EVALUATING THE SUCCESS OF SALES BUSINESS INTELLIGENCE

Lappeenranta–Lahti University of Technology LUT

Master's thesis

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Examiners: Post-doctoral researcher Shahid Ahmad Bhat

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ABSTRACT

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Evaluating the success of sales business intelligence

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69 pages, 16 figures, 9 tables and 4 appendices

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Keywords: business intelligence, critical success factors, content analysis, paired samples t-test

This work focuses on evaluating the success of business intelligence (BI) in the case company. In today’s fast-paced, knowledge-driven corporate world, BI systems are more important than ever. To meet this need, BI tools have been developed to gather, analyze, and convert data into useful information to support decision-making. However, many BI systems fail to deliver their intended benefits. The objective of this study is to define the critical success factors of BI in the case company's sales organization and specify the BI's key areas of improvement. The actual success of BI is also measured from the point of view of sales and data quality.

Both qualitative and quantitative methodologies are used in the study. The theoretical framework of this thesis consists of the concept of business intelligence and the critical success factors of business intelligence. The framework also contains the business intelligence value creation and success measurement of business intelligence.

Data quality, usability of BI tool, data-driven culture, user-oriented development, and BI strategy were identified as the key critical success factors of BI in the context of the case company's sales and sales management. These areas were also seen to have the most need for improvement in the sales management of the case company. With the introduction of the BI system, sales in the company's sales countries have not increased statistically significantly. On the other hand, the completeness of data in the sales countries has increased statistically significantly, which can cautiously be attributed to the introduction of BI, as no other measures have been taken to improve it.

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Tämä työ keskittyy arvioimaan business intelligence (BI) järjestelmän onnistumista case yrityksessä. Nykypäivän nopeatempoisessa ja tietointensiivisessä yritysmaailmassa BI-järjestelmät ovat tärkeämpiä kuin koskaan. Tähän tarpeeseen on kehitetty BI-työkaluja tietojen keräämiseen, analysoimiseen ja muuntamiseen hyödylliseksi tiedoksi päätöksenteon tueksi. Monet BI-järjestelmät eivät kuitenkaan tuota tavoiteltuja hyötyjä. Tämän tutkimuksen tavoitteena onkin määritellä BI:n kriittiset menestystekijät tapausyrityksen myyntiorganisaatiossa ja täsmentää BI:n keskeiset kehittämiskohteet. BI:n todellista menestystä mitataan myös myynnin ja tiedon laadun näkökulmasta.

Tutkimuksessa hyödynnetään laadullisia ja kvantitatiivisia menetelmiä. Liiketoimintatiedon käsite, BI:n kriittiset menestystekijät sekä BI:n arvon luominen ja menestyksen mittaaminen muodostavat tämän tutkielman teoreettisen viitekehyksen.

Tiedon laatu, BI-työkalun käytettävyys, tietokulttuuri, käyttäjälähtöinen kehitys ja BI-strategia tunnistettiin BI:n keskeisiksi menestystekijöiksi tapausyrityksen myynnin ja myynnin johdon kontekstissa. Näillä osa-alueilla nähtiin myös eniten kehittämistarpeita tapausyhtiön myynnin johdossa. BI-järjestelmän käyttöönoton myötä myynti yhtiön myyntimaissa ei ole kasvanut tilastollisesti merkitsevästi. Toisaalta myyntimaiden tietojen täydellisyys on lisääntynyt tilastollisesti merkitsevästi, minkä voidaan varovaisesti olettaa johtuvan BI:n käyttöönotosta, sillä sen parantamiseksi ei ole tehty muita toimenpiteitä.

ABBREVIATIONS

BI	Business intelligence
CRM	Customer relationship management
DDDM	Data-driven decision-making
DSS	Decision support system
ERP	Enterprise resource planning
OLAP	Online analytical processing

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1 Introduction

Timely and effective use of business information is a significant factor in a company's success and even in survival in a quickly evolving business environment where a large amount of data from multiple sources needs to be handled for accurate knowledge (Negro & Mesia, 2020). For this need, business intelligence (BI) tools have been developed to gather and analyze data and convert it into useful information to support decision-making (Lönnqvist & Pirttimäki, 2006; Pirttimäki, Virpi, 2007). In today's knowledge-driven corporate world, which is changing quickly, BI systems are more crucial than ever. However, most BI systems fail. Depending on how the failure of BI is defined 50-70% of BI solutions are at least sub-optimal and not capable of making decision-making more effective which commonly is the reason for the investment (Feng, Richards & Raheemi, 2009; García & Pinzón, 2017; Pirttimäki, Virpi, 2007) .

BI implementation can be considered suboptimal when it fails to meet the reasonable expectations of managers and users (Boyton et al., 2015). Justifying the success of BI implementation doesn’t have universal criteria (Ain et al., 2019; Yeoh & Popovič, 2016). In the measurement of success, there can be used quantifiable benefits like increasing sales or profitability, but some studies also have brought up user adoption and satisfaction as crucial measures of success as well, because BI doesn’t create value with only its existence, but it needs continuous use (Hocevar & Jaklic, 2010; Isik, Jones & Sidorova, 2011; Lönnqvist & Pirttimäki, 2006; Yellowfin, 2024). Also with BI, data quality problems can arise, and measures are taken to improve the quality (Marshall & De la Harpe, 2009). In the success measurement, there should be clearly defined what are the desired benefits of BI and assess the success based on those (Elbashir, Collier and Davern, 2008). However, the financial benefits can be challenging to detect and prove to be a result of BI and not something else (Hocevar and Jaklic, 2010). One reason for that is the time lag with improved decision-making and financial outcomes (Lönnqvist & Pirttimäki, 2006).

As stated before, BI solutions have a high risk of ending up in situations where only part of the aimed goals or none of them are reached. This is often explained by insufficient knowledge of critical success factors of BI (Farzaneh et al., 2018) that construct a guiding framework to follow when implementing, analyzing, monitoring, and assessing BI (Nadeem

Ali El-Adaileh & Foster, 2019). Therefore, identifying critical success factors is especially important for succeeding BI.

In BI system implementation, there are often emphasized technical factors and the BI role as a decision support system and other human elements are overlooked, which may lead to dissatisfaction with the system (Pirttimäki, Virpi, 2007; Riabacke, Larsson & Danielson, 2011). Lahrman et al. (2011) also highlight that evaluating only technical dimension is too limited because even if an organization implements the best BI architecture available, it may not raise overall BI to the desired level if the deployed BI technologies and applications are not utilized at the individual and organizational levels, meaning that the deployment of BI does not improve the performance of the organization. Therefore, organizational factors are recognized as a crucial part of BI success. Previous research has pointed out that management support from business functions is crucial to successful BI implementation (Watson, Hugh J. et al., 2001; Yeoh & Koronios, 2010). Aligning BI to the company's strategy is also more likely to achieve management support when BI supports the company in achieving its strategic goals. The BI also needs to have a clear business case to show the expected outcomes of the BI because if the BI doesn't support business objectives it can fail to satisfy users (Boyton et al., 2015; Yeoh & Koronios, 2010). For optimal BI solutions, there is a needed combination of business understanding and technological skills. It is important to know the business objectives and be aware of the technological possibilities to fulfil them (Kiron et al., 2012). To bridge the gap between BI developers and business users for the championship of BI there are needed people who can interpret business needs as technical requirements for BI development (Yeoh and Koronios, 2010).

1.1 The research objectives and questions

This master's thesis has been concluded for a global B2B company and specifically for its sales organization. The case company's sales organization has adopted a BI system intending to analyze and distribute relevant business information to the company's sales management. The main objectives for BI in a case company's sales organization are to increase both sales and profitability. However, the sales management has not been completely satisfied with the current BI solution and it has been considered necessary to evaluate its success as well as identify key areas for improvement.

As was mentioned earlier BI projects often fail to achieve their goals fully (Feng, Richards & Raheemi, 2009; García & Pinzón, 2017; Pirttimäki, Virpi, 2007). In particular, being unaware of the critical success factors of BI often leads only to suboptimal or even unsuccessful BI (Farzaneh et al., 2018). In terms of the success of the company's BI, it is first essential to identify the most important critical success factors. Therefore, the first research question of the thesis is:

RQ1: What are the main critical success factors of the BI in the context of sales and sales management of the case company?

The first research question gives the company an understanding of the factors influencing the success of its BI tool from the perspective of sales management. As mentioned earlier, the mere existence of BI does not necessarily guarantee the desired benefits (Hocevar & Jaklic, 2010; Isik, Jones & Sidorova, 2011), but it is also important to measure them to verify the potential effectiveness of the tool. To measure the benefits produced by BI, the second research question is the following:

RQ2: Has the sales increased since the introduction of the BI system in the case company?

This question aims to find out whether the sales of the case company's countries have increased after the BI adoption. All the benefits of a BI system are not limited to just the financial side, but also, for example, the data quality can improve as a result of the system's implementation when data quality problems arise (Hovi, Hervonen & Koistinen 2009, 16; Marshall & De la Harpe, 2009). The target company has also faced challenges regarding the completeness of the data, so it is meaningful to investigate as a third research question:

RQ3: Has the data completeness increased since the introduction of the BI system in the case company?

The third research question examines whether the completeness of sales-related data has improved after BI adoption. The case company's sales organization BI solution has had a challenge with data completeness and for example, the missing values have limited the possibility of doing desired analysis in BI reports and reduced overall reliability of them. The target company has focused on improving the completeness of data with the support of BI reports that users themselves can access and monitor the data completeness of their sales area. For other data quality criteria, there hasn't been a similar focus and therefore the

analysis is only limited to data completeness. As a summary of the previous research questions the fourth research question tries to specify the areas of improvement in BI:

RQ4: In which areas should the case company's current BI solution be improved?

The fourth research question clarifies the current state of the company's BI in terms of critical success factors and thus also contextualizes the current problems and needed improvements within the framework of BI. These four research questions provide a user-oriented understanding of BI's critical success factors in sales and sales management, as well as its potential benefits and areas of improvement.

1.2 Conceptual framework

The theoretical framework of this study consists of three parts: the concept of business intelligence, the critical success factors of BI, and business intelligence value creation and success measurement. The theoretical framework outlines the components and the process of BI and the critical success factors of BI. The value created by BI, and its measurement is also part of the theoretical framework.

1.3 Delimitations

As a case study, this research focuses only on one company and more specifically on its sales organization so measuring the benefits of BI has been approached from a sales perspective. The case study does not aim at broad generalizations but relies on the fact that an accurate and illustrative description of the research object provides an opportunity to learn new things about the phenomenon and apply the knowledge in other contexts as well. BI is approached in research from a user-centric perspective and is defined as a process where data is collected and transformed to support decision-making. The thesis does not aim to focus on data storing and warehousing topics.

1.4 Structure of study

Figure 1 introduces the core structure of the thesis. The first chapter of the study will focus on the background and the objective of the study. It will also introduce the research questions and the theoretical framework of the study, and the delimitations. Chapters 2 and 3 consist of the theoretical part and literature review of the study. Chapter 2 clarifies the meaning of BI and data-driven decision-making and chapter 3 focuses on the literature of BI success factors and measurement. Chapter 4 presents the two research methodologies which are applied and the data collection. Chapter 5 presents the empirical analysis of the thesis and in chapter 6 the results of the analysis are discussed. Chapter 7 summarizes the study.

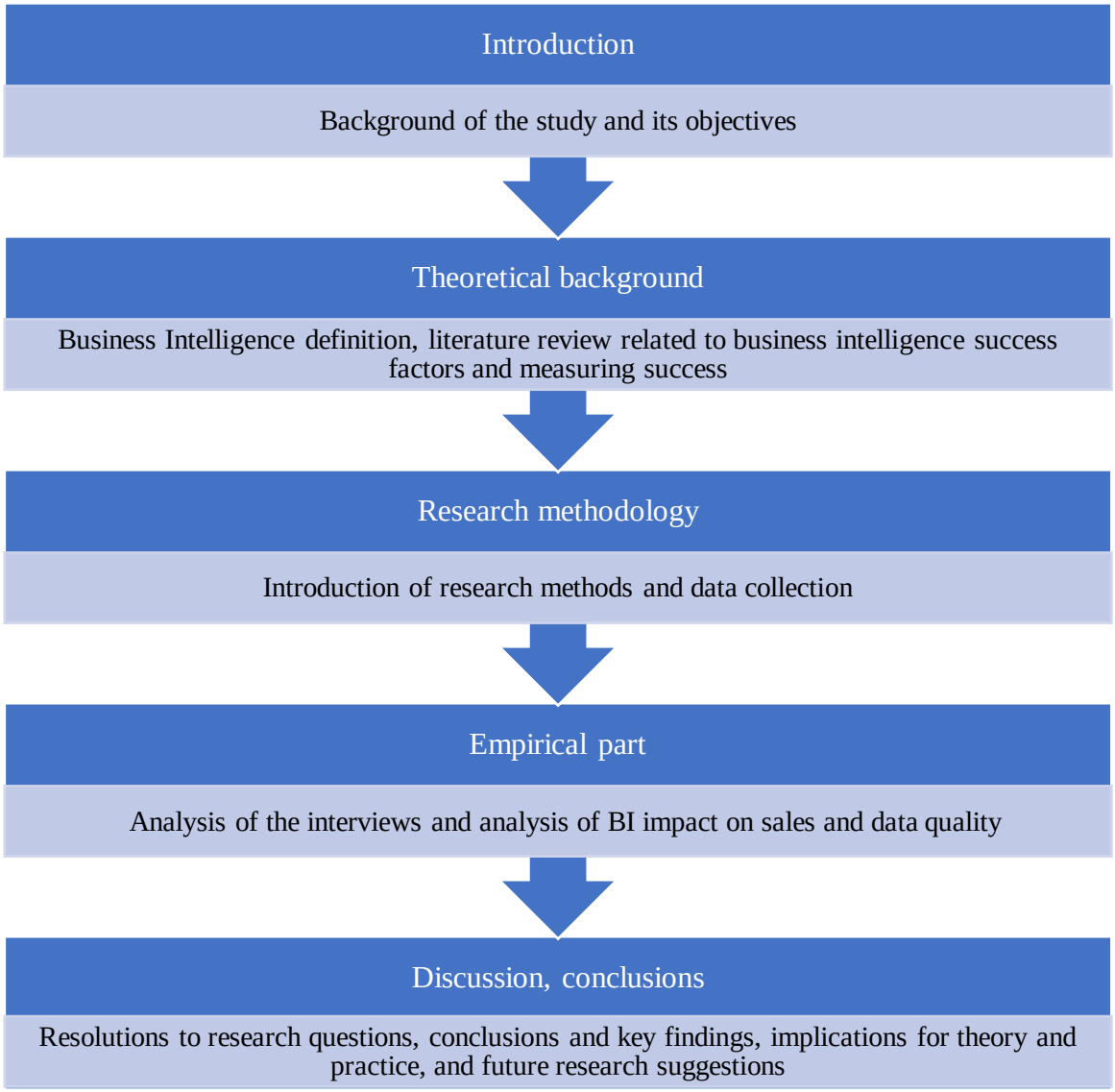

Figure 1. Structure of the thesis

2 Business intelligence

Many organizations have seen a huge growth in the amount of data they deal with in recent years mainly because of the introduction of cloud-based solutions. This has created challenges for many organizations in managing and using this data effectively to help them focus on the key factors that enable business success and to measure the outcomes of their strategies (Cullen, 2021). By using BI, organizations can collect data from different structured and unstructured sources and turn it into useful information that can help them make smart decisions that improve the efficiency and performance of their companies (Niu et al., 2021). This chapter is divided into two parts. The first part is focusing on data-driven decision making and the second part defines the concept of business intelligence.

2.1 Data-driven decision making

Decision-making is the core activity in every organization. It is a process of selecting actions that enable one to achieve certain objectives. How easy or hard it is to make a decision depends on how well-defined our goals are and how much we understand our options (Wei Choo & Johnston, 2004). Decision-making inherently is a process including lots of knowledge formed by data from internal and external sources but in data-driven decision-making, the decision-maker relies more on data than on his own intuition (Brynjolfsson & McElheran, 2016). There is evidence that the best decision-makers rely on comprehensive and real-time internal and external information (Dean & Sharfman, 1996; Eisenhardt & Zbaracki, 1992). However, data alone is not enough to ensure success. An organization also needs a leadership team that can use the data to define goals that are clear and can be measured, sense the changes and possibilities in the business, and act accordingly (Brynjolfsson & McElheran, 2016; Ghasemaghaei, 2019; Ghasemaghaei, 2023; McAfee & Brynjolfsson, 2012). Additionally, there is needed systems designed for business information management, which help to examine the relationships between information, creating a broader picture and a more comprehensive understanding (Vinekar, Teng & Chennamaneni, 2009).

2.1.1 Data, information & knowledge

As was stated earlier data itself is not enough to improve the decision-making or create overall usable business understanding. In the area of data-driven decision making it is crucial to understand the difference between data, information, knowledge, and wisdom. To generate usable business understanding from the data formed during many different business processes or collected from the business environment, this process can be made more efficient by utilizing BI to structure the data. Rowley (2007) states that when data is structured, we are able to interpret different trends and tendencies from it, in which case the data gets meaning and turns into information. When this information is further interpreted, useful knowledge is created, and then the further processed knowledge turns into wisdom, which can be used in decision-making. This distinction is very well presented in the information–knowledge–wisdom hierarchy (DIKW) model which is fundamental and widely recognized in the information and knowledge literature. It is implicitly used in defining data, information, and knowledge in literature related to information management, information systems, and knowledge management (Rowley, 2007). The Wisdom hierarchy is presented in Figure 2.

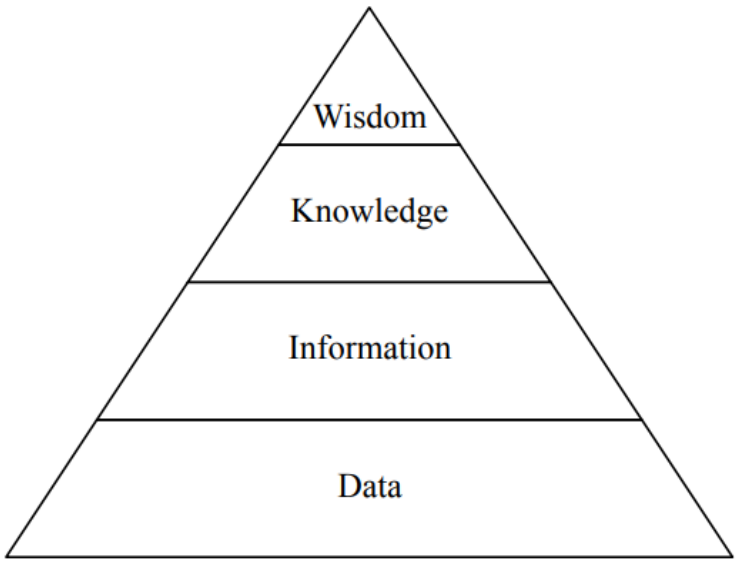

Figure 2. The wisdom hierarchy (Rowley 2007, 163)

Rowley (2007) describes data to be the most abundant but least valuable form of information and to attain wisdom, which is the most valuable but the least abundant form of information,

one must process data, information, and knowledge through many stages. Data only becomes valuable when it is transformed into higher-level information that can lead to concrete actions (Rowley, 2007). To do that, one must first define what one wants to achieve with data. Data is truly valuable when it helps an organization make better decisions (LaValle et al., 2010).

2.1.2 Data-driven culture

Becoming data-driven doesn't happen just by investing a lot of money, collecting a lot of data, and having sophisticated technology. Gupta and George (2016) underlines the importance of having individuals with the appropriate skills and knowledge to work effectively with data for successful data utilization. Furthermore, fostering a culture that encourages data-driven decision-making (DDDM) is crucial. In such a culture, learning is valued, and data is used to generate and act on insights. An organization that wants to get the best of its data needs to have people with the will to do so. The first step to becoming data-driven is to assess own capabilities and identify its strengths and weaknesses in these areas (Gupta & George, 2016).

Data analytics tools can help organizations share the knowledge they get from data, but that is not enough to make better decisions. Ghasemaghaei (2019) highlights the need for organizations to have enough data analytics skills. Sharing knowledge is important, but making better decisions requires advanced analytics competence.

Organizational alignment is also crucial. Business and technology need to have common goals and work together as a team. They need to understand both the business objectives and the technological possibilities to succeed (Kiron et al., 2012). While software can generate data dashboards and summaries, individuals with expertise and insight play a crucial role in interpreting the results and analyzing the data within the appropriate context (Gupta & George, 2016).

2.2 Definition of business intelligence

Business intelligence is a broad concept that has various definitions depending on the context (Pirttimäki, V. & Hannula, 2003). In previous literature, there can be recognized two different approaches, technical and managerial. From a managerial view, BI is defined as a process of collecting data from internal and external sources and transforming that into relevant information for decision-making. The previous literature uses both BI (business intelligence) and BIS (business intelligence system) abbreviations. The first one defines BI as a process and the second one as technologies and applications. In the research that focuses more on the managerial view there is emphasized that the system itself doesn't create value but the system usage and does the company has the capabilities to utilize the system (Fink, Yogev & Even, 2017). From this point of view, the usefulness of the information and how well information demands are satisfied at the right time are also taken into account (Hovi, Hervonen & Koistinen 2009, 74; Wu, Barash & Bartolini, 2007).

The technical approach views BI as a collection of tools that facilitate the process outlined above. Instead of the process, it emphasizes the data and information technologies, algorithms, and tools that allow for storage, retrieval, transformation, and analysis. (Ghazanfari, Jafari & Rouhani, 2011; Raber, Wortmann & Winter, 2013; Ranjan, Jayanthi, 2008)

However, as a combination of these two approaches, BI can be generally defined as the technologies, applications, and processes that aim to help users in strategic and managerial decision-making by collecting, storing, accessing, and analyzing data (Ghazanfari, Jafari & Rouhani, 2011; Shollo & Galliers, 2016; Wixom & Watson, 2010). Olszak & Ziemba (2007) state that even if BI can be viewed from different angles, for decision-makers and organizations, BI should mainly involve adopting a specific philosophy and methodology that relates to working with information and knowledge, open communication, knowledge sharing, and a holistic and analytic approach to business processes in organizations.

The term business intelligence was first introduced in 1958 by Luhn (1958) in an IBM Journal article. He defined business intelligence as the ability to understand the connections between presented facts in a way that guides action toward a desired goal. About a decade later, in the late 1960s, the first decision support systems (DSS) were developed, which are the foundation for modern BI systems (Power, 2007). They were supporting managers plan

and optimize business activities. The business intelligence ended up for more wider use in the 1990s when it was used to describe the various decision support applications by a Gartner analyst (Wixom & Watson, 2010). In Table 1 there are collected and summarized definitions of BI in the literature.

Table 1. Definitions of business intelligence

Author(s)	Definition
(Luhn, 1958)	The ability to understand the connections between presented facts in a way that guides action toward a desired goal.
(Reinschmidt & Francoise, 2000)	Data collection, integration, analysis and accessing data by a set of tools, technologies, and programmed products
(Azvine et al., 2006)	BI is about capturing, accessing, understanding, analyzing, and turning raw data into actionable information to improve business performance.
(Zeng et al., 2006)	The activity of gathering, processing, and spreading information aims to reduce uncertainty in making all strategic decisions.
(Pirttimäki, Virpi, 2007)	Business Intelligence represents a methodical information process encompassing a sequence of structured activities. These activities are tailored to meet the distinct informational requirements of decision-makers, with the goal of achieving a competitive advantage.
(Mikroyannidis & Theodoulidis, 2010)	A set of methods and technologies, designed to help businesses with the necessary support for decision-making
(Turban, Sharda & Delen, 2011)	Business Intelligence can be conceptualized as a form of decision support system with the goal of reaching the gap between the current performance of an enterprise and its desired performance.
(Chaudhuri, Dayal & Narasayya, 2011)	A set of technologies that support decision-making for the enterprise by enabling knowledge workers such as executives, managers, and analysts to make better and faster decisions.
(Fink, Yogev & Even, 2017)	A broad term for systems that support decision-making by integrating and analyzing data resources from the organization to improve business decisions.

All the above definitions agree BI having a role in assisting decision-making. In some studies, the BI has been stated to be the last version of the decision support system (DSS) but on the other hand, these two concepts have a difference in their scope. DSSs usually have a supporting role for specific decisions and decision-makers whereas BI is a broader concept that is a combination of information technology, reporting, and analytics and utilized throughout the organization and therefore supporting a wider audience (Arnott & Pervan, 2014; Arnott et al., 2019). Additionally, BI usually has a strong relationship with other enterprise systems like customer relationship management (CRM) systems and is not a standalone system like DSS has often used to be (Ghazanfari, Jafari & Rouhani, 2011). This research defines BI more like a process and does not focus on the system itself but on the company's capabilities to gather, process, and distribute business-relevant information to improve business decisions.

2.2.1 Components of business intelligence systems

As stated previously the BI can be recognized as a concept combining processes, applications, and technology that aim to support decision-making by producing information and knowledge (Ghazanfari, Jafari & Rouhani, 2011a; Shollo & Galliers, 2016; Wixom & Watson, 2010). In Figure 3 there is illustrated the process of how BI systems transform initial data into strategic decisions that contribute to enhancing competitiveness.

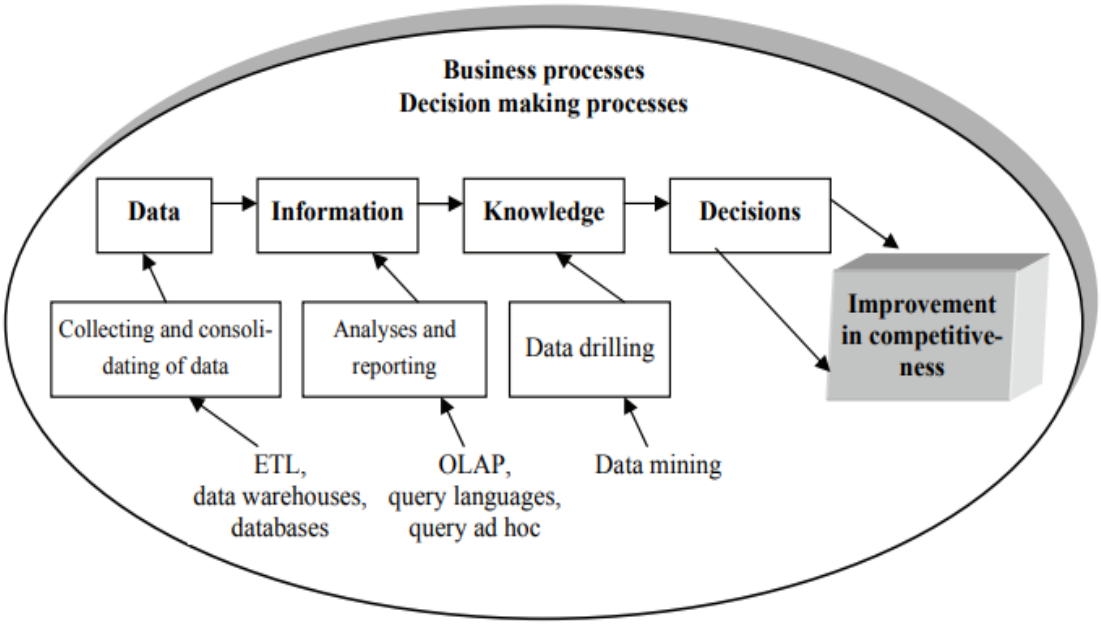

Figure 3. BI system knowledge creation process (Olszak & Ziemba 2007, 137)

The process begins with gathering and integrating data from various sources, both inside and outside the organization. These sources include operational databases from different departments, such as transactional and ERP systems, as well as internet sources, emails, Word documents, and third-party sources (Chaudhuri, Dayal & Narasayya, 2011; Wixom & Watson, 2010). The data from different sources may have different quality and format, which makes it difficult to combine it (Chaudhuri, Dayal & Narasayya, 2011). It is also important to update the data regularly, for example daily, to provide the most recent data for decision-making (Chaudhuri, Dayal & Narasayya, 2011). According to Wixom & Watson (2010), effective data loading is a crucial part of BI systems that enables real-time data for decision-making. The continuous process of extracting, transforming, and loading data into the data warehouse is known as ETL. Ranjan (2009) defines data warehouses and data marts as specialized databases and the fundamental components of the BI environment. Data warehouses store extensive amounts of data for integration, cleansing, aggregation, and query tasks. Data marts, in contrast, store operational data, but they are designed to organize and tailor specific data, often to support a particular business function or unit.

The process continues with data analysis and reporting, which turns data into information. Filtering, aggregation, drill down, and pivoting are typical operations of BI systems that

support analysis. The online analytical processing (OLAP) aims to uncover the multidimensional visibility of data for users and enables common BI tasks such as aggregating, filtering, and drilling down the data (Chaudhuri, Dayal & Narasayya, 2011).

In the last part of the process, the information is transformed to knowledge which is enabling to support decision-making (Chaudhuri, Dayal & Narasayya, 2011; Hovi, Hervonen & Koistinen 2009, 87-90). There are many ways to use BI, the information can be used for example for reporting purposes or as basic information for dashboards. At a management level dashboards and scorecards work as feasible solutions to summarize information (Richards et al., 2014). Various analyses and forecasts are also part of typical BI solutions, although they are slightly more advanced functions. These activities can also be called data mining where patterns of data are discovered (Chaudhuri, Dayal & Narasayya, 2011; Hovi, Hervonen & Koistinen 2009, 87-90). Data presentation methods vary from static tables and diagrams to self-service functions, where the user can choose the data, filters, and presentation format. In addition to the purposes for which the information is used, the method of delivering the information to the user is also essential in BI systems, which can be, for example, a portal on the company's intranet (Hovi, Hervonen & Koistinen 2009, 87-97). When decision-makers are well-informed with relevant knowledge the company can improve competitiveness (Ranjan, 2009).

2.2.2 BI benefits

The benefits sought with BI can be summarized in decision-making (Hovi, Hervonen & Koistinen 2009, 80-81) and that’s the common reason to invest in systems like that (Lönnqvist & Pirttimäki, 2006; Negro & Mesia, 2020). Turban et al. (2011) states BI to be oriented towards management use and strategic decision-making, but on the other hand, Hovi et al. (2009, 82) have stated that typical BI solutions are intended for the entire organization, and not just for management. According to Hovi et al. (2009, 7), some of the desired BI benefits can be received by using other tools and systems as well. For example, it is possible to get different key figures or sales and billing amounts by using spreadsheet programs so BI systems are not necessarily needed. Most systems related to company finance have data export applicable functions and some systems can also produce pre-calculated key figures. By manipulating this data, a wide variety of reports can be further

refined for the company's needs. Reports processed with spreadsheet programs have however their own problems, such as the element of human error, the time spent working on the report, and the problem of information timeliness. By automating such reporting with the help of a BI system, the element of human error is eliminated or at least decreased. Additionally, when the calculation takes place, in the same way, every time the company has its so-called "one version of the truth" (Watson, H. J. & Wixom, 2007) and all are using the same figures in the organization and there is no need to focus on which numbers are correct (Hovi, Hervonen & Koistinen 2009, 15).

3 Related works and critical success factors

This chapter seeks to clarify previous literature on how BI creates value and how the success of BI can be measured. This chapter also aims to specify the critical success factors of BI based on existing literature. It also presents factors found in previous literature that have an impact on the use and intention to use BI.

3.1 BI value creation

The value of BI derives from the capability to utilize the information produced by BI (Fink, Yogev & Even, 2017; Williams & Williams, 2003). Efficient utilization of information resources enhances the company's decision-making process and thus improves the company's performance and creates a competitive advantage (Alzghoul et al., 2022; Rouhani et al., 2016). Investing in a BI system alone is not enough, as the value of BI does not come from the system itself, but from its use and integration into the company's processes (Fink, Yogev & Even, 2017). However, BI benefits can be difficult to detect and prove them to be a result of BI and not something else (Hocevar and Jaklic, 2010). The previous research on the value creation of BI is fragmented and different theories and approaches have been used which don't create a comprehensive understanding of how BI creates value for the organization (Trieu, 2017). Some BI solutions can also have a neutral or even negative effect on the company's performance (Torres, Sidorova & Jones, 2018). Organizations may also achieve different benefits and value from BI (Torres, Sidorova & Jones, 2018). Therefore, it is important to clarify the original reason for BI implementation to understand the expected outcomes and how to evaluate it (Ramakrishnan, Jones & Sidorova, 2012; Rouhani et al., 2016).

In previous research, BI capabilities have been suggested to have a positive impact on organizational performance (Alzghoul et al., 2022). BI capabilities encompass a range of techniques, technologies, systems, practices, methodologies, and applications. By leveraging BI capabilities, organizations can make informed and timely business decisions (Chen, Chiang & Storey, 2012). Alzghoul et al. (2022) suggested model of the positive impact of

BI capabilities on organizational performance is based on knowledge-based theory. The model is presented in Figure 4.

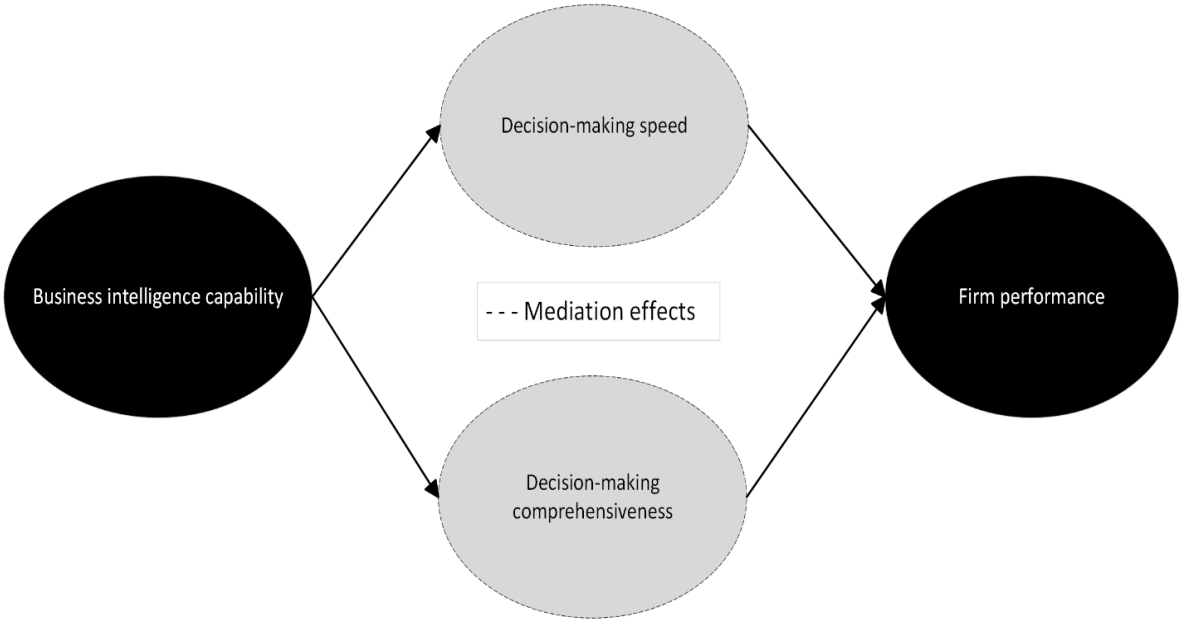

Figure 4. Simplified research model on the impact of BI capability on company performance (Alzghoul et al. 2022, 9)

The assumption of the model is that by effectively utilizing BI tools, it is possible for organizations to make timely strategic decisions based on comprehensive information (Alzghoul et al., 2022) and in particular, the company's ability to utilize its existing information resources and create new knowledge is seen as a significant factor in promoting competitiveness (Alavi & Leidner, 2001). In addition to Alzghoul et al. (2022) research, Rouhani et al. (2016) have end up to the conclusion that BI's various activities have had an impact on the efficiency of decision-making, which has improved the organization's competitive advantage and the satisfaction of its stakeholders. These studies show that BI capability enables managers to get to know with issue and make decisions to the target issue from many different perspectives by utilizing the organization's internal and external information sources, which enables them to consider different options and most likely be able to choose the ones that generate the most value.

Another explaining model of BI value creation is DeLone and McLean's (D&M) IS success model which has been the most often used model in BI adoption, utilization, and success studies (Ain et al., 2019) and is also one of the most significant IS Success model (Yeoh & Popovič, 2016). The model describes the relationship between the identified six different IS

success dimensions: information quality, service quality, system quality, use, user satisfaction, and net benefits. The model is presented in Figure 5.

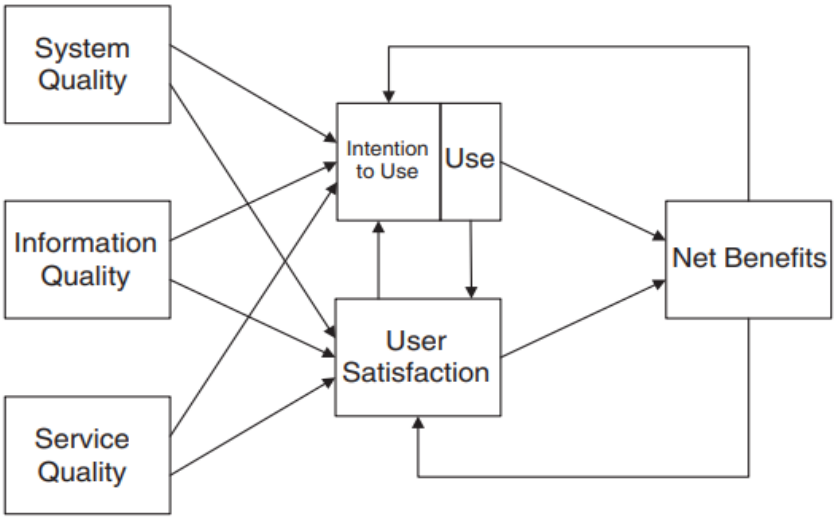

Figure 5. Information Systems Success Model (DeLone & McLean 2003, 24)

The information systems success model developed by DeLone and McLean (2003) states that high-quality system is related to increasing use and user satisfaction which also have positive impact on each other. System usage and user satisfaction are associated with net benefits. On the other hand, poor quality systems can lead to negative net benefits. The model has been applied in the BI context for example by Shin (2003) and Mudzana & Maharaj (2015) where has been found the system and information quality had a positive impact on user satisfaction and BI usage. Also, Jaradat et al. (2022) have found information quality and system quality to have a positive impact on the intention to use BI as a part of the decision-making process.

3.2 BI success

According to Isik et al. (2011), in general the success of BI means the positive value that can be obtained from BI's investment. However, this targeted positive value can vary among companies, and thus there is no common way to measure the success of BI. When measuring the benefits of BI there should be also clearly defined the desired benefits of BI (Elbashir,

Collier & Davern, 2008) and define indicators of BI's success accordingly (Lönnqvist & Pirttimäki, 2006; Mohanty, 2008).

Regarding BI and information systems there can be identified four different groups of benefits: Measurable (Quantifiable), Indirectly Quantifiable, Non-measurable, and Unpredictable benefits (Carver & Ritacco, 2006). Measurable benefits mean benefits like increasing revenue which can be clearly measured (Carver & Ritacco, 2006). On the other hand, even if BI can provide timeliness of information which improves decision-making, these benefits may appear in financial outcomes within a time -lag (Lönnqvist & Pirttimäki, 2006) which can make it difficult to classify them to be the consequence of BI. Measuring in that sense can be very challenging. According to Carver et al. (2006) one example of indirectly quantifiable benefit is customer satisfaction which can have a positive effect on sales or customer loyalty. They also state that non-measurable benefits can be things like improvement in communication and knowledge sharing which can be evaluated in a subjective way but pointing out the real value or benefit is difficult. Unpredictable benefits mean something that is not expected to get because of the system.

One important criterion for the success of BI is the benefit it brings to its users and that it meets the needs of your users (Hocevar & Jaklic, 2010). One way to measure that is system usage or end-user adoption. DeLone and McLean (2003) have proposed system usage to be positively influenced by high-quality system and user satisfaction. Yellowfin (2024), a provider of BI solutions, has also highlighted user adoption as the most important measure of success. In other words, it means that if a BI project has achieved the desired goal, it will be used. Lönnqvist & Pirttimäki (2006) and DeLone & Mclean (2003) mention also subjective user satisfaction as a part of BI success measurement. System usage and user satisfaction are also easy to measure. However, the fact that the BI usage rate is high is not a guarantee that it will generate benefits for the company. Because of this, focusing on the use of the system alone is too narrow and is not sufficient to define BI success on its own. As a result of BI, the quality of information can also improve when the information is available centrally (Hovi, Hervonen & Koistinen 2009, 16).

3.3 Critical success factors of BI

Critical success factors (CSF) are specified areas that will influence positively the success of a specific project or organization (Gaardboe & Jonasen, 2018). Previous research has found that companies that have taken into account critical success factors of BI achieve better results (Yeoh & Koronios, 2010) and failure of business intelligence can be caused by insufficient knowledge of them (Farzaneh et al., 2018). On the other hand, there is no consensus on universal criteria for BI success (Yeoh & Popovič, 2016) so the definition of successful BI and the factors influencing it can vary among studies. This section introduces commonly occurring factors that companies should be aware of because of their significant influence on the success of BI. One commonly cited framework in BI literature for identifying the critical success factors of BI is the one developed by Yeoh and Koronios (2010), which has influenced many subsequent frameworks on the topic. The framework is presented in Figure 6.

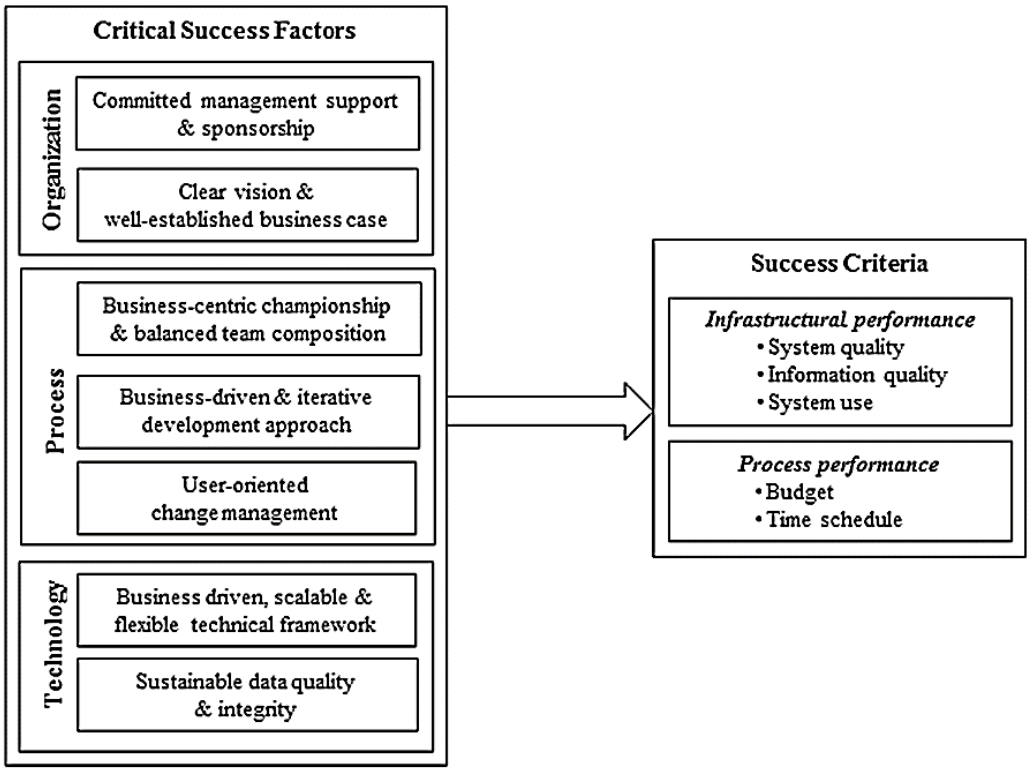

Figure 6. Critical success factor framework (Yeoh & Koronios 2010, 25)

In short, according to the framework, BI is only successful if the CSFs according to the framework are realized. They proposed that organization, process, and technology are the three separate areas of CSFs that affect the success of business intelligence. These three areas include 7 different CSFs. The framework also has two success criteria that involve infrastructure and process performance which describe the success of the overall BI implementation process and the quality of the system. Next, the success factors of BI that have appeared several times in the literature and are relevant from the user's point of view will be presented.

Management support

The literature review of Ain et al. (2019) found that organizational perspective is a key element in the research focusing on the adoption, utilization, and success of BI. Maintaining the committed sponsorship of senior management is seen as the most important success factor of BI (Boyton et al., 2015; Yeoh & Koronios, 2010) which enables the success of other factors as well (Davenport & Harris, 2007). In the previous research, it is also emphasized that the sponsorship should come from the business function not the IT function because BI is a solution for business problems and businesses profit from the successful BI (Watson, Hugh J. et al., 2001; Yeoh & Koronios, 2010). Management support can also ensure that certain people can focus their time on specific BI projects and don't have to spend too much time on other tasks (Hovi, Hervonen & Koistinen 2009, 159).

Vision and strategic alignment

If BI does not support strategy but side functions, its positive effects on business may not be partially or completely achieved (Yeoh & Koronios, 2010). Therefore, the BI project needs a clear vision to connect with the company's strategic goals, and a strong business case to show the expected outcomes of the BI (Boyton et al., 2015). Additionally, aligned BI and overall strategy are more likely to achieve management support. Without a clear business case, BI doesn’t support business objectives and may fail to satisfy users (Yeoh & Koronios, 2010). Sometimes organizational changes are necessary to integrate BI into management decision-making and as a strategic tool. Business and IT processes must be dynamically aligned so that the necessary organizational changes can be made due to strategic IS projects (Schieder & Gluchowski, 2011; Wixom & Watson, 2010).

Data-driven culture

Senior management has a significant role in building a data-driven culture and increasing the usage of BI in the organization (Ashraf et al., 2022; Storm & Borgman, 2020). With their example, they show how data is used and increase employees' awareness of the usefulness of using data for the organization. In addition to top management, the importance of the rest of the work community should not be underestimated in culture change. Colleagues lead by example in data utilization and the data ambassadors share their enthusiasm with the rest of the organization and thus contribute to the change in culture (Ashraf et al., 2022; Storm & Borgman, 2020).

Business-centric championship

For successful BI there is an emphasis on the need for a cross-functional team to combine the business understanding and technical skills. It is also seen as critical that BI is led by a business-centric championship to get business requirements efficiently translated to the BI team and also maintain the cooperation of business units and the BI team (Yeoh & Koronios, 2010).

Business oriented development

The business environment is constantly changing and forcing companies to change their operations. Therefore, BI needs the capability to evolve and adapt according to new objectives. The iterative development and setting of new goals are relevant to the BI's success and keep users satisfied (Yeoh and Koronios, 2010). Fulfillment of objectives means moving in the right direction but objectives without explicit definitions or with too large expectations make reaching them difficult (Hovi, Hervonen & Koistinen 2009, 160). For this reason, the objectives set must be realistic and achievable. Yeoh and Koronios (2010) suggest involving business users in the development process to gain an understanding of the improvements and changes they need. Additionally, in long-term user involvement has been recognized to affect positively usability and also engage the BI in other processes in an organization as well (Audzeyeva & Hudson, 2016). BI can be recognized as a loop where continuously new information needs are analyzed and old solutions are evaluated and optimized (Olszak & Ziemba, 2007). Completed implementation projects don’t ensure success and therefore, it is also better to approach BI development as a process rather than as a single project (Wanda & Stian, 2015).

Necessity

There are numerous BI systems available, each with a unique set of functions that businesses may utilize. Therefore, it makes sense that no single system is ideal for every company's demand in terms of budget, talent level, or business requirements. While some businesses may want pre-defined information in easily navigable ready-made reports, others may require more sophisticated analytical tools. According to Harrison et al. (2015), there isn't a single, generally applicable solution for internal BI systems in organizations but more important is how the tool is integrated into processes. The features should serve the business objectives of the organization. Atre (2004) adds that a business's BI requirements don't always need to be satisfied by a single system and that it is feasible to manage the existence of multiple systems as long as the information systems are based on the company's internal standards.

Flexible BI architecture

The technical framework needs to be scalable and flexible to respond to changing business needs (Boyton et al., 2015). Yeoh and Koronius (2010) stress that by preparing for the future, scalable architecture can achieve significant benefits in further development by meeting needs more easily. Often integrated information infrastructure like ERP has offered an adequate framework for a successful BI implementation. On the contrary, a siloed IS architecture may lead to several versions of the truth, which may mean that the same information differs between systems (Yeoh & Popovič, 2016) and these factors often lead to the failure of BI implementations.

Data quality

Data quality issues are common problems in BI projects. Bad data quality may result in a situation where decision-making can’t get any support from BI which lowers the trust in the system. (Yeoh & Koronios, 2010) Issues with data quality surprise companies many times because users don’t pay attention to data in systems that are not relevant to their work (Hovi, Hervonen & Koistinen 2009, 160). The data quality has multiple features, and it can be divided for example into 8 different dimensions which are completeness, availability & accessibility, currency, accuracy, validity, usability & interpretability, reliability & credibility, and consistency (Jayawardene, Sadiq & Indulska, 2015). In the case company,

there has been a focus on improving data completeness which can be simply defined as having all the values in the data and no values missing (Caserta & Kimball, 2013,115).

The key critical success factors for BI are also summarized in Table 2.

Table 2. Critical success factors of BI

Factor	Definition	Author(s)
Management support	Committed sponsorship from the management supports other critical success factors and ensures that people can use their time on specific BI projects and not on other tasks.	(Boyton et al., 2015; Yeoh & Koronios, 2010)
Data quality	The eight elements of data quality are completeness, availability & accessibility, currency, accuracy, validity, usability & interpretability, reliability & credibility, and consistency	(Jayawardene, Sadiq & Indulska, 2015)
Vision & Strategic alignment	BI needs to be aligned with the business strategy and have a strong business case to show the expected outcomes of the BI.	(Boyton et al., 2015; Yeoh & Koronios, 2010)
Data-driven culture	A workplace where data is regularly used to inform decisions and is not only appreciated but also easily available is referred to as having a data-driven culture.	(Ashraf et al., 2022; Storm & Borgman, 2020)
Business-centric championship	Successful BI needs business business-centric championship to ensure cooperation with the business and BI team.	(Yeoh & Koronios, 2010)
Business oriented development	BI needs the ability to constantly change in accordance with new business needs due to the changing business environment.	(Yeoh & Koronios, 2010)
Necessity	Internal BI systems in businesses don't have a single, widely applicable form instead, how the tool is integrated into processes is more crucial.	(Harrison et al., 2015)
Flexible BI architecture	The technical framework needs to be scalable and flexible to respond to changing business needs.	(Boyton et al., 2015)

3.4 Factors affecting the continuous use of BI

To achieve the benefits of BI, the system needs to be used. However, in many companies, BI is underutilized, which means that potential benefits for improving decision-making may not be obtained (Foshay, Taylor & Mukherjee, 2014). Therefore, it is important to be aware of the factors that are affecting the continuous use of BI. Continuous use refers to the intensive use of BI applications to perform daily tasks and use them for decision-making in the long run. According to Bischoff et al. (2015) there is not as much researched information on the factors influencing the continuous use of BI systems as traditional information systems. Additionally, the previous research on the use of information systems cannot be fully applied in the context of BI, as the use of BI systems is rather voluntary and more broadly innovative.

Research shows that users' experiences of the benefits of a BI system have the strongest impact on application utilization (Chang, Hsu & Shiau, 2014; Foshay, Taylor & Mukherjee, 2014). In addition, the ease of use of systems has a direct and significant impact on the perceived benefit and thus on the use of BI systems (Chang, Hsu & Shiau, 2014). Ease of use was also found in Bichoff's (2015) research to have a significant positive impact on the user's experience of the BI system's usefulness and the value it creates to perform daily tasks. Ease of use has been found to be increased by the suitability and adaptability of the system to the user's needs, response time, and real-time data (Božič & Dimovski, 2020).

Bischoff et al. (2015) state that trust has a key impact on the user's experience of the usefulness of a BI system. The creation of a trust is influenced by management support, organizational initiatives to promote the continuous use of the BI system, and the quality of information. Additionally, user support and user engagement in the development process have a positive impact on the trust of the system.

4 Methodology

This chapter describes and justifies the chosen methodologies for this research and presents the data collected for the analysis. The research approach adopted in this study is a case study, which concentrates on comprehending the specific phenomena within a real-life corporate context (Puusa, Juuti & Aaltio, 2020). The empirical part of this master thesis is implemented using qualitative and quantitative research methods. The chapter is divided into two parts. First, there is presented the research methodologies and data collection of the qualitative research, and then the quantitative research. For the first and fourth research questions, there are applied qualitative methods and for the second and third research questions, there are applied quantitative methods. Figure 7 presents the workflow of the empirical analysis.

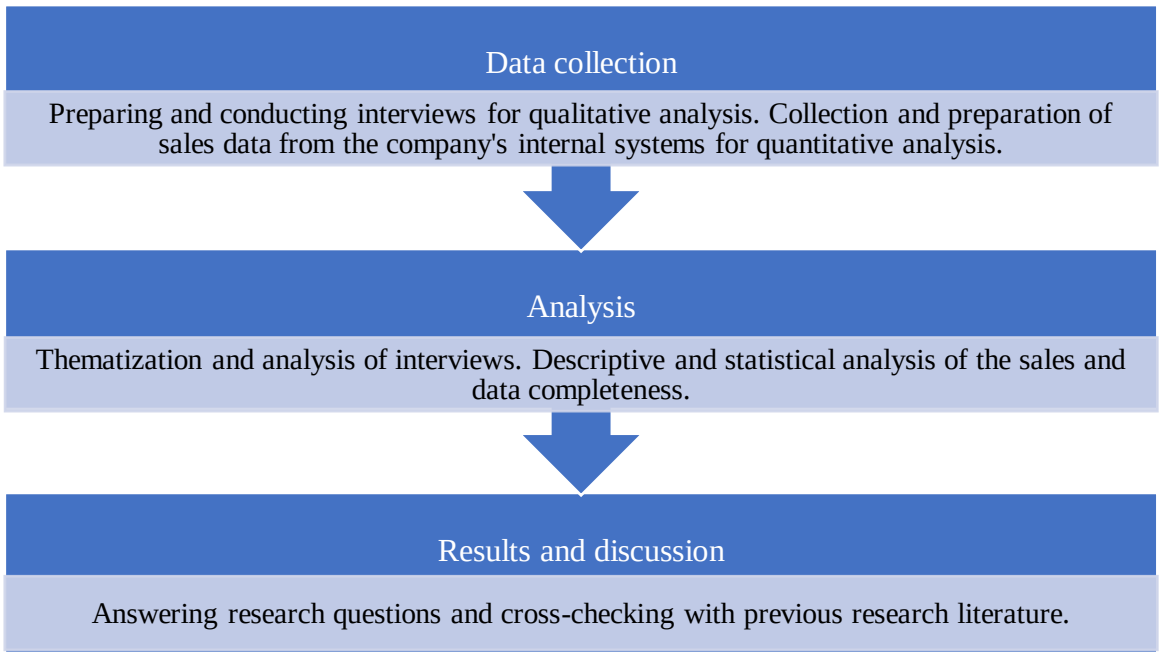

Figure 7. Workflow of empirical analysis

4.1 Qualitative research methods and data

The first research question was: "*What are the main critical success factors of the BI in the context of sales and sales management of the case company?"* and the fourth research question was: *"In which areas should the case company's current BI solution be improved?"*. These questions were approached with qualitative methods to evaluate the experiences, attitudes, and motivation of interviewees (Saldana, 2011). The data to be analyzed for research question 1 and 4 is collected by semi-structured interviews. In the thesis, it was decided to use qualitative methods in addition to quantitative methods, because the evaluation of BI's critical success factors could not be performed with quantitative methods, but the views and experiences of the target company's sales management on BI had to be approached through interviews.

4.1.1 Content analysis

Content analysis was chosen as the analysis method for the interview because it analyzes textual sources and enables a comprehensive analysis of the material (Puusa, Juuti & Aaltio 2020, 144). Content analysis relies heavily on logical interpretation and reasoning, aiming to structure the material into a succinct and coherent format that facilitates the drawing of dependable conclusions (Tuomi & Sarajärvi 2018,122). With the help of content analysis, the material already collected is reduced and classified into different categories by its similarity and this is used for analysis (Puusa, Juuti & Aaltio 2020, 144). Content analysis is used to answer research questions 1 and 4.

4.1.2 Interviews

Interviewing was selected as the data collection method for research questions 1 and 4 due to its flexibility in gathering data from complex and wide processes like BI. The interview data was collected with semi-structured interviews. The semi-structured interview was chosen because of its more interactive essence than structured interviews where the form of questions and order are predetermined (Puusa, Juuti & Aaltio, 2020). Qu et al. (2011) state that in a semi-structured interview, the interviewer follows a systematic and consistent set

of prepared questions based on specific themes. In between these questions, it is possible to ask the more specific questions aimed at obtaining more detailed answers. The interviewees have different knowledge and approaches on the studied topic because of their different roles in the organization so too strictly formed interviews can complicate getting proper answers. With semi-structured interviews, it can be ensured to acquire the same core information of every interviewee but also delve deeper into the insights of every participant which may give richer answers (Belotto, 2018).

The purpose of the interviews is to identify the critical success factors of BI in the context of sales and sales management in the case company and afterward, evaluate and validate them based on the previous literature. Excel sheets were used to compile the transcribed responses, first question by question, and then further subdivide them into common categories by their similarity. The interviews were targeted at sales management which is the target group of the BI system including both product line and regional managers. The interviewees were contacted by e-mail. All those invited to the interviews participated. The aim was to understand their experiences and views of BI success in different areas of BI. Sales managers with different hierarchical levels were interviewed. In addition to the fact that the interviewees were chosen from different hierarchical levels, interviewees were chosen from different geographical locations as well so that all the interviewees were not located in the same place where the BI development team is. The interviews were held in both Finnish and English. To guarantee that participants and interviewer had a consensus on the used terms, it was essential to explain the general topic and research viewpoint to the respondents before the interview. Additionally, brief explanations of the most frequently used terms were given. Anonymity was agreed with the interviewees so that no single person's comments could be connected to the person him or herself. The list of the interviewees is in Table 3.

Table 3. List of interviewees

Interviewee	Region	Has been in the company before BI adoption
A	Global	Yes
B	Europe	No
C	Asia	Yes
D	Global	Yes
E	Europe	Yes
F	Asia	No

The interviews with the users focused on the success of BI from the user's point of view. Critical success factors identified in previous literature, which can be assumed to be significant in promoting the success of the target company's BI system, were used in forming the themes of the interview and thus the interview questions. However, due to the lack of similar studies, forming the interview question was challenging because no comparable studies were found. So, for example, there was no direct comparable research on the way the questions were formulated. The interviewer also needed to use his knowledge of the case company's BI process to contextualize questions. For example, for the questions about data quality, there was a need to form questions so that they are understandable from the user's point of view. Interview questions were grouped into the following four sections: general, strategy and organizational culture, report development, and usability and quality of report. The first group included mostly general questions and the last three were more about the critical success factors of BI. The interview questions were shared with the interviewees well in advance of the interview. The interview questions for sales and product line managers can be found in Appendix 1.

4.2 Quantitative research methods and data

Using quantitative methods, there is aimed to find an answer to the second and third research questions. Quantitative data, analyzed with mathematical and statistical methods (Yilmaz, 2013) complements the empirical data from interviews. Unlike qualitative data, which explores the reasons behind behaviors, quantitative data is more structured and measurable

and can reveal trends and behaviours across data sets or groups (Goertzen, 2017). The data for quantitative analysis is collected from the financial planning tool of the case company which has been used before BI adoption and after BI adoption.

4.2.1 Data

For the quantitative study of the thesis, two different data sets were formed. The datasets were collected from two years before (2017-2018) the BI system was deployed and two years after (2020-2021) the system was deployed. For research question 2 there was constructed data set of the company's sales on the country level. The sales data set used for the study has been collected from the company's financial planning tool. The data set contains a total of 25 observations. In Table 4 there is an example of a data set.

Table 4. Example of sales data

Country	Sales Pre BI	Sales Post BI
Country 1	100000	90000
Country 2	70000	80000
Country 3	65000	70000
…	…	…
Country 25	9999	10000

Table 4 presents the total sales of individual countries in the company for two years before BI adoption and for two years after BI adoption. In the data set, sales are divided by country and the absolute sales volumes have been corrected with quarterly producer price indices to enable their annual comparison. The sales figures used in the study do not correspond to the actual company figures but have been converted for confidential reasons. However, data dispersion and relative changes remain unchanged.

For the third research question, a dataset has been formed to describe the completeness of data in the same countries. The data is described in Table 5.

Table 5. Example of data completeness

Country	Product Assigned Pre BI	Product Assigned Post BI
Country 1	0.6	0.7
Country 2	0.55	0.65
Country 3	0.7	0.55
…	**…**	**…**
Country 25	0.9	0.91

The numerical value "Product Assigned" refers to the relative share of orders where Product information is entered correctly with a product code that can be validated based on the company's master data. The dataset presented above illustrates well how individual countries have evolved in terms of data completeness with the introduction of the system.

4.2.2 Shapiro Wilk test

For questions 2 and 3, it was necessary to verify the normal distribution of the data sets to find a suitable statistical test. In this study, Shapiro Wilk test was used. The Shapiro-Wilk test is a statistical method used to verify the assumption of normality for a single variable's continuous data, derived from a univariate random sample. It is particularly effective in identifying departures from normality that result from skewness or kurtosis. The test statistic W, which is used in the calculation, is outlined in Equation 1 and was first introduced by Razali & Wah (2011).

$$W = \frac{(\sum_{i=1}^{n} a_i y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

Where: y_i= 25^{th} order statistic

$\bar{y}$ = sample mean

$$a_i = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{1/2}}$$

Where:

m = expected values of order statistics

V = covariance matrix of order statistics

The test statistic W indicates whether the data is normally distributed or not. The test statistic gets a value larger than 0 and less or equal to 1 (Razali & Wah, 2011). The null hypothesis (H0) of the test is that the sample is drawn from a normal distribution and the alternate hypothesis (H1) is that the sample is not from a normal distribution. The test statistic with a value equal to 1 means data is normally distributed and a small test statistic value instead rejects the hypothesis of the normality of data (Razali & Wah, 2011).

The Shapiro-Wilk test is a widely used method for testing normal distribution. Moreover, Razali & Wah (2011) used Monte Carlo simulation to investigate the power of the three most common normality tests and found the Shapiro-Wilk test to be the most powerful, further validating its use in this thesis. The Shapiro-Wilk test is also suitable for small sample sizes (Souza et al., 2023) making it an appropriate method for the studied dataset.

4.2.3 Paired samples t-test

Paired samples t-test is used to seek answers to research questions 2 and 3. When two dependent samples are observed in a study, the paired samples t-test is often used (Rietveld & van Hout, 2017). A paired samples t-test is a statistical method that compares the average of two groups that are matched or the average of a single group at two different times (Ross et al., 2017). The t-statistic is calculated from the differences in pairs and is assumed to follow t-distribution under the null hypothesis. The formula of the t-test is following:

$$T = \frac{\overline{X_2} - \overline{X_1}}{\frac{1}{\sqrt{n}} \times \sqrt{s_1^2 + s_2^2 - 2r_{12}s_1s_2}} \quad (2)$$

Where:

n = number of pairs

$\bar{X}_n =$ mean of the differences

s_1^2 and s_2^2 = variances obtained at T1 and T2 respectively

r_{12} = Pearson correlation between the scores obtained at T1 and T2

The interpretation of the t-statistic depends on the defined hypothesis. The null hypothesis (H0) of a two-tailed paired sample t-test is that the mean scores of samples 1 and 2 are equal. The alternate hypothesis (H1) is that the means are unequal. But in the case where you want to study the positive or negative difference in the means, the hypothesis needs to be one-tailed. For right-tailed paired samples t-test null hypothesis (H0) is that the difference in the means is equal to or less than zero and the alternate hypothesis (H1) is that the difference in the means is positive. For left-tailed paired samples t-test null hypothesis (H0) is that the difference in the means is equal to or greater than zero and the alternate hypothesis (H1) is that the difference in the means is negative. The t-test for paired samples has two assumptions. The differences between paired samples are normally distributed and the analyzed observations do not interact with each other.

A paired samples t-test was chosen for this part of the analysis because it is a simple way to gain statistical support to compare the means of paired samples. Additionally, the design of the study also follows the design of the pre-post study, and a paired samples t-test is a classic way to perform statistical tests for a pre-post design study (Hedberg & Ayers, 2015).

4.3 Reliability and validity of the study

This study combines qualitative and quantitative research, so the evaluation of its trustworthiness is not straightforward. Commonly in good quality research, there are often expected three criteria reliability, validity, and generalizability (Hirsjärvi et al. 2009, 232). In qualitative research especially in case studies, these can be difficult to apply (Hirsjärvi et al. 2009, 232). On the other hand, the case study does not attempt to generalize the results, so the criterion of generalizability isn’t in all respects relevant in terms of the quality of this study.

Reliability describes the consistency of the analytical procedure meaning how well using the same design and methods the same results can be repeated (Riege, 2003). The qualitative analysis of this study is very time-bound and repeating it at another time would not necessarily lead to the same results. On the other hand, in a case study that examines a specific phenomenon in a company, reliability may even be irrelevant (Puusa, Juuti & Aaltio, 2020). Regarding quantitative research, the reliability is at a good level because its process is well described, in which case it would be possible to repeat it with the same results. The research aims to improve reliability by describing the research process in every step taken.

The researcher is familiar with the topic and can be assumed to have his own opinions on the topic and have some kind of confirmation bias. People who have this kind of bias are more likely to reject information that challenges their opinions and concentrate instead on finding evidence to support their own beliefs (Ask & Granhag, 2005). In order to avoid confirmation bias, the interview questions are composed mainly of open-ended questions, which is a researched way to control confirmation bias and there is also avoided use of leading questions (Powell, Carolyn H. Hughes-Scholes & Sharman, 2012). Data triangulation was executed by cross-checking the results of the study by existing research.

5 BI characteristics and analysis

This chapter presents the BI of the case company in the sales organization and the preliminary results of qualitative and quantitative analysis. The chapter first briefly introduces the BI tool used by the company, followed by the qualitative and quantitative analysis. The quantitative analysis starts with descriptive analytics and then the data is investigated statistically.

5.1 The business intelligence in the case company

The current BI system was introduced in the sales organization at the end of 2019 across all the countries, with the aim of supporting the decision-making of the sales management. Before that, the interface on the company's operational data was based on various Excel reporting and financial planning tools, the main challenge of which was their maintenance and static presentation of information. The information available through the BI tool is based on operational data which is gathered from multiple source systems. Currently, business data of BI originates from three main data sources: ERP, CRM -tool, and the case company’s pricing tools. Data presentation currently is based on interactive dashboards which have been created for different purposes. The interactive dashboards are the only visible part of the BI process to the users so the process and logic behind dashboards may be unfamiliar to users. Own BI development team of sales is responsible for the development and maintenance of the tool. That includes, among other things collecting BI development requirements from business users, prioritizing, and scheduling the development, supporting the BI tools users in front-end related matters, and the access management of the tool. Information on the use of the system has been collected since 2021. Table 6 presents the usage and user amount of the tool in 2021-2023.

Table 6. Usage of the BI system

Year	Usage	Users
2021	1563	123
2022	4298	184
2023	9682	369

The usage refers to the individual number of times when someone has interacted with Power BI report and the users refer to the number of users in the same period. The usage of the system and the number of users has been on a continuous increase since 2021, and it can be assumed that growth has started since the introduction of the system due to the release of new dashboards. Although the main user group of the system is sales management, part of the BI reports are also available to others which explains the increasing number of users during the timeframe. Figure 8 presents the number of users in different usage volumes based on user data from 2023.

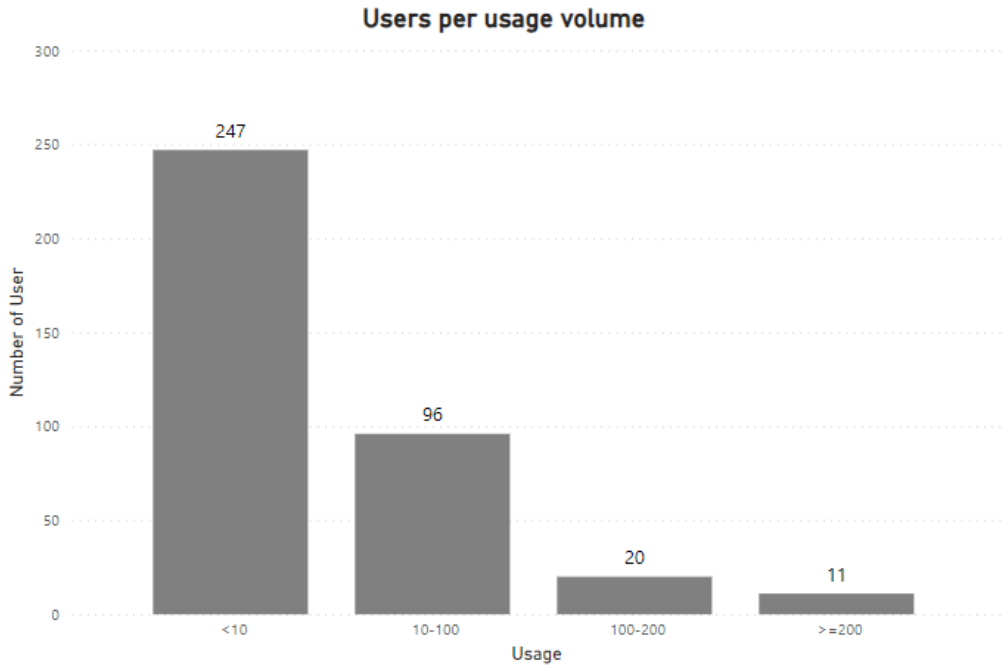

Figure 8. Users per usage volumes

Usage volume refers to the number of uses in a specific period. The BI system has a large proportion of users who do not use the system regularly or have only visited it after gaining access (10 or fewer uses in the year 2023). The system also clearly has some very active users based on the usage data of the year 2023.

5.2 Research question 1

The research question 1 was: *What are the main critical success factors of the BI in the context of sales and sales management of the case company?* The research results have been

divided into subsections based on themes formed from the interview material. The themes were formed by classifying data by its similarity. The five formed themes were Data quality, Usability of the tool, Linking of BI and strategy, Data-driven culture, and Communication and development. The research material is based on the personal views and experiences of the target company's sales management (the BI system's target audience).

5.2.1 Data quality

Data quality in the system became a key issue in the interviews. Various user concerns about the reliability of Power BI report content were categorized under the data quality theme. Incorrect, incomplete, and inaccurate information were considered to be the most significant reason for the lack of data quality. None of the interviewees was satisfied with the quality of the data and data quality problems were described as causing frustration and lowering the reliability of the content of the Power BI reports.

"Incorrect and incomplete information frustrates quickly."

-Interviewee A

There were experienced various issues with the reliability of data. The incompleteness of data was found to be one reason for bad experiences of data quality and reliability. Also, it was mentioned that incomplete documentation of data has in some cases caused misunderstanding and unreliability when the context of data hasn't been clear. In a few interviews, the problem was seen to be especially the discrepancy of information between different systems, which was seen to be caused by the timeliness of the information.

"I think the data quality is not so good. I think that's because of the refresh frequency. When our controller will go to the Financial Planning tool to find data and I will go to the Power BI dashboard to find data, we find that they are not aligned."

-Interviewee C

One interviewee cited the use of an incomplete data source that does not reflect the latest data in their area as the reason for incomplete and incorrect data.

"I think one example (of incorrect information) can be the end-to-end transparency which we are building up based on the sales tool data. I feel it should be based on the SAP because the final data is actually taken from SAP."

-Interviewee F

The problem of data quality was recognized to be particularly significant in a more detailed financial analysis. In some interviews, there were mentioned that Power BI works as an indicative tool and shows trends. However, for financial analysis, the content of Power BI reports is not perceived as reliable, but the numbers need to be compared with the original information at the data source.

"Although this guy has sold x EUR according to this Power BI report, but when you look at the orders in SAP, it is 15-20% more. This kind of manual work needs to be done. The Power BI is indicative, but you can't rely on it."

-Interviewee D

The transparency of Power BI report information was found to be important. The system users mentioned that the option to drill down to the project level of information increases the reliability of the data instead of only showing high-level figures and visuals.

"With drill down, you are able to get a better understanding of the information over there are they reliable or not."

-Interviewee B

5.2.2 Usability of the tool

Necessity for the current number of separate Power BI reports is not necessary in the opinion of the interviewees. Most of the interviewees highlighted the issue that the necessary information is scattered between multiple reports and finding the relevant content can be difficult. Additionally, the large amount of different Power BI reports has forced users to use many different reports for some regular reviews which has not been found user-friendly.

"We are using nowadays maybe too many Power BI(s) reports"

-Interviewee B

"The difficulty is when there are a lot of those reports, so I have often had to use, for example, 10 different reports in certain conversations with senior management."

-Interviewee D

The issue with scattered information is not only Power BI related. In the company there are other systems for company's KPI reporting that are not always align neither with the Power BI reports. To find the actual value for example to some specific KPI therefore can be very time-consuming.

"I feel there are too many places at which the data is. And at all these places for the same KPI there is some variation in the numbers. So actually, to arrive at the actual and the final number, it becomes a very daunting task."

-Interviewee F

At the time of the research, the focus has been creating general reports for the sales management for different purposes like profitability or sales pipeline, and the reports had not been further specified for the needs of different product lines or regions. The concentrated way for Power BI report creation has not been fully satisfying and the system users would like to have more flexibility to create reports for different purposes. Many of the users of the system emphasized that the reports do not always serve them as such, and it would be good to have a report for their individual needs. Due to new information needs, the number of reports has increased continuously, but the need for older reports has not been assessed, which some interviewees think would be necessary.

"But my own wish would be to be able to make a Power BI report suitable for my own purposes, from which I would have taken parts of these existing ones and added a couple of other elements to it so that I could basically use one report to support my own work and management."

-Interviewee D

"When you want to discuss something specific with different people it would be good to find the possibility that everything is in one specific dashboard and maybe you can also somehow develop it by yourself."

-Interviewee B

The visual presentation of information could also be improved. The current way to develop Power BI reports in a sales organization has been to make an interactive Dashboard for users that they can use as such for their own purposes. However, some challenges have emerged. Currently, the BI tool has not been perceived to summarize information effectively, but instead leaves a lot up to the person's own processing.

"The target state is, of course, that if there are 8 numbers in green and 3 in red and each region is at a slightly different level, what does this really mean? At the moment, that processing takes place in one's own head and it is then so limited."

-Interviewee A

Some technical features are also needed, such as adding your own notes to dashboards or freezing the status of information from, for example, a previous month. The content of the reports has also had to be iterated somewhat due to missing features.

"One of the things that I typically do is I add my personal notes directly in an Excel file ... and then send out that you say to the needed people and then also they can come back and say based on what I'm writing there and this is kind of interaction it's not that you say at the moment available in Power BI."

-Interviewee B

Users have considered the quick availability and usability of reports to be significant factors in terms of efficiency and convenience of report's use. Based on the interviews there would be a need to increase the report loading speed. Slow reports cause multiple issues with the users and may lead to situations where the tool itself is not used but there is taken snapshots of the reports and used the time to create Power Points.

"There is still a need to make improvements on the speed. I think most of the managers would like to use the Power BI instead of Power Point. So normally they click once then they need to wait 10 seconds or more to get the right data. That is not efficient."

-Interviewee C

The slowness of reports has also blocked the possibility of using specific reports and information in some meetings.

"Today we just watched one report with the team. I put it to thicken. But 15 minutes passed and nothing happened."

-Interviewee D

One interviewee also mentioned that the quicker report should be prioritized over the most detailed level of information. Slow reports may lead to frustration and stop the usage of some reports. On the other hand, many felt it was important to have transparency of information at the most detailed level, so simplifying reports in this regard is challenging.

The report update frequency should be also increased according to some. Even one or two days old information may be a problem when for example having a meeting with salespeople who have more up-to-date information about some new projects.

"The best would be for the reports to be live. There is always a one-day delay or something like this."

-Interviewee B

5.2.3 Data-driven culture

In interviews, it was relevant to understand what kind of role Power BI has in the company's culture. There was studied in which situations Power BI reports are used and what kind of role the report has in regular work. The interviewees agreed that decision-making needs to be data-driven. For some interviewees, the BI tool is increasing its significance in weekly or daily work.

"It's getting close to being part of our daily life."

-Interviewee B

However, for everyone in sales management, the use of Power BI is not a weekly routine, which is also evident from the system usage data. Although for everyone, the use of Power BI in the short-term review of sales has not yet become routine, it can be said that Power BI has a clear role in the regular monitoring of sales. The usage of Power BI is partly individual, but it is also used in regular team meetings and management reviews.

"An hour per day, you watch the reports by yourself. If we take individual events as an example, they include sales team meetings and division reviews related to sales and marketing. They will be used in management team meetings as well."

-Interviewee D

"Power BI is used in weekly meetings."

-Interviewee E

According to one interviewee, Power BI has also increased the availability and usefulness of data compared to, for example, the company's previous "Excel-driven culture". Which referred to the way that the implementation of sales analytics was largely based on various Excel reports with a complex update process.

"When I came to this job 4 and a half years ago, the culture back then was very excel-driven and even so that those excels were very person-driven, i.e. they depended on a certain person's ability to use excel. And, for example, business forecasting was really bad and uncertain."

-Interviewee A

In any case, even though Power BI and information generally play a significant role at the global level of sales management, the local level of the organization is not necessarily so committed to these processes, for example collecting certain information. The CRM tool's instructions can also be unclear and incomplete at the local level and the complex organization model can also become a problem, which can lead to a situation where the instructions for data collection can be contradictory when they are given from multiple directions.

"Many countries are not committed to the use of the Customer relationship management tool."

-Interviewee A

"Different product divisions may have different instructions for salespeople on how to enter information."

-Interviewee E

Commitment at the local level can also be affected by the fact that the BI tool for sales is primarily developed for sales management and its use is not aimed at salespeople. One interviewee is a candidate for expanding the user base.

It would be nice also for the individual to utilize this kind of tool to get an understanding a little bit better (of sales/business) while they are working. For example, what is the situation with their customer and making their own analysis. Nowadays it is a little bit more tool for managers.

-Interviewee B

5.2.4 Communication and development

Communication between report owners and users has not been entirely successful. Interviewees commented that they are not always aware of who to contact if some questions or development ideas arise. One interviewee mentioned that the report users should be more clearly pointed out the owner of specific reports.

"Well, I don't know (the report owners) that would be good information to be found. There could be some question mark button to find it."

-Interviewee D

"There is less awareness of whom to approach for any of the needs."

-Interviewee F

There is no common practice on how users should contact the report owners. Some users use Power BI ready-made features, while some use Teams or e-mail. Some, on the other hand, directly contact the manager of the Power BI development team.

The report user would need to know the status of the report more transparently. The interviews highlighted that information about the timeliness of a Power BI report should be clearly available and the errors or data update delays would be good to proactively communicate to the users.

"There have been some problems with the updates. It's good that those dates are there, but should there still be a green or red light in the corner of the report to indicate whether it has been updated or not?"

-Interviewee A

The interviewees saw user-driven development as important. However, users' experiences of development according to their needs varied. Some of the development requests have been well supported, but for some, the larger development needs are stopped due to insufficient resources.

"The implementation of the developments is a different matter, whether there is time for them and then we have to get buy-in to them from the management if you want to get resources for the development."

-Interviewee D

In some interviews, the development of BI was seen to be too concentrated on the sales organization's global Power BI development team. In one interview there was also proposed to involve local teams more in the development process and make the report better available on those as well.

"I think even the local teams should be involved in understanding what information or ideas should be utilized to develop new reports. Because you would surely get something, something fresh from that."

-Interviewee F

However, although respondents' views varied about their possibility to affect report development. There seemed to be agreement that various bugs or report's malfunctions, and various issues related to license management have been handled efficiently and have not affected user experience negatively.

5.2.5 Linking of BI and strategy

Interviewees were mainly satisfied with Power BI's coverage of all strategical important measures even if there was one strategic measure which cannot be showed in Power BI

because of data quality issues. However, to getting the information in just the correct form or granularity has been an issue.

"You would probably find all of them (measures). Information is so scattered in different places that you need to use the business controller quite a lot, you can get just the right granular level of information."

-Interviewee D

In some of the interviews, it was also mentioned that the sales management has not clearly highlighted the key areas that should be monitored. One respondent for example commented that there should be considered in sales management that what are the key areas that should be focused on sales and based on that input define the necessary reports.

"We in sales management should think even more carefully that these are the things we lead with and then provide input for reports. And specify which metrics are relevant in which area."

-Interviewee E

Some of the interviewees, on the other hand, believe that the creation of a completely unified BI strategy is challenged by the geographical scope of the company. Because different countries and regions may have different strategic goals, which means they may have different needs for different data, indicators, and KPIs.

"Different regions will have different kinds of strategies. It depends on what kind of specific strategy or tactic we will use in different countries."

-Interviewee C

5.3 Research question 2

The research question 2 was: *Has the sales increased since the introduction of the BI system in the case company?* As mentioned earlier the BI system was introduced at the end of 2019, so therefore the datasets to be compared have been collected from the two years before the system's adoption year and from the two years after the system's adoption year. The pre-adoption period is therefore 2017-2018 and the post-adoption period is 2020-2021.

We are interested in the change between these two periods. The distribution of sales per country before and after BI adoption is presented in Figure 9.

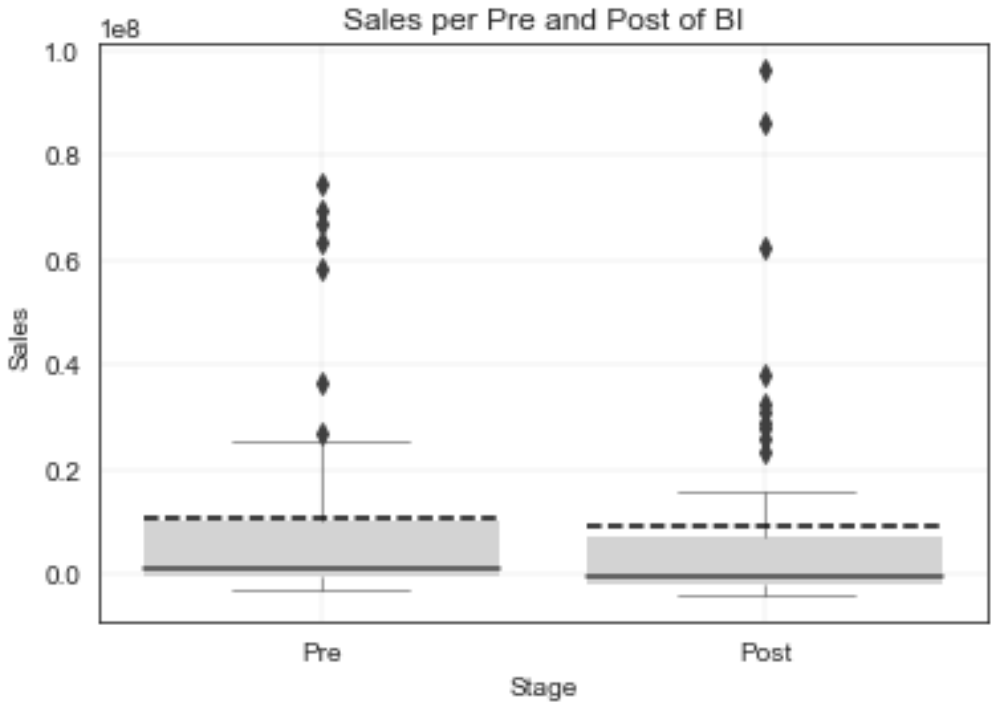

Figure 9. Sales 2017-2018 (pre-adoption) and 2020-2021 (post-adoption)

In the figure above we see median and mean (dotted line) of sales have declined in the studied timeframe. The interquartile range has also decreased during the studied period, but the post-BI implementation observations have higher maximum values than pre-BI. Overall, the sales of individual countries vary a lot and there are multiple outliers. The average in both stages is higher than the median which means that both samples are right-skewed. Figure 10 presents the relative differences in sales volumes between before and after values.

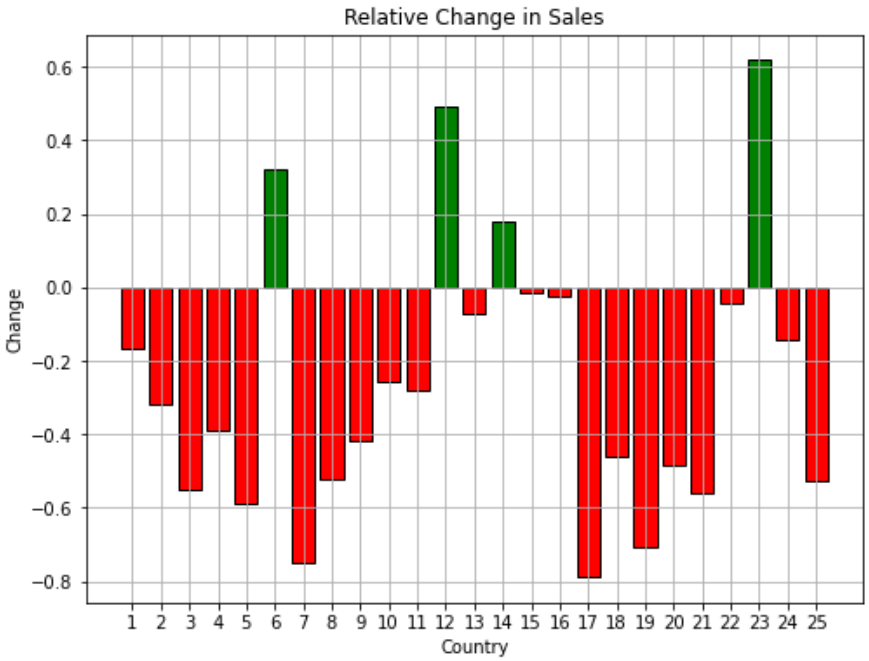

Figure 10. Relative changes in sales between periods 2017-2018 (pre-adoption) and 2020-2021 (post-adoption)

A positive change refers to the increased sales compared to the time pre-BI and a negative change to the decreased sales. The change in inflation-adjusted sales has been negative in most of the countries. However, in some countries, sales have increased a lot and the negative change in sales is moderate in some countries. Appendix 2 presents descriptive statistics of relative changes. Figure 11 presents the distribution of sales.

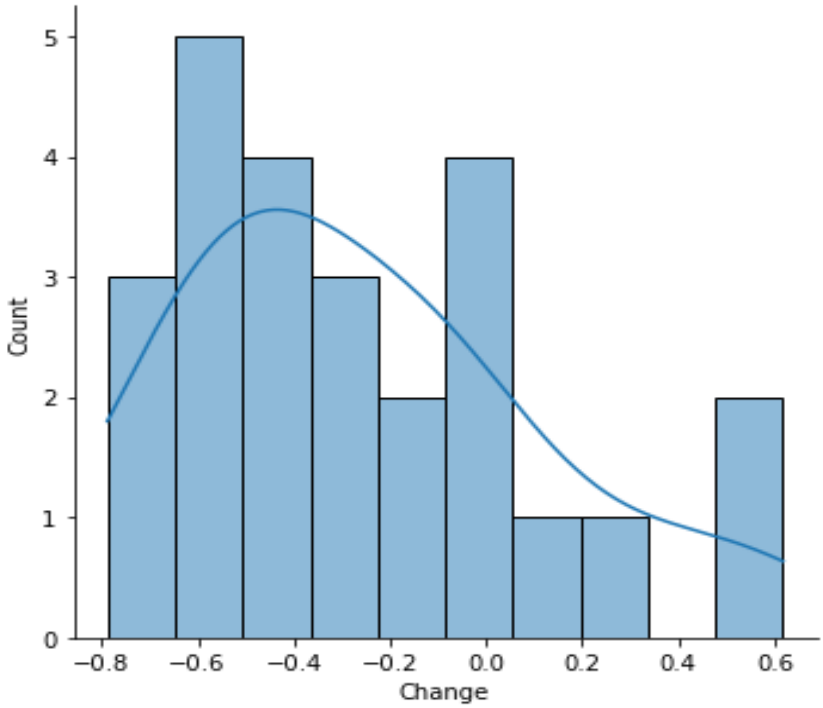

Figure 11. Distribution of relative change of sales between periods 2017-2018 (pre-adoption) and 2020-2021 (post-adoption)

The data presented above is slightly right-skewed and needs to be tested for normality to find a suitable statistical test to determine whether sales have increased statistically significantly since the introduction of the BI system. As mentioned earlier, the data is weighted on negative values, and positive values are deviations from the rest of the data distribution, so it seems inflation-adjusted sales have declined between the periods studied.

5.3.1 Testing for normality

As mentioned previously to select an appropriate statistical test to answer in research question 2, it is necessary to determine whether the relative changes follow a normal distribution. In Figure 12 is presented a quantile-quantile plot (Q-Q plot) where the distribution of the dataset is compared to the theoretical normal distribution.

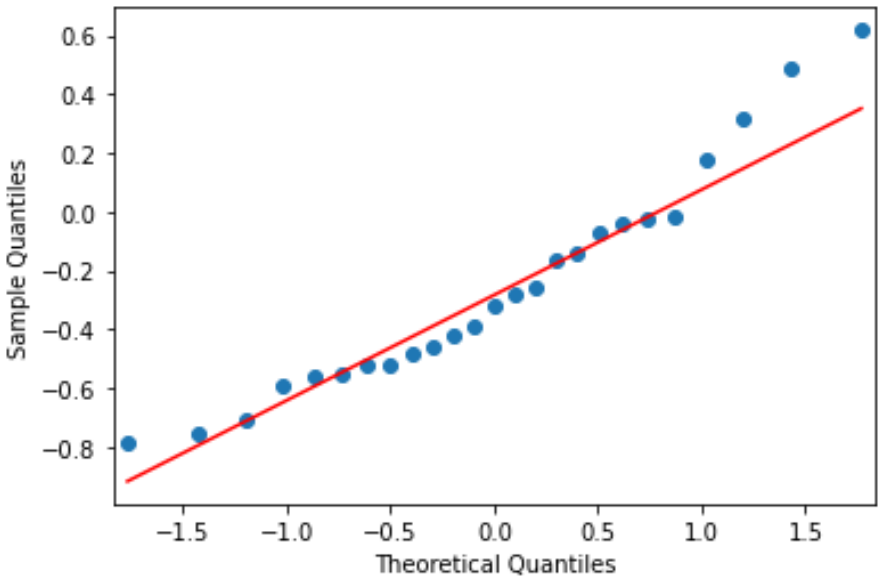

Figure 12. Q-Q plot of sales data set

From the plot we can see that the points don't perfectly fall along a straight diagonal line and especially in the tails there are larger deviations. However, we need to analyze data further with statistical tests for normality. A Shapiro-Wilk test was conducted to assess the normality of the variable. The results indicated that the null hypothesis of the normal distribution of data cannot be rejected so the variable was normally distributed with a p-value of 0.156. The Shapiro-Wilk results are presented in Appendix 3.

5.3.2 T-test results

Next, the actual statistical test was conducted for the data to study whether the relative change in countries' sales has been greater than zero. This was tested with a right-tailed paired samples t-test. For the t-test, there was formed the following hypotheses:

H0: The relative change in sales is less or equal to zero.

H1: The relative change in sales is greater than zero.

The results of the t-test are presented in Table 7.

Table 7. Research question 2: Results of right-tailed paired samples t-test

Alternative hypothesis	right-tailed
T-statistic	-3.456
P-value	0.999
df	24
Coheen's d	0.978
Confidence Interval (95%)	[-0.39, inf)

Based on the t-test results we don't have confidence enough to reject the null hypothesis. This means that we cannot reject the possibility that change has been less or equal to zero. The t-statistics is significantly smaller than the right-tailed critical t-value which is 1.71. The results show clearly that the difference is not positive. Next, a left-tailed paired samples t-test was conducted with the following hypothesis.

H0: The relative change in sales is greater or equal to zero.

H1: The relative change in sales is less than zero.

The results of the test are presented in Table 8.

Table 8. Research question 2: Results of left-tailed paired samples t-test

Alternative hypothesis	left-tailed
T-statistic	-3.456
P-value	0.001
df	24
Coheen's d	0.978
Confidence Interval (95%)	(-inf, -0.13]

The p-value is less than 0.05 and therefore we can reject the null hypothesis. Because the left-tailed critical t-value is -1.71 and the t-statistic is -3.456 we can say that the relative change of countries' sales between these two periods has been negative. This means that the sales of the company's countries have not increased since the introduction of the BI system statistically significantly but on the contrary, it has decreased.

5.4 Research question 3

The research question 3 was: *Has the data completeness increased since the introduction of the BI system in the case company?* The comparable datasets have been collected from the same years as for the research question 2. Figure 13 the data completeness is presented before and after BI adoption.

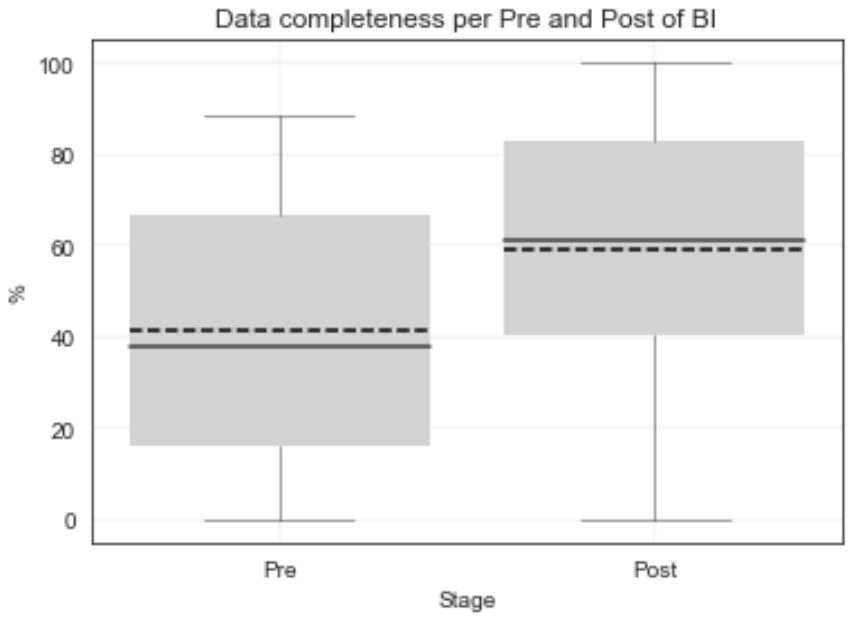

Figure 13. Data completeness 2017-2018 (pre-adoption) and 2020-2021 (post-adoption)

Data completeness refers to the relative share of orders where Product information is entered correctly with a product code that can be validated based on the company's master data. The completeness of the data has risen relative to both the median and the average. The values between the first and third quartiles are clearly higher in the post-BI adoption. In the graph above we see that the data does not include any outliers, but the interval of observations is wide. Figure 14 presents the changes in data completeness.

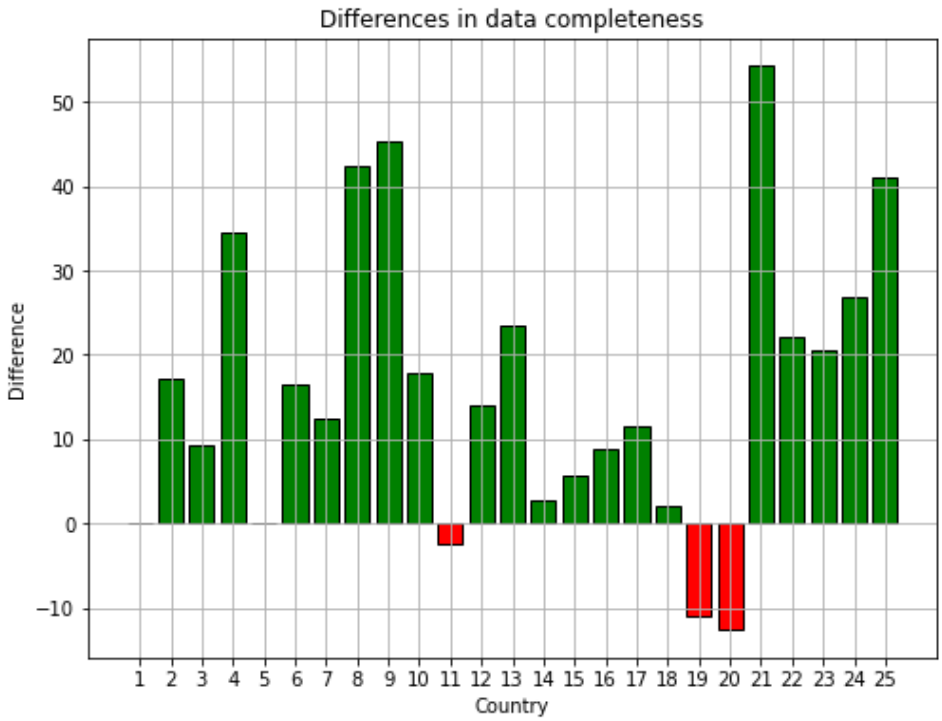

Figure 14. Changes in data completeness between periods 2017-2018 (pre-adoption) and 2020-2021 (post-adoption)

A positive change refers to the increased data completeness compared to the time pre-BI and a negative change to the decreased data completeness. In most of the countries change in data completeness has been positive. 15 countries have increased the data completeness by over ten percentage points. Figure 15 presents the distribution of data completeness changes.

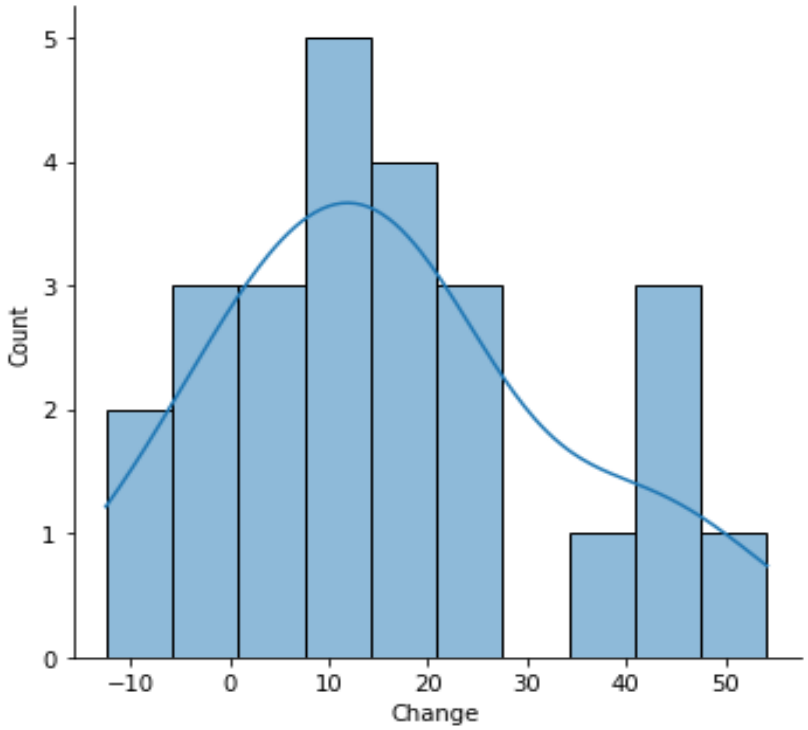

Figure 15. Distribution of data completeness change between periods 2017-2018 (pre-adoption) and 2020-2021 (post-adoption)

5.4.1 Testing for normality

In order to select an appropriate statistical test for answering whether the data completeness has increased since the introduction of the BI system in the case company, it is necessary to determine first whether the data follow a normal distribution. In Figure 16 is presented Q-Q plot where the distribution of the dataset is compared to the theoretical normal distribution.

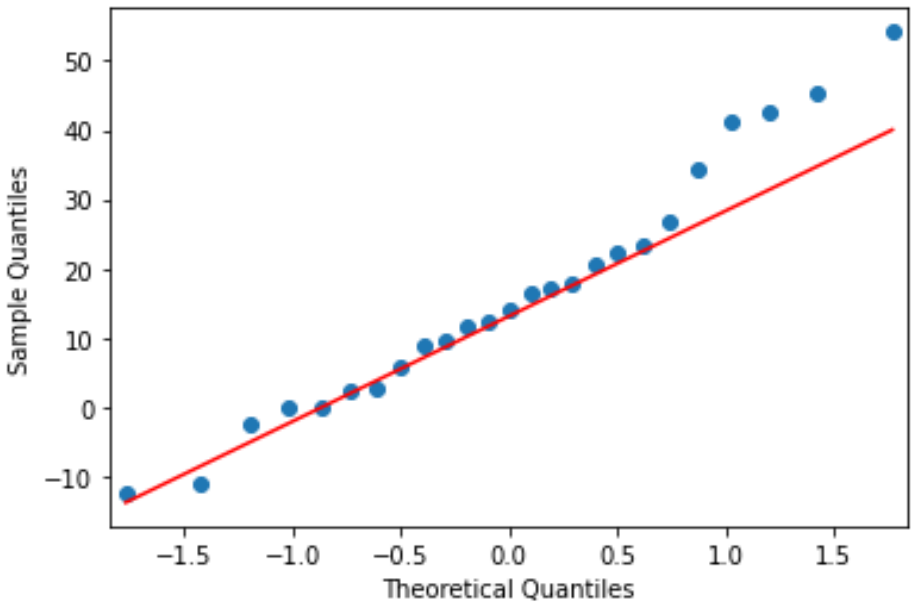

Figure 16. Q-Q plot of data completeness data set

The data is quite well falling along the line which means that it is normally distributed. The normal distribution was also tested by using Shapiro Wilks test. The Shapiro-Wilk results are presented in Appendix 4. The p-value of the test was 0.537 so the null hypothesis of normal distribution of data cannot be rejected. Therefore, we can assume our data to be normally distributed.

5.4.2 T-test results

Next, there was conducted t-test to find out has the data completeness improved after BI adoption statistically significantly. For the paired sample t-test there was formed following hypothesis.

H0: The mean of data completeness post-BI adoption is less or equal to the mean of data completeness pre-BI.

H1: The mean of data completeness post-BI adoption is greater than the mean of data completeness pre-BI.

The results of the t-test are presented in table 9.

Table 9. Research question 3: Results of right-tailed paired samples t-test

Alternative hypothesis	right-tailed
T-statistic	4.650
P-value	0.00005
df	24
Coheen's d	0.538
Confidence Interval (95%)	[10.19, inf)

The t-statistic is larger than the critical t-value which is 1.71 at 95 % confidence level. The p-value of the t-test is presumably less than 0.05 so the null hypothesis can be rejected. As a result of the test, we can conclude that the mean of the data completeness is larger post-BI adoption than it was pre-BI adoption. This means that the completeness of the data has improved statistically significantly since the introduction of the BI system.

6 Results and discussion

The objective of this study was to define the critical success factors of BI and specify the areas of improvement in BI in the context of the company's sales and sales management. There was also aimed to study whether BI adoption positively influenced sales or data quality. This chapter presents the results of the research questions and cross-checks them with previous research. The research questions 1 and 4 were:

RQ1: What are the main critical success factors of the BI in the context of sales and sales management of the case company?

RQ4: In which areas should the case company's current BI solution be improved?

Technical and non-technical critical success factors of BI were identified based on the analysis of interviews. The data quality of the system emerged as a central topic in the interviews. Issues with data quality are common in BI projects and it is one of the key critical success factors of BI (Yeoh & Koronios, 2010). Bad data quality may result in a situation where decision-making can't get any support from BI which lowers the trust in the system (Bischoff et al., 2015; Yeoh & Koronios, 2010). Data quality issues were faced mainly in the incompleteness and inaccuracy of the data, but also the timeliness of the data and missing context were mentioned as issues. Data quality problems are also supported by the quantitative part of the study, which shows that although data's completeness has improved since BI's introduction, its average and median in 2020-2021 was around 60%, while the target for it is around 100%. It would therefore be important for the case company to be able to improve the data quality. Data quality problems were approached in the interviews from the perspective of BI users, so a more detailed view of their root causes was not discussed. In the BI process, as in data warehousing, data quality problems can arise at any stage, from the data source to data modeling in the database (Singh & Singh, 2010). Therefore, in the first stage, the reason for bad data quality needs to be defined because there can be many reasons for poor data quality. Assessment of data quality is a multi-staged process but to simplify, it includes mapping and contextualizing the organization's processes, evaluating the quality of the desired information, and improving the information (Batini et al., 2009).

BI was also felt to lack clear goals and a strategy for supporting sales which can be defined as the second observed critical success factor. The beneficial effects of BI on business may not be realized if it only supports side functions rather than strategy (Yeoh & Koronios, 2010). BI needs a strong business case that demonstrates the expected advantages of the BI project and links it with the company's strategic goals (Boyton et al., 2015). Additionally, there is a greater chance of gaining management support when BI and overall strategy are in sync. If BI doesn't support business objectives it might not satisfy the users (Yeoh & Koronios, 2010). The case company needs to define more specifically what is the desired outcome of BI and connect it to the company's strategic goals which have been seen as very crucial factors in BI success (Boyton et al., 2015; Yeoh & Koronios, 2010).

The third emerging critical success factor was the usability and necessity of the BI. Currently, the main challenge was the large amount of the reports which made the knowledge acquisition time-consuming and impractical especially when the same information could be presented more succinctly. Based on previous research, no one-size-fits-all way of presenting information can be determined, but it is more important to make BI a part of the company's processes (Harrison et al., 2015). However, previous research has found that excessive information load reduces the usefulness of information in decision-making (Eppler & Mengis, 2008). In developing BI, the load of information should be taken into account. For example, in the study of Burnay et al. (2023) it has been observed that an excessive amount of informative content, non-informative content such as titles and captions, and the choice of visualizations, has a negative effect on the perceived usefulness and usability of the dashboard. It is therefore important to determine which content is necessary without cutting out too much content that is essential for decision-making. The user interface of the BI tool was also seen to lack some useful technical features like communicating privately among your team or freezing figures for a certain moment.

The fourth identified critical success factor and area of improvement was a data-driven culture. BI has taken on a significant role in sales management, but the usage of the BI has not taken on such a significant role at the local level and there has not been the same commitment to it. A data-driven culture is one of the critical success factors of BI and has been identified as having a significant role in the adoption of the tool (Ashraf et al., 2022). The company's management as well as colleagues play a significant role in supporting a knowledge-based culture. The management and other actors controlling the use of BI can by

their own example encourage and show the use of BI in different functions (Ashraf et al., 2022; Storm & Borgman, 2020).

There was also room for improvement in communication and user-oriented development which was the last identified critical success factor. Various requests have been answered quickly but some development requests failed due to a lack of resources. Especially in the case of larger development tasks, resources have not been able to be allocated sufficiently or quickly enough. In the existing literature, business-oriented development has been recognized as one of the critical success factors of BI. BI needs to be adaptative to new business objectives and continuously developed (Olszak & Ziemba, 2007; Yeoh & Koronios, 2010). The BI development was also recognized to be too centralized so involving more users is recommended. Audzeyeva et al. (2016) state user involvement also increases the engagement of the BI to the other processes as well which can positively influence a data-driven culture in the organization.

One of the goals of the company's BI has also been to increase sales. So, measuring sales change between the pre-and post-implementation time of a BI system is a good way to measure BI success. Therefore, the second research question of the thesis was:

RQ2: Has the sales increased since the introduction of the BI system in the case company?

The sales of the company's countries have not increased since the introduction of the BI system statistically significantly but on the contrary, it has decreased. However, it is not possible to make a more precise assessment of the effectiveness of BI in this regard because the research has not been able to exclude other factors affecting sales. In any case, increasing sales which has been one of the desired benefits of BI in the company has not been successful by utilizing BI in the studied period. Previous research has also identified the challenge of measuring BI's impact on financial performance (Hocevar and Jaklic, 2010).

With BI, the company has also woken up to data quality problems. In particular, the incompleteness of information has been a problem. BI has been used to create dashboards for monitoring data quality, which has made it possible to monitor and develop quality. In other words, data quality can be defined as one measurable BI goal. Based on this, the third research question was:

RQ3: Has the data completeness increased since the introduction of the BI system in the case company?

The completeness of the data has improved statistically significantly during the period studied. In only 3 (of 25) of the company's sales countries, the change in data completeness was negative. A direct causal link between BI adoption and improved data completeness cannot be established, but no other actions have been taken to improve data quality, so to that extent, BI can be considered to have a positive impact on data completeness. In previous research, the direct influence of BI on data quality has not been studied much, but it has been noticed that BI often brings data quality problems to the fore, which may have led to various data quality improvement initiatives (Marshall & De la Harpe, 2009). It is also easier to examine the quality of information when everything is available centrally (Hovi, Hervonen & Koistinen 2009, 16).

7 Conclusions

This thesis has aimed to evaluate the success of BI in the case company's sales organization. The goal of the research has been to determine BI's critical success factors in the context of the case company's sales and sales management, and to specify BI's key areas of improvement. BI's success has also been measured from the point of view of both sales and data quality. Both qualitative and quantitative methods were used in the research.

Data quality, usability of the tool, data-driven culture, user-oriented development, and BI strategy were identified as the key critical success factors of BI in the context of the case company's sales and sales management. These areas were also seen to have the most need for improvement in the sales management of the case company. The quality of the data was considered very important for the perceived benefit and reliability of the system. It was also important that the BI tool is easy to use and that there is no need to search for information in several places. The management also identified the entire organization's commitment to the BI process and a clear vision of BI as crucial factors. The use of BI should also be extended to the local level, which could also contribute to the development of the system and better engage people in the BI process.

With the introduction of the BI system, sales in the company's sales countries have not increased statistically significantly. On the other hand, the completeness of data in the sales countries has increased statistically significantly, which can cautiously be attributed to the introduction of BI, as no other measures have been taken to improve it.

7.1 Limitations

This study focused on just one global B2B technology company and more specifically on its sales and sales management. BI was also approached from a user-oriented point of view in the study, and processes related to data warehousing, for example, were not discussed. The interviewed persons evaluate the BI tool from their point of view and not so much from the point of view of the company as a whole. The results related to critical success factors of the work thus describe the view of the users on the BI and not necessarily the situation of the entire company. The thesis was concluded to the sales organization of the case company and

therefore it was wanted to study the views of the business users, and it was not experienced necessary to interview people outside the sales organization. In addition to BI, other factors potentially affecting sales could not be ruled out.

7.2 Future research

Although there is a lot of existing research on BI's critical success factors, not much research has been done on how to develop these different areas. For example, it would be useful for the case company to understand the best concrete measures to develop the critical success factors it has identified. Research on the effectiveness of BI is still incomplete. There are hardly any comprehensive models for studying effectiveness in individual organizations. Often the effectiveness is limited to the utilization rate, which does not yet guarantee financial benefits.

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Appendices

Appendix 1. Interview questions

1. **General questions**
    a. Tell briefly about your business role and main responsibilities?
    b. How long have you been in your current position?
    c. What kind of typical decisions you make daily/weekly/Monthly?
    d. What kind of information do you need to do them?
    e. What sources of information do you use to establish/obtain this information?
    f. Tell me how Sales & PM Power BI reports affect your decision-making.

2. **Power BI as part of strategy implementation and organizational culture**
    a) What is our strategy?
    b) What do you see as part of sales/sales teams in the implementation of the strategy? Does it have any particular objectives?
    c) How the role of information/Power BI can be seen in the implementation of the strategy? Both in general and in sales.
    d) What are the primary key performance indicators (KPIs) for achieving the sales goals and implementing the strategy?
    e) How well Sales & PM Power BI reports are covering these KPIs?
    f) What kind of situations/meetings do you use the Sales & PM Power BI reports?

3. **Purpose of reports and continuous development**
    a. How do you perceive the purpose and role of the different Power BI reports in monitoring specific areas and supporting related decisions? Have you noticed any overlap between the reports?

b. How easy is it to bring up new information needs or development ideas for reports? And how have you brought ideas up so far?

c. How satisfied are you with the ability of Power BI development team to meet new information needs as they arise?

d. Is there any information that you would like to get to Power BI reports, but has not been possible to add it? Can you give an example?

4. Usability and quality of reports and user support

a. How well the reports are available and up to date when you need them?

b. What is your experience with the loading speed and functionality of the reports?

c. In what ways do you process the information received, and how often do you need to use tools like Excel for further processing?

d. How detailed the content of reports should be? (e.g. order level)

e. How would you describe the ease of use and understandability of the reports? How well-documented do you find their content?

f. What aspects of the information in the reports do you find trustworthy or not, and can you provide examples?

g. Who do you contact for developments, corrections, or questions regarding the report, and how clear is this process to you?

h. How satisfied are you with the speed and efficiency of error handling in the reports?

Appendix 2. Descriptive statistics of relative changes

	Mean	std	Min	25%	50%	75%	Max
Change	-0.26	0.37	-0.79	-0.53	-0.32	-0.04	0.62

Appendix 3. Shapiro-Wilks test's results of research question 2

Test	Statistics	p-value
Shapiro Wilks	0.94097	0.15589

Appendix 4. Shapiro-Wilks test's results of research question 3

Test	Statistics	p-value
Shapiro Wilks	0.96562	0.53728