UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Improving Decision Making Through the Use of BI&A and a Data-Driven Culture

Bachelor Thesis in Business Administration
Management Accounting
Spring 2020
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Abstract

Type of thesis: Bachelor Thesis in Business Administration, 15 credits

University: University of Gothenburg, School of Business, Economics and Law

Semester: Spring 2020

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Background and problem: Today, businesses act in an increasingly complex environment, that requires organizations to be more adaptive. This increases the value of data analytics and decision support systems such as Business Intelligence & Analytics (BI&A) for decision makers and enables them to make better and quicker decisions. At the same time, there is a lack of understanding of the data-driven cultures that support the use of BI&A and BI&A in relation to the decision process itself.

Research aim: To expand the understanding of organizational decision making under the presence of BI&A.

Research questions: "How can a data-driven culture support the use of Business Intelligence & Analytics?" and "How does the use of Business Intelligence & Analytics, facilitated by a data-driven culture, support the decision process?".

Research design: The research questions were studied using an exploratory approach with semi-structured interviews. Three Swedish organizations active in the logistics sector were interviewed as well as an external BI consultant. Through this approach, detailed information on how BI&A and data-driven cultures affect decision making were collected from the different organizations and was complemented with general knowledge on the topic from the BI consultant.

Discussion and conclusion: The findings suggest that the influence of BI&A supports decision making, whereas the extent and type of support depend on the organisational level of the decision. Further, the findings highlight the importance of a data-driven culture, which supports the use of BI&A by facilitating data-driven decision making. Similar to prior research, a data-driven culture is found to be built on a set of enabling factors, although some new aspects are identified.

Keywords: Decision Making, Data-Driven Decision Making, Data-Driven Cultures, Data-Driven Organisations, Management Accounting, BI&A, BI, Business Intelligence.

Acknowledgements

Writing this thesis has been an exciting and challenging undertaking, and we would like to express our gratitude to all our contributors. For had it not been for them, the thesis would never have been what it is. First, we would like to thank all the respondents of this thesis. Without your commitment, our work would not have been possible. Thank you for your eagerness to participate, contribute and share your valuable experience. Second, the people in our seminar group, thank you for your valuable feedback and discussions throughout the semester. Finally we would like to express our gratitude to our supervisor Elisabeth Frisk. Thank you for the continuous support throughout the semester, your guidance has finally taken us to the finish line!

Fredrik Öberg & Gustav Öhman,

Gothenburg, May 30th, 2020

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1.0 Introduction

This chapter begins with a description of the challenges businesses face today and how decision makers are provided with decision support tools in the form of BI&A. This falls into a problem discussion highlighting the need for a data-driven culture to support the use of BI&A tools and the need for more research on BI&A's influence on the decision process itself. Further, the research aim and questions are synthesized in relation to this gap and finally delimitations are made and the thesis disposition is presented.

1.1 Problem Background

Organizations act in a changing and increasingly complex environment. Product cycles are shortening, the pressure to reduce costs is increasing, and unstructured information is now available in volumes and varieties never encountered before. A dynamic environment and a rich amount of information creates strategic opportunities for the extraction of unique and relevant business insights from data. Likewise, the exploitation of organizational data provides operational and strategic opportunities. (Davenport & Patil, 2012; Chen & Chiang, 2012; Kiron & Prentice, 2014). Hence, many executives consider data analysis and decision support essential for creating value for their companies (Elbashir et al., 2013; Kiron et al., 2014). They recognize the importance of asking the right questions and being able to identify the significant business questions from today's plentitude of unstructured and structured data (Davenport & Patil, 2012). They have become more demanding about the type and quality of the information they expect to receive. Decision makers need real-time information, not seldom on short notice (Rikhardsson & Yigitbasioglu, 2018). Likewise, there is wide agreement today that the decision process cannot be reduced to choice and the role of information and the building of possible alternatives are widely regarded as critical (Pomerol & Adam, 2004).

In a decision-support context, Business Intelligence and Analytics (BI&A) have emerged as technological solutions in the form of systems and processes that are designed to support organizational decision making (Popovic, Hackney, Coelho, Jaklic, 2012). BI&A comprises solutions for integrating, analyzing, and presenting data to provide decision makers with valuable information. Hence, BI&A support decision-activities on all organizational levels, including management, operations and planning levels, through what has been termed *data-driven decision making* (Bihimani & Willcooks, 2014; Rikhardsson & Yigitbasioglu, 2018). BI&A and data-driven decision making have the potential to radically improve company performance, since they enhance data utilization and enable organizations to discover and capitalize on business insights. Research seems to confirm this, seeing that top-performing companies appear to use analytics to a larger extent than their competitors. (Mcafee & Brynjolfsson, 2012; Berndtsson, Forsberg, Stein & Svahn, 2018). Consequently, BI&A has attracted attention from the academic literature. There is currently research on a range of topics related to BI&A, including the design, implementation and outcomes of BI&A (Rikhardsson & Yigitbasioglu, 2018).

1.2 Problem Discussion

From the earlier discussion, it is obvious that Business Intelligence & Analytics (BI&A) have the potential to improve organizational decision making. Research on the benefits of BI&A is limited however (Popovic et al., 2012). A literature review performed by Rikhardsson and Yigitbasioglu (2018) suggests that the implications of BI&A on the decision process is a potential research area. Hence, whilst there is research on the outcomes, design, and implementation of BI&A, there is reason to examine the implications of BI&A on the decision process itself.

Nevertheless, the information that is provided by BI&A is only *potentially* valuable. For instance, the benefits of BI&A on decision making is contingent on both system-and information quality, as well as on user consumption of the data. (Popovic, Hackney, Coelho, Jaklic, 2012). Current literature highlights that organizations must pay attention to a diversity of aspects if BI&A is to support decision making. (Berndtsson, Forsberg, Stein & Svahn, 2018; Kiron & Prentice, 2014; McAfee & Brynjolfsson, 2012; Rikhardsson & Yigitbasioglu, 2018). Some studies discuss the role of processes, technologies, applications, tools, and similar (Popovic et al., 2012). There is also research with a more user-focus, including user flexibility and interaction with the solutions. Many of these studies conclude that decision decision quality improves when these aspects fit together. (Rikhardsson & Yigitbasioglu, 2018). Overall however, the literature on what determines a successful use of BI&A is limited. (Popovic et al., 2012). Furthermore, the research on BI&A that does exist has been criticized for being too focused on the technical aspects of BI&A (Shollo and Kautz, 2010).

Several authors argue that it is critical to develop a so-called *data-driven culture,* as it influences the use of BI&A. A data-driven culture encourages data-driven decision making, where data outweighs opinions, and where data is the driver of organizational action. (Schein, 1996, Davenport, 2006, Berndtsson et al., 2018; Popovic et al., 2012). Additional studies on the topic of fostering an analytical decision making culture is needed (Rikhardsson & Yigitbasioglu (2018).

1.3 Research Aim and Questions

The aim of the thesis is to *expand the understanding of organizational decision making under the presence of Business Intelligence & Analytics (BI&A).* Based on the problem discussion and the identified research gaps, there is a need to increase the understanding of both data-driven cultures as well as the decision process itself in relation to BI&A. Therefore, this thesis will first investigate how a data-driven culture supports the use of BI&A. In order to do so, general knowledge about data-driven culture and its components must be established. Secondly, this thesis will examine how BI&A supported by a data-driven culture impacts organizational decision making, and more specifically the decision process. This will extend the current research that discusses decision making cultures in the context of BI&A; both in how such a culture constitutes itself, and how it supports the use of BI&A. It will also contribute to the research on BI&A in relation to decision making by examining BI&A:s implications for the decision process, which was identified as a gap. Altogether, it results in the two following research questions:

- How can a data-driven culture support the use of Business Intelligence & Analytics?
- How does the use of Business Intelligence & Analytics, facilitated by a data-driven culture, support the decision process?

1.4 Delimitations

To study these research questions, some limitations are advantageous. First, the thesis will be limited to the logistics and transportation sector in Sweden. Further the thesis will not attempt to provide normative suggestions, but rather use an exploratory approach to provide a snapshot of how BI&A, supported by a data-driven culture, can support the decision process. Moreover, the thesis will have a user perspective of BI&A, focusing on how BI&A support individual decision making, and how an organization can enable BI&A to support employee decision making. Also, as requested in the current literature, technical aspects will not be the focus of this thesis, although they are hard to fully ignore. Implementation challenges will not be a focus area either. Finally, the thesis will focus on factors that can be controlled by the organization to some extent, as opposed to environmental conditions which fall outside the scope of this study.

1.5 Thesis Disposition

The following parts of the thesis is structured accordingly:

2. Frame of Reference: Summarizes the current relevant research on BI&A, data-driven cultures and the decision process, resulting in the authors analytical framework that is used for the data collection and analysis.

3. Research Approach: Accounts for the methodological choices and methods used in this thesis.

4. Findings: Accounts for the empirical data gathered through the qualitative interviews.

5. Discussion: Analyses the collected data through the authors analytical framework.

6. Concluding Comments: Summarizes the author's findings through an attempt to answer the research questions. Discusses the theoretical and managerial implications.

2.0 Frame of Reference

In this chapter, existing research relevant for the research questions are presented. First, Business Intelligence & Analytics is defined and put into its organizational context. Second, the concept of a data-driven culture is presented and broken down to enabling factors. Lastly, a decision process is conceptualized using Henry Mintzberg's (1976) framework. The three parts are finally synthesized into the authors analytical framework.

2.1 Management Accounting Systems and Business Intelligence & Analytics

Management Accounting Systems (MAS) are systems designed to provide information to support decision-making. Managers may employ these systems to assist their own decision making activities, but they can also be targeted to enable their subordinates to make the "right" decisions. However, the subordinate activity in the system is typically not monitored or guided by the manager. and hence MAS can be defined as pure decision-support systems. (Malmi & Brown, 2008). Business Intelligence & Analytics (BI&A) are decision-support tools and processes that can be categorised as Management Accounting Systems.

2.1.1 Business Intelligence & Analytics

Business Intelligence & Analytics as decision support

Business Intelligence & Analytics are solutions for integrating, analyzing, and presenting data to provide decision support (Rikhardsson & Yigitbasioglu, 2018). BI&A transform raw data to valuable information that, in turn, is used by individuals to improve their understanding of the business and its activities, and thereby enable them to make better decisions;

> *"....through BI initiatives, businesses are gaining insights from the growing volumes of transaction, product, inventory, customer, competitor, and industry data generated by enterprise-wide applications" - (Chen, Chiang & Storey, 2012)."*

Business Intelligence thus has the potential to improve business performance and decision making through an efficient use of data and information (Turban, Sharda, Delen, King & Aronson, 2011).

Business Intelligence

Turban et al., (2011) divide the structure of Business Intelligence into four components: *business analytics*, *data warehousing*, *business performance management (BPM)* and *user interface*. Moreover business analytics is divided into two categories to separate its use: *self service BI* and *data analytics*. Technical aspects of incorporating data through data warehouses and developing user interfaces fall outside its scope, and are not discussed further. This results in three remaining categories of BI: *self service BI*, *data analytics* and *BPM*.

Self-service are user friendly analytical tools designed to make casual users more self-reliant. Self-service allows casual users to access data and perform their own analyses resulting in efficiency by having them less dependent on the IT-department. It creates flexible and autonomous decision makers, who have the ability to make real-time, accurate decisions. (Turban et al., 2011; Lennerholt, Laere & Söderström, 2018)

Furthermore, *Data Analytics* comprises powerful, advanced analytical tools used to analyze vast amounts of data in order to find patterns, relationships and perform predictive analyses. It includes tools such as machine learning, advanced statistical methods and data mining. Input data can be structured as well as unstructured. Data Analytics utilizes the vast amounts of data available and can provide powerful insights to the organization. The nature of the analysis requires specialized staff and is not as democratized as self-service. (Turban et al., 2011)

Finally, *Business Performance Manageme*nt (BPM) is more characterized by traditional top-down control. Here, monitoring of performance is central, and feedback-loops are a main component. Strategic objectives are broken down to success-factors, which enables the organization to set standards which are compared to actual outcomes. Deviations are then acted upon in a feedback-loop fashion. (Turban et al., 2011) A second perspective on BPM is presented by Eckerson (2009) that differentiates the required information for different organizational levels. Eckerson (2009) suggests that the strategy is cascaded into key performance indicators (KPI:s) adapted to each organizational level. These KPI:s are further aggregated at the strategic level.

Analytics

Davenport (2013) describes three types of analytics known as: Descriptive, Predictive and Prescriptive. For readers of this thesis it is essential to understand the differences between these and to be able to distinguish between them. Descriptive analytics are characterized by providing data about the past, Predictive analytics are characterized by the use of past data to predict the future and Prescriptive analytics are characterized by specifying optimal behaviours and actions through models. Prescriptive analytics are the most advanced form of analytics among these three and it's emphasized to be of growing importance as analytics develop.

BI 1.0, BI 2.0 and BI 3.0

Chen et al. (2012) argues that BI&A can be separated into BI 1.0, BI 2.0 and BI 3.0. BI 1.0 heavily relies on database management where data is collected, extracted and analyzed. In BI 1.0 data is generated internally and mostly structured in a common database. The data mining and data analysis techniques that have their roots in the late 20th century are used to explore key data characteristics. Data-mining, dashboards, reporting, interactive visualization and predictive modelling are all main components of BI 1.0. BI 2.0 emerged along with the arrival of the Web, which made information from outside the company's boundaries available; about the company, industry, product and customers. The Web enabled companies to present their business online and to interact with customers online. Web analytics, crowd-sourcing systems and user-generated content are some of the components of BI 2.0. As the Web developed, companies were also provided with the opportunity to get more real-time information, primarily in the form of customer feedback and opinions according to Chen et al. (2012). BI 2.0 thus comprises a greater diversity of types of data, where text and content analysis is more central. It also requires a more efficient integration of data. BI 3.0 is an emerging research field with emphasis on mobile and sensor-based content. BI 3.0 has its roots in the introduction of mobile, internet-enabled devices. This brings new opportunities for the collection, processing and analysis of data, as these devices support location-aware, person-centered and context-relevant transactions that can be leveraged by the organization.

2.1.2 Data-Driven Decision Making

Business Intelligence & Analytics have the potential to make an organization data-driven. What distinguishes data-driven organizations is that data is the driver of action. Attempts to define data-driven organizations typically include a decision process that is characterized by: i) collecting data, ii) use of analytics to derive insights, and iii) make a decision based on derived insights. A true data-driven organization is a data democracy and has a large number of stakeholders who are vested in data, data quality, and the best use of data to make fact-based decisions and to leverage data for competitive advantage. (Berndtsson, Lennerholt, Larsson & Svahn., 2020) Another characteristic of data-driven organizations who use BI&A, is the access and use of real-time information (Bihimani & Willcooks, 2014). Likewise, Rikhardsson and Yigitbasioglu (2018) claim that BI&A and data-driven decision making has the potential to immensely improve decision making since it can identify trends and patterns, which can act as a basis for decisions.

Risks With the Use of Data

Analytics and a richer amount of data have the potential to improve business, but it also brings risks. Although data can be secured and accessed, a richer amount of data does not guarantee better decisions since it brings its own statistical analysis problems. Biases in the collection, processing and application of the data may lead to inferior decision making, even compared to decision making when access to data is limited (Bhimani & Willcocks, 2014; Waterman & Bruening, 2014).

Regarding the collection of data in the context of BI&A, there is a risk that the entry and/or the merging of data may be inaccurate (Waterman & Bruening, 2014). However, even though the collection and entry of data is executed correctly, the data may not be suitable for the intended analysis (WillisTowersWatson, 2018). The user needs to ensure that the right data is chosen for the right purpose. Moreover, the data can be irrelevant or outdated, since historic data does not eternally remain appropriate for predicting future outcomes. More data also tends to result in more time and resources allocated to manage the data (IBM, 2016). Finally, there is the risk of information overload, where the users spend their time looking for hidden trends, correlations, etc. in all the data.

Utilizing data and analytics requires organizational expertise and skills. It is not simply a matter of collecting and installing the data, the user must understand what the input the data represents, and what story the output is telling (Waterman & Bruening, 2014). Determining the appropriate tool for the analysis is not always obvious, and the tool of choice can affect the outcome. A final issue related to the processing and analysis of the data is the general willingness of the user to confirm his or her thesis (WillisTowersWatson, 2018).

Several authors have discussed how the increased access to data is not necessarily value-creating in itself. McAfee & Brynjolfsson (2012) discuss how the power of IT doesn't erase the need for human insight. They argue that successful strategies require leaders who can set clear goals, articulate compelling visions, contribute with novel thinking and spot an opportunity. Similarly, Bhimani & Willcocks (2014) argues that valuable knowledge can be lost if analogue knowledge is translated into data, and used as the main source of knowledge.

2.2 Data-Driven Culture

It has been suggested that in order to truly become data-driven, which is discussed in 2.1.2, the decision-making culture must be managed, as it influences the use of Business Intelligence and Analytics (Berndtsson et al., 2020; Popovičet al., 2012). Establishing a so-called *data-driven culture* is hence argued to enable organizations to fully benefit from Business Intelligence and Analytics, as it will facilitate the creation of business value from analytics (Kiron & Prentice, 2014). There are several conceptualizations of what can be termed as a data-driven culture, however many of these conceptualizations share some recurrent elements. Likewise, these conceptualizations typically share the perspective that a data-driven culture is built on a set of enabling factors (Berndtsson et al. 2018; Kiron & Prentice, 2014; McAfee & Brynjolfsson, 2012), which the next chapter will elaborate on.

2.2.1 Characteristics

A data-driven culture can be conceptualized as a culture that facilitates a decision process that favours data rather than opinions, and allows experimentation (Berndtsson, Forsberg, Stein & Svahn, 2018). Kiron & Prentice (2014) discuss how an effective analytics culture is built on the backs of more advanced data management processes, technologies and talent. The components of a data-driven culture that are highlighted in their article are behaviours, values, and (decision making) norms, which together result in a change of how business is conducted (outcomes). Decision making norms are essential to encourage the use of analytics, Kiron and Prentice argue. Likewise, they argue that organizations ought to have a shared language about how to talk about data. Having a common set of reporting processes and performance measurements, as opposed to performing these activities in silos, is mentioned as examples of this.

In the literature review conducted by Berndtsson et al. (2018), 5 key enabling factors were identified to establish a data-driven culture*; management, data, tools, organization and decision process,* illustrated in figure 1. This framework and its categories will be used as a basis for the subsequent description of the data-driven culture's components and how it supports data-driven decision making according to current literature.

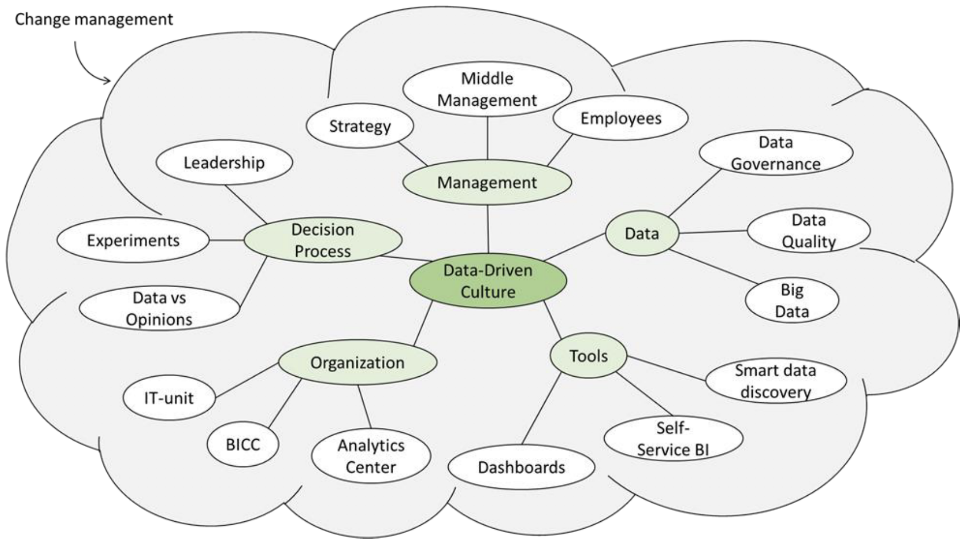


Figure 1. Enabling factors affecting a data-driven culture. From Berndtsson, M., Forsberg, D., Stein, D., Svahn, T. (2018). Becoming a data-driven organisation. *Twenty-Sixth European Conference on Information Systems (ECIS0218).* Portsmouth, UK.

Management

Transitioning into a data-driven organisation is very much about managing change. A highly engaged top level management involved in the development of a strategy to establish a data-driven culture is important. Otherwise, the transformation will be confined to silos within the organization. According to Halper and Stodder (2017), the biggest barrier to become data-driven was "lack of business executive support" and corporate strategy. It is also important for the top level management to be actively engaged in discussions and to highlight the importance of a data-driven culture for the organization. Similarly, Kiron & Prentice (2014) argues that changing the way employees think and operate requires senior management pressure.

Moreover, introducing a data-driven culture often faces challenges as managers, especially middle managers, feel threatened when insights are delivered by data scientists, thus challenging their skills and salaries. Issues also arise as employees and middle management have too high expectations of advanced analytics.

Data

Further, Access to high quality data and data governance is essential to any type of data-driven organization. The lack of these features create a lack of trust in business insights and undermine the transformation towards a data-driven culture. Berndtsson et al. (2018) argue that many organizations have their historical data in good shape, due to data warehousing initiatives, but are finding this data unusable as old data is now analyzed in new days than what was originally intended. The use of external data contributes to difficulties with data quality.

A literature review conducted by Lennerholt et al., (2018) concludes that there are 6 overall challenges with regards to access and use of data. The review suggests that access to sources of data need to be accelerated and simplified, end users need to be selective of data based on quality criterias, correct data queries needs to be used to avoid misleading insights, who are entitled to use and add data, how long data should be stored and the minimum quality criterias needs to be defined and data governance and management needs to be implemented.

Tools

Moreover, tools that are user-friendly should be provided. Berndtsson et al., (2018) suggest that employees should be able to use any tool they wish, and develop a dashboard that is suitable for their daily work. Even though the tools might be very technically advanced, the interface and visualizations should be user-friendly and recommendations should preferably be available. The information needs to be understandable for the users and there needs to be definitions explaining what type of data is required for a specific analysis. Different users are in need of different tools and a challenge is thus understanding the capabilities of specific BI tools and its user requirements. The users need to be trained to be proficient in analytics meaning that they both need to be trained in how the tools work but primarily how they could choose and interpret data based on what analysis is needed. (Lennerholt et al., 2018). Altogether, this is argued to generate business insights faster. One step further would be to implement more advanced tools and data mining techniques, which possibly allow organizations to generate semi-automated insights (Berndtsson et al., 2018).

On the subject of flexible and user-friendly tools, Self Service Business Intelligence (SSBI) is of particular interest. In accordance with chapter 2.1.1, SSBI comprises tools that are intended to be user-friendly. SSBI implies that end users perform descriptive analysis to some extent on their own, without the assistance of power users. This requires organizations to train employees in tools such as Power BI, Tableau, Watson or Qlik Sense, as well as the theory and algorithms behind them. A SSBI approach requires the IT-Unit to provide easy access to data (Berndtsson et al., 2018)

Organization

Furthermore, Berndtsson et al. (2018) discuss how most companies have some sort of IT-unit or IT-competence in-house, some even have a specialized Business Intelligence Centre. These units typically produce standardised reports on a regular basis, as well as ad hoc reports if requested from an end user. However, as noted earlier, a data-driven culture puts more emphasis on test and learn, rather than standardised reports. Hence, it is necessary that the IT-unit has a user focus and enables easy access to data, which is quality-assured and can be manipulated to test ideas and possibly generate insights. The traditional request-response process with the IT-unit is suboptimal.

A data-driven decision process

This factor is of certain interest, since the decision process will act as a signal to whether the adaptation of a data-driven culture is working or not. If the 4 other enablers mentioned above are in place, a data-driven decision process with the following characteristics will emerge: (Berndtsson et al., 2018)

- A learn and test environment, where failures are accepted by the management and encouraged to be viewed as learning opportunities (Berndtsson et al., 2018)
- Insights generated from data analytics are respected independent from whom in the organization delivers them as long as it is correctly generated. A junior employee’s insights derived from data have the same legitimacy as insights generated from senior management and business findings are not ignored. In the data-driven organization, cooperation is essential, even cross-functional. The “not invented here”-syndrome is one example of a barrier for this (McAfee & Brynjolfsson, 2012).
- Management does not have a veto solely based on instinct over data generated insights. (Berndtsson et al., 2018). Otherwise the effort to become data-driven will be undermined. McAfee & Brynjolfsson (2012) argues that decision makers tend to rely too much on experience and intuition. Whilst this can be beneficial, especially for particularly important decisions, executives should be willing to override their intuition when data doesn’t agree with it. When data is scarce and expensive to obtain, opinions of the highest paid people typically weigh heavily. But when data no longer is scarce or expensive, that rationale ceases to exist. Similarly Kiron & Prentice (2014) argue that there are few things that have more impact on a data-driven culture than seeing an executive concede when data disproved his or her gut-based proposal.
- The first question a data-driven organization asks itself, as McAfee & Brynjolfsson (2012) formulate it, is not “What do we think?” but “What do we know? “.

Finally, McAfee & Brynjolfsson (2012) it is essential that the choice of data is based on the problem to be solved. Data scientists and managers need to cooperate to gain new insights from which decisions can be derived from. Hence, it is also important to know *what questions to ask.*

2.3 Decision Making

As discussed in previous chapters, BI&A is at its core a decision support system. BI&A, supported by a data-driven culture, is argued to have the potential to improve organizational decision making. Hence, it is of interest to thoroughly explore the decision process.

A number of frameworks have been developed to describe the structure of decision processes, including the *Economic man* and Herbert Simon's *Intelligence-Design-Choice* and the contributions of Mintzberg (Mintzberg, 1976; Simon, 1955; Simon, 1960) The following chapter will elaborate on the framework presented by Mintzberg (1976).

2.3.1 A simplified Model of Organizational Decision Making

Mintzberg (1976) discusses what he calls "unstructured" decision processes, which are characterized with novelty and uncertainty. Mintzberg (1976) suggests that these processes can be structured into a set of phases consisting of several routines, and a set of supportive routines. He also identified a set of dynamic routines, which describes the relationship between the central and supporting routines. The 3 phases, he claims, are *identification*, *development*, and *selection*. These phases cover the point in which a crisis or opportunity is recognized, to the presentation of a solution. This is illustrated in figure 2. Mintzberg´s (1976) conceptualization of the decision process is heavily influenced by Simon´s (1960) *Intelligence-Design-Choice* trichotomy, which is perhaps the most well-known model of human decision making (Mintzberg, 1976).

The Three Phases of the Decision Process

Identification is when an opportunity or a problem is recognized and defined. The opportunity or problem must be identified in the streams of ambiguous data that decision makers receive, which Mintzberg (1976) calls "recognition". If the circumstances are enough to stimulate a response from the decision maker, it will result in the assembly of resources and actions taken to tackle the opportunity or crisis. Whether the stimuli is sufficient or not depends on the threshold, which is determined by the current situation or some expected standard, whereas the standard depends on past trends, expectations, comparisons with similar organizations, and similar. The decision maker typically has very little understanding of the issue initially. This novel issue is then defined through existing knowledge and the opening of new information channels, which Mintzberg (1976) calls "diagnosis". The identification phase largely resembles what Simon (1960) calls the *intelligence phase,* where the decision maker detects a problem that is in accordance to plan or some standard, and then tries to understand the problem, i.e. its source, causal relations etc.

The *development phase* is where most of the resources are typically consumed. Mintzberg (1976) based this phase partly on the proposition by Witte (1972), that "*human beings cannot gather information without in some way simultaneously developing alternatives*". This phase is divided into two basic routines; search and design. In the search routine, the decision maker chooses from a set of pre-existing solutions. The search can be either narrow or wide, and can be performed, through scanning the memory or utilizing so-called "search generators" for instance, which essentially are sources of information that potentially assist in finding a solution. The design routine includes either modification of pre-existing solutions, or designing new, unique solutions. This process resembles working through a decision tree, where the decision maker factors the decision into a sequence of nested design and search cycles, which the decision maker then works his way through without really knowing what the end-product will look like, until a solution ultimately crystalizes. This phase corresponds to what Simon (1960) describes as *design,* where the decision maker pursues to find a solution for the problem once data have been gathered. Basic criteria are chosen to evaluate the options.

Selection consists of selecting one solution, preceded by a deepening investigation of the developed solutions. This phase is also separated into 3 routines, namely screening, evaluation-choice, and authorization. In the screening phase the decision maker attempts to reduce the amount of solutions, and to find a feasible solution. Evaluation-choice is then used to further investigate the feasible solutions. Here, the solutions are typically examined by both the individual decision maker, in a group - which potentially consists of individuals with different perspectives and goals -, as well as a more technical analysis. Finally, in the authorization routine the decision maker evaluates the solution(s) in relation to other strategic decisions. A major obstacle residing the *choice* phase, according to Mintzberg (1976), is that proposals are presented to, and choices are made by, people who do nor fully comprehend the solutions.

Supportive and Dynamic Routines

Mintzberg (1976) also defines a set of supporting routines. These routines concern the planning of the actual decision process, internal politics, and communication with the purpose of finding new information, reaching a consensus and/or assessing the information. Finally, Mintzberg (1976) elaborates on a set of dynamic routines that illustrate that the decision process "... *is not a steady, undisturbed progression from one routine to another; rather, the process is dynamic, operating in an open system where it is subjected to interferences, feedback loops, dead ends, and other factors"*. The path taken through these phases and routines differs between organizations, with regards to which routines are employed and which are most significant in the decision process.

Herbert Simon and the Critique Towards the Rational Man

Moreover, the human limitations inherent in the decision process ought to be acknowledged. Simon (1955), has contributed with significant input to this topic, including his critique towards the Rational man. Simon argued that the assumption of a fully rational decision maker - with knowledge of all relevant aspects, with perfectly organized preferences, and the ability to calculate the probability as well as the utility of his/her options - is not realistic. Influenced by psychology, he presented some general constraints which result in the decision maker making some simplifications. One simplification is what he calls satisficing, which essentially is a problem solving shortcut used by decision makers who act in a complex environment. The decision maker then settles for a certain level of utility, rather than trying to maximize it. Mintzberg (1976) integrated several of these constraints into his own model, including elements of satisficing in the selection phase. He also discusses how the decision maker divides each decision into sub decisions in the design phase, thus making the process feasible.

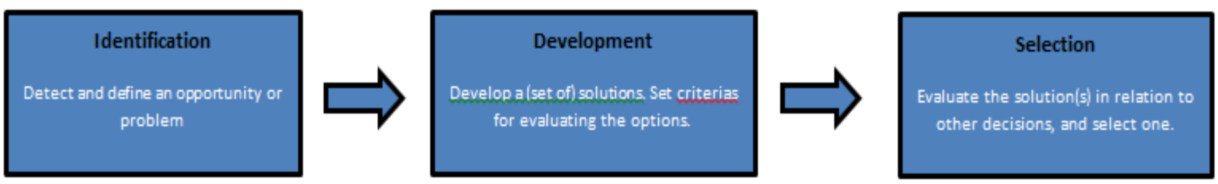


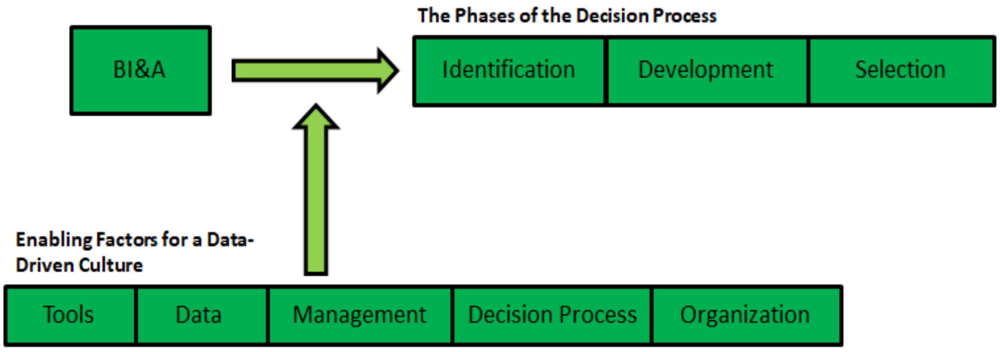
Figure 2. The decision process, illustrated by the authors.

2.4 Analytical Framework

Based on the frame of reference discussed above, an analytical framework is created and illustrated in figure 3. The framework merges the use of Business Intelligence & Analytics, the decision process framework and the enabling factors of a data-driven culture. More precisely, the framework is presented to visualize the relations between BI&A, a data-driven culture, and the decision process. As illustrated by the figure, BI&A is suggested to influence (organizational) decision making. This influence is in turn conditional on the existence of a data-driven culture, as described in Chapter 2. In order to make the analysis feasible, the framework by Mintzberg (1976) will be used as a basis for description of the decision process. Data-driven culture is divided into a set of factors, as discussed in chapter 2.2.

This framework will be used in chapter 5 when the impact of BI&A, supported by a data-driven culture, on the decision process is discussed.

Figure 3. Analytical Framework



3.0 Research Approach

The purpose of this chapter is to account for how the writing of the essay has progressed. Initially, the scientific starting point is presented where the problem in the situation is briefly described. Thereafter follows a description of the choice of method and approach for the thesis before a description of the data collection is presented. A deeper account of the interviews conducted and the selected respondents then follows before the chapter concludes with the author's own reflections on research quality and the research ethical requirements.

3.1 Methodology

A qualitative research method was chosen to discover and identify qualities and attributes related to the phenomenon of interest. Given the nature and complexity of the examined phenomena along with the research questions - to expand the understanding of organizational decision making under the presence of BI&A - a qualitative research approach is suitable (Patel & Davidson, 2011). The collection of data was conducted through multiple interviews with respondents from three organisations within the logistics sector.

Given the topics of this thesis, flexibility is essential, where the specific research questions are successively reexamined and deepened. Likewise, it is advantageous if the results are based on a small set of individuals and a large set of variables, where the researchers deep dive in a specific context. Therefore, a qualitative approach is justified. (Öqvist Seimyr, 2020) Through qualitative interviews insights on different aspects can be generated, which lead to nuanced descriptions of general and everyday events in the interview subjects life (Patel & Davidson, 2011).

The alternative would have been to conduct a quantitative study, where focus would be on a structure that allows for an increased response rate and generalizability. However, the studied phenomena is difficult, if not impossible, to examine through a quantitative approach. The time limitation also had to be taken into account. Hence, the authors considered a qualitative approach more suitable, which would provide good conditions for the collection of data about the phenomenon that can act as a basis of the discussion. (Patel & Davidson, 2011)

As discussed in previous chapters, the objective of this thesis is to identify relationships between certain phenomenons, more precisely between a form of organizational culture, decision making and Business Intelligence & Analytic. Thus the thesis is explorative. This approach was chosen due to the difficulty of building a testable theory and hypothesis for the chosen subject.

3.2 The Research Process

In the initial steps of the process, a literature review was conducted. A comprehensive research area was identified, namely Business intelligence (BI) in relation to decision making. Preliminary research questions as well as an objective was set. Considering that the phenomenon at hand is relatively unexplored in existing research, relatively broad research questions were selected in order to permit flexibility, which tend to be typical for qualitative research approaches. (Patel & Davidson, 2011) Next step was to decide and plan how research subjects were to be selected, how the information was to be processed and analyzed, in accordance with Patel & Davidson (2011). Thenceforth we contacted and performed a pilot interview with an employee at a local consulting firm, who was assumed to have general knowledge of BI. Following the pilot interview, contact was made with 3 companies that had implemented BI-tools and interview dates were set.

The collected material from the interviews was analyzed in relation to the material from the literature review, followed by a compilation of the relevant parts of the material including the results and a discussion.

Throughout the research process our text was, as suggested by Patel & Davidson (2011), regularly reviewed by colleagues and our supervisor to get comments, new ideas and perspectives.

3.3 Literature Review

At the start of the research process a basic literature review was conducted with the purpose to deepen the authors preexisting knowledge within the chosen subject. The information presented in this thesis that was gathered through this literature review primarily consists of information from scientific articles retrieved through the University of Gothenburg's databases. Some material was also obtained through the supervisor. Through the literature review insights were provided as of what was previously discussed regarding the research purpose and questions. At the start of the process, information and data was gathered through many databases with the aim to provide a general understanding of the situation, whereas the starting point of the frame of reference gradually narrowed down based on the previously chosen problem area. The narrowing down is essential for the progression of the research, since the available literature can be overwhelming (Patel & Davidson, 2011). Keywords were then identified, such as *data-driven culture, enabling factors, Business intelligence*, etcetera. Recurrent terms and models were noted. This process of narrowing down the search is vital for identifying more explicit research questions (Patel & Davidson, 2011).

The authors have in the process of completing the thesis primarily read scientific articles that account for the decision process and its complexity, data-driven cultures and research on organizations using Business intelligence and analytics. Articles are generally more suitable when the studied phenomenon is novel, since books require longer time to be published (Patel & Davidson, 2011). In order to get a sufficient overview of the relevant research during a limited amount of time, the focus was initially on reading abstracts and conclusions, thus enabling a separation between useful and not useful literature. The literature review was very helpful for the analysis of the interviews, because a solid theoretical basis is important when interpreting the responses, especially when the study is qualitative (Patel & Davidson, 2011). One disadvantage however is that the researched topics are a relatively new phenomenon, which might have impacted the quality of the literature review and should be considered. Some material was also fairly old, particularly the literature on decision making. This should not be an issue for this thesis however, as the literature on decision making that was collected can be presumed to still be applicable.

3.4 Data Collection

For this thesis, primary data together with earlier research in the form of articles and books, as discussed in 3.3, has been used. The main instrument for collecting data and answering the research questions however were qualitative interviews. Interviews have the advantage that they enable more in-depth answers through qualitative data. This provides a better opportunity for the respondents to develop their reasoning and thus provides a better foundation for the authors to base their discussion on (Patel & Davidson, 2011). The data collection approach through interviews was chosen instead of focus groups and case studies to avoid that the respondents' answers were influenced by other respondents' opinions which is a risk when using focus groups. A further argument for the choice of interviews was that the authors wanted to reach respondents actively making decisions with the help of BI&A. To increase the likelihood that time was allocated for interviews, they were conducted one by one to maximize flexibility for the respondent regarding both time and place.

3.4.1 Pilot Interview

At the early stages of the research process, we contacted an employee at a local consulting firm, who we knew had general knowledge of BI. We performed a pilot interview with the consultant, since this can be an efficient way to test an instrument and research questions (Öqvist Seimyr, 2020). The consultant shared his viewpoints on the execution of the research, and whether the planned parts of the study is relevant and practically feasible The consultant also contributed with opinions and new viewpoints on the study, as well as potential research topics. Considering that BI is a relatively new concept, as discussed earlier, and the fact that the literature generally struggles with following the pace of the practice, the benefits of such a pilot was assumed to be immense. Further, the pilot interview was complemented by a second interview with the consultant once a more specific research topic had been selected, to deepen the understanding of BI&A in relation to data-driven cultures and decision making.

3.4.2 Sampling of Researched Organizations

In order to conduct the study, organizations using BI had to be identified. Aiming to increase understanding and not deduce generally applicable truths, statistical generalization was not significant in the research design and selection of organizations. The sampling was performed based on the *available group* due to time and resource constraints (Patel & Davidson, 2011). The organizations were contacted using the consultant´s and supervisor´s networks. The intention was to get in touch with companies with somewhat different BI capabilities, because this will most likely increase the generalizability of the thesis' conclusions. Moreover, the thesis is limited to the logistics sector. This sector was chosen based on access to quality research subjects, who we were ensured to use BI. Despite not being eligible for statistical generalization, this thesis can be argued to constitute a basis for analytical generalizations; Limiting the research to one sector, as well as using research subjects who use similar techniques and technologies for similar purposes, although to varying extent, most likely enables more reliable comparisons and generalizations for that specific context. However, the limited amount of organizations makes generalizations less valid.

3.4.3 Interviews

Interviews with 1 or 2 employees from each of the 3 selected organizations took place, as well as an interview with the BI-consultant, visualized in table 1. The intention was to conduct these interviews face-to-face, as this can have some quality- and validity benefits (Patel & Davidson, 2011). However, due to Covid-19 the interviews had to be done through telephone or other digital solutions, such as Microsoft Teams that could have a negative effect on the quality and validity. The interviews were carried out in Swedish.

The interviews were of qualitative character. Qualitative interviews have a lower degree of structure, which essentially implies that the questions are relatively open. This provides space for the respondents to answer with their own words, and to interpret the questions based on their own experiences. (Patel & Davidson, 2011). However, some degree of standardization is beneficial, so an interview guide, including the major themes of the interview, was created. This made the interviews resemble so-called semi-structured interviews, where the respondent has a list of topics but with the possibility to discuss these topics freely (Patel & Davidson, 2011). In these standardized interviews, the interview guide created a framework that nevertheless allowed for follow-up questions. A high degree of standardization and low degree of structure increase the need to cover all relevant topics (Patel & Davidson, 2011). One potential risk with respect to this is, as discussed earlier, the limited wealth of previous research on the topics of interest. Potential gaps in the literature thus creates the risk that not everything of relevance will be included in the interview guides. Nevertheless, the literature review and pilot interview were very helpful in constructing the interview guides.

Initial contact with the interview subjects always consisted of an introduction of the subject and the planned study, which helped the respondent to gain an understanding of the purpose of the research (Patel & Davidson, 2011). After this first session, and ahead of the actual interview, the interview guide was sent to the respondent so he or she could be better prepared for what the interviews would entail. This provided the respondents with the time to prepare for the subject, and in a more thoughtful manner answer the questions asked at the time of the interview. During the interview, a more exhaustive presentation of the planned study was given to the respondent. The interviews were all recorded, once permission to do so had been expressed by the interview subjects..

Employees from different levels within the organizations and with different roles were interviewed. This enabled the authors to get diverse perspectives on the studied phenomenon. Given that the respondents differed in role and responsibilities at their respective organization, the skill sets and perspectives, the interview guides had to be slightly modified and customized for each interview. This is essential for making the respondent understand the purpose and use of the study, although it can be a disadvantage for generalization purposes (Patel & Davidson, 2011). The major themes of the interviews remained the same for all interviews however, as well as the order of the questions, regardless of organization and respondent. The interviews can thus be argued to have a high degree of standardization, which is advantageous for generalization- and comparison purposes (Patel & Davidson, 2011).

The interview technique that was used resembles what Patel and Davidson (2011) call a *funnel-technique*, where the first questions of each topic are rather open and neutral. As discussed earlier, it is important to let the respondent gain an understanding of the problem, and elaborate on his thoughts and opinions, especially for this study given the chosen research- and interview setting. The open questions enables the respondent to do so, whereupon the follow-up questions and additional predetermined questions are more specific.

Qualitative interviews typically generate *thick* descriptions, including the respondent opinions and perspectives (Patel & Davidson, 2011). The interviewers therefore aimed to make the interviews resemble a conversation rather than a one-way monologue. The language was adjusted, and some terms that might have been unfamiliar to the respondent was avoided or explained before using them. The follow-up questions also contributed to creating a conversation, where the interviewers sought to support the reasonings as much as possible, in order to proceed and gain deeper insights. The downside of this is that the interviewers potentially help the respondents throughout the interview, and thereby guides his or her responses. The authors thus attempted to be as non-conductive as possibly.

Respondent 1 (Boat)	**Respondent 2 (Boat)**	**Respondent 3 (Train)**	**Respondent 4 (Train)**	**Respondent 5 (Truck)**	**Respondent 6 (Consultant)**
- Member of the nordic expanded management board. - Head of Nordic BI.	-Efficiency Manager. -Works with supporting decision makers.	-Finance Director for the Nordic Region.	-Head of Global BI.	-Traffic controller. -Partner.	-BI Consultant.

Table 1 - an overview of the respondents illustrated by the authors.

3.5 Analysis of Collected Data and Conclusions

The data analysis was characterized by an ongoing process of reviewing the material. Most of the material was in text-form, and thus a journal-like document was continuously updated as material was added and new thoughts and reflections emerged. We also had weekly scheduled meetings with our supervisor and colleagues, where the work was examined in order to ensure quality and that the work was on an appropriate path. This ongoing process facilitated the occasional emergence of new ideas. Analyzing the material frequently can also make the text more alive (Patel & Davidson, 2011). Finally, it most likely makes the compilation and discussion more accurate when the material is noted or analyzed shortly after obtaining it.

As mentioned in 3.4.3, the interviews were carried out in Swedish. The interviews were recorded and then transcribed. The interviews were not translated to English immediately, however. The translation was made when the quotes were integrated in the thesis.

3.6 Research Quality

Validity and Reliability

Validity and reliability are very correlated when a qualitative research approach is adopted, and they will therefore not be discussed separately (Patel & Davidson, 2011).

Validity entails not only the data gathering, but the entire research process. The most basic requirement for research quality, is that the research adds something of value to the issue of interest. Hence, the pilot interview and discussions with the supervisor were very useful in the sense that they contributed with insights into what topics are considered valuable based on current practices and existing research. The validity of the thesis can further be strengthened by a solid frame of reference, good instruments and accuracy in the data gathering. (Patel & Davidson, 2011) By including both old and recent theory that highlights different perspectives on the concerned subject, the authors have attempted to achieve a solid frame of reference. Ensuring that the theoretical foundation was gathered from up to date sources ought to make the thesis more relevant and improve the validity, especially considering that Business intelligence is a relatively new concept. Moreover, by studying other interview instruments and with a starting point in Patel and Davidson's suggestions (2011), the authors have attempted to make the interview guide as good of an instrument as possibly.

Regarding the accuracy within the data gathering, the authors who have been cooperating throughout all interviews have both recorded and taken real time notes of the interviews. The notes have been reviewed and processed whilst the recordings have been transcribed directly after the interviews to better reflect what has emerged in the interviews. Making the transcriptions realistic is problematic however, considering that there is typically a risk that the person making the transcription adjusts for colloquial and sentence structure (Patel & Davidson, 2011). This was kept in mind, but the risk cannot be ignored, especially considering that the interviews had to be translated to English. It was thus of particular importance to not take the quotes out of their context when presenting the findings. Another risk is the limited amount of time the authors had available for the literature review. However, the literature review enabled a nuanced interpretation of the interview material, and communication of the findings.

Finally, analytical generalization ought to be possible due to the systematic choice of interview subjects, in accordance with what has been said in earlier chapters.

3.7 Research Ethics

The aim of all research is to reach new knowledge and understanding, but this does not sanctify any means. Therefore research ethics is an important topic that needs to be taken into account. The authors have thus followed the four overall ethical rules produced by the Swedish Research Council (Patel & Davidson, 2011).

1. **Information requirement**. All participants have been informed of the purpose of the thesis and accepted it by participating.
2. **Consent requirement**. All participating respondents have independently decided to participate in the thesis. Consent has also been given by the respondents employers as they have been involved in the process of selecting the candidates.
3. **Confidentiality requirement**. All data regarding the respondents is confidential and has been managed accordingly. The names of the respondents and organizations has been left out of the thesis as a result of this, primarily because the authors see no added research value by including the names.
4. **Utilization requirement**. Data collected concerning any individuals have only been used for the purpose of research.

4.0 Findings

In this chapter, the findings from the interviewed BI Consultant and the researched organizations are presented. First the findings of the BI Consultant are presented, followed by the three researched organizations.

4.1 Interview with a BI-consultant

This chapter provides a general account of the implications of a data-driven culture and the possibilities of BI&A for decision making.

The Consultant's Perspective on A Data-Driven Culture

The consultant suggests that decision making in an organization with a data-driven culture contradicts the traditional way of decision making, where decisions are typically based on the opinions of the employees at the top levels in the organization. He also discusses the potential disadvantages with relying too much on data;

> *”...but what happens if you solely act in accordance with data? Then what? If you, for example, base all your purchases on data from previous years, what happens to innovation then?”*

The consultant does stress, however, that the traditional way of making decisions is not sustainable and the rational thing to do is to rely on facts. Hence, working with the decision making culture is fundamental, although culture is quite hard to change, the consultant argues.

Getting the Tools and Data are the Easy Part

Changing the decision making culture is not an easy job, the consultant continues. Acquiring the tools and data is quite easy, although it might be most commonly highlighted as a success factor because it is so tangible. The challenging task is changing how employees think and act, as changing the culture means that the already existing culture must be replaced, the consultant argues; “*Changing the culture is difficult, as the existing culture likely is embedded in the ‘corporate soul’. You must consider how the new way of thinking fits with how it presently is”.*

Create a “Buzz”

Due to the complexity in changing the culture, it is essential that the analytics-vision is dispersed throughout the organization. The consultant describes this as creating a “buzz”, where the end-users are actively engaged in the work towards a data-driven culture. The buzz can be created in several ways, even by making the use of BI&A more fun through what the consultant calls “gamification”, such as awarding active users and announcing the “visualization of the week”. The key is to communicate the vision, the consultant finishes;

> *“Some people easily see the benefits (with BI&A), some do not. During cultural changes particularly, you need to communicate why the change is important; Why all these focus and resources on change? Why are new roles created? Without this, you will likely meet resistance”*

Information Makes Rational Decisions Possible
The Consultant further sees many opportunities for BI&A to support decision making and summarizes it by arguing information is necessary to make informed decisions. By having access to data all kinds of decisions are improved, even though it can be in different ways.

"If you have information you can make a rational decision. This says it all. Data clearly supports decision making, and that is at all levels."

Lead Times and Transparency issues
Despite these opportunities, the Consultant also sees obstacles, such as BI development lead times in relation to the real time data, which often is crucial;

"When the solution finally is finished the decision was made a week ago. Self-service is a way of tackling this issue but it's still data that needs to be collected and utilized which creates a development lead time."

Another obstacle highlighted by the Consultant is the lack of transparency concerning concepts and definitions. The decision maker may think he's looking at a certain dimension, when in reality, it's something completely different with the same name. Both could be extremely relevant, but faulty decisions could be made if the decision maker does not know the difference.

"Few companies have a solid understanding of their definitions. They don't know what version of the data they're looking at right now. Sales could be based on either order date to understand order intake or invoice date to understand the financials. Both could be relevant but since they're both named 'Sales' the decision maker does not know what he's looking at"

The Consultant argues that these obstacles prevent the organizations from utilizing BI&A in relation to decision making fully;

"The tools can be used fully, but from the business perspective the decisions might not be as good as they could be or that too much time is spent arguing what kind of data the decision makers are looking at, even though it's extracted from a BI system."

4.2 Researched Organizations

The organizations showed signs of different BI use ranging from simple tools that are beginning to be adopted to advanced BI portals that are both comprehensive and flexible. Therefore the organizations highlight different ways BI is used in practice to support an organization's decision process. Each case begins with a brief account of the organization and its BI capabilities, followed by an account of the organization's data-driven culture and finally the implications of BI&A on the decision process. An overall finding is that BI&A's influence on the decision process varies depending on the organizational level. Therefore the sections concerning the decision process will be structured in a way that differentiates between the strategic, tactical and operational level. Further, the analytical framework will be used to categorize the specific findings in relation to the phases of the decision process for clarity.

These categorizations will further serve as the foundation for the discussion concerning the decision process in chapter 5.

4.2.1 Organization A (Boat)

Boat is the Swedish subsidiary of a global logistics company that consists of divisions within land, sea, air and contract logistics. The company has a long history and is one of the market leaders within the logistics sector in Europe. Today the company employs a total of 76000 people worldwide of whom 3500 are located in Sweden. The size of the company and the nature of the logistics sector generate vast amounts of internal data which the company is harvesting and applies in different Business Intelligence solutions to, among other things, support decision making throughout the organization. The company has recently begun integrating external data in some Business Intelligence applications together with its internal data, however this integration is still in an early phase.

"We are in an initial phase where we are using BI tools to analyze our internal data and are starting to load some external market information in our systems. But we are not collecting information externally in the sense of big data and performing such types of analysis. We are not there yet." - Respondent 1

Dedicated BI-unit with a User Focus

The company has a dedicated BI-unit that focuses on categorizing and defining data to make it available for the end users. The BI-unit are responsible for building applications that can take advantage of the data collected and that are in demand by the users.

"We have a team of 3-4 people that manages the data warehouse by receiving and adapting data to fit our business needs" - Respondent 1

To ensure that the BI-unit develops applications that are in demand by the end users the company has developed a program labeled "BI-Forum" where each branch of the organization elects representatives that are responsible for their branch development of BI-solutions. They are up to date regarding what needs arise in their side of the organization and are responsible for communicating these demands to the BI-unit.

"These are people that have different roles as their ordinary responsibilities but since they are elected BI-representatives they are the channel for needs, development within the BI-portal, highlighting the requirements of their branch of the business, creating new orders or acting as application owners that are process owners of a specific BI-application" - Respondent 1

These BI-representatives, that also act as application owners sometimes, often have a large responsibility in the sense that they are responsible for the data contents of the applications that are meant to be used in specific contexts. This is due to the BI-unit being criticized to have a lack of interest in the content of the applications.

"The BI-unit does not care too much if the raw data is correct, if they see a 1 they categorize it with the other 1's. The issue arises when it should not have been a 1 but a 10. They make sure all the technical aspects are running smoothly whilst the content itself is valued lower by IT. The application or process owners are the ones that need to make sure the data content is correct." - Respondent 1

Partial Self-Service Capabilities

The BI-platform that is being used by the end users could be categorized as a mixture between a fixed layout and elements of more flexible self-service-like tools. The level of flexibility depends on who the user is, but generally the platform is interactive with the possibility to make choices to adapt the users analysis. The BI-applications are developed specifically to meet user needs and are granted access to by role.

> *"We don't have full self-service. We do towards certain users. Otherwise there are applications that you enter and are faced with a fixed dashboard, but as a user you can scroll down, make adjustments and shieldings from the information through different option menus and timeframes and such."* - Respondent 1

The users throughout the organization are deemed to be self-reliant in their use of existing BI-tools but the level of use varies from user to user. More advanced users, characterized by being both experienced and with some technical knowledge, are often more interested in the source data itself. They are interested in exploring further dimensions than what is initially offered in the fixed dashboard and they want to be able to connect data themselves to find the optimal dimensions to analyze situations. The more casual users are instead more interested in receiving the data as simplified as possibly, preferably in a fixed report.

> *"There are large differences between those that are data and IT interested and that perform deeper analyses and other users. The advanced users want the raw data itself, they want to know what measurement values are available, what dimensions that exists, they want to be able to connect data themselves. If they want to check the cost per kilometer then they want all the kilometer distances in Sweden. They want to be flexible. Most people on the other hand want the data as simplified as possibly, meaning that they want a finished report that shows what they want to look at."*- Respondent 2

The 3 Ingredient Recipe to a Data-Driven Culture

Succeeding with BI&A is threefold, according to respondent 1. First, it is about getting sponsorship and support from top management. Without the support and resources, it is very difficult, the respondent states. Promoters of BI&A must get their initiatives and propositions approved. Second, it is about creating user-friendly tools. Boat strives for uniformity in their tools, respondent 1 claims. If an user can handle one application, he or she should be able to use the other applications because the functions are essentially the same. This is partly to ensure that education is not needed to a great extent, although they work with education to some degree, especially when a new application is introduced.

> *"There is always one "superuser" who can support, educate and 'sell' the new application to the other users. We also provide digital training and layouts. There are tools available that include clear definitions and FAQ´s, which are supposed to make the users more self-reliant.* - Respondent 1

The importance of user-friendly tools is further emphasized by Respondent 2, as well as the importance of having someone who promotes the benefits of the tools by:

> *"Me myself become enthusiastic when talking about BI solutions, but reaching out to some other employees is a constant process of promoting BI and encouraging users to continue to use it. It is not*

difficult to see the benefits once you actually use the tools….but, some people always need that push and reminders" - Respondent 2

The third aspect mentioned is about data quality, to audit the data flow and establish clear definitions. This aspect was particularly emphasized, because a data-driven culture relies heavily on that employees trust the available data, which "*does not come naturally*" according to respondent 1. Boat therefore works with what they call quality assurance monitoring, which includes automatic controls and other functions that are designed to review the data and to signal "red alerts". These types of functions are currently in development, including a large project aimed at developing these functions and processes. Likewise, Respondent 1 argues that trusting the data also requires that the employees always critically examine the data:

"It is very important that you signal if something does not appear to be correct, which is really about openness, and I think that we have that….you can not ignore that the individual decision maker is at the core of Business Intelligence"

BI&A and Decision Making - The Strategic Level

At the strategic level the BI-tools are mainly used to monitor the organization's performance with regards to specific strategic measurements that the decision makers are able to expand upon and analyze:

"It provides both an overall picture and a detailed picture on how our company is doing compared to our strategic goals, our budget goals and our historical data." - Respondent 1

The BI-tools are central in the information provided to the strategic decision makers and gives them a quick and comprehensive overview of strategic areas:

"The BI-tools contributes to us strategic decision makers of the organization very much. We have a strategic overview dashboard in our BI-portal where we can track the overall strategic key figures for Sweden and the Cluster. Here we can easily see how we are doing in comparison to previous years and the budget divided on strategic areas. We can then further expand on each area. So it's an ongoing work where we before each management review go through the strategic key figures that we alter from time to time."- Respondent 1

In regards to obstacles with the use of BI in the strategic decision process, Respondent 1, who is works at strategic the level, considers the benefits to outweigh the obstacles in the form of long lead times:

"Yes of course there are some dedicated resources that could be a bottleneck for the speed in modifications and such but on the other hand we are significantly more blind without BI. So that's no benefit either." - Respondent 1

Hence, at the strategic level we can see that the phase primarily indicated to be supported by BI&A in the strategic decision process is the *identification* phase, as shown in table 2.

	Identification	Development	Selection
Strategic Level	Up-to date overview picture of the organization in regards to strategic measurements.		

Table 2 - The strategic decision process at Boat illustrated by the authors.

BI&A and Decision Making - The Tactical Level

At the tactical level the BI-tools are used to both provide an up to date overview of the organization through the BI-portal dashboard but also to support decision makers in evaluating different scenarios such as the closure of an organizational unit or the location of a new cargo terminal:

"It can also be economical decisions, meaning that we distribute out different costs down to a product or something to simply see if it's a product, terminal or organizational unit that we should keep or if we should make any significant changes. We're analyzing scenarios to produce material that we can act upon." - Respondent 2

Respondent 2 further underlines that even though they have powerful BI tools, decision makers still face some problems.

"We've created a BI portal where we attempt to provide users with the same image of reality…… Oftentimes users have different definitions of things depending on the purpose of the analysis and it could end with me having 1 million shipments in my calculation whilst my colleague has 1.2 million shipments, what's the difference? He included this as well. He's not supposed to do that. Well yes, from his perspective he should. So it's not always making sure everyone has the same picture of reality all the time."

Overall, tactical decision makers at Boat are indicated to be supported in all three phases of the decision process, in accordance with table 3.

	Identification	Development	Selection
Tactical Level	Up to date overview picture of the organization that can help identify problem areas.	Support in finding solutions through the usage of BI&A	Support in evaluating different solutions, such as the closure of an organizational unit or the location of a new terminal.

Table 3 - The tactical decision process at Boat illustrated by the authors.

BI&A and Decision Making - The Operational Level

At the operational level there are many specific applications that are powerful and useful for the decision makers. The decision makers have access to up to date overviews of the organization. They also receive comprehensive support in task such as summer planning and cargo planning:

"We have applications where we load information from our time management systems every night. Our TMS systems with cargo volumes, different types of cargo volumes and different kinds of handling update on a half hour basis so the next morning the sailor or the manager at the terminal can see: How did yesterday look like? Staff? How large cargo volumes are at each sub-process? When will these volumes enter the facility? Do we have the right amount of staff at that time? How efficient are we? Then we can further go back in time and look at Tuesday's one year back, or Fridays, or certain weeks or certains months at my specific terminal. How does the other 24 terminals compare? Then we can bench towards each other, add goals and adjust our staffing." - Respondent 1

The operational decision makers are also able to receive support in *evaluating* operational decisions in regards to certain metrics.

"Daily they can load reports that shows we had x % right and y% wrong. This is conducted daily on many operational units."- Respondent 1

Hence, the operational level is indicated to be supported in both the *identification* and *selection* phase, but not in the development as there were no signs of BI&A as a tool for finding or designing solutions or alternatives.

	Identification	Development	Selection
Operational Level	Up to date overview picture of the organization.		Support in evaluating options such as support in optimal summer and cargo planning.

Table 4 - The operational decision process at Boat illustrated by the authors.

4.2.2 Organization B (Train)

Train is the Swedish subsidiary of a global logistics company which consists of divisions within supply chain optimization, freight forwarding, contract logistics, distribution & express and road transport. Today the company employs a total of 41.000 people worldwide of whom 350 are located in Sweden. The size of the company and the nature of the logistics sector generate vast amounts of internal data which the company is harvesting and applies in different Business Intelligence solutions, to among other things, support decision making throughout the organization.

Dedicated BI-unit Centrally Controlled

The company uses the tools qlikview and qliksense to utilize internally generated data with many specific applications. The systems are in turn managed by a dedicated BI-unit that supports the entire, global organization. *"It's qlikview and qliksense, where the BI unit has constructed lots of applications."* - Respondent 3

The development of the BI applications is conducted at the request of senior management at the global headquarter, and there is little possibility for the users themselves to suggest change:

"I would have wished it were the users that suggested new changes, but it's a very hierarchical company which means the orders must come from the global headquarter."- Respondent 3

Fairly Self-Reliant Users

The users are fairly self-reliant in the use of the BI tools but when it comes to more advanced analytics it's often conducted by the business controllers, that have more flexibility and options than the others.

"A lot of the use is by the users and not specialists…… But more advanced analytics is usually performed by the business controllers, some of them have access to all operational data that they can

generate dynamic reports from where they can, independently, choose what parts they want to include."- Respondent 3

A data-driven culture is all about facts

The implications of a data-driven culture for decision making was very definite and concise at Train; That facts should always constitute the basis for decision making. As respondent 3 describes her work; *"it is all about facts facts facts, and not simply gut feeling"*. The respondent also shared the perspective about not being limited to the data:

"Data is necessary for us to understand our activities, we handle massive amounts of transactions and data. But then, how you make your decisions is not necessarily limited to what the data tells you".

Lack of a User-Perspective

The centrally controlled BI-unit provides little opportunities for the end users to suggest development of the BI applications.

" *Due to the BI unit being located in Sweden we're able to have a close relationship with the unit and suggest changes, but we still don't have the official mandate to drive change. Without this relationship we would have big problems."*- Respondent 3

Trusting the Data

The second aspect is, similar to what was discussed with Boat, trusting the data. Since facts and data are central for Train decision making, Respondent 3 claims, it is necessary that the data is trusted and of course correct. Hence, Truck continually works with quality-assuring the data, whereas the respondent herself has been part of some projects targeted at quality-assuring the old Swedish data warehouse before BI&A initiatives become globalized. These activities are done in form of both standardized processes as well as more spontaneous checks:

"If someone feels that something is not correct, then he or she log onto our systems to look into it by going directly to the source and possibly make some adjustments. We always double check things that does not feel right, and this feeling is of course based on the gut-feeling and the knowledge about the real-life cause for the data." - Respondent 3

BI&A and Decision Making - The Strategic Level

Respondent 3 underlines that the BI tools are vital for her strategic decision making as they provide a quick and comprehensive overview for the decision maker: *"It's the only way for me to retrieve a comprehensive overview of the data and analyze"*

The BI tools provide this quick and comprehensive overview through it's monitoring capabilities and it helps the decision maker identify strategic areas that need to be looked into.

"The data clearly shows what has happened, so it's a good way to identify strategic areas that need to be looked into." - Respondent 3

At the strategic level we can see that mainly the *identification* phase is indicated to be activated in the decision process in accordance with table 5.

Strategic Level	Identification	Development	Selection
	Monitoring of the organizations performance to recieve indications of issues.		

Table 5 - The strategic decision process at Train illustrated by the authors.

BI&A and Decision Making - The Tactical Level

At the tactical level, the BI tools are used frequently by business controllers to retrieve data and perform analytics to, as an example, renegotiate customer prices.

"The controllers could be looking at a big client together with the sales department before a negotiation. They see that the client is generating a good profit for the organization, but if we were to lower the price for certain destinations that the customer does not have much traffic at, indicated by the data from the BI tool, we could increase our profit further."-Respondent 3

Further, the tactical decision makers have access to a comprehensive overview of KPI:s that they can compare their units with other units to identify issues.

"KPI:s are frequently used by tactical decision makers to compare different units and find issues that need to be addressed." - Respondent 4

At the tactical level, all phases are indicated to be activated in the tactical decision process in accordance with table 6.

Tactical Level	Identification	Development	Selection
	Monitoring of the units performance in relation to other units to recieve indications of issues.	Support through BI&A to find options.	Perform analytics to evaluate options.

Table 6 - The tactical decision process at Train illustrated by the authors.

BI&A and Decision Making - The Operational Level

At the operational level the organization mainly uses the BI tools to monitor, quality assure and evaluate.

"Operationally BI tools are mostly used for monitoring, evaluation and quality assurance to indicate when action needs to be taken such as improved invoice quality." - Respondent 4

Further the operational decision makers have access to tools that evaluate their operational decisions and that indicate when a decision is faulty, such as faulty data in a shipment.

"The freight forwarders can enter this tool at any time to see which and how many files have faulty data in them" - Respondent 4

Thus, we can see that on the operational level, similar to Boat, mainly the *identification* and *selection* phases are indicated to be supported by the use of BI&A in accordance with table 7.

	Identification	Development	Selection
Operational Level	Utilization of data to gain an overview of potenital problems.		Evaluate decisions and gains upport in correcting faulty decisions.

Table 7 - The operational decision process at Train illustrated by the authors.

4.2.3 Organization C (Truck)

Truck is a Swedish subsidiary and member of a recently started global logistics group which consists of over 80 European, American and Asian companies. The companies act independently from each other and are competing with each other, although sharing some common centralized services & resources. Today the subject of our thesis, a Swedish subsidiary of the group, has approximately 10 employees and a turnover of 150 million SEK. The nature of the logistics sector generates large amounts of internal data which the company is harvesting and is beginning to apply in different Business Intelligence solutions to, among other things, support decision making throughout the organization.

Shared Infrastructure

The company utilizes a Transport Management System (TMS) that is shared with the entire group and its infrastructure is managed centrally. The system is maintained and updated locally. The system processes the transport data, generated from customers, carriers and terminals and visualizes it for the dispatchers. From this static view it's up to each dispatcher manually to prioritize and plan the routes.

"*It's no AI or similar that does the dirty work, it's up to each user's knowledge to see what works and what doesn't work to create as profitable solutions as possible*." - Respondent 5

The operational users are deemed to be self-reliant in the use of the TMS to plan and understand their shipments but more advanced analytics are performed by a single user.

"*In the daily operations the users are very self-reliant, the system is in place to help each individual to their job. With a quick overview the dispatchers can see that these shipments will generate this income, these costs and whether it's a good decision to take."* - Respondent 5

Further, the company has no dedicated analytical tool for analyzing this data but relies on the statistics that the TMS generates in the form of reports and KPI:s and analyses it through excel formulas.

"*What I think is the best is to extract the statistics from the TMS and analyze it through excel formulas and pivot tables. Then we can see how any changes affect our costs. But it's not a finished tool, it's advanced excel formulas where we enter our calculations."* - Respondent 5

Data-Driven Culture; Data First - Decision Second

Respondent 5 strongly believes that his organization had a data-driven culture. The respondent defined a data-driven culture in terms of a *data first - decision second* philosophy;

"Why bother with having discussions and arguments about suspicions….like whether a customer is profitable or not, when you can simply look it up. My myself is like that, I always want to see the numbers first." - Respondent 5

He continues with noting that not everybody is like him though, and that how decisions are made very much depends on personal preferences. It is therefore difficult to discuss culture, he claimed, as it is so dependent on the employees. At Train, there are only 10 employees and so every individual has a great effect on the culture.

Data is Vital, so is Business Insight

The respondent from Train emphasizes that they rarely make decisions without supportive data. It is important, however, to consider *how* data is used to support decision making:

"There is a huge difference between looking at the numbers and then thinking 'ok the numbers tell us this so we have to do that', and looking at the numbers and thinking 'ok these are the numbers, what do we do with this'. Because you know that there are so many factors at play, not only the numbers" - Respondent 5

Respondent 5 explains that while data is always necessary to consider, it does not tell you the whole story and that a decision maker therefore cannot be limited to the data. You can not assume something when there are data available, but you need to understand the logic behind the data. In this sense, the respondent thinks that it is advantageous that Train is a relatively small organization.

"It makes it so much easier because we have better knowledge of the numbers we are looking at. At bigger organizations, where people sit at the head office in a foreign state and try to understand the business at the other side of the world, you do not have that knowledge." - Respondent 5

Communication is Key

Lastly, respondent 5 from Truck highlighted the importance of communication, which typically originates from top management. He describes this in terms of communicating a set of values; Why do we exist? What should be prioritized?

"How we talk and what we talk about is very influential on how the rest of the organization acts and reasons….We, for example, are very result-driven. All employees know this." - Respondent 5

BI&A and Decision Making - The Strategic Level

At the strategic level of Truck the BI-tools are hardly used at all, other than to support the strategic decision makers intuition.

"*The use of BI is smaller and smaller the more strategic you become but of course we still have underlying data that can support your intuition and the direction you want to take.*" - Respondent 5

The reason behind this lack of BI use is explained as the company's position in its sector allows it to adjust to the market conditions rather than having to predict them.

"*If we would have been in a different sector, the strategic part would have been more interesting, where you can analyze customers and buying habits. We don't do this. We're more dependent on the economy, but we have nothing to gain from trying to predict the shifts and how it will affect our fleet since we can adjust when the shift actually happens."* - Respondent 5

Hence, at the strategic level no phase of the decision process is indicated to be supported in accordance with table 8.

	Identification	Development	Selection
Strategic Level			

Table 8 - The strategic decision process at Truck illustrated by the authors.

BI&A and Decision Making - The Tactical Level

At the tactical level the BI-tools are used to primarily evaluate scenarios such as the commitment to a new customer or how the profit margins are affected by a decision.

"When we sign a new client we don't invent the wheel yet again. We look at our current customers and their historical data that is extracted from the TMS as reports, excel files and KPI:s. Then it's helpful that we can see, alright, currently we have these customers, routes and profit margins, if we bring in another customer it will affect the profit margins this way. Since we already have a client at their location we might not have to charge as much as the first customer, but if we add the two customers the profit margin will rise." - Respondent 5

Respondent 5 underlines that it is still the operational data that everything is based on and that this provides the foundation that the tactical decisions are based on; *"Everything is based on what is done on the operational side so that we can build a database."*

At the tactical level we can see that mainly the *development* and *selection* phase is indicated to be activated in the decision process in accordance with table 9.

	Identification	Development	Selection
Tactical Level		Utilize data to find options	Utilize data to evaluate options

Table 9 - The tactical decision process at Truck illustrated by the authors.

BI&A and Decision Making - The Operational Level

At the operational level there are many purposes that the BI tools assist decision makers with. The decision makers have access to an up to date overview of the operational work. and they receive support in evaluating options. Further, the respondent expresses enthusiasm BI tools.

”*All the shipments are posted in a dashboard that we use for planning. The bookings contain data such as, pickup and delivery locations, volumes, times and requirements*.” - Respondent 5

All this data that is presented to the operational decision makers further support them to evaluate their decision options:

”*We sometimes perform scenario analytics, but it depends on the shipment. If it's a small shipment the risks are not very large, but when the volumes rise we perform more precise analysis based on the data*.” - Respondent 5

Further the respondent emphasizes that the operational business is the focus of the company:

”*If we're speaking about our business really consists of, it's the operational business that turnover time and capital*.” - Respondent 5

At the operational level the *identification* and *selection* phase is indicated to be supported by BI&A, in accordance with table 10, similar to the other two organizations.

	Identification	Development	Selection
Operational Level	Quick overview of the current shupments	Utilize data to find options	Suppported with data to perform scenario analytics and evaluate options.

Table 10 - The operational decision process at Truck illustrated by the authors.

5 Discussion

The following chapter discusses the findings made from the BI-Consultant and the organizations. First, what BI capabilities are available and the information sources they utilize are discussed. This is to create an understanding of the differences between the organizations respective BI capabilities. As discussed in chapter 3, the organizations were chosen based on the presumed differences in BI capabilities, in order to increase generalizability of the conclusions in 5.2 and 5.3. Second, how a data-driven culture can support f BI&A will be discussed. Finally, the implications of BI&A supported by a data-driven culture on the decision process will be discussed.

5.1 BI-Capabilities

The three organizations showed signs of a wide range of BI capabilities; from Truck's Transport Management System (TMS) and Train's use of Qlik Sense tools, to Boat with an integrated, flexible, BI-portal. Further, Train and Boat both had a central BI-unit who managed and developed it's BI capabilities whilst Truck did not. Overall, the BI tools that were used by the organizations differed and they were used for different purposes. All organizations are actively using BI as a monitoring system in line with Turban (2011) who emphasizes BPM's reporting and monitoring capabilities. An example of this is Boat and Train's tools that are used to present a quick overview of the organization. Boat also uses BPM system in line with Eckerson (2009), who describes BPM as an information pyramid where a strategy is cascaded into operational measures and KPI:s.

Next, partial self-service was available for all decision makers in Boat and some at Train, where the users were expected to perform their own analysis independently through the BI-portal and Qlik Sense tools respectively. Unlike Boat and Train, Truck did not provide any self-service capabilities for the users as they had a dedicated user devoted to the analytics. This was justified by Truck as a logical solution for their small organization as the most technical and knowledgeable user should perform the analysis to prevent errors.

Overall, in the context of what data is utilized the organizations still used BI from a BI 1.0 approach, based on the framework developed by Chen et al. (2013). The organizations' use of BI&A primarily utilized internal data, but Boat has begun experimenting with integrating external data consistent with BI 2.0 Chen et al. (2013). Truck expressed no desire to begin integrating external data as it deemed itself small enough to simply adapt after the market rather than trying to predict it whilst Train expressed a desire to do this in the future. Thus, Boat was indicated to have the most advanced BI capabilities, Train was indicated to have less advanced BI capabilities & Truck was indicated to have the least BI capabilities.

5.2 How can a data-driven culture support the use of BI&A?

The findings from the researched organizations seem to validate the discoveries in prior research. First, the findings indicate a data-driven culture that is vital for the use of Business Intelligence & Analytics. Second, the findings indicate that attempts to establish such a culture demand attention to various elements, similar to what has been suggested in the existing literature (Berndtsson et al., 20181; Kiron & Prentice, 2014; Rikhardsson & Yigitbasioglu, 2018; Popovic et al., 2012).

5.2.3 The components of a data-driven culture

In order to properly discuss how a data-driven culture supports BI&A, it should first be established what a data-driven culture is. The findings suggest that a data-driven culture can be divided into a set of categories. This categorization largely resembles the framework presented by Berndtsson et al. (2018), although slightly modified where *tools* and *data* can be combined to create one single category, and with one additional category; Having a user-perspective. Hence, the findings can be separated into *Tools & Data, Management, Organization and User-perspective.*

Tools and Data - The Fundamentals

The fundamental aspect in this context is making data and tools accessible, which both the findings and previous research confirms (Berndtsson et al., 2018; Kiron & Prentice, 2014). Differences in BI capabilities and organizational size seem to determine time and resources allocated to these types of activities however. Boat & Train allocated more resources to build a data warehouse, quality-assuring it, making data available for the users, and acquiring tools that can be used to handle the immense amount of data, compared to the relatively smaller organization Truck. These differences were not evident in the existing literature.

Moreover, prior literature typically highlights that the tools should be user-friendly (Berndtsson et al., 2018; Kiron & Prentice, 2014). The findings suggest that if the tools are too complicated, or if the user struggles with seeing the benefits of BI&A, then the user will resist them. Data must be easily accessible, and the utility should be obvious. If not obvious, it was argued that it should be accentuated, which will be discussed in the following section. However, training and educating employees was not common at the researched organizations, although it recurrent in prior literature (McAfee & Brynjolfsson, 2012; Berndtsson et al., 2018). At Boat for instance, education was not a major focus area, but making the tools as uniform and user-friendly as possible was emphasized instead. Thus, making the tools user-friendly could potentially be a substitute for education.

Finally, the decision maker must trust the data. This was obvious during the interviews, especially with the respondents from Boat and Train. Trust is partly dependent on quality assuring the data, they suggested, which is also emphasized in prior literature (Kiron & Prentice, 2014; Berndtsson et al., 2018). The findings indicate however, that trust also relies on a critical approach towards data, in the sense that users signal if something looks suspicious and that they have the openness to do so. This aspect was not explicitly mentioned in previous research, although the findings suggest that it is complementary to standardized processes of quality assuring the data.

Management - Communication is Key

Prior research suggests that managers should be actively engaged in discussions and highlight the importance of a data-driven culture to support data-driven decision making (McAfee & Brynjolfsson, 2012; Berndtsson et al., 2018). The findings support these suggestions, in the sense that working with BI&A was typically described as a constant process of promoting and encouraging the users to use, and see the value of, BI&A. The consultant strongly emphasized the importance of communicating the vision. This belief was shared among many respondents, particularly in the interview with respondent 1 from Boat who had recognized this issue and worked on a regular basis with these promoting activities. The findings also indicate a communication where company values are set by senior management. More specifically, the nature of the discussions within the organization - or as respondent 5 put it; *how*, and *what* is discussed - was sometimes argued to have a major impact on how the organization and its employees operate and reason. If top management emphasizes numbers, and short-term payoffs, then this will naturally affect the decision making within the organization. Likewise, if data and facts are promoted then this will most likely affect the individual decision maker. This form of communication is performed in a very direct manner, which appears to be the focus in prior research, with the exception presented by Kiron & Prentice (2014) where the communication can be performed through a set of shared performance measurements. However, the findings indicate the presence of communication in a more indirect manner, more specifically that how top management makes decisions tends to affect other employees; If managers advocate for more facts when making a decision, then the individual decision maker on lower levels will need facts too in order to get management support.

Furthermore, prior literature typically emphasizes the importance of executive support and corporate strategy for developing a data-driven culture (Halper & Stodder, 2017; Berndtsson et al., 2018). The topic from the findings that is most closely related to this, and the most fundamental, is acquirement of resources. This was particularly emphasized by the respondents from Boat, who argued that receiving the funding for BI-related projects is the single most important aspect to succeed with the use of BI&A. An aspect that is not evident from the findings however, is resistance from users of BI&A, which is surprising considering previous research. This is sometimes argued as a barrier for a data-driven culture that supports data-driven decision making, as users and managers in particular resist the use of BI&A because they feel like their skills are threatened, or that they have too high expectations. (Berndtsson et al., 2018) This was not evident from this thesis´ findings, although it is possible that this is due to the respondent wishing to appear successful with BI.

Organization - Employee Empowerment and Access to the Same Truth

In current literature, organizational aspects generally include the existence of a IT or specific BI-unit, which supposedly ensures that quality assured data is accessible and sometimes possible to manipulate for the decision maker (McAfee & Brynjolfsson, 2012; Berndtsson et al., 2018). This was typically discussed in the sense of employees sharing the same "truth" by the respondents, where they work with the same data and definitions. The researched organizations all had some sort of BI- or IT-unit to ensure this, although to a varying degree. It seems that these processes are easier when the organization is smaller and has fewer employees, whereas larger organizations must invest more resources on centralized processes that ensure that all decision makers use the same data and definitions. These processes was also discussed in terms of "empowerment". Consistent with previous research, the findings suggest that in order to make data-driven decisions, the individual decision maker must have the information and capacity (be empowered) to make such decisions. Thus, empowerment relies on the access of tools and data.

The Importance of a User Perspective

One aspect that appears to be decisive for building a data-driven culture, which was evident in the findings but not in prior literature, is having a user-perspective. This was described as particularly important by the consultant, who argued that having a user perspective is a part of promoting the use of data, as discussed earlier. In the researched organizations, the IT-unit or specialists are generally responsible for tasks such as cleaning, merging, quality assuring and making the data accessible. They do not push the development of the BI, neither does the management. At Train however, most of the BI solutions were implemented on request from the headquarter. This was described as a major problem, and that they should involve end users

to a greater extent. On the other hand, Boat had an entire forum and BI-ambassadors dedicated to the communication of needs and requirements from the demand-side. Altogether, it seems that organizations working with BI and a data-driven culture, should employ a "bottom-up", rather than a "top-down" mindset, in order to be successful.
Relating this to the framework developed by Berndtsson et al. (2018), this issue can potentially be categorized as basically any of the categories included in the framework. It can be related to management, where management employs a bottom-up mindset to promote a data-driven culture. It can also be related to tools or data, considering that these categories are very much about making the tools user-friendly. It can also be categorized as organization, since a user-perspective requires the establishment of a link between end-users and the employees who manage the development of BI&A. Hence, the findings suggest that having an user perspective complements the other components of a data-driven culture, thereby strengthening them and thus the culture.

Data-Driven Decision Making, Facilitated by a Data-Driven Culture
In prior research it is argued that a data-driven culture facilitates data-driven decision making (Berndtsson et al., 2018; Kiron & Prentice 2014). The common denominator for the various definitions of data-driven decision making presented by the researched organizations, is that facts/data are the basis for decision making. Although all organizations classified themselves as data-driven viewed data as a core asset, all respondents seemed to agree however that data is not necessarily the driver of action, nor that it should be trusted blindly. Rather, a balance was proposed, where information provided by BI&A is exploited in symbiosis with experience, which is sometimes referred to as intuition or gut feeling in the existing literature. This balance partly depends on the complexity of the decision. Whilst complex decisions, with several relevant factors in play, benefit from the use of data, they also call for a greater need of experience and knowledge of these factors and the business in general. The rationale for this is simple; If the user does not understand how the data was generated, or its implications for the business, the benefits of having data diminishes. This finding is somewhat surprising, considering the strong focus on data in prior literature, and its deprecatory of "gut feeling" (Berndtsson et al., 2018); Kiron & Prentice, 2014). It is generally suggested in the literature that intuition and opinions should not have a veto against data (Berndtsson et al., 2018), but rather that data and facts should act as the basis for action. Based on the findings, it is obvious that this logic is not strictly followed in practice. The general attitude appears to be that information provided by BI&A always should be considered, without being limited to it. This corresponds to McAfee & Brynjolfsson (2012), who discuss how data do not eliminate the need for human insight.

5.2.3 Supporting BI&A through data-driven decision making
One of the thesis' research questions was to examine how a data-driven culture supports the use of BI&A. Altogether, the findings indicate that a data-driven culture will encourage data-driven decision making, which better utilizes BI&A; Where the individual decision maker acknowledges the value of data and will find it difficult to legitimate his decisions without supportive data. However the findings suggest that the characteristics of a data-driven culture does not fully correspond to the definition presented in prior research. The researched organizations illustrated that the reality is not black and white, but that there is a balance between data and intuition, which depends on various aspects such as the complexity of the decision at hand. This corresponds particularly well to McAfee & Brynjolfsson (2012) but differs from the otherwise predominant perspective in prior literature, which advocate for a

more strict adoption of data (Berndtsson et al., 2018). Likewise, a data-driven culture that enables data-driven decision making facilitates a trusting environment with regards to data, which is built on a critical approach to data in the sense that users detect and correct any flaws in the data. This critical approach requires human insight, and general knowledge of the business and the factors affecting the data. It should be noted however, that this may be of particular interest in the logistics sector, as basically all data is generated from the organization's own operations.

The organizational factors that were found to facilitate a data-driven culture correspond well existing literature, especially the framework presented by Berndtsson et al., (2018). However, the findings contribute with some new input. First, the findings indicate that tools and data act as the fundamentals. This is unsurprising, as an organization simply needs the capabilities to make data-driven decisions. Second, the other factors appear to have more of a supportive character, in the sense that they are needed for the tools and data to be utilized optimally. These findings are in accordance with the BI-consultant who described data and tools as the most basic part of changing the decision making culture. Third, a separate category that was not present in prior literature was identified; having a user perspective. This last category appears to complement the other categories, as discussed earlier. Together, these factors enable data-driven decision making. Hence, the findings suggest a remodeling of Berndtsson et al. (2018) ´s model, as illustrated in the modified analytical framework below:

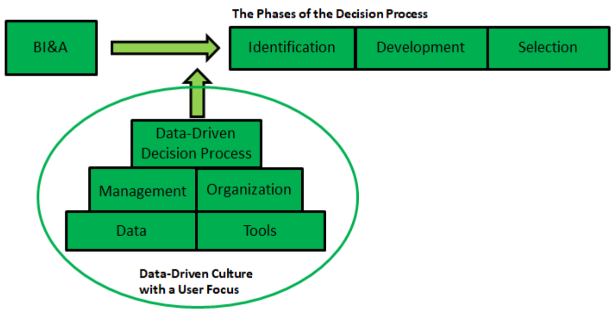


Figure 4 - Developed analytical framework illustrated by the authors.

5.3 Implications of BI&A Utilization on the Decision Process

The previous section illustrates that a data-driven culture supports the use of BI&A by encouraging data-driven making. This chapter will discuss how BI&A, facilitated by a data-driven culture, support the decision process. The starting point for this discussion will be Mintzberg's (1976) framework of the decision process discussed in chapter 2.3.

As table 10 illustrates, the findings suggest that the use of BI&A does not have the same effect on decision making at all organizational levels (Strategic, Tactical & operational).

		Identification	Development	Selection
Strategic Level	Boat			
	Train			
	Truck			
Tactical Level	Boat			
	Train			
	Truck			
Operational Level	Boat			
	Train			
	Truck			

Table 11 - Aggregated decision process findings illustrated by the Authors.

The Strategic Level

The findings indicate that on the *strategic level*, the main benefit of BI&A is the provision of quick and comprehensive overviews of strategic areas. Strategic decision makers were also able to communicate the strategic goals down the organization through real time tracking of strategically important KPI:s for the employees, which was the case at Boat. This way, strategic decision makers can follow the progress of strategically important areas and identify needs and/or demands that need to be addressed. These findings correspond to what Mintzberg (1976) defines as *recognition,* where problems or opportunities are identified by comparing certain events to a set of standards or expectations, for instance. In the researched organizations, this was typically made through KPI:s or other forms of expectations that were shared through BI&A, as showcased in Boat. Moreover, some respondents also illustrated that, besides the comprehensive overview, they are also provided with highly valuable detail-information. This appears to be essential for the routine called *diagnosis* in Mintzberg's (1976) framework, where the decision maker attempts to deepen the knowledge about the newly discovered issue. Whilst an overview enables strategic decision makers to identify strategic areas of interest, the detailed information can then be used to better comprehend the problem or opportunity, such as discerning the cause of the issue. Consequently, BI&A support the *identification phase*, as indicated by the findings. This support was only present at Boat and Train however, and not at Truck, which may be due to differences in their BI-capabilites.

It was occasionally argued by respondents at lower levels that managers, such as the people at Train's headquarter, all too often delve into detailed information that the top management does not understand. This can cause confusion and misunderstanding, the respondents claimed. This is described as a potential issue in Mintzberg's (1976) framework, although related to the *selection* phase; That decision makers are presented with proposals or making choices that they do not fully comprehend. The general implications from this are threefold:

First, it may imply that this issue is not only present in the *selection* phase, as suggested by Mintzberg (1976), but also in the *identification* phase, considering that this issue was present in the findings, although strategic decision makers were found to be supported in the identification phase only.

Second, it might imply that the strategic level is in fact supported by BI&A in the *selection* phase, considering that the issue was apparent in the findings and that the same issue was argued to be related to the *selection* phase by Mintzberg (1976).

Third, it extends the discussion in 5.2. In 5.2 it is argued that complex decisions shifts the balance between intuition/experience and data towards the former, because the value of data is dependent on that the decision maker understands its practical implications. This is of certain interest at the strategic level, since strategic decisions are characterized by a higher degree of complexity. Strategic decision makers were found to have access to a great variety of information - either through BI, but also from other sources that are harder to quantify in BI&A tools, such as market surveys, management reports and macro signals. This is a possible explanation to why the strategic decision makers are supported in the *identification* phase, but not in the *selection phase,* as they can find it difficult to fully understand the practical implications of the data, such as the root to the identified problem. On the other hand, the fact that strategic decision makers at Truck was *not* supported in the identification phase may indicate that the benefits of BI&A decreases when the organization is smaller. Decision makers in smaller organizations have better knowledge of the operations in general, which decreases the need for BI&A, even in the identification phase. It should be noted however, that this finding might be due to the delimitation to the logistics sector, where most of the data is generated through the company's own operations.

Finally, the findings indicate that a supportive routine is supported by BI&A, especially at the strategic level. Mintzberg (1976) argue that decision making is partly about evaluating decisions in a group and reaching a consensus, which is part of the supportive routine *politics*. This routine was supported through what was discussed in chapter 5.2 in relation to data and tools, namely that decision makers share the same "truth". Some respondents, especially at Boat, suggested that by having access to the same information, less time is consumed to legitimate one's decision or argument as well as the basis for it. In this context, data quality is essential too, since it is important that the data is reliable and trusted, which was discussed in chapter 5.2. Hence, BI&A supported the *political routine.*

The Tactical Level

Tactical decision makers at all interviewed organizations showed signs of being supported by data-driven decision making to a great extent. Similar to the strategic decision makers, tactical decision makers typically have access to a real time overview of the organization and a set of KPI:s, which can assist them with identifying needs and/or demands that need to be addressed. At Train, KPI:s were widely used to benchmark against other divisions within the organization, in order to identify areas that require particular attention. Hence, the tactical level was indicated to be supported by data-driven decision making in the *identification* phase, like what was suggested for the strategic level. The only organization that was not supported in the identification phase was Truck, which may be due to their size, in accordance with the discussion in the previous section.

Consistent with Mintzberg (1976), who argues that the *development* phase is essentially the search for a solution once data has been gathered, the use of BI&A in the *development* phase enables tactical decision makers to find solutions from much larger data-sets than if BI&A would not be used. Tactical decision makers were able to perform various types of analyses that ease the search for solutions, such as scenario-analysis and determining price margins. At Train for instance, the importance of being able to quickly examine previously set prices when determining the price for a shipment was highlighted. These activities resemble both the search and design routines in Mintzberg (1976)'s framework, where the decision maker either exploits the (organizational) memory or search generators (BI&A) to find a solution, or to modify an existing one.

The findings further indicate that data-driven decision making supports users in evaluating and choosing solutions. More precisely, activities such as distributing costs and evaluating options were explicitly mentioned several times during the interviews. Truck for example, whose cost-profit focus was explicitly recognized by respondent 5, primarily benefited from being data-driven by assessing costs and profit-margins for shipments and thereafter evaluate alternatives and make the decision. Hence, tactical decision makers are indicated to be supported in the *selection* phase, as defined by Mintzberg (1976), by being able to compare different alternatives to each other and find the best decision based on the available data.

The findings also suggest that experience and intuition is vital for decision making at the tactical level. Looking at KPI:s is of no use if you do not comprehend the reality behind the indicator, it was suggested. Likewise, evaluating an option by simply looking at the price margin is hazardous if you do not have the business insight to put the option in relation to other decisions, it was suggested in the interviews. This strengthens the proposition that tactical decision makers are supported in the *selection* phase, as Mintzberg (1976) describes how an important aspect of this phase is to evaluate the solution with respect to other decisions. It also confirms the description of a data-driven process in chapter 5.2, about the importance of a balance between data and intuition.

The Operational Level

The findings indicate that BI&A support operational decision making in *identification* and *selection,* although in varying ways depending on the organization. All organizations provided a clear overview of the operational work through Transport Management Systems (TMS), including an up to date image of how the operational work is progressing, and how it has progressed. This overview typically has a follow-up character, where the decision maker can see whether they progress according to standards and/or summaries of various aspects from previous periods. Through their quality assurance work for instance, Train provided decision makers with reports on where, and at what rate, the operations tend to fail. This finding suggests that operational decision makers are supported in the *recognition* routine, as problems or opportunities are detected through reports that enable comparisons to a certain standard or expectation. Hence, the operational is indicated to be supported in the *identification* phase, similar to the other two levels although problems and opportunities are identified through more detailed information about the daily activities.

Finally, the detailed information enables decision makers to take several dimensions into account when making a decision. This in accordance with Mintzberg (1976)'s description of the *selection* phase, both in the sense that the decision maker can relate their decision at hand to other decision, and that the decision can be based on a set of relevant variables, which corresponds the part in the selection phase where decisions are evaluated based on criteria(s).

Hence, the findings suggest that operational decision makers are supported in the *identification* and *selection* phase. The implication of this finding could be that BI&A provide operational decision makers with information that enables them to evaluate and perform their daily work, whereas the task of finding and developing alternatives is left to the employee's own skills and intuition. A possible reason for this could be that operational data within the logistics sector is typically quantifiable in terms of errors and similar, which a computer easily can summarize for the decision maker. Consequently, different data sources, intuition and experience could be considered more important at higher organizational levels, which expands the discussion about the balance between intuition and data in chapter 5.2.

The data-driven decision process, facilitated by a data-driven culture

Chapter 5.2 illustrated that a data-driven culture supports the use of BI&A by encouraging data-driven making. This chapter has attempted to concretize how BI&A, supported by a data-driven culture, affect the decision process. This was motivated by the identified research gap in chapter 1, that an increased understanding of the decision process itself in relation to BI&A is necessary. Based on the framework developed by Mintzberg (1976), the use of BI&A evidently affects all three phases of the decision process in varying and distinct ways depending on the organizational level and size; where tactical decision makers as well as larger organizations were indicated to be notably supported by BI&A in their decision making. This is in turn consistent with Berndtsson et al. (2018), who argue that the use of BI&A differs depending on the organization's maturity rate in terms of BI&A. By finding support for the varying influence of BI&A on the decision process that varies depending on the organizational level, the findings further extend Berndtsson et al. (2020) by identifying these differences in data-driven decision making that needs to be taken into account. Moreover, the findings extend the knowledge regarding the decision process and its supportive routines defined by Mintzberg (1976), as it adds another layer of how the use of BI&A influences decision making.

6. Concluding Comments

This final chapter concludes the study by addressing the research questions and discussing theoretical contributions. In addition, managerial implications and potential limitations are discussed followed by suggestions for future research.

Previous research has identified the need for extended knowledge on the relation between the decision process and Business Intelligence & Analytics. Similarly, the importance of a data-driven culture for the value creation from BI&A has been suggested as a problem area that requires additional attention. (Rikhardsson and Yigitbasioglu, 2018) Consequently, this thesis aim was to expand the understanding of organizational decision making under the presence of Business Intelligence & Analytics (BI&A). This was accomplished through two research questions, made viable through the analytical framework.

The first research question was "How can a data-driven culture support the use of Business Intelligence & Analytics?". Consistent with the current literature (Schein, 1996, Davenport, 2006, Berndtsson et al., 2018; Popovic et al., 2012)), a data-driven culture was found to support the use of BI&A through data-driven decision making. Data-driven decision making implies that the individual decision maker acknowledges the value of data and will find it difficult to legitimate his decisions without supportive data, as suggested by the findings. However, the researched organizations demonstrate that data-driven decision making is not black and white, as data does not eliminate the need for intuition. Rather, a balance between intuition and data was highlighted by the researched organizations. Also, the findings indicate that a data-driven culture can be separated into a set of components, which resembles the enabling factors in Berndtsson et al,. (2018) literature review, although slightly modified where tools and data can be combined to create one single category, and with one additional category; Having a User-perspective. Tools and data were found to constitute the foundation of a data-driven culture, and the other components can be seen as more supportive factors that enable organizations to fully utilize the tools and data.

The second research question was *"How does the use of Business Intelligence & Analytics, facilitated by a data-driven culture, support the decision process?*". The findings indicate that there are distinct variations in the implications of BI&A on the decision process, which are dependent on the organizational level of the decision. First, at the strategic level, decision makers were provided with an overview as well as access to more detailed information about the business. This supported the *identification*, by enabling decision makers to identify problems or opportunities, through the use of KPI:s for instance. Second, operational decision makers were also provided with an overview, although in a more detailed nature in the form of reports, through which they could track their and their colleagues daily work. The operational level was thus indicated to be supported in the *identification* and *selection* phase. Finally, most of the analyses were performed at the tactical level. BI&A enabled decision makers to perform scenario-analyses, determining price margins, distributing costs, and setting a price on offers, and more, which in turn indicated that the tactical level is supported in all phases.

Theoretical contribution

This thesis contributes to the existing research in several ways. First, it contributes to the literature on BI&A and its relation to the decision process itself (Rikhardsson & Yigitbasioglu, 2018). The findings from the thesis indicate that the use of BI&A has a distinct influence on the decision process that varies depending on the organizational level of the decision. Consequently, BI&A can not be considered to have a general effect on decision making through all organizational levels as it does not support each level equally. Further, the study extends Berndtsson et al. (2020) by suggesting these differences within data-driven decision making between different organizational levels that likely should be taken into account. As such, the thesis extends the understanding of BI&A in relation to decision making.

Further, it has been suggested by previous research that a data-driven culture is essential for the value creation from BI&A. A data-driven culture encourages a decision process in which data outweighs opinions, and where data is the driver of organizational action (Popovic et al., 2012; Schein, 1996, Davenport, 2006, Berndtsson et al., 2018). The findings support this statement but also contribute to the literature by suggesting that it's not a definite choice between data and opinions but rather a balance between these two factors. This finding corresponds well with McAfee & Brynjolfsson (2012), who emphasize that the existence of data does not eliminate the need for human insight. Moreover, prior studies on BI&A has discussed data-driven culture as the result of a set of enabling factors (Berndtsson et al. (2018). This thesis confirms that a data-driven culture is built on a set of factors, although some appear to be supportive and thus complements current literature on data-driven culture.

Managerial implications

The thesis has managerial implications as the findings highlight the possible value of BI&A for decision making. Moreover, the factors that are found to facilitate a data-driven culture also enlightens what an organization ought to pay attention to, in order to build an appropriate decision making culture and thus improve value creation of BI&A. More specifically, the thesis emphasizes the importance of end users being able to influence the development of BI&A, by adopting a more bottom-up mindset. This way, more user friendly and adapted systems can be developed that enhances the value of BI&A for decision making.

Limitations of the thesis

The thesis contains many potential limitations. Although multiple organizations were studied, they were limited to the same sector and a limited number of respondents were interviewed. Consequently, the findings might be difficult to generalize to different contexts, but on the other hand they provide a qualitative description on the influence of BI&A and data-driven cultures on organizational decision making that can be useful in different circumstances to compare conditions. Likewise, the findings ought to be able to generalize for organizations that act in a similar context. However, whilst organizations were chosen with varying degrees of BI&A usage to increase generalizability, this is also a limitation. More research focusing on similar topics as this thesis, but focusing on organizations with a similar BI-capabilities is needed to understand how the findings may vary depending on BI-capabilities. Further, the studied organization's worked almost exclusively with internally generated data, which may influence the descriptions of a data-driven culture, as well as its implications for decision making. Also, the organizations were sampled by the "available group" concept through the networks of a local BI consultant and the authors supervisor. This too provides limitations to the study and might jeopardize generalizations. Finally the study is made primarily from a strategic and tactical perspective. Despite this the respondents could provide the authors with an indirect view of the effects of BI&A on decision making at the operational level since they were all involved in the BI project of their respective organization.

Future research direction

The findings of the thesis indicate paths for further research on the relation between BI&A and decision making. For the purpose of this thesis an analytical framework was created that aims to illustrate how BI&A, supported by a data-driven culture, affect the decision process. Further testing is required to determine its validity.

Additionally, while much of the previous research has requested more knowledge on how BI&A affects the decision process itself, the thesis indicates variations in how BI&A support decision making based on the organizational level. Therefore, further studies need to take this into account. More research on the variances in the support provided by BI&A on decision making depending on organizational level is needed. Further research on this topic could be to investigate the result of decisions taken with the support of BI&A in contrast to decisions taken without the support of BI&A. Another option is to further investigate what effect the differences in BI Capabilities has on the decision process.

Finally, a future path for research is to investigate how the end users communicate their needs to the BI&A/IT unit to further develop the systems. Although prior studies have touched upon this topic, such as having user-friendly tools, additional research on how organizations can adopt a user-perspective, and a "bottom-up" mindset, in general. Future research could investigate this further by in-depth studies across organizations by interviewing end users, decision makers that place orders with the BI-unit and the BI-unit itself.

7. References

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