Using BI solutions, such as dashboards, is something that can facilitate for data-driven decision making (DDD). The respondents also indicate that, when dashboards facilitate for decision making and containing the necessary system features, this supports their decision making and the desired purpose with the dashboard is achieved. However, this requires that the features of the dashboard, both functional and visual, match and support the users and their actual needs, and by that makes it easier for them to make decisions. DDD is also emphasized by Brynjolfsson et al. (2011) who have found it to create value for companies. On the other hand, Quattrone (2016) indicates that it may also augment uncertainty due to overwhelming amounts of data and increased distance to the origin of the source. This is especially important to consider due to the developments of the decision-making process, where he states that it may lead to people taking suboptimal decisions more quickly, with reduced room for judgement. This raises the point that even though BI solutions such as dashboard may facilitate for DDD, Equinor should be careful to implement it just for the sake of implementing it, without thorough consideration of the implications it may have on both the users and the decisions made.

6.2.2. Implications- Characteristics and Needs

The second main implication caused by the finding of an unachieved fit between system features, user characteristics and task specifics is related to the implications due to a questionable fit between the current user characteristics and the user's actual needs for system features based on their task and context at hand.

It is clearly stated that attaining the fit is important for the use of BI solutions as decision support in MA. Both Dilla et al. (2010) and Yigitbasioglu and Velcu (2012) support that if such a fit is present, the performance of the decision maker improves as a result of increasing efficiency and quality where they further connect this to the user's cognitive abilities. This substantiates the importance for Equinor to better match the dashboard solutions with the present needs of the users. However, in the quantitative analysis, the compatibility (C) factor is one of the factors that varies the most. In addition, in the qualitative analysis, the respondents emphasize different needs which imply that the fit contains different elements for different users. This highlights one of our important findings, which is that for the current solutions used in Equinor, the fit varies for the different users. Furthermore, H. Chen et al. (2012) have acknowledged that varying knowledge and skills affects the user's comfortability in using a BI solution, where this leads to different ways of interpreting data and this might hamper the insights of analysis presented in unfamiliar solutions and settings. Given the range of users that emphasize different needs, for Equinor it would therefore be valuable to more specifically map out current user characteristics and the users' needs, to more systematically work towards a better matching of this moving forward.

In cases where the fit between current system features, user characteristics and the users' system feature needs is not attained and the user characteristics are not at a satisfying level, Tang et al. (2011) found that this may lead to an increase in overconfidence and decrease in calibration, which may lead to suboptimal decisions. This further substantiates the importance of the user element of the fit. Tang et al. (2011) also states that decision makers are typically overconfident, and to reduce this, implementation of specific system features, especially features for interactivity, should be carefully considered before included in the dashboards. Specific features for interactivity, e.g. drill-down, are also stated by Peng et al. (2007) as something that may lead to suboptimal decision in cases where the fit between user characteristics and needs are not present. For Equinor, this means that when the fit is not attained, they should be careful with introducing specific system features. This means that they need to establish the fit between user characteristics and needs before proceeding to implement the system features aimed at fulfilling these needs. It is very important that this is done in the right order, to avoid complications or substantiating the unfavorable characteristics of the users.

In cases where the user characteristics do not match the system features, Peng et al. (2007) emphasize that training of the decision makers may improve the quality of decisions, as it increases their knowledge and expertise in using the included system features, and by that utilizing the dashboard in the best possible way. As training of users is also found by Z. Lee et al. (2008) to increase efficiency, and by that increase the utilization of dashboards as decision supporting solutions, we find this important for Equinor to consider moving forward, given that we have found that the fit is not attained. Even if the users have the necessary skills for using todays solutions, if these solutions change it may bring new and more advanced demands to the users' characteristics. If such characteristics are not at a satisfying level, findings have shown that it will impact the quality of decision making and lead to suboptimal decisions. As the dashboard solutions develop, ensuring a continuous process of change and development of the users' knowledge and skills is an essential element for Equinor. This is something that they should direct resources to when using BI for facilitating data-driven decision making in MA.

6.3. Summary of Discussion

In the previous chapter we answered our research question and discussed our findings in light of relevant literature and previous research. When answering our first research question, compatibility (C), and hence the fit between system features, user characteristics and the task, was found as the most important factor affecting the acceptance and use of BI solutions. Furthermore, we concluded in the second research question that the present user characteristics and system features do not match the current needs the user have for BI solutions. Consequently, as this fit is not attained, this has implications for the quality of the decision making, mainly due to the limited rationality and the level of expertise and knowledge of the users. If the use of BI solutions in MA should facilitate for data-driven decision making in Equinor, they need to work with improving the matching between the relevant elements.

6.4. Limitations

In this section we will present some limitations with our study. Firstly, one of the main limitations in our research is that the data collection is focused on a rather small sample for one single company. The selection of the unit of analysis is a potential threat to external validity and the generalization of the study. To gain deep insights, we chose to analyze a group of people within the same company, and even though our sample is a somewhat homogenous group, this can also be said about the group containing similar roles in other companies. The characteristics of the decision making itself can also be compared. Thus, reasoned in company similarities and characteristics of the respondents and tasks, we found our thesis to contribute with general insights on how BI can facilitate for data-driven decision making in MA.

Second, the sampling strategy used was a form of non-probability, convenience sampling based on certain criteria. The sampling was done by our contact persons in the case company, which may imply that biases may have been present. Even though the respondents were sampled based on certain criteria to obtain a representative sample, the chosen respondents were already somewhat involved with using the use of dashboards as decision support. This may indicate a “ceiling-effect” and lead to a top-heavy sample when it comes to technological skills and familiarity with BI solutions.

Lastly, a cross-sectional survey study was chosen for this research, and while this can encourage replicability and comparability for future studies, an in-depth case study of the BI phenomenon could yield valuable insights as it is rather new. With a cross-sectional study we are not able to capture changes and developments over time which can be a valuable contribution for research on this field.

7. Conclusion

In this thesis we have aimed to answer our main research question: *How can the use of BI solutions in MA facilitate data-driven decision making?* To answer this, we opted for answering two sub questions: *Which factors affects the acceptance and use of BI, such as dashboards, as a decision supporting solution in MA?* and *How do the current needs for BI solutions match the present user characteristics and system features?* Our discussion of our findings has resulted in three main findings.

The first regards the finding of a missing match between the current system features, user characteristics and the users' system features needs. In addition, the compatibility (C) factor was shown as being the most important for the acceptance and use of BI solutions and this seems to vary for the users in Equinor. As their needs are highly affected by their task and context at hand, our findings show that the current dashboard solutions used in Equinor do not provide a satisfying solution for decision support for all users. To ensure that dashboards are used efficiently and in accordance with the desired purpose, it is important to both take the clearly stated needs of the relevant users into account, and further map out specific needs where these are not clearly stated. We find this as a fundamental element in how Equinor can facilitate for data-driven decision making in MA.

The second main finding is regarding the importance of that the dashboard tells the user an uncomplicated story about the data. Our findings support the fact that, given that the exercise of judgement has moved to a smaller time horizon later in the process, combined with a dynamic and hectic workday of our respondents and limited rationality, it is highly important that the information presented in a dashboard supports the user to make an effective and well-informed decision. Subsequently, the users mentioned needs for system features and data infrastructure are important elements. Furthermore, given our findings of a missing fit between current system features, user characteristics and users' system feature needs, Equinor should, in the process of meeting the users' needs, carefully consider the elements included, as large amounts of data, number of features, etc., may be overwhelming for the user and affect the quality of the decision making.

Lastly, the third finding is the importance of a continuous improvement and change of the users' knowledge and skills in using dashboard as decision support in MA. Given our findings of a missing fit, the future dashboards may include different features than the current solutions. Consequently, even if the users have the necessary skills for using todays solutions, if these solutions change it may bring new and more advanced demands to the users' characteristics. Keeping the users' level of knowledge and skills at an adequate level is especially important, given the limited rationality of the users and the limited exercise of judgment in the decision-making processes. In addition, this finding further shows that Equinor should be careful with implementing specific features before the level of knowledge and skills of the users is satisfying, as this affects the quality of the decision making. This further substantiates the fact that in this digital era, technologies should not be implemented for the sake of implementing it, but it should be grounded in the needs of the users and all necessary knowledge and skills need to be present.

This study offers new and valuable insights into the relatively new and yet not so discovered field of using BI solutions in MA for decision support. As mentioned, in this research we have seen MA as a broader, holistic process where it is described as a business partner for decision support. The research has gained valuable insights by mapping out which factors that affect the acceptance and use of BI solution, as well as different needs our respondents have and how this should be matched with user characteristics and task specific factors. By doing this, we have also contributed to a research field that has been requested, e.g. by Rikhardsson and Yigitbasioglu (2018) and Nielsen (2018).

Further cross-disciplinary research with different samples could give additional insights into how dashboards can be used as decision support and would be valuable for a broader picture of the phenomenon. In addition, future studies on this can provide generalization to the study and provide a strengthened picture on the acceptance and use of BI solutions for decision support in MA. Future research on the acceptance and use if BI in MA may also benefit from conducting a longitudinal study. Since this phenomenon is rather new, a study with the ability to investigate changes and developments over time would contribute with a more detailed picture. Thus, a broader, longitudinal case study, including several factors not covered in this research may be relevant to conduct in the future.

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Appendix

Appendix 1: Introduction page questionnaire

NHH

Bruk av visualisering for å presentere finansielle data

Takk for at du vil delta i denne spørreundersøkelsen!

Undersøkelsen inneholder spørsmål om dagens situasjon og ønsket situasjon angående visualisering av finansiell data. Tilbakemeldingene vil hjelpe oss å kartlegge hvordan dagens verktøy for visualisering brukes i beslutningstaking i Equinor. Resultatene vil hjelpe Equinor å forbedre bruken av verktøy og visualisering av finansielle data. Gjennom optimert bruk av BI-løsninger og visualisering av finansielle data håper vi å kunne forbedre grunnlaget for beslutningstaking. Spørreundersøkelsen er utviklet av to masterstudenter på NHH, som en del av en masteroppgave som omhandler bruk av BI-løsninger for visualisering av finansielle data.

Undersøkelsen vil ta omtrent 10 minutter å gjennomføre. Din respons er anonym, og all data vil bli behandlet konfidensielt og resultater vil bli rapportert på aggregert nivå uten mulighet for personlig identifisering.

Før du starter spørreundersøkelsen ønsker vi å definere noen begreper som vil bli brukt i spørsmålene.

Business intelligence løsninger - Business Intelligence (BI)-løsninger er et sett med metoder og teknologier for å klargjøre, presentere og hjelpe til å analysere data. Disse løsningene gjør data om til tilgjengelig informasjon med intensjon om å hjelpe beslutningstakere og sluttbrukere til å ta mer effektive datadrevne beslutninger.

Dashboards - Et dashboard er en visuell og lett tilgjengelig måte å presentere data på. Et dashboard med god datavisualisering kan gi brukere innsikt i data i ett skjermbilde slik at de raskt og enkelt kan danne seg en oversikt. Dette åpner for at man kan dykke ned i dataene i dashboardet istedenfor å måtte be om en ny rapport med egne spesifikasjoner.

Beslutningstaking - Den sammensatte prosessen med å velge et logisk valg fra de tilgjengelige alternativene, basert på tilgjengelig informasjon og tidligere kunnskap. I denne spørreundersøkelsen refererer beslutningstaking til beslutninger som omhandler finansielle data.

Med vennlig hilsen,
Helene Lunde Bjørvik og Tone Vinge Fanavoll

Appendix 2: Factor analysis

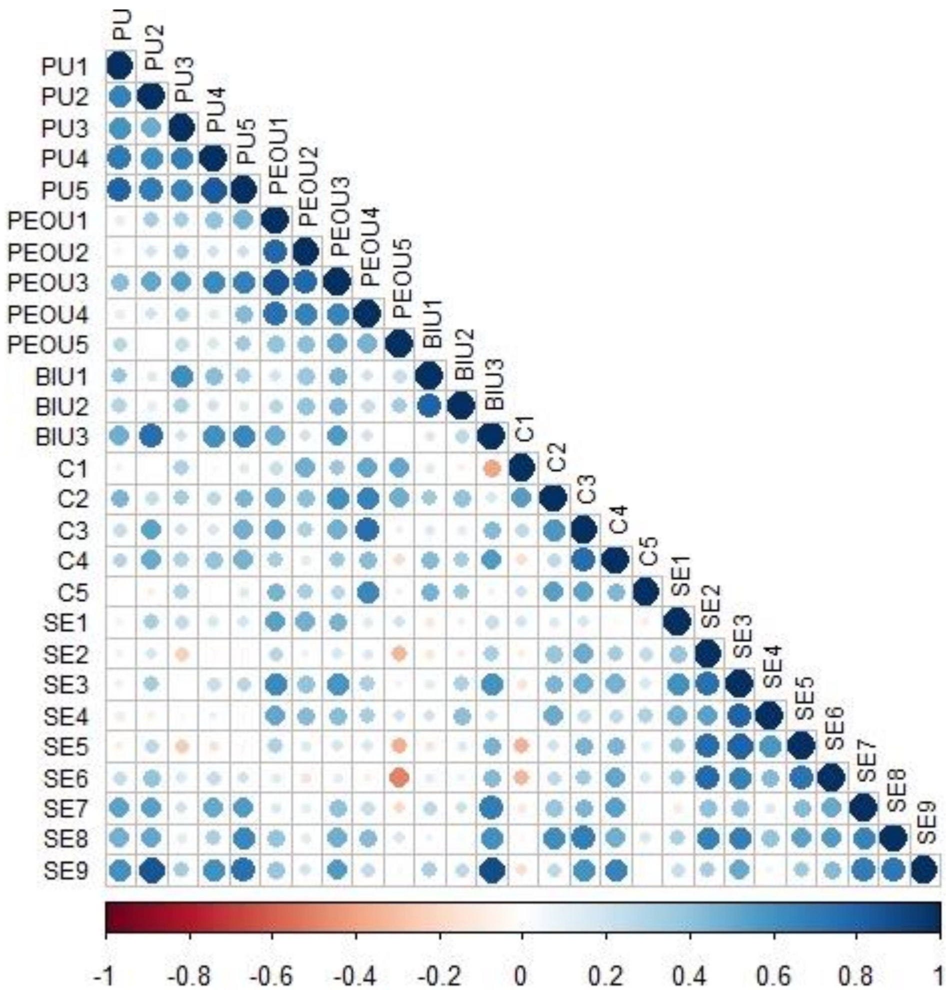
2.1. Initial KMO and Bartlett's Test

Kaiser-Meyer-Olkin measure of sampling adequacy (KMO)		X
Bartlett's test of sphericity	Approx. Chi-Square	59.461
	df	26
	p-value	0.000198

2.2. Initial Reliability Assessment

Construct	Item	Cronbach's Alpha if Item Deleted
Perceived Usefulness Cronbach's Alpha: .908	PU1	.880
	PU2	.907
	PU3	.908
	PU4	.877
	PU5	.862
Perceived Ease of Use Cronbach's Alpha: .873	PEOU1	.839
	PEOU2	.830
	PEOU3	.814
	PEOU4	.851
	PEOU5	.891
Behavioral Intention to Use Cronbach's Alpha: .620	BIU1	.409
	BIU2	.235
	BIU3	**.878**
Compatibility Cronbach's Alpha: .758	C1	.815
	C2	.655
	C3	.626
	C4	.751
	C5	.696
Self-efficacy Cronbach's Alpha: .893	SE1	.907
	SE2	.869
	SE3	.856
	SE4	.885
	SE5	.870
	SE6	.874
	SE7	.894
	SE8	.875
	SE9	.891

2.3. Correlation Plot



2.4. Initial Pattern Matrix and Communalities

	PU	SE	PEOU	BIU	C	Communalities
PU1	**0.83**	-0.23	-0.13	0.14	0.03	0.73
PU2	**0.87**	0.09	0.06	-0.13	0.00	0.77
PU3	**0.52**	-0.34	0.13	0.34	0.09	0.59
PU4	**0.81**	-0.16	0.16	0.19	-0.15	0.75
PU5	**0.90**	-0.20	0.10	-0.01	0.20	0.93
PEOU1	0.15	0.16	**0.63**	0.10	0.30	0.78
PEOU2	-0.06	-0.02	**0.68**	0.23	0.25	0.72
PEOU3	0.43	-0.01	**0.63**	0.23	0.20	0.97
PEOU4	0.00	-0.07	0.25	0.03	**0.85**	0.90
PEOU5	0.07	-0.46	**0.53**	0.09	0.22	0.59
BIU1	0.15	-0.10	-0.05	**0.89**	0.04	0.87
BIU2	-0.02	0.11	0.10	**0.87**	-0.06	0.78
BIU3	**0.74**	0.39	0.10	0.04	-0.16	0.81
C1	-0.08	-0.49	0.33	-0.14	**0.57**	0.64
C2	0.11	0.05	0.19	0.17	**0.63**	0.66
C3	0.26	0.29	-0.12	-0.10	**0.80**	0.89
C4	0.36	**0.40**	-0.31	0.32	0.33	0.71
C5	-0.28	0.10	-0.14	0.44	**0.68**	0.70
SE1	0.11	0.29	**0.75**	-0.24	-0.14	0.67
SE2	-0.05	**0.83**	0.02	-0.19	0.26	0.82
SE3	0.11	**0.80**	0.46	0.10	0.01	1.00
SE4	-0.28	**0.59**	0.47	0.29	0.08	0.73
SE5	-0.06	**0.95**	0.05	-0.03	0.05	0.90
SE6	0.24	**0.78**	-0.17	0.08	-0.04	0.74
SE7	**0.60**	0.33	-0.23	0.08	0.13	0.63
SE8	**0.49**	0.43	0.04	-0.20	0.39	0.78
SE9	**0.83**	0.27	-0.02	0.04	0.02	0.86

Appendix 3: Responses open-ended questions

Construct	Responses – Not condensated
Percieved Usefullness (PU)	#1 - Ønsker en standard visualisering av oppdaterte estimater, forecast, endringer, beslutningsmilepæler osv der alle driftskostnader for feltet kommer inn (opex/capex). Viktig her er våre interne støttespillere i OTE/JOS. #2 - Innholdet i dashboardet er avgjørende - Eksempelvis er det vesentlig å se både fremover (planlagt aktivitet) og bakover (belastede kostnader) samtidig - I dag bygges det mange dashboard som bare viser fragmenter av den helhetlige informasjonen som er nødvendig. Eksempelvis er det uinteressant å se akkumulerte belastede kostnader, dersom fremtidig aktivitet og antatt total belastning ikke er synligjort i samme dashboard. #3 - Dashboards er nyttig, men det er svært viktig at det er mulighet for drill down for å komme inn i underlagsdata for å forstå det som synliggjøres i dashboard #4 - Det var mange spørsmål som går litt på det samme..... #5 - Ift beslutningstagning brukes dagens dash board i liten grad til det. Størrelsen på beslutningen avgjør kvaliteten i beslutningsunderlaget for den enkelte beslutning. Kunne tenke meg BI verktøy eller RPA løsning som hevet kvaliteten i estimering av KV og som enkelt ga oversikt på hvor vi kan ta ut læring på feil i estimering eller styring av den enkelte jobb.
Percieved Ease of Use (PEOU)	#1 - Kompetansen og helhetlig forståelse for forretningsbehovet er avgjørende når det bygges dashboards. Dette er ikke optimalt i dag, ettersom det bygges mange dashboards ut fra ulike behov - som ikke nødvendigvis er relevant for alle. Det glemmes at et dashboard skal støtte opp under beslutninger tatt av brukeren- Om ikke de visuelle elementene forteller om noe er akseptabelt, ikke akseptabelt, stigende, fallende mot et akseptabelt/ikke akseptabelt nivå så oppnås trolig ikke ønsket effekt eller formål med dashboardet. #2 - Svarer nøytralt på siste spørsmål pga det kommer an på hvilken type beslutning. #3 - Dashboard er gode verktøy, men det stiller samtidig store krav til

	kvalitet i data som fremlegges, både mht relevans og vasking for feilkilder. #4 - Dashbord/drilldown i MIS under feltkost kan være vanskelig å navigere i om du ikke bruker dette mye/ofte #5 - Det må bli enklere å tilpasse dashboard for å få ut informasjonen man trenger. #6 - Øko dashboardene har ikke alltid vært enkle å bruke. Siste verktøy i power BI er det beste så langt. # 7 - Forutsetninger/filtre som er benyttet for å fremskaffe dataunderlaget som vises i Dashboards er i noen tilfeller ikke tilgjengelig eller oppgitt. Det kan føre til at vi misforstår eller feiltolker resultatene.
Behavioral intention to use (BIU)	#1 - Avhengig av kvalitet/ formål med dashboardet. #2 - Dashboard er nyttig verktøy, men det er viktig å ha fokus på hvilken type informasjon bruker trenger.
Compatibility (C)	#1 - Tidvis mismatch i data fra PowerBI mot SAP dashboards. Unødvendig problemstilling. #2 - Det er utfordrende at er kultur om at de fleste dashboard skal brytes ned over den aktuelle driftsenheten. Dette er ikke alltid like relevant, særlig for de deler av organisasjonene som arbeider på tvers av driftsenheter. #3 - Spørsmålet her ble litt generelt. I noen sammenhenger så er det gode løsninger i forhold til beslutning (arbeidsprosess) andre ganger har vi mindre gode løsninger.
Self-Efficacy (SE)	#1 - Jeg har generelle god innsikt og forståelse for de dashboard jeg bygger selv, men i mindre grad eierskap og behov for dashboard bygget av andre. Det vil være en forutsetning at brukeren til en grad kan påvirke sine dashboards.