Utilizing business intelligence at the operational level

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Master’s Thesis
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Abstract

The objective of this thesis is to explore how business intelligence can be utilized at the operational level of the case company. The stakeholders of the study are two teams working on the customer interface of a Finnish software company. The case company wishes to explore the use of business intelligence in a new context where it has not been utilized before. Providing stakeholders with the capability to utilize business intelligence tools can help them streamline their reporting tasks, as well as provide them with capabilities to visualize data, filter data based on their needs, and provide access to aggregated data.

The study includes a literature review on business intelligence, business analytics, and analytical maturity. The research method used in this study is design science research, which involves designing and developing an innovative artifact to address problems that the case company is currently facing. The research data was gathered through interviews, in which nine senior-level employees were interviewed to gather insights about the current situation of the reporting, data, key figures, and their previous experiences with business intelligence. This resulted in an in-depth snapshot of the current problems detected in reporting solutions captured in the form of qualitative data. This data was analyzed to establish the objectives and requirements that the artifact should aim to address, following the principles of design science research methods. Based on these objectives and requirements, the artifact was designed and developed. The functionalities of the artifact were demonstrated and subsequently evaluated by forming illustrative scenarios to support the artifact's effectiveness.

The main findings of this study indicate that the artifact can serve as an efficient addition to the current reporting tools. It offers easier access to data and introduces functionalities that are not currently available with other reporting tools. However, these findings were overshadowed by two major limitations discovered during the design and development phases. The limitations encompassed the current availability of the licenses required to utilize the artifact and the case company's data governance policies. These limitations, combined with the time constraints of this thesis, resulted in the artifact not being evaluated with stakeholders.

Keywords
Business intelligence, business analytics, analytical maturity, design science research

Supervisors
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Foreword

This master's thesis was written for an unnamed case company between February 2023 and May 2023. First, I would like to express my gratitude to the case company for providing me with an opportunity to explore and write about this topic. I would like to extend my heartfelt appreciation to Jukka and Olli for their unwavering support. Their contributions have played significant in this thesis. I would also like to express my gratitude to everyone else from the company who participated in the interviews and provided valuable feedback.

I extend my gratitude to my instructors from the University of Oulu, Pasi and Sami, for their invaluable guidance, and fruitful discussions throughout the course of this study. Their expertise and input have been instrumental in shaping the direction and quality of this research.

Finally, I would like to express my deepest appreciation to my family, girlfriend, and friends for their unwavering support and understanding during these demanding times. Their encouragement, patience, and belief in me were a constant source of motivation and strength throughout this journey.

Oulu, 22.5.2023

Jesse Rontti

Abbreviations

API = Application Programming Interface

BA = Business Analytics

BI = Business Intelligence

BIS = Business Intelligence System

B2B = Business-to-Business

B2C = Business-to-Consumer

CIS = Customer Information System

CO = Customer Operations team

CRM = Customer Relationship Management

CSV = Comma-Separated Value

DAX = Data Analysis Expressions

DSR = Design Science Research

DSRM = Design Science Research Method

DSS = Decision Support System

ERP = Enterprise Resource Planning

ETL = Extract-Transform-Load

JSON = JavaScript Object Notation

JQL = Jira Query Language

KPI = Key Performance Indicator

SaaS = Software as a Service

SLA = Service Level Agreement

SME = Small and Medium-sized Enterprise

TSO = Technical Service Operations team

Contents

1. Introduction

The utilization of data has become more democratic in the sense that a greater variety of tools are now available to businesses of varying sizes. Technologies, like cloud computing, have enabled business intelligence (BI) vendors to create more affordable solutions to meet the needs of businesses of different sizes (Papachristodoulou et al., 2017). It is not surprising that data and the ability to derive insights from it has been trending for a while. as some sources portray it as a primary driver of economic success in the 21st century (NewVantage Partners, 2023). In this era of data-driven decision-making, businesses need to start paying attention to how they can utilize both internal and external data. To stay competitive, businesses need to leverage their competitive advantage. One effective way to achieve this in an analytical setting is by leveraging BI (Eidizadeh et al., 2017).

While both practitioners and scholars have praised BI for its significant impact on company performance, understanding the mechanisms of how BI capability can affect organizational performance is still in the earlier stages (Alzghoul et al., 2022). Is the BI the game-changer here, or have the preparations made to facilitate conditions that support BI helped employees to understand the usefulness of the data? Utilizing BI is a great way for companies to embark on their journey to become analytical competitor (Davenport & Harris, 2017). It allows them to gather data from a variety of sources and centralize it in one place. Successful BI initiatives allow companies to access historical and current data, which can lead to acquiring fresh insights when data from multiple systems are joined together.

The purpose of this master's thesis is to help the case company utilize BI at its operational level. This is done by designing, developing, and implementing report templates that can be used with the BI tool for the stakeholders recognized during the study. The motivation of the study originates from wanting to help the case company utilize its internal data more. Utilization of the internal data can help the case company to perform better data-based decision-making while building better data culture. The goal of the study is to bring awareness that how data and business analytics can be utilized, by providing ways to utilize the BI tool in a new context, such as helping employees at the operational level to perform their reporting tasks more effectively.

1.1 Research method

Design science research (DSR) is a research approach that is used to solve complex problems by creating and evaluating innovative artifacts (Hevner et al., 2004). This formerly used method in engineering has gained significant attention during the last two decades in Information Systems (IS) and has started to be accepted in top IS publications outlets, like Management Information Systems Quarterly (Goes, 2014). Companies implement information systems to pursue and improve efficiency and effectiveness. Hevner et al. (2004) argue that IS research can provide significant contributions to problems faced when applying information technology by complementarily engaging in design science and behavioral science. Figure 1 below introduces our conceptual framework presented in this thesis.

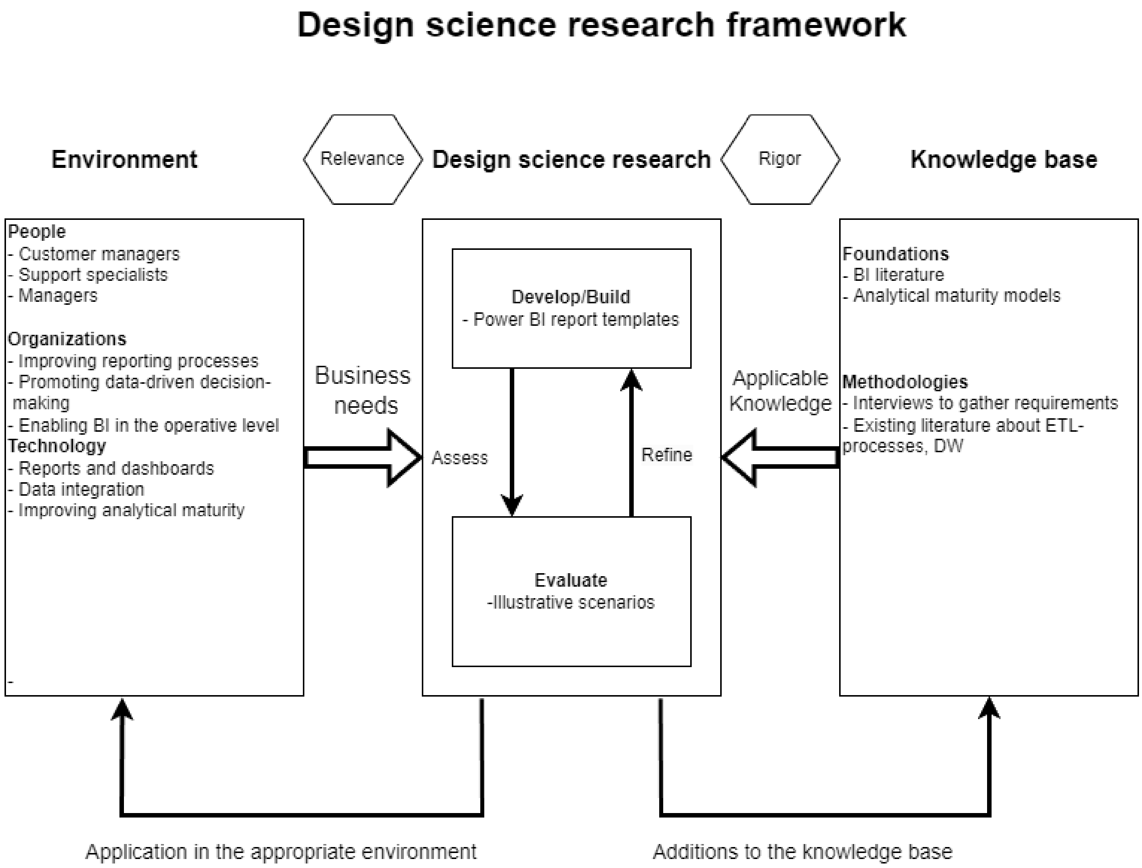

Figure 1. The DSR framework for this study (Adapted from Hevner et al. 2004).

This IS research framework was first introduced by Hevner et al. in 2004. It introduces us to how the design science approach is utilized in this study, by introducing existing conditions in the form of environment, and related literature as a knowledge base. Relevance and rigor are two elements of the framework that are balanced to keep the theory produced in this study valuable for real-world context and potentially for researchers (Ropes, 2018). Hevner et al. (2004) remind that rigor must be applied with respect to the generalizability and applicability of the artifact, as an overemphasis on rigor can make lessen the amount of relevance. However, as this study aims to provide a functional implementation of an artifact, it is crucial to address its relevance for people and the case company while also considering the technological needs during its construction. The balance between rigor and relevance can provide additions to the knowledge base and give application to the appropriate environment. To present how design science is approached in our study, we portray how environment, DSR, and knowledge base come together. (Hevner et al., 2004)

Environment: Stakeholders include employees from two different teams working on the operational level of the company. These employees are interviewed to gather information about how their current reporting solutions perform. Summarization of the interview results gives us the current state of how reporting solutions and processes are experienced currently, creating business needs for problem identification in the DSR process. Should the development process be successful, the thesis has the potential to improve existing reporting solutions, help the company to become more data-driven, and open the possibility of utilizing BI at the operational level of the company. Adopting the use of descriptive analytics can improve a company's analytical maturity level. This also helps employees by presenting them with new approaches to succeed in their reporting tasks, in the form of reports and dashboards from Power BI. Artifact uses existing internal information systems as data sources; thus, it has the capability to provide information from a new perspective of the data integration of these systems, which has been inspected individually earlier.

Design science research: The artifact developed in this study is a functional Power BI report template for two different stakeholder teams. Report templates aim to provide value for stakeholders by giving them access to real-time data, having the capability to visualize data, and offering them a new perspective on internal data by combining internal information systems' data. The goal is to justify the value provided by the solution while raising awareness of analytical initiatives and motivating them to pursue the use of analytical applications. Building this artifact also takes the first steps towards providing self-service BI for the employees, as the dataset of the artifact with a built-in data model can be used by the relevant stakeholders to build their own reports, once their knowledge and know-how about the tool are sufficient. This study aims to provide information to the existing knowledge base, that how reporting solutions can be improved by adopting BI tools. At the operational level of the case company, this smaller-scale project can demonstrate how functionalities of BI tools can be accessed with relatively low effort. The study can also appeal to academics, as it demonstrates how DSR can be utilized with analytical software implementations, especially in Finnish software companies.

Knowledge base: Existing literature on BI and its history was studied to understand why companies use BI: Data helps managers and other decision-makers to make better decisions. To understand how successful BI solutions were implemented, the use of BI systems, and their architecture had to be studied. These were the foundations of how BI can and should be utilized. However, in order to keep creating value from analytical applications, we must actively pursue more sophisticated analytical applications with BA. To gain an understanding of how analytical capabilities can be built, analytical maturity levels are introduced. Understanding analytical maturity levels can help companies measure their analytical level and capability in multiple different sections while giving guidance on how companies can advance to the next level in their roadmap. Methodologies used to gain information from the operational level of the case company included interviews to gain an understanding of the current situation of the reporting processes.

1.2 Research questions

The research questions of the thesis consist of one main question and two sub-questions. The main research question is based on the case company's desire to investigate how BI tools can be utilized in the fields they are not currently seized. The second research question is a sub-question, which helps the main research question, by identifying current potential areas in the field where BI could be utilized. Developing analytical applications for a company is an ongoing process, which requires vision beyond current tools. The third research question is also a sub-question, which aims to investigate what kind of elements must be improved for the case company to keep pursuing more sophisticated analytical methods.

RQ1: How can business intelligence be effectively utilized at the operational level of the case company?

BI is not currently being utilized at the operational level of the case company. The main goal of this thesis is to offer a solution in the form of an artifact, that allows BI tools to be used by employees working on the operational level. Giving the capability to use these tools is not enough, the artifact must be carefully designed based on the needs of the employees to provide them valuable information effectively.

RQ2: What are the current challenges faced by the case company's employees in performing reporting related tasks?

Identifying current challenges that employees face during reporting related tasks is important, as it can set requirements that the artifact should fulfil. Additionally, the thesis can provide in-depth information for the case company about the challenges that the artifact cannot handle. This information can be further reviewed and used to improve the case company's policies regarding reporting, data sharing, and data governance.

RQ3: How can the case company enhance its current level of analytical maturity?

Utilizing BI requires knowledge and know-how in the companies. When resources are used to develop BI capabilities, employees and managers can look forward to utilizing BA and its more sophisticated analytical methods. This is why the last research question is about improving the case company's analytical maturity. Implementing more sophisticated analytical tools requires the company to improve its analytical maturity if they desire to gain a competitive advantage in return.

1.3 Structure of the thesis

This thesis is divided into the following chapters. Chapter 2 reviews existing literature related to BI, BA, and analytical maturity. BI is reviewed to identify commonly used practices and concepts in the field, and later this information is utilized in the practical part of the study. To understand further how data can be utilized, BA is also introduced during the chapter. To bridge the gap between these concepts, analytical maturity is introduced.

In Chapter 3, the research methods used in this study are introduced more extensively than in the upcoming Subchapter 1.1. DSR, its guidelines, process model, and the artifact of the study are introduced and explained how these methods apply in this study. The chapter also introduces how data is collected for the study in the form of empirical evidence, its relevance to this study, and the analysis of these results. Finally, the case company and the stakeholders of the artifact are introduced. Subchapter 3.2 focuses on data collection and introduces the first activity of the DSR process.

Chapter 4 focuses on the artifact developed in this study. The process sequence for the chapter is provided from the DSR methodology. Subchapter 4.1 begins the DSR's first activity: *Identify the problem and motivation*. Subchapter 4.2 is based on the second activity of the process: *Define objectives and solution.* Subchapter 4.3 is focused on design as the third activity, *Design and development.* The artifact and its use are demonstrated in Subchapter 4.4, which is based on the fourth activity: *Demonstration*. The artifact and its utility are compared against the analyzed results of Subchapter 4.5 and the fifth activity from DSR, *Evaluation*, is utilized. The results of the study, its limitations, and suggestions for future research are discussed in Chapter 5. Finally, the conclusions concerning this study are delivered in Chapter 6.

2. Background

In these chapters, we introduce the theoretical background for BI, BA, and analytics maturity. These are important concepts that need to be understood to help companies take the first steps toward becoming analytically competitive.

2.1 Business intelligence

Similarly, to the definition of intelligence within humans, the definition of BI has evolved based on the years it was used. Inventor and text analysis expert H.P. Luhn (1958) proposed that systems could be designed and used for automatically analyzing and distributing documents based on the needs and interests of "action points" in companies. Luhn (1958) also emphasized the importance of efficient communication in companies, while describing the flow of information becoming ever-increasing. During the 1980s, BI was described to include a set of technologies or analytical tools to detect trends and help with more effective decision-making inside companies (Ghoshal & Kim, 1986). This was also when the recognized goal of a BI system was to collect raw data from certain environments for decision-makers to use during decision-making (Gilad & Gilad, 1986). The modern definition of BI was introduced by H. Dresner in 1989 while working as an analyst at the research company Gartner. (Nylund, 1999), which described BI as a way to deliver a variety of selected, structured, and analyzed information for end users, without requiring them to have prior knowledge of operational research (Martens, 2006).

The definition and contents of BI can also vary based on different factors and backgrounds. From a technology-oriented viewpoint, BI can include integrations of different data sources, full-stack programming, and providing data warehouse solutions. Managers can view BI as a tool for reporting, data extraction, data integration, and statistical analysis. While all these things can be part of BI as a product or process, we will base our definition of BI on a process of delivering information to end users, which is how Howard Dresner described BI in 2006 during being interviewed by Martens (2006). Products of BI that are used to achieve this delivery of information are referred to as BI systems or BI tools.

To understand how BI can generate value, we must remind ourselves of the interrelationship between data, information, and knowledge. Data consists of discrete and objective facts about events, which are stored in a record of transactions (Davenport & Prusak, 1998). When this data is explained with a certain context it becomes information (Debra, 1997). Finally, knowledge is a mix of contextual information, expert insights, values, and framed experience that helps us in evaluating and incorporating new experiences and information (Davenport & Prusak, 1998). In BI, the data is usually stored in data warehouses, or in their own information systems where the data is gathered from. Data is then mined and loaded into BI systems, where this aggregated dataset can be used to produce information. The dataset is visualized in the form of reports or dashboards, to show relevant information, such as trends or outliers. By delivering this information to the correct audience, the definition of BI has been fulfilled, by allowing the audience the opportunity to act on this information using their knowledge. The role of BI is not always about providing solutions when specific decisions are made, it can also help decision-makers ask the right questions based on assumptions and opinions (Pirttimäki, 2007).

Companies have access to more internal data than before, as they deploy different internal information systems, such as enterprise resource planning (ERP), or customer relationship management (CRM) systems. These systems in addition to financial & transaction data, human resources data, and research & development data form the company's domain for internal data that are suitable for analytics. The challenge in the utilization of data is not about storage, but about how to properly mine, utilize, and analyze it (Hovi et al., 2009). In addition to growing internal data reserves, companies have options to obtain external data. Commonly these external sources can include data that is acquired from customers, or businesses, depending on whether the company operates in a business-to-business (B2B) or business-to-consumer (B2C) context. Alternatively, third-party companies like data brokers can be used to acquire aggregated datasets containing market information (Koski, 2018). While the possibilities of external data offer a lot of potential, it also requires careful assessment from companies whether the value gained from utilizing this type of data is worth the effort (Aaser & McElhaney, 2021).

To accomplish sustainable competitive advantage, companies need to concentrate on multiple aspects that differentiate them from others, like price, speed, quality, customer responsiveness, and innovation (Darroch et al., 2014). Companies that can sustain competitive advantage have been able to provide more value for the customers and thus achieve a better position in the market (Jap, 2001). Based on the different aspects that can give a competitive advantage, Darroch et al. (2014) point out several studies that focus on the impact of BI. When it comes to innovation, BI can provide necessary conditions, in the form of supplying data, knowledge, and information, that can provide a positive and meaningful impact (Maghrabi et al., 2011; Eidizadeh et al., 2017). Companies using BI can authorize employees to make data-driven decisions without waiting for additional approvals to improve decision-making speed (Alzghoul et al., 2022). Gessner and Volonino (2005) compared the potential return of BI investments by improving their customer responsiveness, where they found out that customer profitability can be improved while decreasing customer attrition. This was done by enabling BI technology to recognize real-time opportunities for potential interventions. These examples show that pursuing the use of BI can enable its users to gain a competitive advantage in various ways.

2.1.1 Business intelligence systems

BI systems operate as data-driven decision-support systems that connect data gathering and storage functions while offering analytical tools to support decisions (Davenport et al., 2010; Negash, 2004). These systems are being used in various areas of businesses involving decision-making to create value while receiving interest from both academia and industry (Shollo & Kautz, 2010).

The complexity of adopting BI systems and using them can vary based on the company's background, size, and analytical maturity level. Deploying BI systems requires resources and commitment before it starts to generate value. Earlier, the acquisition of BI systems has been considered to be difficult, especially among small and medium-sized enterprises (SMEs), but cloud computing has enabled BI vendors to offer affordable, and effective solutions for smaller companies (Papachristodoulou, 2017). However, adopting BI systems and using them routinely has been linked to impacting company performance positively even in SMEs (Popovič et al., 2018). Popovič et al. (2018) also suggest that in addition to conventional business areas of marketing, sales, management, and internal operations, BI systems should be encouraged to be used in other innovative ways.

The scope of BI has expanded from strategic questions to operational tasks, meaning that more employees could utilize BI (Böhringer et al., 2010; Elbashir et al., 2008). BI systems' dashboards and reports are needed to utilize all relevant available data to make a time-critical business decision. However, this expansion created a bottleneck, where there simply are not enough BI specialists to allow efficient use of BI systems for everybody (Kobielus, 2009). As a response to this problem Imhoff and White (2011), suggest enabling self-service BI. In Figure 2, Alpar and Schulz (2016) present a suitable model for assessing the self-reliance of the users, while showing the required system support needed for specific levels of self-service BI.

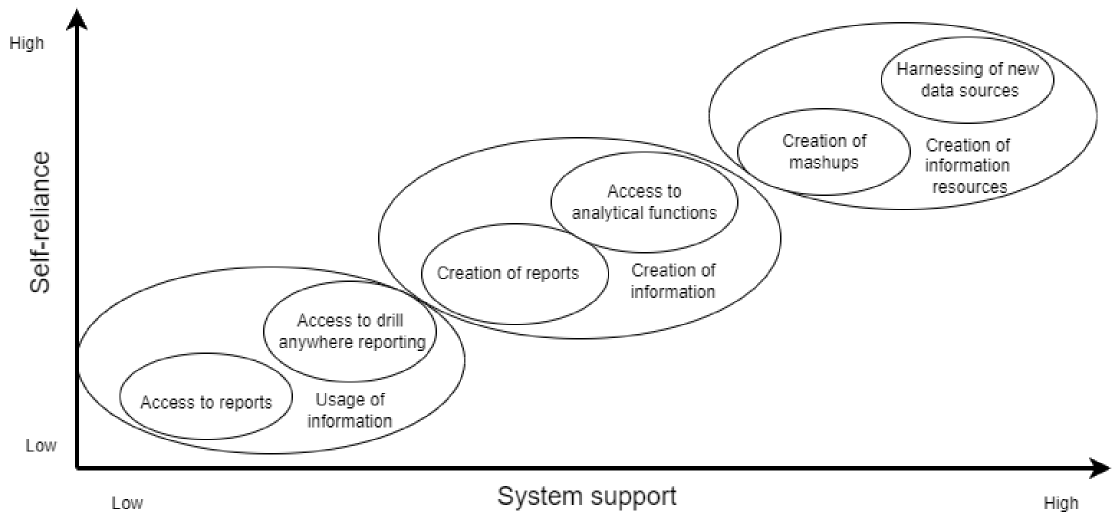

Figure 2. Levels of self-service (Alpar & Schulz, 2016).

According to Alpar and Schulz (2016), in the lowest level of self-service BI, users should have access to the different premade reports, with the potential to drill in information inside the reports. While requiring low system support, users can access potentially relevant reports with the newest available data, while not possessing any special analytical or tool skills. At the second level users are allowed to access to create reports based on datasets within their access. This allows users to create specific reports from available data while requiring some knowledge of the BI tool that is used. While they are no longer dependent on BI specialists to select data, Alpar and Schulz argue that this can risk the quality of data delivered, as casual users may not have enough understanding of relational data models and their relationships included in reports. The same level also provides access to perform analytical functions, however with a risk of faulty analysis, as statistically unskilled users might not be able to estimate the correctness of their analysis. The third and final level of self-service BI introduces the creation of mashups and harnessing new data sources to an existing workspace. Combining new data sources that are not pre-processed by specialists may become progressively demanding for normal users. Alpar and Schulz claim that this is because amateur users might be unfamiliar with existing rules and relationships with existing data in the BI system, so the complexity of this approach may remain hidden from users while creating new pitfalls.

The positive influence of BI systems on decision-making in highly competitive domains has been emphasized widely in IS literature (Popovič et al., 2012). To measure the BI system's success, Popovic et al. (2012) presented their success model (Figure 2.) based on commonly used IS success characteristics and IS success model (DeLone & McLean, 1992, 2003).

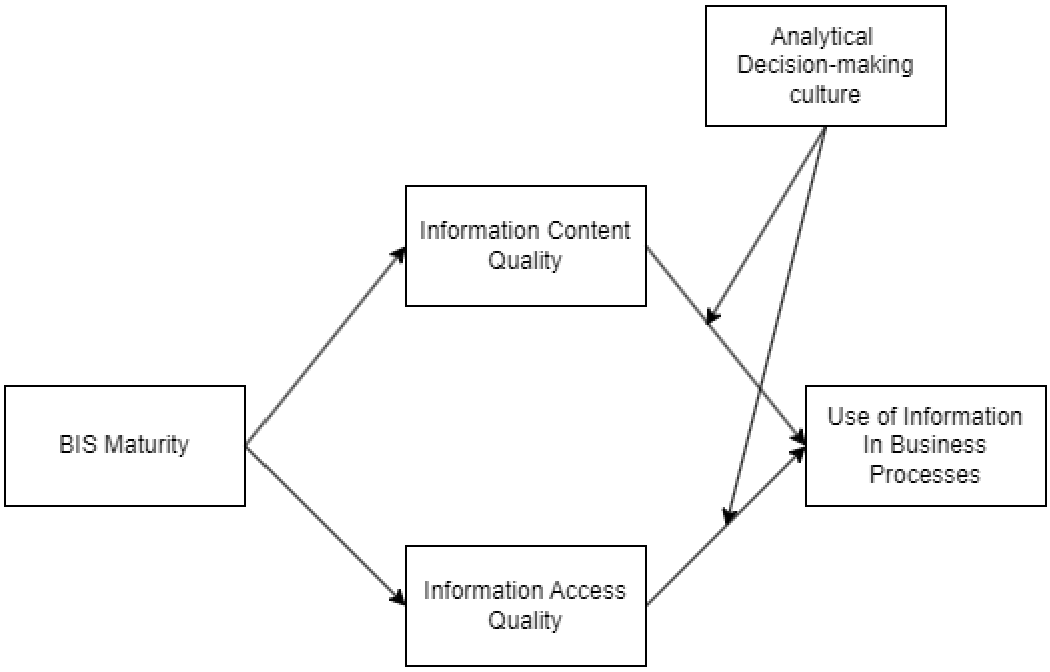

Figure 3. The BIS success model (Popovič et al. 2012).

In the model, BI system (BIS) maturity explains how developed the system is, while fully developed BIS has reached "maturity". This can also be referred to as the BI system's quality (Rajterič, 2010). According to Popovič et al. (2012), this BIS maturity measure can be explained by two different factors: Information content quality, and information access quality. The information content quality factor is dependent on the quality of the data, the scope of information available, and the usefulness of information provided by the BI system for its audience. Information access quality factors consists of BI system's customization capabilities, interactivity, and bandwidth. Information quality factors (Information content quality and information access quality) affect the use of information in business processes. Indicators measuring the use of information in business processes are a) if all available information is used for the management of business processes, b) the usage of information in decision-making regarding business processes, and c) the benefits companies achieve by managing information. Popovič et al. (2012) argue that analytical decision-making culture affects the relationship between information quality and the use of information in business processes. Analytical decision-making culture factor measures if companies utilize the available information in decisions to be taken and if its decision-making process exists and is being used properly.

2.1.2 Business intelligence architecture

When providing BI solutions with large amounts of data, basic architecture must be based on and built with effective data integration capabilities, data warehousing possibilities, and analytical tools (Hovi et al., 2009). Figure 4 introduces technological components of BI in four different layers.

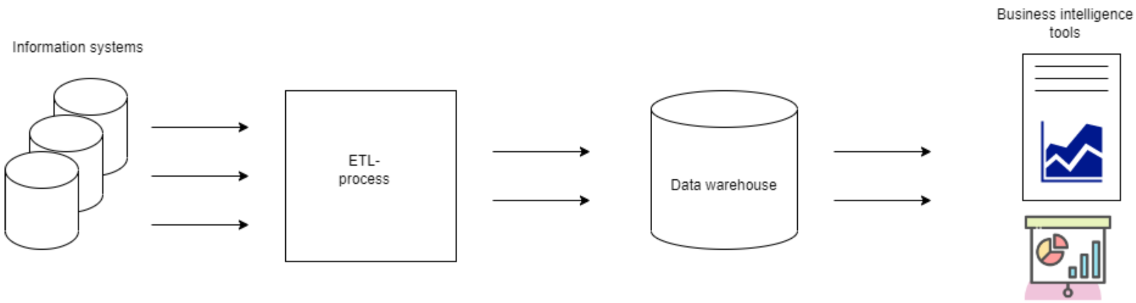

Figure 4. ETL, data warehouse, and BI layers (Adapted from Hovi et al. 2009).

These four layers demonstrate how data is processed in each layer (Hovi et al., 2009):

1. Using information systems' databases as data source. Using information systems that are used daily in companies are common data sources for BI tools to further inspect internal processes. These information systems can include ERPs, CRMs, and financial management systems.
2. Data integration layers. Extract-Transform-Load (ETL) is a pivotal process, where data is extracted from data sources, and transformed to be compatible with other data. Finally, the transformed data is loaded into data warehouses.
3. A data warehouse includes integrated data, which is gathered for reporting and analyzing. A data warehouse itself can act as a data source for BI tools, or as a temporary storage location for data that is further processed by users requiring more specific information about the data. Data's specificity is based on the data warehouse's use scenarios. Data used as a data source for BI tools can be used as they are, while data used for further processing is usually stored in data marts, which are used as smaller data warehouses for specific purposes.
4. Reporting and utilizing the data. The final layer is about utilizing the gathered data in the most useful forms for end users. This layer also defines the methods that end users can use to access the information. These methods usually include using premade reports, utilizing integrated data, tracking KPIs, and making new queries.

Planning suitable architecture for BI helps companies to manage their data supply chain. While modern BI software manages to utilize all four layers presented in Figure 4 by themselves, the use of ETL tools and data warehousing should be investigated as well to provide sustainable BI solutions. Data warehousing solutions often utilize the star-schema model, which is also used to represent analytical models (Ferrari & Russo, 2017).

Software that handles the loading and the periodic refreshing of data warehouse contents is commonly known as ETL tools (Vassiliadis, 2009). Since data warehouse data is collected from multiple operational or external systems, it needs to solve several problems before further use. Vassiliadis (2009) introduces the first problem to be differing schemas between incoming data sources. Structures between data sources need to be transformed into one global data warehouse schema that is commonly used with all upcoming data from data sources. The second problem concerns data quality problems, as implementing data from the operational sources can contain a lot of unwanted noise, in the form of misspellings, value inconsistencies, database constraint violations, and missing information. This highlights the importance of data cleaning, as end-users should be provided with as clean, accurate, and complete data as possible. The last problem concerns issues encountered in data warehouses is how current the data is. Frequent automatic refreshes are required to provide users with up-to-date information. When these problems are dealt with, data warehouses can be populated with accurate and complete data. Hovi et al. (2009) introduce ETL tools to enforce certain practices, such as documenting and version control, while decisively decreasing dependencies on individual employees' effect on data management.

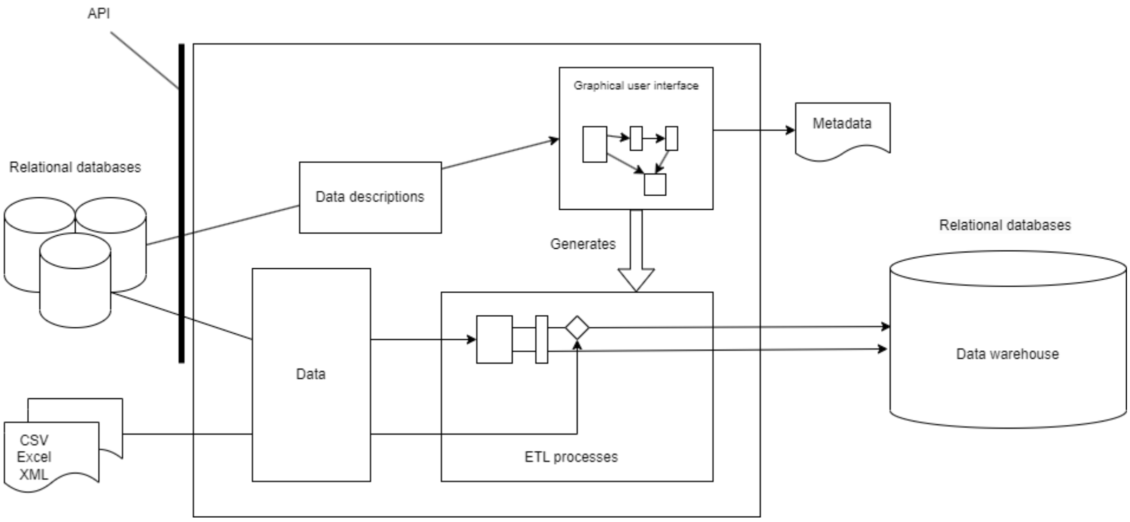

Figure 5. ETL tool (Adapted from Hovi et al. 2009).

To further illustrate how ETL tools operate, we can observe Figure 5 which zooms in-to ETL process presented earlier in Figure 4.

ETL tool is presented to include entities inside of the box. As presented in figure 4, ETL process gains data from different information systems. The way how data is gotten from these information systems differs, as the way the data is received is based on the information system's capabilities. Application programming interfaces (APIs) are used by developers to implement functionality to perform different tasks (Robillard, 2009). In the case company, the developers are using APIs to get data from these information systems. If these information systems do not have APIs implemented, developers might need to build their own web connector to receive these data periodically or resort to manually exporting files to the ETL tool. The importance of receiving up-to-date data from this certain data source determines if the time should be spent on setting up periodical refreshing. Inside the ETL tool itself, information from different sources is imported into ETL processes. Data descriptions are also required when transferring data to the ETL tool, as these are used in the graphical user interface part. In the graphical user interface, users can map the data and schedule refreshes, by using drag-and-drop windows to generate code, which is run in ETL processes while generating metadata. These ETL processes are used to transform the data to the required format and then are loaded into data warehouses, or to other destinations.

2.2 Business analytics

Business analytics (BA) is a relatively new term compared to BI. While Subchapter 2.1 has mostly dealt with structured data, the introduction of unstructured data is important when trying to understand what BA can bring to the table. Laursen and Thorlund (2016) define BA as the delivery of the right decision support to the right people and processes at the right time. The difference to Dresner's definition of BI (Martens, 2006) is about including decision support to help people make decisions, while BI only offered information. In addition to what kind of help is offered, the BA definition includes processes as to whom the help is offered. Processes are included in the definition because BA is progressively applied in automated digital processes (Laursen & Thorlund, 2016).

Based on these definitions of BI and BA, these two concepts serve similar purposes and may be used interchangeably. Laursen and Thorlund (2016) use the term BA to shift the focus to elements that are missing from BI: the potential of utilizing predictive and prescriptive analytics and utilizing messy mass of unstructured data. While BA can sound like an extension of BI or a subset of it, analytics has also been linked it to larger-scale definitions. Some of the perceptions include mentions of BA as being a movement that drives the company towards data-driven culture (Almazmomi et al., 2022; Duan et al., 2020).

The momentum of BA and big data has increased unparalleled because of the arrival of artificial intelligence (Conboy et al., 2020). Artificial intelligence (AI) has been noticed to improve analytics by developing and testing models while providing more sophisticated and automated solutions (Davenport, 2018). These AI solutions usually rely on rule and pattern recognition, like machine learning or deep learning, which can collect, process, interpret, and learn from data to provide a variety of different types of analytical outcomes (Davenport & Ronanki, 2018). Combining these possibilities offered by AI with big data analytics has been described to bring revolutionary progress to the business ambiance (Vidgen et al., 2017).

While BA is a hot topic and companies want to improve competitiveness by adopting the newest technologies, it is still important to remember the requirements that are needed to harness this potential. Feeding malformed data to AI-driven systems will slow the entire system down, and in the worst cases, it will bring the whole system to its knees (Tse et al., 2020). Wrong technology solutions are also seen as a probable cause of failure to grow business (Marks, 2008) while causing issues such as security risks and privacy risks (Post & Kagan, 2006). As part of data analytics, AI requires governance just as data does. Neglecting this governance can cause technological strategies to become flawed when implementing AI-integrated BA (Rana et al., 2022).

While BI dealt mostly with structured data, BA is designed to use unstructured data also. This kind of data usually struggles with carefully designed schemas from relational databases, and it is referred to as big data (Madden, 2012). Data in big data is often accompanied by the following data characteristics: volume, velocity, and variety (Zikopoulos et al., 2011). A variety of analytical methods can be used with big data. These methods can include predicting the likelihood of medical conditions, predicting consumer choices, detecting political extremism from social networks, and managing better traffic networks (Vidgen et al., 2017). However, as more and more companies are reaching out for big data using analytical initiatives, the understanding of how this potential can be transformed into business value is limited (Mikalef et al., 2019).

One of the key questions raised by IS researchers is whether big data, analytics, and data science are something new, or rather older concepts that are being presented in a different light (Agarwal & Dhar, 2014). Agarwal and Dhar (2014) believe that some components of BA and data science have been around for a longer time, but the availability of big data and AI has raised new opportunities and questions for the field. As the majority of data including economic and social transactions have been digitalized, this data can be more efficiently utilized. Researchers have access to large and complex data sets relating to any phenomenon from emerging medical conditions to observing consumer responses to different marketing concepts. Easy, affordable, and user-friendly analytical software has caused the data science field democratization allowing both practitioners and scholars to pursue different opportunities enabled by data. Agarwal and Dhar (2014) have even described that the attracted attention gained from data science and big data research has created the golden age for IS researchers. Agarwal and Dhar argue that the core competencies of these technologies, largely associated with IS and IS researchers, have been instrumental in ushering in the golden age of digital advancements. These competencies have played a central role in enabling the unfolding of the digital world.

2.2.1 Challenges of business analytics

The benefits of BA are compelling, but they are not always that easily achieved. While adopting the use of analytics for a company might sound like a technology-orientated initiative, in reality, it requires effort from all levels of a company. Existing literature argues that leveraging analytics for performance gains requires strong analytical capabilities (Mikalef et al., 2019). It is also important to remember that to become data-driven companies need to align their analytical capabilities with their business strategies (Vidgen et al., 2017). Analytical maturity levels also affect the capability of companies to utilize more sophisticated technologies, as early adopters of analytics tend to be able to apply more complex technologies (Lismont et al., 2017). Finally, the value generated and received by the companies from BA might be uncertain, or not well understood (Vidgen et al., 2017; Tim et al., 2020; Delen & Ram, 2018).

To understand BA and its components more comprehensively, we can utilize the existing literature's frameworks that identify different factors affecting BA. Conboy et al. (2020) and Vidgen et al. (2017) have both used similar frameworks adapted from Leavitt's (1965) diamond model of a company, where BA acts as a mediator between data and value creation (Vidgen et al., 2017). Figure 6 shows the components of the BA dimension and its relationships with data and value creation.

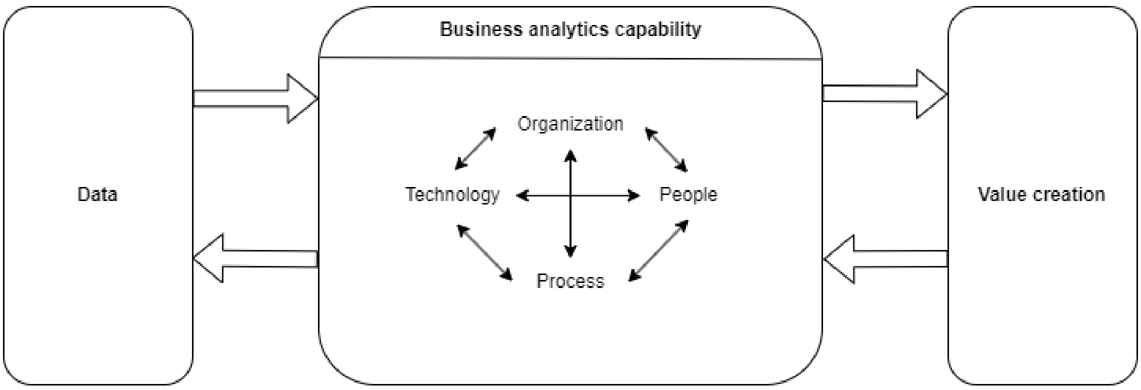

Figure 6. Business analytics framework (Vidgen et al., 2017).

In the framework, we can recognize Leavitt's (1965) diamond model of organization under business analytical capabilities, and the principle behind this is that these major components are interdependent with each other. Take technology as an example, implementing a new system inside a company requires training for people. If the use of BA excels to a level where processes can be automated, people have a chance to use their expertise on different matters. Framework also presents how company's data can be used as a leverage for insights and to provide value from better decisions (Vidgen et al., 2017).

Vidgen et al. (2017) also points out that the value generated from these decisions can lead to generating more available data. The framework from Figure 6 helps us to tackle different kinds of challenges that companies face when adopting BA. In the following paragraphs the focus is on different dimensions presented in Figure 6, and demonstrating what kind of challenges their components are affected by.

Starting from the top of the diamond, we introduce organization as part of BA. To become analytically competitive, companies must have executives who support fact-based decision-making from data. Based on the level of support the analytical initiative receives, different paths can be chosen. Davenport and Harris (2017) introduce two different paths on their roadmap to becoming an analytical competitor: The prove-it path, and the full-steam-ahead path. Organizations that have a passion for analytics and commitment from the top management level can utilize the full-steam-ahead path. The main challenges for a full-steam-ahead path are to acquire and deploy both human and financial resources to build up the company's analytical capabilities. This requires a heavy level of commitment, as organizational resistance might affect building support for the benefits of analytics. The prove-it path can be used with a smaller amount of managerial support, as the team can try to build up momentum with localized analytics, and by succeeding attract top management's attention. Having to take a prove-it path can stall a company's analytical improvement indefinitely if the executives do not see or approve the results. Subchapter 2.3 will be discussing more about companies' maturity levels and will present the different steps that this roadmap includes. (Davenport & Harris, 2017)

Figure 6 shows the relationship between technology and data, as technology is being used to generate, manage, access, and analyze data. Cosic et al. (2015) present in the BA capability framework that technological capabilities consist of data management, systems integration, reporting BA technology, and discovering BA technology. While IT is an important factor in supporting the technological requirements of BA, Davenport and Harris (2017) emphasize that architectural planning of BA systems should not be left for IT alone. Instead, IT infrastructure should always require support from executives to guide development to work with the organization's strategy (Davenport & Harris, 2017). Failure to do so can stall a company's progress to become an analytical competitor. Other technological challenges with BA include restriction of existing IT platforms, and managing data volumes (Vidgen et al., 2017). Failing to develop data-orientated management systems leads to not being able to make sense of large volumes of data, which is considered to be the baseline of analytics (Kiron & Shockley, 2011).

While the term BA can make one think about AI, sophisticated analytics software, data mining processes, and automated processes, it is important to remember that it is the people of the company who are behind it. Davenport and Harris (2017) describe people as a scarce resource of analytical competition. Succeeding with BA is often linked positively to affecting companies' data-driven culture (Almazmomi et al. 2022; Duan et al., 2020). And after all, it is people who make the company's culture. While it is important that management is committed to BA, the people of the company also need to be convinced. CEO of Microsoft, Satya Nadella, mentioned in 2014 that a data culture is not only about technology, instead it is about changing the culture for every team and individual so their work can be empowered by possibilities that were only possible by data scientists earlier (Nadella, 2014). However, a survey from 2023 shows that only show only 20.6 per cent of surveyed companies had established data-driven culture, a per cent that has steadily declined from 2018 when around one-third of the companies had considered to have established data-driven culture (NewVantage Partners, 2018, 2023).

Processes are one of the differences between BI and BA. As descriptive analytics detects patterns for certain problems or opportunities in businesses, predictive analytics aims to predict the possibility and the timing of these occurrences happening (Lepenioti et al., 2020). Companies are applying analytics to their business processes in internal and external application domains (Davenport & Harris, 2017). Aligning BA within business processes shows that companies can achieve significant performance (Ramanathan et al., 2017). Challenges in processes when applying BA relate to the final dimension: value generation. Davenport and Harris (2017) suggest that when companies are identifying potential internal applications for BA use, they should aim for clearly strategic options that will make an impact. Challenges in applying BA to external processes include cooperation with other actors, as organizations cannot directly control them and their resources (Davenport & Harris, 2017).

One of the key BA challenges for companies is understanding how to create business value (Vidgen et al., 2017). Ultimately, value means the monetary worth of benefits that are received compared to price and costs, meaning that providing more value brings a competitive advantage (Lindgreen et al., 2012). Some of the articles point out that just having access to BA tools may not be enough, as organizational aspects play an important role when pursuing effective BA strategy (Trieu, 2017; Vidgen et al., 2017). Harnessing value from analytics can often suffer from not technological barriers, but managerial and cultural barriers (LaValle et al., 2010).

2.2.2 Descriptive, predictive, and prescriptive analytics

Types of analytics can be categorized into three different main stages based on difficulty, value, and intelligence: Descriptive analytics, predictive analytics, and prescriptive analytics. Descriptive analytics examines data or content to answer questions, such as “What happened?” or “What is happening?”, and it is often visualized with different types of graphs, charts, or tables (Gartner, n.d.). Predictive analytics uses statistical modeling, data mining, machine learning, and historical data to make predictions about future outcomes (IBM, n.d.). Questions that predictive analytics aims to answer are “Why is this happening?” and “What will happen next?” (Davenport & Harris, 2017). Prescriptive analytics seeks to find the best actions for the future, and aims to answer questions: “What should I do?” and “Why should I do it?” (Lepenioti et al., 2020). Diagnostic analytics is often associated with these three main types of analytics as a natural extension of descriptive analytics (Delen & Ram, 2018). By using exploratory data analysis like drill-downs and visualization, diagnostic analytics aims to discover the root causes of emerging problems (Delen & Zolbanin, 2018). Delen and Ram (2018) associate descriptive analytics and its extension to BI while describing predictive and prescriptive analytics as advanced analytics. The reason behind this taxonomy is that the level of sophistication required to jump from descriptive to advanced analytics is considered to be significant (Delen & Ram, 2018).

In their article, Lepenioti et al. (2020) investigate prescriptive analytics in existing literature, and methods for its implementation, and provide clarity for the research fields studying prescriptive analytics. Figure 7 displays the business value of three methods of analysis in a temporal context (Lepenioti et al., 2020).

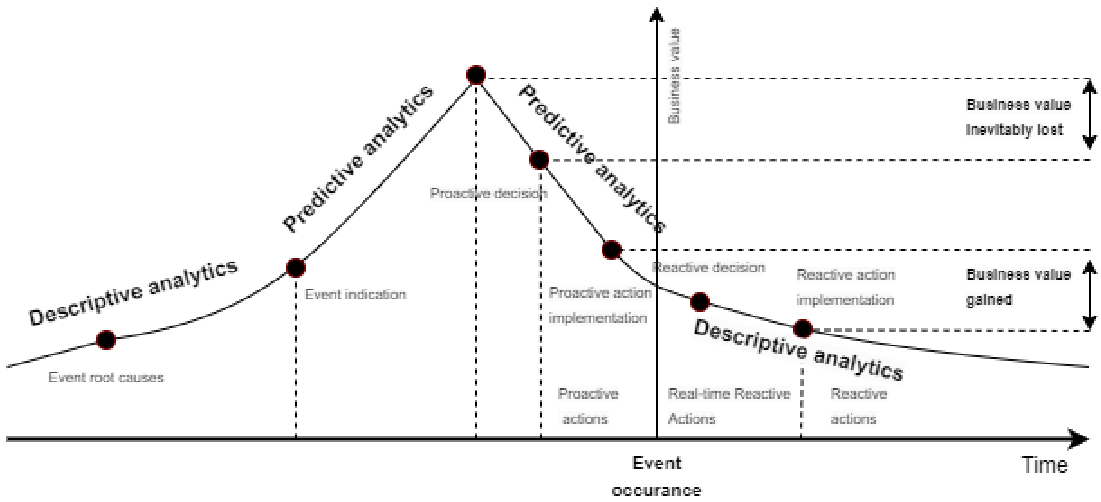

Figure 7. The business value of analytics in temporal context (Lepenioti et al. 2020).

Lepenioti et al. (2020) describe Figure 7 beginning with descriptive analytics as a way to determine what is happening at the moment by gathering and analyzing information related to the root causes of events. When descriptive analytics successfully detects patterns that can either cause a problem or provide future opportunities, predictive analytics are used to predict the possibility, timing, and reason of the occurrence. The business value peaks at the middle of the figure, where predictive analytics are contributing significantly to business value. On the other hand, utilizing this value depends on the type of decisions that are made, and actions that are taken. It is good to keep in mind that human decisions are often dependent on their previous experience and knowledge. Based on the company's capabilities to utilize predictive analytics in conjunction with prescriptive analytics, the amount of business value gained is dependent if the decisions and actions are either proactive or reactive. Between decisions and actions, there is a time interval that depends on many variables provided by the computational environment, such as offline vs real-time, and the application's domain. To provide maximum value from these analytics, the key is to utilize proactive decision-making and minimize the interval. Being able to minimize the interval eliminates the lag in decision-making, resulting in faster reactions and more business value from their analytics.

In their book, Davenport and Harris (2017) introduce various ways for companies to become analytically competitive. While presenting different techniques that can be used in different types of analytics, they present Figure 8, to show the potential competitive advantage gained from the more sophisticated analytics.

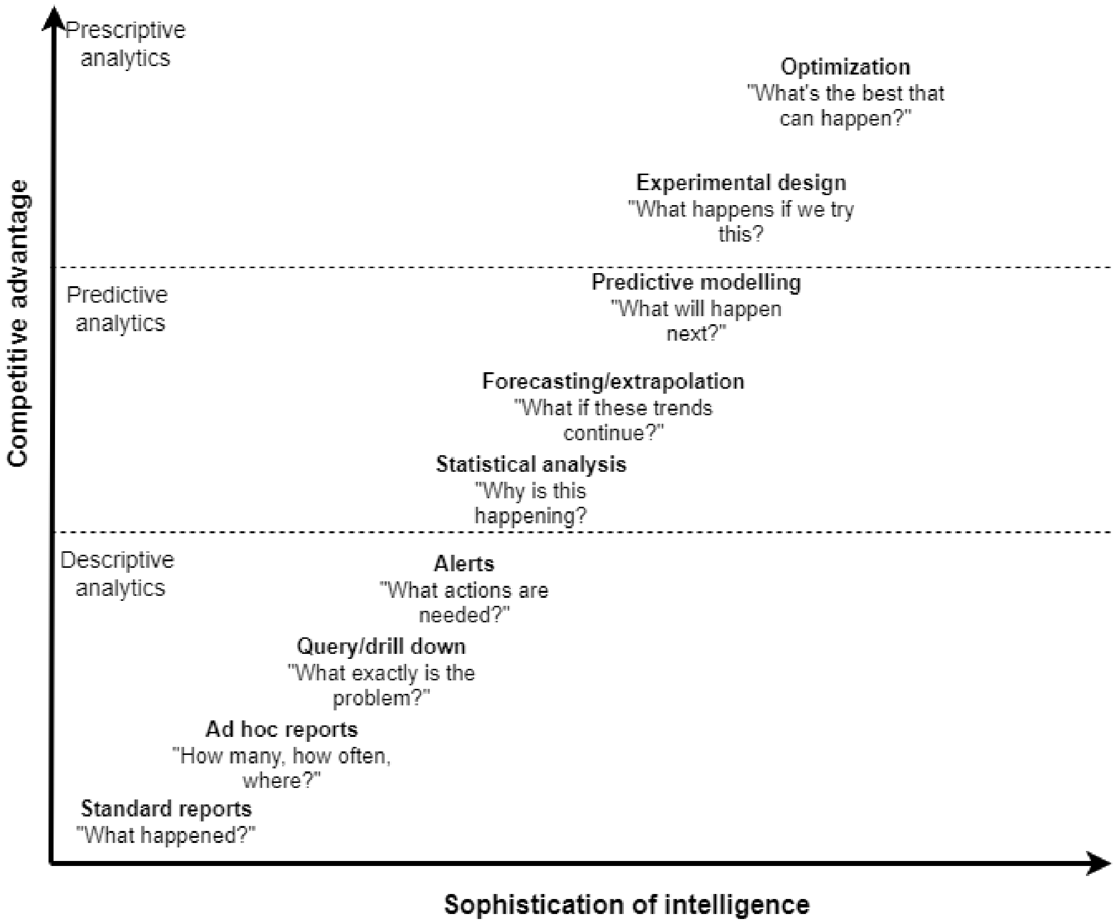

Figure 8. Increasing potential competitive advantage with increasingly sophisticated analytics (Davenport and Harris, 2017).

Starting from the least sophisticated type of analytics, descriptive statistics includes standard reporting, ad hoc reporting, queries and drill-downs, and alerts. While Davenport and Harris (2017) do not include diagnostic analytics in Figure 8, some of the techniques mentioned in it relate to them (Delen & Zolbanin, 2018). The next step from descriptive analytics is predictive analytics, which includes statistical analysis, forecasting and extrapolation, and predictive modelling. While this section deals with the previous section's data, the jump in the level of sophistication is big, as sophisticated data mining techniques need to be implemented to support predictive analytics (Delen & Ram, 2018). The final level of figure is prescriptive analytics, which includes experimental design, and optimization as analytical techniques. In an illustration to Figure 8, Delen and Ram (2018) characterize prescriptive analytics as decision-focused, while describing earlier levels of analytics as information and insight focused.

2.3 Analytical maturity

Leem et al. (2008) describe maturity as a state of being fully developed while referring to maturity stages as a series of changes that have led the current entity to the state it is in now. Maturity models are composed of various stages that show the development, progressiveness, and directional sets of changes that are noticed to increase performance over time (Leem et al., 2008). While these definitions of maturity from IT literature serve the purposes of how we determine maturity, we need to examine BI's and BA's specific maturity models to gain an overall, wider spectrum of understanding different levels of analytical maturity. While maturity models are being used to clarify, explain, and evaluate growth life cycles (Król & Zdonek, 2020), the concept behind the models is based on the prediction and regulation of changing aspects (Rajterič, 2010).

Król And Zdonek (2020) describe a company's analytical maturity as the company's ability to integrate, manage, and leverage both internal and external data. Analytics maturity is not only having certain technologies in place, as it involves data management, analytics, governance, technological capabilities, and organizational structure. Traditional methods for measuring analytical capabilities can include qualitative interviews, quantitative studies, and self-assessment tasks. Approaching the assessment of analytical capabilities traditionally comes with limitations, as self-assessments and quantitative studies can be implemented using a checklist, and they might not be able to assess if the particular company uses these analytical capabilities to make business decisions. Qualitative interviews for management can also be selective in scope and even anecdotal. Thus, different authors and companies have started creating their own analytical maturity models.

Król And Zdonek (2020) introduced eleven types of analytics maturity models that were reviewed from existing scientific literature, reports, and publications from the analytics sector. In all these models three major factors were identified and emphasized to be crucial: Human resources, infrastructure, and appropriate organization (Król & Zdonek, 2020). In order to provide an example of the maturity model, the DELTA model from Davenport and Harris (2017) was selected, as it also provides a roadmap and practical examples in the journey to becoming analytically mature. The model describes typical conditions for each maturity stage of a certain element. DELTA itself stands for Data, Enterprise, Leadership, Targets, and Analysts. Table 1 describes these elements, their different stages, and typical conditions that apply to different elements in their current stage.

Table 1. The DELTA model (Adapted from Davenport et al. 2010).

	Stage 1: **Analytically impaired**	**Stage 2:** **Localized analytics**	**Stage 3:** **Analytical aspirations**	**Stage 4:** **Analytical companies**	**Stage 5:** **Analytical competitors**
Data	Inconsistent, poor quality and organization. Difficult to do substantial analysis. No groups with strong data orientation. Basic reporting tools and descriptive analytics.	Much data is usable, but in functional or process silos. Senior executives don't discuss data management. BI and basic analytical tools.	Identifying key data domains and creating data warehouses or data lakes. Expansion into unstructured NoSQL data.	Integrated, accurate, common data in central warehouse. Data is still mainly an IT matter. Little unique data. Use of unstructured NoSQL data analysis	Relentless search for new data and metrics. Organization separate from IT oversees information. Data managed as strategic asset
Enterprise	No enterprise perspective on data or analytics. Poorly integrated systems.	Islands of data, technology, and expertise deliver local value.	Process or business unit focus for analytics. Infrastructure for analytics beginning to coalesce.	Key data, technology and analysts are managed from an enterprise perspective.	Key analytical resources focused on enterprise priorities and differentiation
Leadership	Little awareness of or interest in analytics.	Local leaders emerge but have little connection	Senior leaders recognize the importance of analytical capabilities.	Senior leaders develop analytical plans and build analytical capabilities.	Strong leaders behave analytically and show passion for analytical competition
Targets	No targeting of opportunities.	Multiple disconnected targets, typically not of strategic importance.	Analytical efforts coalesce behind a small set of important targets.	Analytics centered on a few key business domains with explicit and ambitious outcomes.	Analytics is integral to the company's distinctive capability and strategy.
Analysts	Few skills and those are attached to specific functions.	Disconnected pockets of analysts. An unmanaged mix of skills	Analysts are recognized as key talent and focused on important business areas.	Highly capable analysts explicitly recruited, deployed, and engaged.	World-class professional analysts. Cultivation of analytical amateurs across the enterprise.

Davenport and Harris (2017) portray the first of the elements as *data*, which is considered to be a prerequisite when starting to use analytics. Data is described to have more impact when used in bigger quantities, while the importance of diverse, dynamic, and high-quality data is also emphasized. Data needs to be stored and easily accessible for users in either data warehouses, data marts, or data lakes, to provide better results. Companies whose use of data is in the final stage of the Table 1, analytical competitors, treat data as a strategic asset that needs maintenance to provide value for the company.

According to Davenport and Harris (2017), the second element is enterprise. Without an enterprise perspective, understanding of the issues facing the company is incomplete and fractured, and resources are rarely distributed to address correct issues. Executives need a comprehensive business perspective to address strategic issues of business competitiveness and effectiveness. Vital analytical resources, like data, technology, and analysts, need to be functionally siloed to affect multiple functions of the organization.

The third element presented by Davenport and Harris (2017) is *leadership*. Without committed analytical leadership, the use of analytics is limited. Leaders with analytical mindsets are described to be highly experimental and innovative, who often seek innovative ways to collect more insights. Leadership as an element of the DELTA model determines which kind of path a company should take in pursuing competitive value from analytics. High-level support from the top management can lead the company to a full-on path when pursuing analytical capabilities, while the managerial level of recognition usually leads companies towards a prove-it path.

Davenport and Harris (2017) present *targets* as the fourth element, which means prioritizing most potential investments in analytics. Investing in these right targets should have the potential to make an impact on a company's profitability by optimizing processes, improving customer relations, or cutting costs. Choosing the correct targets depends on the company's business strategy, industry, and analytical maturity. The number of targets can increase when a company's analytical maturity level increases, but this focus should be on the company's targets that improve its distinctive capabilities.

The final element of the first version of the DELTA by Davenport and Harris (2017) model is *analysts*. Developing analytical talent in the company requires more than acquiring a few analytically skilled employees. While these analytical professionals are useful in building and maintaining models used in companies, emphasis should also be put on analytically aware decision-makers and the information workers that can routinely apply insights gained from data to their work. An executive level of commitment is required to oversee analytical initiatives, which are implemented by analytical professionals, and utilized by "analytical amateurs."

In addition to these five elements in the DELTA model, Davenport and Harris (2017) have later introduced two new elements: technology and analytical techniques, creating the DELTA plus model. These elements were considered to be useful during the advent of big data and other new analytical techniques, such as AI (Davenport & Harris, 2017). This relates to one of the limitations presented by Król and Zdonek (2020): Current dynamics of data analytics development can cause existing analytical models to age quickly and be replaced by newer models with more relevant tools and measurement techniques.

The DELTA model includes 5 different stages for each element shown in Table 1. The five stages are named: 1) Analytically impaired, 2) Localized analytics, 3) Analytical aspirations, 4) Analytical companies, and 5) Analytical competitors. These stages and their definitions will be introduced more in-depth in the upcoming chapter.

2.3.1 The five stages of analytical maturity

Davenport and Harris (2017) refer to different categories presented in Table 1 and Figure 9 as stages instead of levels because they argue that to become an analytical competitor, companies need to progress through all these stages. They also suggested that the average company requires between 18 to 36 months regularly working with data to develop steady streams of insights that can further be utilized in practice. Companies lacking the will or not putting the effort to develop their analytical prowess, are mentioned to take longer time when applying insight from data to practices.

Table 1 introduced the DELTA model's elements and stages, but the previous chapter only focused on the elements of the DELTA model. Figure 9 illustrates the stages and criteria for these stages. The stages of the DELTA model are following:

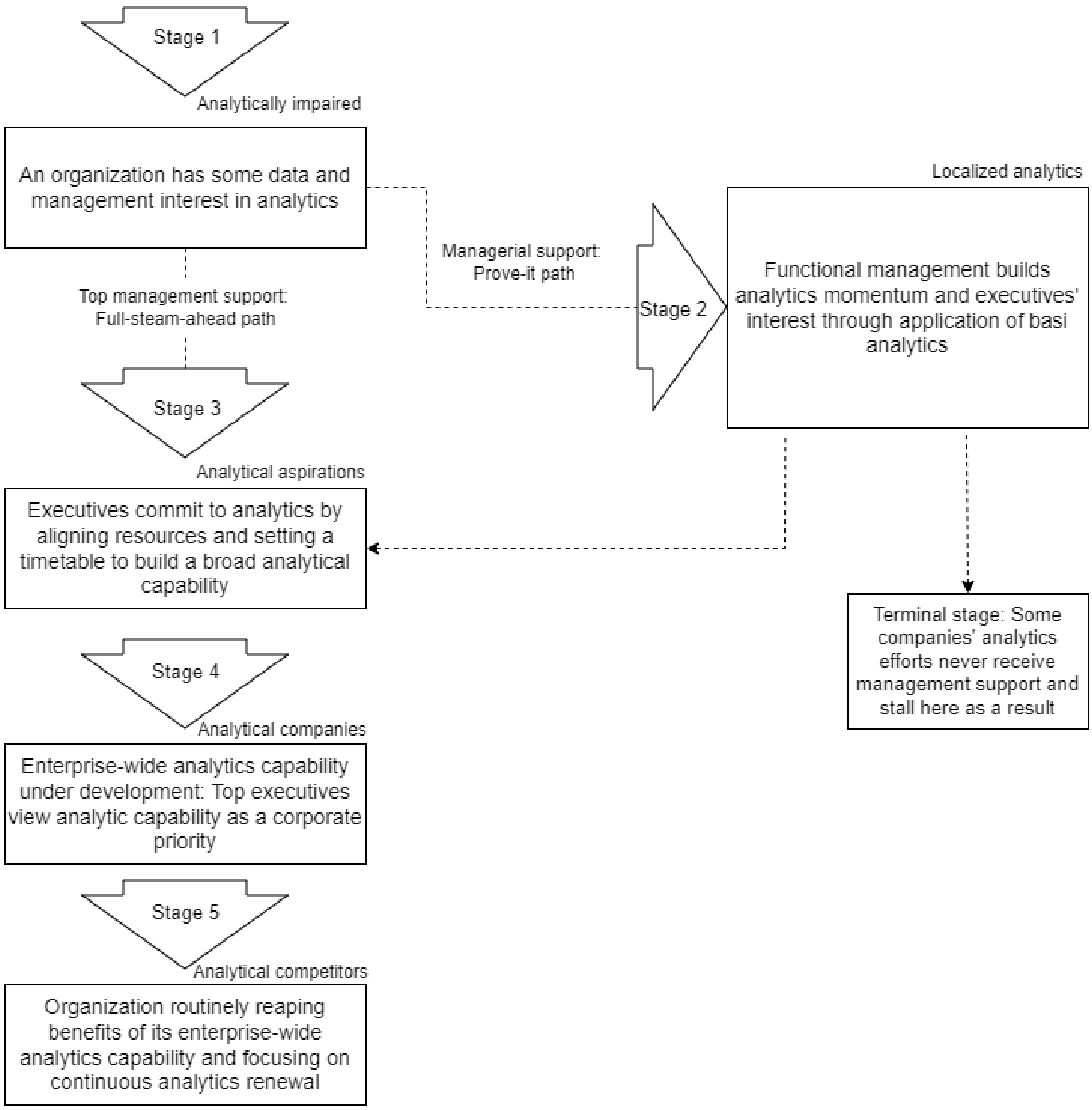

Figure 9. Becoming an analytical competitor roadmap (Davenport et al., 2017).

Stage 1: *Analytically impaired*. In the first stage, Davenport and Harris (2017) mention that companies do not have the prerequisites for analytics yet. They desire to become more analytical, but they face barriers to analytical competition, as hardware, software, and skills are required to do analysis. Companies in the first stage need to improve their data environment to a level that provides consistently quality data. Emphasis of the data quality is prioritized, as if the data is poor-quality, the plans of analytical competition should be postponed fixing the data first. In addition to data quality, the management roles need to be familiar with fact-based decision-making. Management teams operating with gut-based decisions will unlikely be supportive, and analytical initiatives in these companies will have limited impact. The usual objective of analytically impaired companies is improving operations with accurate data. Figure 9 shows that from the first stage, companies can progress to either Stage 2 or Stage 3. If the company's top management is committed and passionate to pursue analytics, it can take full steam ahead path straight to Stage 3, if not they have to take a prove-it detour to Stage 2.

Stage 2: *Localized analytics*. According to Davenport and Harris (2017), companies in this stage do analytical work, but these analytical activities are not yet enough to influence the company's competitive strategy. Senior executives of these companies lack the passion and commitment to pursue analytical competition with full force. Prove-it detour is considered to add from one to three years to the time that is usually required when pursuing the analytical competitor status. Usual sponsors of these smaller case analytics come from the managerial level, as their objective is to use analytics in improving functional activities. While this path takes notably longer, it comes with certain advantages. Documenting a series of experiments and the value gained from the localized analytical projects helps companies accumulate empirical evidence. The use of smaller, localized applications also helps managers to get more experience in how these insights can be translated into value. Starting small also helps managers to utilize analytics to improve the effectiveness of their departments, without having to get buy-in from other departments. To progress from Stage 2, smaller localized projects should be implemented to generate value. Documenting the potential benefits gained from these projects with stakeholders raises awareness. Finally, when a string of localized successes has generated and attracted top management's attention, the needed amount of sponsorship can be received in order to pursue a wider level of analytics at Stage 3.

Stage 3: *Analytical aspirations*. Davenport and Harris (2017) mention that companies reach this stage when analytics have gained executive sponsorship. These companies have noticed the potential value of analytical competition but are still in the earlier stages of it. Their objective is to use analytics in order to improve their distinctive capabilities, such as integrating data from multiple sources to widen their level of analytics. Depending on the path the companies took, analytical aspiration companies might have analytical groups and tools already in use. But this stage is about taking a more broad and strategic perspective of their analytical prowess. Vision is needed to picture the benefits that are expected from pursuing analytical competition, as these can act as targets. Management needs to plan their use of analytics based on their distinctive capabilities and to address their strategic business problems. Defining and adopting the set of different achievable performance metrics is considered to be critical, and further tracking their progress.

Stage 4: *Analytical companies*. According to Davenport and Harris (2017), Analytical companies are implementing their plan that was developed during Stage 3, while progressively improving their culture, skills, insights, data, and technology needed for analytical competition. Companies in this stage are able to use analytics more broadly than in earlier stages shifting perspective towards enterprise-wide analytical usage. Analytical techniques used by analytical companies are strongly present, but not yet fully bound to the company's strategy. They usually are on the verge of becoming an analytical competitor, but still miss out on getting to their full potential because of some hurdles. Lacking elements in reaching Stage 5 can be either related to analytical activities, as they might not be based on the company's distinctive capabilities, or insufficient passion of the executive team, as they can support it but are not willing to fully commit to it. One of the most critical challenges analytical companies face is about giving enough attention to managing cultural and organizational challenges.

Stage 5: *Analytical competitors*. Davenport and Harris (2017) portray analytical competitors as companies that have reached the final stage of analytical maturity. These companies have an enterprise-wide approach to analytics and exploit their analytical activities to support distinctive capabilities. Their top management level is passionate about driving the company's analytical initiatives. The gained advantage is sustainable and usually provides solid results, as the company focuses on the most significant capabilities that its strategy requires. Analytics is used as a primary driver for value and performance. They use internal performance measures to reinforce analytical integrity. To sustain their competitive advantage, analytical competitors continuously monitor external factors to modify their assumptions, analytical models, and rules. Commonly, they share a passion for analytics and enjoy the results of strong financial performance as a result.

2.3.2 Analytical capabilities

Analytical capabilities are a company's actions that they can do with their existing company, human knowledge, and technology. Like typical behavior and challenges, these capabilities vary when going through the roadmap presented in Figure 9. At the beginning of this roadmap, a company needs to assess its current analytical capabilities in three different main areas: Organization, people, and technology (Davenport & Harris, 2017). However, this might prove to be a difficult task, as different business units can have different levels of sophistication used in analytics and different demand for analytics. Take the finance team as an example, where BI tools can be used to monitor and estimate the budget. While they are utilizing analytics, there can be teams in the company that do not have such tools at their disposal. Even when some of the individuals could be using some sort of analytical applications and reports integrated from multiple data sources, these are hidden in the mass of non-existing fact-based culture. While analytics can sound like they are mostly technology-driven, they should not be considered as only the IT department's objectives.

Davenport and Harris (2017) mention that a capable organization possess the following key elements: 1) Using insight into performance drivers, 2) Choosing suitable distinctive capability for the company, 3) Managing performance and strategy execution, and finally 4) redesigning and integrating processes. Performance drivers are associated with key performance indicators (KPI), but instead of being single objective tools, like KPI is, performance drivers are activities that when done daily should produce desired KPI results (Blake, 2016). Blake also mentions that KPIs' significant weakness is being backwards-looking, meaning that there is an information lag between activities and KPI reports. Having a distinctive capability is about having something that your competitors don't have. Davenport and Harris (2017) recommend choosing a distinctive capability that can have strategically focused insights, processes, and capabilities to empower the distinctive capability to increase competitive differentiation. The third key element in organizational capability is about aligning analytical strategy to strategic enterprise objectives. Performance must be defined, measured, and monitored with metrics tied to these objectives. Finally, processes must be designed to comply with analytical models, as insight is gathered. Without proper alignment between business strategy and BA capabilities, a company can have a hard time becoming data-driven (Vidgen et al., 2017).

As mentioned earlier, people are an important part of the analytical competition. The following human capabilities are mentioned to be key elements by Davenport and Harris (2017): 1) Leadership and executive-level commitment, 2) establishing a fact-based culture, 3) securing and building skills, and 4) managing analytical people in the company. The roadmap in Figure 9 already emphasizes the meaningfulness of the executive level of commitment, as it mentioned two different paths that could be taken depending on what level of managerial commitment and sponsorship is attracted around analytical development. The first and second key elements share a relationship, as it is up to the leaders of the company to establish a fact-based culture. Building analytical understanding is important, as the company tries to adopt the use of analytical tools. Davenport and Harris have identified three important groups inside the company: 1) Senior management team, 2) professional analysts, and 3) analytical amateurs which means basically everybody else not included in previous groups. The senior management team's analytical skills and orientation are important because they set the tone for analytical culture and make important decisions regarding it. The second group, "analytical professionals", are in key roles in managing the company's analytical journey. They are the ones creating the predictive and prescriptive analytical applications that are used in companies, in addition to other data mining and statistical analysis of key data. The final group covers the rest of the company, who have limited analytical skills, but still work with business processes based on analytics. To progress in the analytical competition, these members have to be data literate, experimental, and numerate.

Finally, Davenport and Harris (2017) introduce two key elements of technological capabilities: quality data, and analytical techniques. The quality of data needs to meet certain standards before companies can start competing in analytics. These companies need to have functional transaction data environments to supply quality data consistently for decision-making. Davenport and Harris emphasize the required quality for data and discourage companies from pursuing plans for analytical competition if their data quality is not at the required level. A few studies have also emphasized data quality, as the study done by Vidgen et al. (2017) implicated data quality to be essential, and vital to be addressed should the companies create value from data. Kwon et al. (2014) found data quality management to have a positive effect when shaping the intention to adopt the use of big data analytics. Davenport and Harris (2017) continue introducing the elements by introducing the second key element, analytical techniques, including different kinds of analytical tools and applications. Companies should choose their tools and applications by determining how deeply decision-making can be embedded into existing business processes. The following important categories of analytical software tools are mentioned: Spreadsheets, data visualization, rule engines, machine learning, data mining tools, natural language processing tools, and web or digital analytics. The most commonly used analytical tools are spreadsheets, such as Microsoft Excel, where data can be presented in a report or graphical forms for decision-makers. While being useful for certain tasks, it can be prone to human errors and can be ill-suited for some more complicated tasks, where other tools could be utilized more efficiently for the task. (Davenport & Harris, 2017)

3. Research methodology

This chapter explains research methodology used in this thesis. After opening the methodology, the collection of the data for these methods is presented. The third subchapter explicates our artifact and its history that is made during the study. The Case company subchapter presents the environment of the case company where the thesis aims to implement the BI tools. The final subchapter analyses the results of the interview which were introduced in Subchapter 3.2.

3.1 Research methodology

According to Hevner et al. (2004) two different paradigms are found to be foundational for the information systems (IS) discipline: behavioral science and design science. Behavioral science in IS is about developing and verifying organizational or human behaviors, while design science focuses on extending boundaries of both human and organizational capabilities by providing innovative artifacts. Together these two paradigms are in the confluence of technology, people, and organizations. *Design science research* in IS was conceptualized by Hevner et al., (2004) in the form of a framework and guidelines to help researchers understand, execute, and evaluate their DSR research. Later in 2016, Goes mentions that DSR is recognized as one of the main paradigms for IS research. Briefly, DSR seeks to utilize existing knowledge bases and technology to create innovative artifacts to solve problems.

Artifacts created by DSR are purposefully created to address certain important organizational problems, and they must be effectively described to enable the artifact's implementation and application in the context (Hevner et al., 2004). According to Hevner et al. IT artifacts are not only limited to instantiations, as the DSR artifact can also be a construct, method, or model that is applied to the use of information systems. Artifacts are rarely full-grown functional information systems, but instead smaller-scale innovations.

DSR has been utilized in BI and BA development earlier. Arnott and Pervan (2014) recognized design science to be one of the major categories in their study of decision support systems (DSS). One of the forecasts of a study by Arnott and Pervan (2014) was that design science was going to dominate DSS research. Earlier concepts, such as DSS and data warehousing, are usually nowadays included inside the umbrella term of BI (Watson, 2010). Some of the studies that have utilized the DSR approach in BI and BA have been about using BI in the cloud (Mwilu et al., 2016), designing and evaluating BI systems in the healthcare industry (Kao et al., 2016), and developing BA capability maturity model (Cosic et al., 2012). Many studies from the past indicate that DSR can be useful to technology-driven problems presented in the BI and BA fields.

Hevner et al. (2004) introduced 7 guidelines that are applied to succeed in DSR. While it is mentioned that following these guidelines is not mandatory, the researchers should use their creative skills to judge how, when, and where these guidelines can be used in research projects. Finally, Hevner et al. emphasize that guidelines in DSR should be approached reasonably and systematically. Ultimately, the judgement of whether the guidelines have been met should be left to the discretion of readers and reviewers. These guidelines are shown in Table 2 below.

Table 2. DSR guidelines (Hevner et al., 2004).

Guideline	Description
Guideline 1: Design as an artifact	Design science research must produce a viable artifact in the form of a construct, a method, a model, or an instantiation.
Guideline 2: Problem relevance	The objective of design science research is to develop technology-based solutions to important and relevant business problems.
Guideline 3: Design evaluation	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.
Guideline 4: Research contributions	Effective design science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies,
Guideline 5: Research rigor	Design science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Guideline 6: Design as a search process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Guideline 7: Communication of research	Design science research must be presented effectively both to technology-oriented as well was management-oriented audiences

In addition to framework and guidelines, Hevner et al. (2004) provide additional practice rules for DSR. These rules mention that DSR must produce an artifact that addresses a problem, and it should be relevant to an unsolved and important business problem. The research itself requires contribution from the existing knowledge base, so the rigor is applied to the development and evaluation of an artifact (Hevner, 2004). Peffers et al. did a study to compose DSR's methodology in 2007, where they compared and compiled various methods from existing DSR studies and presented their proposed DSRM process model based on the earlier studies. DSRM introduces a process model, where six different activities are introduced: 1) *Identify problem & motivate*, 2) *Define the objectives for a solution*, 3) *Design and development*, 4) *Demonstration*, 5) *Evaluation*, and 6) *Communication*. While these activities are presented in sequential order, the starting activity for the process can depend on the entry point of the researcher and the type of solution that is looked at from the DSR. Process iteration can be done in the later activities 5 and 6, where the process can be taken into activities 2 or 3. At the end of the evaluation (Activity 5), researchers can potentially iterate back to Activity 3 to improve the effectiveness of the artifact, or to continue to the final activity, while leaving potential improvements for upcoming projects. In Figure 10 below we introduce the DSRM process model used for this study. The final activity, communication, is modeled with dashed lines, as it is not clear yet whether this activity is included in the study.

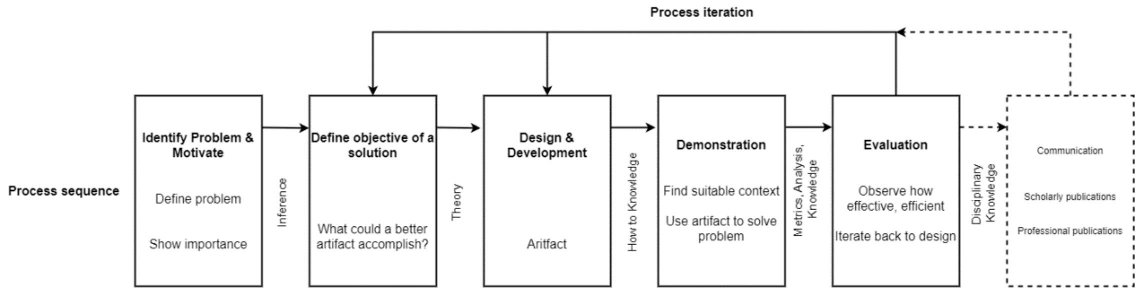

Figure 10. DSRM process model (Adapted from Peffers et al. 2007).

First of the DSRM process model's activities is *Identify problem & motivate*. Peffers et al. (2007) describe this activity to focus on defining the specific research problem and motivate part of the activity focuses on justifying the value of a solution. Justifying value can motivate both the researcher and the audience to pursue the artifact's solution and accept the results that the researcher implies in understanding the problem (Peffers et al., 2007). In this study, problem identification is done by interviewing senior-level employees of the case company. The motivation for applying the use of an artifact in the form of a BI tool comes from background research, as providing the artifact for these employees can help them access the data of the information systems easier while providing capabilities to visualize data, filter the data based on their needs, and access to linked data. This activity's problem identification part is performed in this study in Subchapter 4.1, while the motivation part consists of Subchapter 2.1 possibilities shown by BI.

The second activity, *Define objectives of a solution*, aims to infer the objectives of the artifact within the problem definition that can be feasible (Peffers et al., 2007). These objectives can either be quantitative or qualitative, demonstrating how a desirable solution could be improved, or how a new artifact can support solutions that have not yet been addressed (Peffers et al., 2007). The objectives of this study's artifact are qualitative. These objectives have been made from analyzing the interview's results, by forming issues that the artifact can affect in Subchapter 4.1. Additional objectives to ensure the artifact's efficacy, usability, and security requirements are made in Subchapter 4.2. The chapter also includes introducing current problems, how they were formed to objectives and problem domain introduction.

The third activity, *Design and development,* focus on creating the artifact. Determining the artifact's functionality, design, and architecture are core parts of this activity, in addition to creating the actual artifact (Peffers et al., 2007). This thesis does this activity in Subchapter 4.3, where used design and architectural solutions used for the artifact are explained. The chapter also explains tool-specific modifications that were made to improve the artifact based on background literature.

The next activity of the DSRM process model can be *Demonstration* to prove that idea works or a more formal *Evaluation*. Both activities are included in this study, meaning that the fourth activity is a demonstration. Peffers et al., (2007) describe this activity's tasks to demonstrate the use of the artifact to solve instances of the problem defined in the first activity. In Subchapter 4.4, the artifact's functionality is demonstrated by illustrative scenarios, showing how the artifact can affect the current problems identified in the first activity.

The final activity of this thesis is *Evaluation*. Here, the objectives of a solution are compared to actual observed results done by the artifact in the demonstration activity (Peffers et al., 2007). This study will be using illustrative scenarios as an evaluation method type, where the artifact is applied to a real-world situation aimed to illustrate the suitability or utility of the artifact (Peffers et al., 2012). In addition to this, the subchapter compares how the issues detected during the first activity are considered in the artifact. The evaluation activity is done in Subchapter 4.5.

3.2 Data collection

This thesis collected data with interviews from the case company's employees on the operational level. The data is used to gain a deeper understanding of the current reporting solutions, data used in reporting, and key figures. Data collected by these interviews is utilized in the DSRM process model's first activity: *Identifying the problem and motivation*. The goal of this activity is to define the current state of the problem that employees face with current reporting solutions and the show importance of possible solutions offered by this thesis. The interview aims to answer RQ2: "*What are the current challenges faced by the case company's employees in performing reporting-related tasks*"?

The interviews were conducted as semi-structured interviews. Before the interviews, an email was sent to potential participants to inquire about their interest in the possibility of being interviewed for this thesis. In this email, the general purpose of the thesis was introduced, the questions were presented, and the participants were asked to fill out the form in Google Forms whether they wanted to join the interview. In the form, participants were acknowledged their rights in the interview and informed how their data was used. Filling out this form and giving permission was required before the interview could be held. Questions asked in the interview were open-ended, but improvisation in the form of additional questions was used to supplement the questions. Interviews were held in Microsoft Teams to utilize the recording functionality, which helped in going through answers. The interviews were held between the 28th of March and the 3rd of April in 2023. Interviews were held in Finnish with the Finnish version of the questions. These questions and answers were later translated into English. The list of questions asked in the interview can be found in Appendix A. Thirty-five minutes were reserved for each interview and most of the interviews were completed in this duration.

In total, nine individuals were interviewed. Four people worked in the technical service operations team, and the remaining five were part of the customer service operations team. This target group was selected, as they directly operated at the operational level of the case company, and they were in contact with both internal and external personnel. Background information about the participants can be seen in Table 3 below.

Table 3. Participants of the interview.

Job title	Job experience in current position	Job description	Approximate time used in reporting per month	Team
Senior support specialist 1	7.5 Years	Solving issues and requests in customer interface. Additional tasks include maintenance of the following: server infrastructure, databases, Jira, and internal measuring system.	20 Hours	Technical service operations
Senior support specialist 2	20 Years	Solving issues and support requests.	15-20 Hours	Technical service operations
Senior support specialist 3	6 Years	Solving issues and support requests. Maintains production environment's SLA measuring software. Occasional DevOps and infrastructure maintenance.	8 Hours	Technical service operations
Head of technical service operations team	2 Years	Managing technical service operations team, oversees SaaS and production tasks.	16 hours	Technical service operations
Service manager 1	1 Year and 3 months	Customer communication, monthly reporting, steering group meeting preparation, invoicing,	35-40 Hours	Customer operations
Service manager 2	1 Year and 3 months	Point of contact for customer communication. Communicates information between product development and customers.	5- 10 Hours	Customer operations
Service manager 3	1 Year and 3 months	Customer experience improvement, coordinating the needs of SLA (invoicing, meetings steering groups), and communicating incidents.	20 Hours	Customer operations
Service manager 4	2 Years	Communicates with customers about open tickets, version updates, operational meetings, and steering group meetings	28-36 Hours	Customer operations
Head of customer operations	4.5 Years	Coordinating project deliveries and managing customer service teams.	45 Hours	Customer operations

Members of these teams actively work in customer interface and co-operate in solving incidents. The members of these two teams were stakeholders of this research project. They were directly involved in the project as participants in interviews. They are also aimed to be potential beneficiaries of the project. Their interest in this project included the possibility of getting the BI tool as part of their repertoire, designed based on their needs to be used daily in their everyday work.

3.3 Artifact and its earlier generations

The artifact done in this thesis has been under development before the study. However, this development has been a side project that has been developed during the less busy times at work. Parts of the older generations of the artifact have also been developed during time outside of work due to personal enthusiasm toward the project. Based on the goals set for the artifact, it can be considered that the artifact has already gone through two iterative cycles. From now on these iterative cycles are going to be referred to as generations, to simplify referring to the artifact's different versions. Stakeholders that are interviewed are aware of the development of the BI tool, as it has been briefly introduced as a potential tool that can be utilized in the future. However, the participants have not used the current tools or have had access to them, except for the head of the technical service operations team, who has been part of the BI tool's development. This thesis aims to complete the third generation of the artifact with the help of methodology. DSR was not applied to the first or second generations of the artifact. To summarize artifacts from previous generations and the current one, see Table 4 below.

Table 4. Artifact and its earlier generations.

	Generation 1 (6.2022 - 9.2022)	**Generation 2** (9.2022 – 12.2022)	**Generation 3** (1.2023 ->)
Artifact type	Individual ad hoc reports	Dashboards	Example dashboards for both teams in the target group. "Golden dataset" to use as master data for self-service BI.
Reporting type	irregularly	irregularly	Weekly/ Monthly/ Ad hoc
Data sources	1	2	2
Requirement gathering	Teams chat history	Weekly meetings, Confluence	Interviews
Data refreshing	Exported files	Import connection from Jira's REST / Exporting files Dynamics	Scheduled refreshing REST and Dynamics
Goal	Extract the data from Jira	Mapping and connecting data from multiple data sources (Jira – Dynamics)	Help the company's operational level by providing solutions to existing recognized reporting problems. Providing data visualization for stakeholders.
Evaluation	Continuous evaluation during the project to ensure the quality of data	Data and its quality. Suitability of integration between different data sources	According to design science research's evaluation techniques and guidelines.

The first-generation artifact was mostly an experimental test to investigate the BI tool's potential in displaying data from one data source. The technical service operations team had developed features to measure performance metrics introduced by service level agreement (SLA). This data source was commonly used in issue & project tracking software, Jira. However, the reporting functionalities offered by Jira did not match existing reporting requirements and needs. This initiated a small side project which progressed beyond normal working hours, and the goal was to utilize Microsoft's Power BI, by using Jira as a data source. Without prior knowledge, the development was started to extract the data from this issue tracking software, to transform and load it in Power BI.

While the BI software itself was unknown, most of the time in the first-generation artifact was spent cleaning the data and experimenting with different possibilities for visualizing the data. Requirements in this generation were not clearly defined, as the focus was mostly on exporting the data from the source to the BI tool. Data was exported to the BI tool as text files, such as comma-separated value (CSV) files, meaning that this data was only a snapshot of certain times about the situation of the tickets from Jira. Successfully evaluating the data compared to Jira's corresponding values allowed the creation of simple reports filled with different KPIs and graphs to display data in a simple form with options to filter and drill down the data. Later, this data was evaluated based on the central tendency measures of the numerical values compared to equivalent values seen from Jira's spreadsheets. Easy and clear visualizations, good filtering options, and the potential to extract data from multiple different data sources to integrate the data inside the BI tool were considered to be the reasons that development would be continued.

The second-generation artifact started to represent the strengths gained from using the BI tool, instead of using just various data visualization tools. The main reason for this was the utilization of the REST API of Jira. Data could be refreshed from the BI tool itself with a few clicks of the mouse in the form of a direct connection, instead of importing text files from Jira and using export functionality in Power BI. After managing to create a pipeline from the data source to the BI tool, additional data sources could also be considered to use in the form of aggregating data from multiple different sources. More frequent refreshes in data allowed the artifact type to be considered as a dashboard of technical service operation's current situation issue-wise. Multiple data sources allowed the use of data integration, as introducing data from Dynamics could show where most of the time was spent in the team. The second generation included more planning which resulted in more documentation from the development process, as requirements for the second-generation artifact were gathered in Confluence, which is Atlassian's wiki platform used in the case company. Unlike in the first generation, these requirements now could be prioritized which made this second generation's development phase more fluent. As data integration was introduced, the goal of this generation became clear: Connect the data from the different sources by creating relationships and utilize this integration by exploring why certain types of issues would take longer to solve than others.

The third-generation artifact is designed and implemented initially in this thesis. Limitations for full implementation of the artifact are time constraints of available time to use for the thesis, and the company's structural reasons, such as getting access to the Power BI software for all planned users on the case company's operational level. While all the users might not need extensive rights to edit the artifact, the possibility of using the case company's wiki-like software, Confluence, and its third-party tools to embed the artifact could be considered, as most users would benefit from being only able to monitor the data of multiple different systems from the artifact. The third-generation artifact type differentiates from earlier generations because it is designed to be used by multiple people from the case company's operational level. This requires clearer data visualizations, more descriptive measures and calculations, and transparency. By improving these elements, reports and their use is aimed to be easier to use, while decreasing the support required for the system. The artifact takes place as several different types of template reports, where data that is usually used or queried is now presented in the BI tool. Should the users want to develop their own tailored reports, they can use the master dataset used for the artifact, which is often referred to as the "golden dataset" by practitioners of the field (Allington, 2020). The amount of data sources used for the third generation's artifact will be decided based on the interview results that are held to gather requirements for the artifact. Data refresh intervals will be decided based on the requirements of the interview participants, but the artifact would benefit the most from daily scheduled data refreshes. As mentioned earlier, this third-generation artifact will be developed based on the requirements gathered from the interviews, while earlier generations have had their requirements based on the goals of that generation's development. Ultimately, the goal of the third-generation artifact is to detect current problems from the interviews and provide solutions to these current problems based on reporting or information sharing. The goals are to help stakeholders, by developing artifact in the form of a BI tool, which provides an alternative means to complete the reporting tasks, while giving access to visualize data more easily, and being able to monitor data from multiple different sources from one tool.

3.4 Case company

The case company participating in the thesis is a Finnish software company operating in the B2B, and it provides software as a service (SaaS) for its customers. These two teams featured in the interview operate on the case company's customer information system (CIS) product, which can be seen in Figure 11.

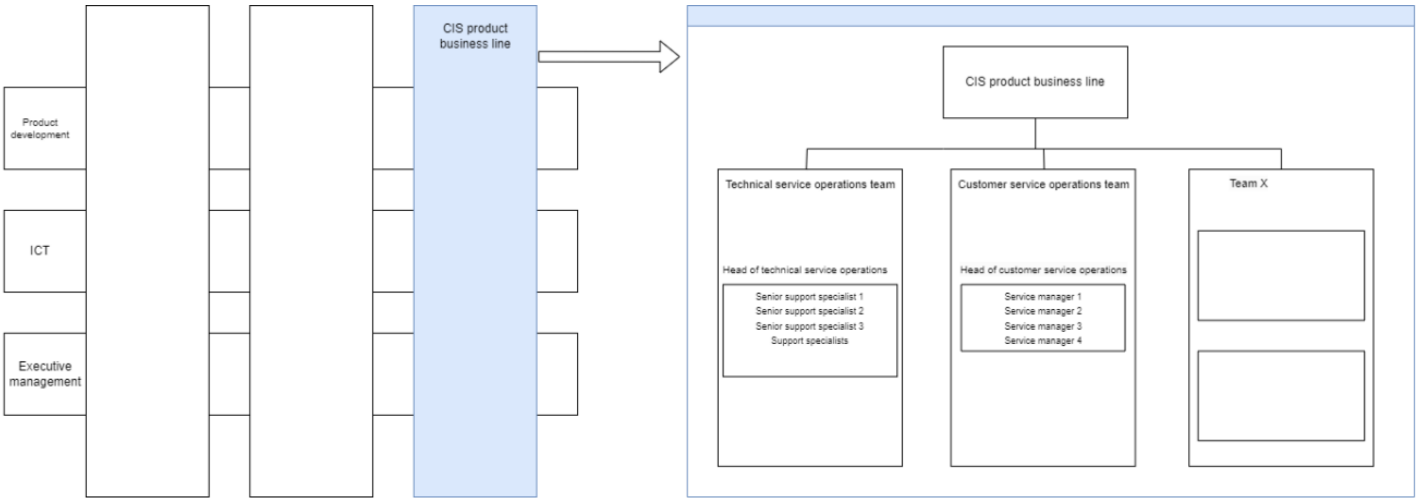

Figure 11. Case company's organization chart and stakeholder teams.

The technical service operations team is filled with support specialists who operate in proximity to all components of CIS, by solving various types of tickets, such as incidents, and support requests. Incidents are usually caused by connection problems, momentary breaks in data exchange, or software bugs. Support requests are requests made by the end users, and they usually include different types of data transformation tasks, tasks that cannot be completed in CIS, or inquiries about upcoming features. Members of this team are also responsible for handling the service outages that may occur in CIS and look actively to improve infrastructure or existing monitoring systems. The second featured team, customer operations, is populated by service managers, and other personnel operating in ongoing projects, and upkeeping the current systems for customer companies. Service managers are the main source of communication with customer representatives, coordinate the prioritization of different types of tasks done to CIS, and participate in steering group meetings.

The most relevant information system that is used by these teams is Atlassian's agile project management tool, Jira. End users of CIS submit tickets to Jira, where technical service operations teams submit potential solution proposals to these tickets. While this software is often used as an issue-tracking and project-management tool, it also contains massive amounts of data. Additional software that is used includes monitoring software Paessler PRTG, internal data exchange software, and Microsoft Dynamics to monitor resources. Additional systems that can be considered as data sources are different types of databases used for CIS. The technical service team uses PRTG to monitor the current situation of the sensors measuring different functionalities that are vital for CIS to prevent outages. The service operations team uses most of these systems monthly to create reports for the customer company.

4. Results

In this chapter, we focus on the artifact developed in this thesis. Artifact development begins with analyzing interview results, which is part of the DSRM model's first activity, *Identify problem & motivate*. These issues set requirements for the artifact and what can be expected from the artifact. The requirements chapter is based on DSRM model's second activity: *Defining objectives and solutions*. After requirements, the artifact is designed and developed. The design subchapters aims to model the structural design of the tool and solutions used to develop it. The use of these selected solutions is explained in the subchapter, as selected decisions used to develop the BI tool might vary from the most optimal version, because of the time constraints, and supporting infrastructure around the data flow of the case company. The design chapter is based on DSRM's third activity: *Design and development*. The demonstration subchapter focuses on the fourth activity of the DSRM process model: *Demonstration*. Finally, the artifact is evaluated in its evaluation subchapter, which is based on DSRM's fourth activity: *Evaluation*.

4.1 Interview results

Interviews were organized and targeted at the stakeholders of the project. These stakeholders were two different teams working at the operational level of the company: The technical service operations team, and the service operations team. The interview served as a starting point for the third-generation artifact's DSR process and aimed to identify current problems faced in the everyday work of stakeholders. The interview and its content were discussed with participants before starting the interview. During that part, the different sections were introduced, explained, and the motivation behind the questions was explained. Participants were reminded that there were no right or wrong answers, and their point of view on these themes of the sections was appreciated, in order to form an in-depth understanding of the current solutions used in the case company.

Before the actual interviews, a pilot interview was held to test interview questions. Pilot interviews are usually used to practice interviewing techniques and can be used to test if the interview questions need modifications (Majid et al., 2017). Unlike the actual interviews, the pilot interview was held locally instead of using Microsoft Teams. The results of the pilot interview were that the planned time of 35 minutes was suitable for the number of questions that were included. Clarity of the questions and potential repetitiveness were also considered during the pilot interview. The clarity of questions was clear, as the pilot interviewee did not spend any extraordinary time answering the question and managed to answer the question within time limits. The repetitiveness of the questions was inquired about after the pilot interview, and the interviewee implied that no repetitiveness was found, at least in consecutive questions.

Microsoft Excel was used to analyze interview results. The duration of the interviews varied from 19 minutes to 41 minutes. The average duration of the interview was 29 minutes and 55 seconds. The interviews went as planned without technical difficulties.

The interview included five sections: Background, reporting, data, key figures, and business intelligence. In the background section, the participant's basic information was gathered. This information included job title, duration of employment in current job title, main responsibilities of the job, and estimation of hours used in reporting monthly. The second section, reporting, was used to inquire participants about the type of reporting done daily, to whom the reporting is done, the tools that are used currently, the efficiency of these tools, current processes, and potential improvements for current reporting solutions. The term “reporting” was used in the second section, as this was believed to be the most associated term with current information-sharing customs similar related to BI. The third section, data, was used to find out where participants usually needed the data from, and what kind of transformations it needed before it could be used for their reporting needs. The fourth section was key figures, and it was done to gain an understanding of the most important key figures that stakeholders followed. The final section was the BI section where participants were asked if they were familiar with BI and if they had used these kinds of tools earlier. The final question of this section was whether the participant would find this BI tool to be useful in their current work.

4.1.1 Background

A total of 9 people were interviewed from two different teams. Four of the participants were part of the technical service operations team, and the remaining five participants were part of the service operations teams. Participants from the technical service operations team had the following job titles: Head of technical service operations team, and three senior support specialists. Five participants of the customer operations team included the next job titles: Head of service operations team, and four service managers.

The main responsibility of participants in the technical service operations team included solving incidents and support requests from customer companies, and individual senior support specialists had additional tasks including maintenance of infrastructure related to the product and the systems team operating daily. These infrastructural pieces maintained included databases, servers, internal monitoring systems, and Jira development. The approximate times used in reporting monthly differed from 8 to 20 hours, with an average of 15.3 hours per month.

The other stakeholder team, the customer operations team, mentioned the following tasks as main responsibilities: Frequent customer communication about open tickets, arranging operational meetings, arranging steering group meetings, reporting potential outages and incidents, version announcements, and invoicing. Later sections revealed that tasks which were unclearly defined usually ended up on the service manager’s task list, occasionally bringing unexpected tasks. The approximate hours used in reporting in the month differed from 5 to 45 hours, with an average of 28.4 hours per month.

4.1.2 Reporting

Interview questions in reporting section inquired participants about what kind of reporting they currently do in their job, who are the stakeholders in reporting, what kind of tools are utilized in reporting, and how these tools suit their needs in reporting.

Members of the technical service operations team described that their reporting mostly consisted of tickets, their types, and amounts, and measuring the availability of the servers and platforms. In addition to these tasks, the manager of the team also mentioned the following tasks: Cost accounting, resource management, and monthly customer reports. Stakeholders of these reports were done for were other members of the team, the manager, customer end-users, and service managers.

> *"We create monthly reports about the availability of the customer environments, and I usually explain the unexpected disruptions, so you could say that I handle the anomalies that our environments face."* (Senior support specialist 3)

The customer operations team's service managers list of reporting done was broader than other team's: invoicing, monitoring of the availability based on the customer's Service Level Agreement (SLA), internal reporting of the incident, monthly ticket amounts, progress of the high priority tickets, hours spent on customer support by technical service operations team per customer, upcoming functionalities, upcoming changes, and version announcements. Many of these statistics used in reporting were based on SLAs that the case company had defined with customers during the delivery of the product. Additional types of reporting mentioned by the manager of the team included monitoring the ongoing projects, monitoring financial figures, personnel work hours, and both external and internal invoicing. Stakeholders of these types of reporting were customers, team members, executives, the financial department, and various other internal teams, such as the technical service operations team, DevOps team, infrastructure team, and product development.

> *"Reporting consists of delivering information to customer organizations about the current situation of tickets, for example, the number of tickets and the current situation between open and closed tickets. Internal reporting includes summaries of the overall situation of tasks related to certain customer organizations, and this information is usually delivered to stakeholders operating near customer interface."* (Service manager 2)

When asked about specific tools and techniques, both teams reported using Jira and its functionalities as a part of reporting. In addition to Jira, Excel as a tool and different database tools were utilized by most of the participants. Other mentions by the technical service operations team were additional monitoring software, like PRTG, and an internal data exchange system to monitor the product's data flow. The manager of the technical service operations team also mentioned that Power BI was used to monitor broader masses of integrated data to detect trends. Another manager from the customer operations team also mentioned frequently using an internal invoicing system.

Neither of the teams mentioned that they are required to use certain specific tools. Senior support specialist 1 mentions that choosing the tools to use in work is open-minded, as long as the case company has approved these tools, and the tools include needed functionalities. In another interview, senior support specialist 3 points out that specialists have chosen suitable tools to use, and constant comparison is being made repeatedly to ensure that current tools are suitable for current activities. The manager of the technical service operations team notifies that certain tools are predetermined, such as project management tools, but they are allowed to explore the options independently and based on their own interest. Senior support specialists and the manager agreed that there could be more training on a comprehensive level.

> *"I don't think that there have ever been direct orders to use specific tools or software for certain tasks in the history of the company. The employee has a possibility to choose their own tools, as long as the company approves this tool."* (Senior support specialist 1)

"I would say that process has gone the way, that earlier our experts have stated that these tools are good for handling these types of tasks, and the maintenance still continues with those tools." (Senior support specialist 3)

The customer operations team's members emphasize that there have not been direct commands to use certain tools, but instead, the daily work has adapted the best customs based on certain tools. Customer managers had subjective views on these questions, whether the instructions or the training were sufficient. Answers point out that there have not been bigger predetermined policies, but instead, each customer manager applies their own customs. Differing answers based on the questions raise the question that should there be general policies that can be applied in this manner. The nature of the answers also shows that some customer managers felt that their work is encumbered because certain tools were harder to use. For example, Jira was seen as a potentially great data source, but to get the data queries had to be done in Jira query language (JQL) which ended up preventing some customer managers from accessing the data. Service managers and their manager generally agree that there has been a basic level of training for some tools, but they could benefit from more comprehensive training.

"I have been instructed to use, but not trained. I usually have to resort to Google. What kind of JQL query I have to enter to get this specific information I need." (Service manager 1)

"I think I've learned the hard way how to use our tools, and I still think that there are more optimal ways to use these tools than mine. I don't think that there has been a training session about Jira and its tools, that's why I usually have to ask my teammates and try these types of things on my own." (Service manager 2)

"We haven't been commanded to use specific tools. When I joined the company, my predecessor instructed me how to use these tools and I still use them the same way. Without a doubt, you would be allowed to use additional tools and improve your way of working." (Service manager 3)

When interviewees were asked about the current suitability of the tools, participants of the technical service operations team commented that the number of current tools is enough, but additional development is required to unleash the full potential. Jira was mentioned to have a great number of additional tools that could be used in daily working, but the deployment of these tools requires careful planning, as tools might not be compatible with each other, and updates can break these integrations. Senior support specialist 2 mentioned that current tools are suitable for current needs, but pointed out that this view could be limited, as there is no earlier experience with other optional ways that how these things are usually handled. Other mentions from senior support specialists include finding out ways to integrate data and browse it effortlessly. Participants also presented a few limitations in certain areas of reporting, where information could not be monitored, and gathered due to non-existing tools, or performance issues.

"I have no knowledge about other potential tools that are usually used instead of these." (Senior support specialist 2)

"The current palette of tools is good, but there is still development to do to get these tools working properly. System-level reporting tools are okay, and Power BI is going to be great addition to existing tools. However, we still

> *require development to get it running on the level we want to."* (Head of technical service operations team)

The customer operations team, which usually does more reporting, presented more limitations about the suitability of the current tools. Two of the customer managers described tools used in reporting as troublesome, one described simple tasks simply taking too much time, and the other felt that his know-how of the tools was not on the required level. Two remaining customer managers felt that current tools are suitable, but pointed out that certain parts of reporting could be more automated and flexible. When participants were asked how the current tools should be improved, they answered the following. The difficulty of analyzing the present data from multiple different systems was mentioned to be a problem when trying to solve and manage incidents and outages. The manager of the team pointed out some of the problems concerning Dynamics: exporting files from the software is necessary but leads to a lot of manual work with Excel, and the integration between Dynamics and working hours monitoring software is slow. All the customer managers agreed that current reporting solutions required too much manual work when dealing with some of the systems. One of the commonly mentioned problems was making availability reports from PRTG, as this process included a massive amount of manual labor, depending on the number of customer companies the customer manager was responsible for. Other problematic systems that required a lot of manual work were mentioned to be systems required when invoicing. Service manager 2 commented that tools used in reporting should have capabilities to provide data visualization easily to support reports. The way information is shared was also described to be complicated, as different teams used various ways of reporting policies resulting in different types of reports. The absence of common templates contributed to this problem.

> *"Current solutions used for invoicing are frustratingly troublesome, compared to earlier experiences."* (Service manager 1)

> *"I feel that the current way of working involves too much manual work. There also is no general policies including the way we report things. Many of the teams might be doing the same type of reporting, but they all do it in their own ways."* (Service manager 2)

> *"Dynamics requires too much time first when exporting the data, and then having to transform the data in Excel suitable format. Working hour tracking software, which acts as a data source for Dynamics is rigid and does not either offer any helpful reporting solutions. Excel is the best tool of the tools at my disposal. There also are no general templates available."* (Head of customer operations

The technical service operations team pointed out two problematic different things about current reporting processes: Continuous searching for information is required from internal wiki and databases to progress in work, and customer environments required multiple different manual tasks monthly. The first point refers to Confluence, the case company's wiki that is used for documentation and information about product, as retrieving information can be hard due to its bloated state. Some of the problems encountered in the previous question are also relevant here: Multiple different reporting and documentation styles can lead to different amounts of information presented about the product. The manager of the team mentioned that processes could be improved by developing them more specifically based on the highlights required by the audience. Current processes that apply in daily work include customs that have been noticed to be the best policies in the current situation. As an improvement, the manager hoped for more information sharing and transparency with the data. Differing reporting policies slow down the process of acquiring information from other teams.

> *"There are some policies used similarly in reporting processes, but it could benefit from more structured policies. Data sharing would be more encouraged if the different teams would be using the same kind of standard when reporting their results."* (Head of technical service operations team.)

The customer operations team's feelings about the current state of reporting processes were mixed. One of the service managers improved reporting processes by using data visualization, which was described to help with monthly reporting needs. Practices like these were mentioned and they could be useful for other service managers as well, but the clarity of these implementations was not yet on the required level. Other mentions included that tasks were hard to prioritize, as two of the service managers mentioned that some not-so-well-defined internal processes can provide sudden tasks for service managers when there is no one else to delegate to. Service manager 4 mentioned that sometimes processes were too slow to be useful in certain situations, and in times like these, they had to resort to more direct actions, for example, contacting specialists during outages.

> *"I have made my own dashboards in Jira, but they should be developed further. These are not currently optimal, but I feel that they are quite well. My goal is to develop these dashboards and reports so good, that any other service manager could fill in for me if I was absent."* (Service manager 1)

> *"I do acknowledge how certain things should go according to the processes, but sometimes improvisation is required. For example, during outages, communicating through tickets to your teammates is simply too slow."* (Service manager 4)

The final questions of the interview asked what kind of improvements could help the participants reach their current goals in reporting, and whether they considered reporting to be a significant part of their job. Participants from the technical service operations team hoped that they could have access to more data from the product, and by getting that data be able to offer the data to the customer. Jira was seen to have a huge potential as a data source, but participants felt that it was hard to achieve its full potential from it. Data integration was seen as problematic because currently there are no tools to handle it. As an example, ensuring the availability of the product environment required three different queries in different systems. The manager of the team wished to participate more in the development of current reporting practices. The manager of the team also commented that knowledge-based management is something that the case company should pursue, as the quality of the data has been managed to improve to a certain level. Two senior support specialists out of three, and the manager considered reporting to be a significant part of their job.

> *"Data-based decision-making is the modern way to handle things, and it should be encouraged. As long as the data is reliable, data-based decision-making is the way to go."* (Head of technical service operations)

The customer operations team's members and manager prioritized that similar reporting practices should be more common at the organizational level. By adopting common practices, the reporting processes, and certain parties responsible for certain states would be clearer, while diminishing the number of sudden tasks that service managers must take care of. Templates for commonly used reports should be more available and instructed to use them to follow guidelines set by the company. Service manager 2 mentioned that reporting should be handled with professionalism, as it is how the case company presents itself to its customers. Three of the service managers also commented that it was hard to give concrete examples for question 9, as they felt that they had no prior experience with solutions that could be available instead of current tools and practices. All 5 participants from the customer operations team considered reporting to be a significant part of their job.

> "*Reporting is a significant part of my job. It is the way how we represent our company for external companies, and it should be done properly.*" (Service manager 2)

4.1.3 Data

The data-related questions began with asking the participants if they knew where to find all the data they required, and if it was easily accessible. All senior support specialists and the manager from the technical service operations team were aware of where they could find the information they needed. The manager of the team pointed out that not only knowing where to look for was enough, as the desire was to make integrations between data management software and systems acting as data sources. When asked if the data was easily accessible, the answers were more mixed. Senior support specialist 2 commented that the way data or information was scattered usually dropped off the feeling of accessibility. While other senior support specialists agreed that the data was easily accessible, the final specialist had mixed feelings, because gathering data from multiple sources and cross-checking it was not easy.

> "*Data is too scattered to be considered easily available. Too many different information systems that require their own login information constantly.*" (Senior support specialist 2)

Service managers and the team's manager agreed with senior support specialists on knowing the location where data could be found but also raised some concerns. Specific systems were described to be problematic, as they knew data was from there but getting it would take an excessive amount of time. Jira was mentioned to be one of the potentially great data sources, but its queries required knowledge of JQL to be effective, making it a more valuable tool for proficient users. When asked about accessibility, answers were again mixed. Periodically needed data was described to be found easily, while ad hoc queries done in an exploratory mindset usually were not successful.

> "*I know where the data is in theory, but another matter is that am I easily going to find it. Essential data is not always easily accessible, or the data mass is not filtered enough.*" (Service manager 2)

> "*Finding and accessing data that you need frequently is quite easy, but getting data that you usually don't need is harder. This is partly because of Jira's JQL.*" (Service manager 4)

Senior support specialists agreed that data is most of the time good quality. A few minor hiccups have been caused earlier due to the migration of older systems done in deployment, but these kinds of problems are mentioned to stay in past. The manager also notified that data generated by systems or machines have usually been good quality, but data with human input should be treated with possible error margins.

> "*I feel that data gathered by the system is more accurate than data gathered from the human. You have to analyze human-generated data with a grain of salt.*" (Head of technical service operations)

The team with more reporting needs, the customer operations team, had more mixed feelings about data quality. Two of the service managers mostly considered to data be good quality, apart from a few systems that varied in data quality. The other two remaining service managers pointed out that data required cleaning and transforming in order to get useful information out of data. The manager of the team commented that integrations between systems often had problems, which caused problems in getting the data. Additional remarks were about data input by humans, such as monitoring working hours, as this information had simply contained errors, or there were unclear policies in filling in the working hours.

> "*Comparing estimated hours vs. actual hours in projects is frustratingly hard. This is complicated because reported hours contain errors, and the integration between the working hour reporting system and Dynamics does not always work properly.*" (Head of customer operations)

Specialists from the technical service operations team agreed that data does not require an excessive amount of manual transformation before it is usable. The manager commented that some transformation is needed for the data, but the amount of it was dependent on the system's export functions.

> " *Some systems require data transformation before it is usable, depending on whether the data is generated by machine or human.*" (Head of technical service operations)

Service managers and their manager mutually agreed that the data they needed usually required transformation before it was usable.

> " *If the working hours were reported correctly, my invoicing tasks would be considerably easier. When some of the hours are reported incorrectly, I am usually the one who has to communicate between employees, that could they clarify some of these reported hours.*" (Service manager 1)

The next questions inquired about the number of different systems they required data from. Participants from the technical service operations team required data from approximately five different systems or data sources for reporting. To get through reporting they had to integrate data from multiple sources. Senior support specialist 3 pointed out that the total amount of data sources was much higher than the amount of systems data required from, as server availability reporting consisted of every customer company case company had.

> "*My current reporting tasks require data from each customer environment. The report itself consists of XML files, database queries, and REST queries.*" (Service manager 3)

Customer operations team members, and their manager all had to get data from multiple different systems, except for one service manager. Invoicing was one of the tasks that mostly relied on getting data from multiple systems. The manager of the team had additional tasks that needed data from multiple systems, like project monitoring. Project monitoring was considered to be difficult, as information about planned and actual hours used in the project needed to be monitored using different systems. Finally, different systems had varying levels of granularity on data, which complicated the use of data. When participants were asked whether they needed to integrate data from multiple different systems, three participants out of five needed to integrate data for reporting.

> "*Comparing estimated hours vs. actual hours is incredibly hard. Additional ways to compare these values without too much manual work is required."* (Head of customer operations)

4.1.4 Key figures

All participants from technical service operations teams, except one specialist, agreed that there were some KPIs that they had to monitor periodically. These KPIs included some key figures from SLA, information about tickets, and the availability of the servers. The manager of the team also followed working hours used for certain customers, financial key figures, and profit and loss statements. Most of these figures were monitored on a monthly basis, but the number of tickets received from customers was followed more frequently, as suddenly rising amounts of tickets could be caused by problems in the current version or server infrastructure.

> "*I have to monitor high-priority incidents, and that they are solved in time. I have also developed Jira for our team to show the durations when these types of tickets should be solved, based on the customer organization's SLA."* (Senior support specialist 1)

Participants from the customer operations team followed some key figures regularly. Most of the key figures came from certain standards that needed to be followed based on SLA. Other monitored key figures were about the number of tickets received monthly, have these tickets been solved in the required time, and the current situation between open and resolved tickets. Key figures from SLA included information about the availability of the product. The manager of the team added that key figures from current ongoing projects were some of the metrics needed to monitor. Participants from this team all had to monitor these key figures on a monthly basis.

> "*I monitor SLA breaches, tickets received monthly, and availability of the product. Customer organizations that I work with require reporting of these key figures monthly and quarterly."* (Service manager 1)

All the participants mentioned that these KPIs connection to business was direct. Failing to follow certain standards set by SLA could cause sanctions for the case company. Meanwhile, services that are not mentioned in SLA can bring extra income for the case company. Keeping the service level at predetermined standards ensured that the case company would get their estimated amount of compensation from the product.

When participants were questioned if they knew where the KPIs were monitored from, answers were mixed. Mixed responses were caused by unclear definitions of the actual

KPIs. Some of the participants mentioned that not many of the KPIs have actually been introduced to them as indicators of key performance. However, some of these indicators' importance has been highlighted from SLA, where certain standards have had to be fulfilled for the case company to receive full compensation from the product. When asked how they can access these KPIs, participants answered that some could be seen from various systems, while some of these key figures were not so easily available, meaning that systems required some queries, and transforming the data to reveal the current status of certain key figures. One of the service managers mentioned that self-made data visualizations in dashboards helped keep track of these key figures. Many participants wished for easier access to monitor these key figures. Managers of both teams agreed that access to KPIs was quite unclear. They mentioned that financial key figures were quite easily accessible, but non-financial key figures required some queries and transforming the data.

> " *I have developed some dashboards with Jira. This is the way I usually keep track of the current values of these KPIs."* (Service manager 1)

> "*There are no standard policies on how and when these KPIs should be tracked. Access to these values should be always available."* (Head of technical service operations)

4.1.5 Business intelligence

In this section, participants were first asked whether they were familiar with the definition of BI meant, and then explained how BI has been defined in this study. This was done to clarify that the interviewer and interviewee had the same definition of the BI. Six out of nine participants were familiar with or knew what BI was. Both managers were familiar with the subject. The definition of BI from the participants was heavily associated with large-scale software companies that offer BI systems for end-users.

Four out of nine participants had used or have been in a team where BI tools have been used frequently. Three of these participants had utilized Microsoft's Power BI earlier, and two of these participants mentioned that they have developed their own reports or dashboards with Power BI. Fourth participant who had used BI tools mentioned that the tools that were used were a while ago and couldn't remember the names of these tools. All participants that answered yes to question number 23 mentioned that they found these tools useful. BI tools' ability to integrate the data from many different data sources was found to be useful functionality. This functionality was mentioned to be important, as a well-built BI report or dashboard usually contains correct data that can be accessed by multiple people, instead of many people independently working on the same data. Other mentions about BI tools included, that it gave simple access to data visualization, helped to detect trends based on data, and reports were easily tailored based on the needs of the audience.

> " *Some of my former workplaces had Power BI templates that could be used freely. This helped me with my reporting tasks, even though I myself have not developed these reports."* (Head of customer operations)

Once previous experiences were asked from the participants, they were all asked if they would think that BI tools could be useful in their daily work. Eight people of nine mentioned that this kind of tool could be useful in their work, and the last person clarified that this kind of tool would be useful for his team, but not for him personally.

Technical service operations team members mentioned that this kind of tool would help them, as they could more easily see developing trends based on the tickets they receive. One specialist mentioned that this tool would provide a big help in monitoring the contents of Jira if the data visualizations and filters were provided. The manager of the team also mentioned that the BI tool could provide valuable information, as the data of multiple different systems were integrated, and data would be presented in crosstabs. Final specialist, who mentioned that the BI tool would not help him personally but the team instead, described that BI tools becoming more common could potentially create a positive feedback loop between their team and the product development team. By gathering data from tickets about the product, the information could be shared with other teams, where potential investigations could be done to the product's part that required the most tickets, resulting in fewer tickets for the technical service operations team in general.

> ” *Providing better feedback for product development could improve the product that we work with, which could eventually lead to less number of tickets that we receive.”* (Senior support specialist 3)

Members of the customer operations team all agreed that the BI tool could be useful in their daily work. Two of the service managers thought that getting a fresh view of things with reports or dashboards could help their current reporting practices. The manager of the team mentioned that BI tools would provide help for the team, if the basic templates were on a good level, and team members could access and tailor them for personal use. The manager also comments that other benefits that could come from these kinds of tools are usually data warehousing solutions that are usually made for these kinds of tools, as this would provide a centralized source of data for multiple different stakeholders. Finally, one of the service managers commented that analytical tools like Power BI becoming more common in the case company could potentially help the company to move into more sophisticated analytics in future, such as predictive analytics.

> ” *I feel that I can handle my current reporting needs, with some dashboards and report templates I've made. However, if Power BI had the possibility to predict something based on the data it has, it would help me and the other service managers.”* (Service manager 1)

> ” *Based on a brief introduction of BI that you gave, definitely! As I've mentioned earlier, I have no prior knowledge about available tools that could be utilized for my current tasks. I feel that introducing these new systems could make my reporting tasks easier.”* (Service manager 3)

4.1.6 Summary of interview analysis

When interview answers were analyzed, two different kinds of issues could be spotted: Issues that artifact of this study can impact, and organizational issues. The first type of issue is used to form requirements for the artifact in the following Chapter 4. Organizational issues are further analyzed and discussed in Chapter 5. Tables 5 and 6 display current issues based on the interviews analyzed. In these tables, the subject column displays the interview section where the issue was detected, the issue description column describes the issue, the question section shows in what interview questions the issue was present, and team specific column displays that the issue has been noticed in both teams. To clarify, team-specific columns use abbreviations of the teams, where the technical service operations team is TSO, and the customer operations team is CO.

Table 5: Detected artifact related issues from the interviews.

Subject	ID	Issue description	Discovered in question	Team specific
Reporting	1	Accessing data from Jira can be complicated	5	Yes, CO
	2	Limited experience from other reporting solutions	6, 7, 9	No
	3	More effortless ways to integrate data, and monitor it	6, 7	No
	4	Eliminating manual work, especially tasks done with PRTG, and Excel	6, 7,	Yes, CO
	5	Capability to visualize data for reports	6, 7	Yes, CO
	6	Jira is huge data source, but full potential is hard to capitalize	9,12	Yes, TSO
	7	Data integration is problematic with currently available tools	9, 11	Yes, TSO
Data	8	Cross-checking data from multiple different sources is difficult	12	Yes, TSO
	9	Commonly needed data is found easily, but queries done in an exploratory mindset are rarely successful	12	Yes, CO
	10	Data requires manual cleaning and transformation	13, 14	Yes, CO
	11	The granularity of the data varies	16	Yes, CO
Key figures	12	Key figures are not always easily available	21	No
	13	Key figures require manual calculations, and data transformations to monitor	21	No
Business intelligence	14	Detecting trends is hard with existing tools	24	No
	15	Requires well-designed templates with specific measures and data visualization	24	No

Table 6: Detected organizational issues from the interviews.

Subject	ID	Issue description	Discovered in question	Team specific
Reporting	16	General policies for reporting are missing, service managers do not have consistent ways to report	4, 5, 6, 7	Yes, CO
	17	Tool-specific training is insufficient	5	No
	18	Absence of commonly used general templates	6, 7	Yes, CO
	19	Retrieving information and documentation from product in Confluence	8	No
	20	More transparency in information sharing and data usage between teams	8	Yes, TSO
	21	Unclear responsibilities in internal processes can lead to additional tasks for service managers	8	Yes, CO
Data	22	Data input by humans is often inconsistent	13	No
	23	System integration between Dynamics and working hour monitoring software	13	No
Key figures	24	The definition of KPIs is unclear or non-existent	21	No
Business intelligence	25	Using BI tools usually requires data warehousing solutions	24	No

4.2 Requirements

The objective is to support the use of information for the case company's employees on the operational level by utilizing BI tools. Current challenges include the diversity of data sources, non-optimal ways to query data from these sources, and the fact that data integration is not supported for current reporting processes. The artifact is aimed at providing real-time information for the employees, monitoring key figures of certain teams, and having access to a centralized source of data from multiple different systems that employees use daily. The long-term goal for the use of the artifact is to help people make more data-driven decisions and gather value from analytics to win support for broader analytics initiatives.

Two teams are identified as stakeholders, which work daily at the case company's operational level: The TSO team, and the CO team. Reporting, information sharing, and information seeking are considered to be part of the daily tasks that employees of these teams do. While these teams present some individual needs according to interviews, similar types of problems also occur when employees try to get through their reporting tasks. Limited knowledge of other available reporting solutions was one of the issues identified in the interviews (Issue ID 2). Employees can get used to even non-optimal solutions that are currently available if they do not have previous experience with other working solutions. This is one matter that the artifact can provide value to stakeholder as an optional tool to be utilized when dealing with reporting tasks.

The functionality of the artifact can be presented when considering how it can deal with the problem domain. The interview summary's Table 5 shows that monitoring and comparing data from multiple different sources is currently problematic, and the current tools are not suitable to do this effectively. This can be seen from the summary's issue IDs 3 and 7. Other functionalities that the artifact can provide is giving easier access to data from Jira, which is detected to be an issue in IDs 1 and 6. Another issue emerged from issue ID 5 which is related to data visualization. Issue IDs 12 and 13 show that currently, key figures are not as easily available to monitor, as they require multiple queries or manual calculations just to see their value. These issues were identified to be requirements based on the interviews, and they need to be addressed when implementing the artifact. These issues suit well the functionality of the artifact, as the BI tool is often utilized to integrate data from multiple sources, while providing an alternative way to browse data from certain data sources, like Jira, and it can be easily used to provide data visualizations to visualize certain attributes, such as key figures.

Performance requirements

Requirements based on performance can be harder to formulate, as there is no prior knowledge, or experts to consult for potential suggestions. As the artifact will be mostly used as an internal tool, current stakeholders were not asked about potential performance requirements, but instead, it will be developed further in the future based on their feedback. However, performance is crucial when implementing artifacts of this nature, as it can also affect how the stakeholders experience the usability of the artifact. The reliability of the artifact must be high, and the BI tool should produce accurate and reliable results. Speed and scalability must be handled as well, so the users can process and analyze data in a timely manner. Integrations with systems acting as data sources must be robust and real-time data acquisition should be pursued. Failing to fill the basic performance requirements is likely to make the artifact unusable.

Usability requirements

Usability requirements have gained importance for the third-generation artifact as the user base of the artifact increases. For some of the users, this might be the first contact they have with BI tools, so the importance of usability and ease of use is highlighted. Unpleasant experiences with the tool can affect the user's interest to use these kinds of tools in the future, which is contrary to our purposes of developing the artifact. One of the important goals to achieve in the third-generation artifact is to get rid of person dependency on the reports and dashboards. Visualizations and measures made in the BI tool should be understandable with minimal guidance. In the artifact, this means clarifying how users can filter data with slicers, cross-filter data by clicking on the visualizations, and use drill-through functionality in the graphs. The user interface should be designed to help users navigate through different pages of reports with ease while informing users what kind of data they are currently seeing. Power BI's buttons should be used to be able to reset all the filters currently set and navigate through the pages.

Security and privacy requirements

Security and privacy requirements need to be set on the level at which users currently have access to information. While the CO team's users already have access to Dynamics, where they usually do invoicing based on the hours used for service operations, the members of the TSO team should not have access to that information, as they usually cannot monitor this information. Should the information be available also to the TSO team is debatable, as it can contain information about how much time is used for certain customer companies. While this information can lead to becoming more aware of why certain customer companies require more service hours, it is better to leave the speculation to decision-makers, when they specify data governance policies for the case company.

4.3 Design

In this chapter, the artifact is designed and developed. Acknowledging and fixing design flaws of the previous generations can result in more long-lasting use of the artifact.

4.3.1 Data sources

Designing the BI solution and its architecture includes introducing data integration solutions that are used for the artifact. Existing literature is unanimous about how the data integration flow should be designed traditionally: Data sources should act as a data source for ETL tools, from where data is loaded to data warehouses, where from it can be used in analytical applications (Dayal et al., 2009; Wu et al., 2007; Hovi et al., 2009). An example of this type traditional of data flow can be seen in Subchapter 2.1.2 Figure 4. This poses a risk to the design phase, as the case company does not have existing data warehouse capabilities that we could utilize with our artifact. However, considering the structured nature of the data and its volume allows us to design the artifact in a way that can differ from common implementation methods. Should the data be unstructured, or the amount of data gathered from systems multiple more exponential, the situation would be different. Designing BI implementation without data warehousing solutions is doable, but it does not scale well to bigger environments and can cause more error susceptibility (Hovi et al., 2009, p. 7). The artifact's data integration flow is shown in Figure 12.

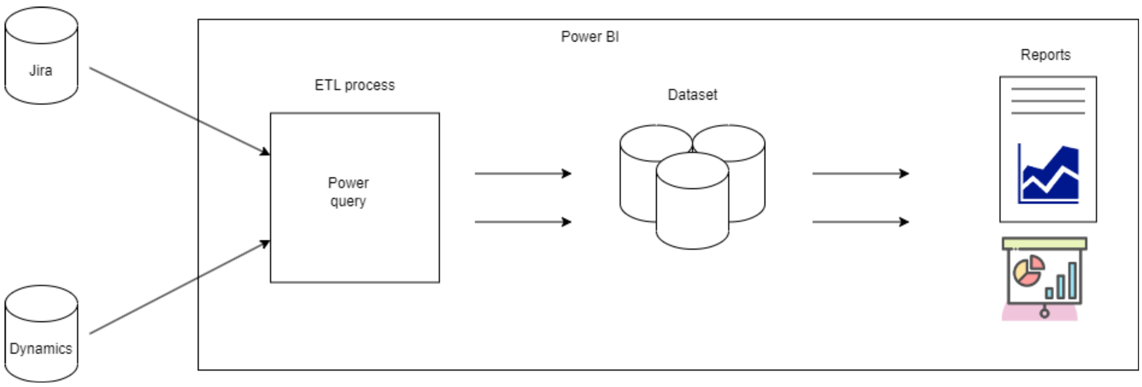

Figure 12. Artifact's data integration flow modelled without data warehousing.

Modern BI tools, like Power BI, which is used for the artifact, store their data in the cloud. This is one of the reasons that this type of design could be possible in this situation, as the data warehouse is not required to hold massive amounts of data. This reasoning only applies to storing the data, as data warehousing is still the most applied solution and is often familiarized with BI. The absence of a data warehouse also affects how to extract, transform, and load the data. Luckily, modern BI tools can handle these tasks more efficiently than their predecessors. Power BI provides Power Query tool that can be used as an ETL tool to aid in loading the data from data sources to data models used for analysis and reporting. Figure 13 below explains how data processes from data sources to reports in the artifact.

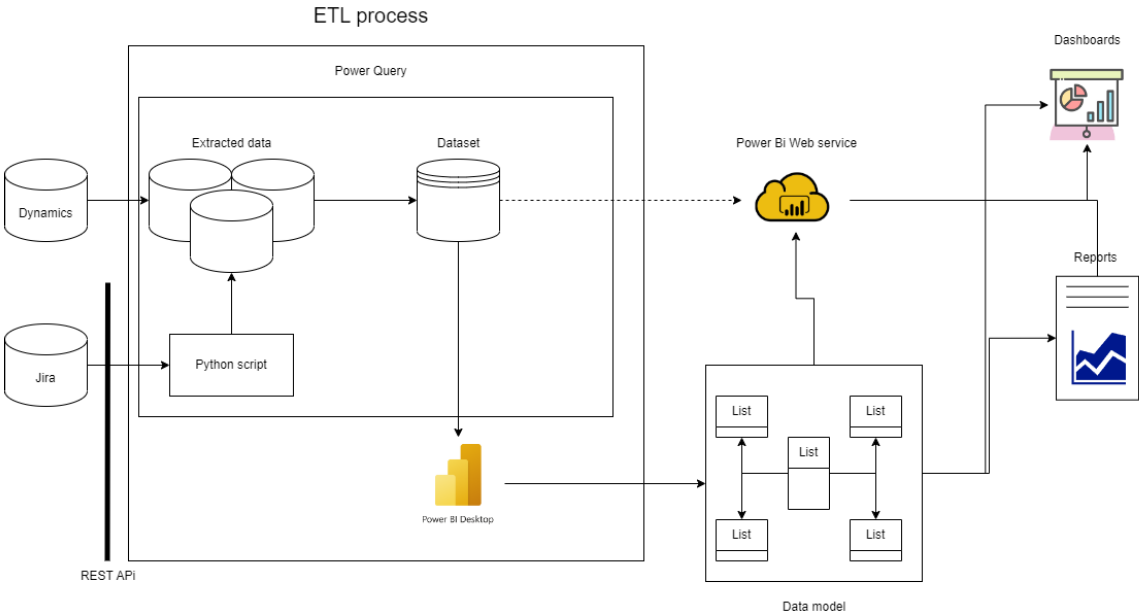

Figure 13. Artifact’s ETL process.

One of the main data sources is the case company’s issue-tracking software, Jira. While offering efficient issue tracking with commercially available plugins, it has been noticed to be inefficient while accessing the data or importing data. Jira also offers the capability to visualize data with commercial plugins, but just with data in the software. By utilizing Jira as a data source in the artifact, the aim is to help stakeholders utilize Jira more efficiently, as an answer for issues 1 and 6. When using Jira as a data source, the ticket ID, its fields, and current status are collected into a row of data. Figure 14 shows Jira’s view from the graphical user interface when stakeholders receive ticket. From the top right category “SLAs”, we can see a calculated field for the duration of when the ticket should be resolved. If the ticket is not solved in that duration, the SLA is breached, and it can cause sanctions to the case company. The duration is calculated based on the ticket’s details from the left side from the values of the type and priority. All the fields from the categories are gathered when data is fetched from Jira’s API, but the number of fields is filtered down in Power BI’s Power Query and only the remaining fields are loaded into the data model.

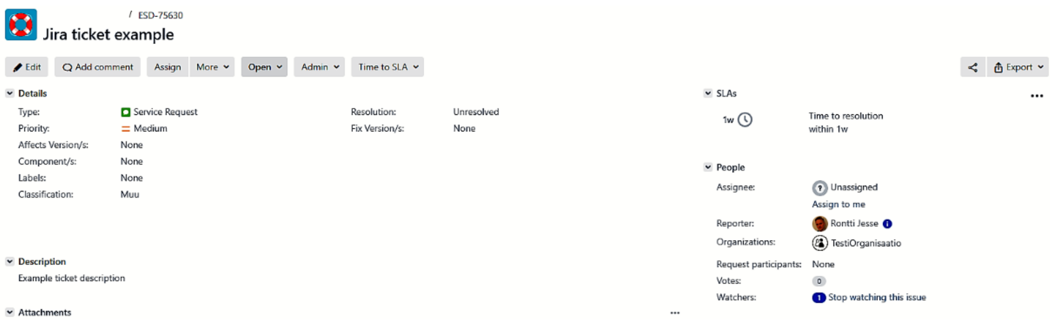

Figure 14. An Example ticket from Jira

Queries are done in JQL, where different clauses are used to extract only the tickets fulfilling certain conditions. For example, when extracting data from Jira to our artifact, we specify that we want to select tickets done to our stakeholder's project starting from the year 2021. The data is accessed using Jira's REST API in Power BI's Power Query. In Power Query, M code is used to transform the data to the desired format. For example, in our artifact's M code script, we declare the variable "URL" to be a link leading us to the case company's Jira's REST API, while using JQL to filter tickets we want to extract. The content of this site, which is visually just text, is then converted into JavaScript Object Notation (JSON) document, which is a commonly used API output for different applications. Once data transformation is done, and data is readable in a table for both humans and machines, Power BI's graphical user interface can be used to select which fields we want to include from Jira in our dataset. Python script is used to map how many seconds the ticket has been in different statuses. This is required to detect predetermined SLA breaches in tickets, as differently prioritized tickets have been set the value that in what time these tickets should be solved. As an example, high-priority tickets, that affect the stability of the product have smaller time durations than they should be solved when compared to low-priority tickets about cosmetic issues. When the dataset is complete, it is loaded into the report, where it can be used in the data model to display relationships with other tables of the report.

Another data source used for the artifact is Microsoft Dynamics, which gets data from the working hour reporting software. This data shows how many hours have been spent on certain types of tasks for different customer companies. As an example, solving service requests are reported in different project codes, while investigating incidents uses another project code. This is because incidents are usually caused by problems encountered with the product, and service requests can be requested by customers because certain types of tasks can be more convenient to complete by the TSO team. Take updating data in databases, for example. Offering solutions to mass update data with SQL is more convenient than updating data through the graphical user interface. Adding Dynamics as a data source can provide help for service managers, as Power BI can display resources used for certain tickets. This automates their usual process of manually counting distinct hours used for certain tickets.

4.3.2 Data modelling

To improve the technical perspective of the artifact, existing literature on the tool used was studied. This also ensures that rigor is taken into consideration when constructing the artifact. Reviewing existing literature on Power BI was done in order to get answers for two issues that were detected during the development of earlier generations: Handling multiple data sources' relations and fixing automatic date and time intelligence.

An automatic date/time option might be a useful feature for users that deal with only a single data source, when it is turned on Power BI creates and allows easy browsing of the data by date, monthly, quarterly, and yearly basis. However, when multiple data sources and tables are introduced to the report, slicers earlier set to filter data suddenly stop working, because it is only set on a certain table's date. To solve this issue, Ferrari and Russo (2017, p. 66) introduced a method for creating and using tables for date and time. Creating these tables is required in order to do time-intelligence calculations and functions. Ferrari and Russo describe the appearance of these tables in reports as a date table is always needed in the models, while a time table appears less frequently. This is dependent on the level of detail that is needed to know about the date of the transactions. For example, in our artifact, we want to know what day our tickets arrived in our system, but while solving incidents that cause downtime, it is a matter of hours and minutes. Both date and time table have been created for the third-generation artifact, as multiple data sources require date table to have functional slicers that enable filtering the data based on time. A time table has also been created, but it does not currently have relations to other tables in the model. In future generations, a time table could come in handy, if one of the potential data sources, PRTG monitoring system, is integrated into the artifact. In general, building these custom tables for date and time is preferable to using automatic date and time handling capabilities provided by the tool itself (Ferrari, 2020).

Another issue detected in the earlier generation was that the current data model is not well defined, as currently is only a few tables from data sources linked to each other via a date table. This makes offering self-service BI a difficult task, as data or its model is not easy to read or understand. Development during earlier generations has not been as structured or planned, as it has been now during the third-generation artifact. This has led to the use of non-optimal solutions, but as the goal for third generation artifact is to raise awareness of analytical solutions and to promote the value this software can create, they should be clear and well-built to give a good impression about this current technology used in the artifact. In Figure 15, the non-optimal way of data modelling is displayed.

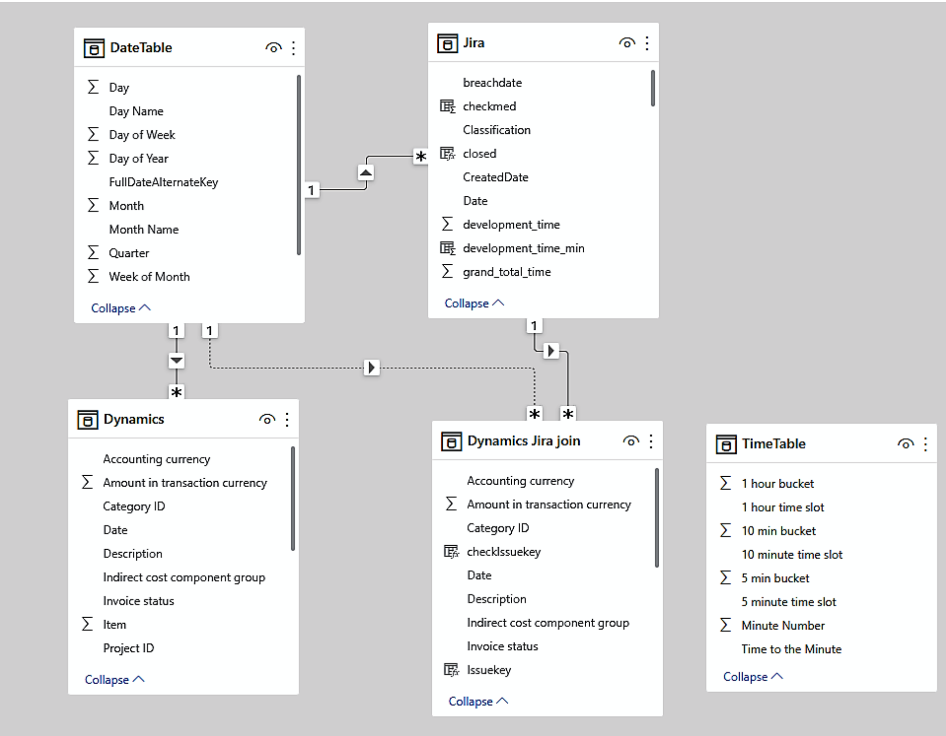

Figure 15. The second-generation artifact data model from Power BI Desktop's Model-view.

To clarify the data model, additional ways to model data in BI tools were explored. One of the most mentioned schemas, star schema, was selected as potential way to model data. While the artifact operates without a proper data warehouse solution behind the scenes, a star schema is highly used in the data warehousing industry and is considered the standard way to represent analytical models (Ferrari & Russo, 2017, p. 16). Star schema divides tables into two different categories: Dimensions and facts. Naming tables in Power BI, while using star schema, usually means either putting “Dim”, or “Fact” in front of the table while naming them, which clarifies is the table is considered to be a dimension or a fact table. Star schema’s name comes from its design, where all dimension tables are put around the single fact table, forming the typical figure of a star schema (Ferrari & Russo, 2017. p. 15). However, our data sources do not come through data warehousing solution, which requires a more flexible approach to the data model that is used in the artifact. This requires a snowflake approach, which is a variation of star schema, and it allows dimension tables to be linked to other dimension tables (Ferrari & Russo, 2017, p. 18). While adopting this sort of hybrid model between star schema and snowflake schema might violate the rules of star schema, it is the solution that needs to be used for the artifact because the artifact lacks a data warehouse. A picture of this hybrid schema can be seen below in Figure 16.

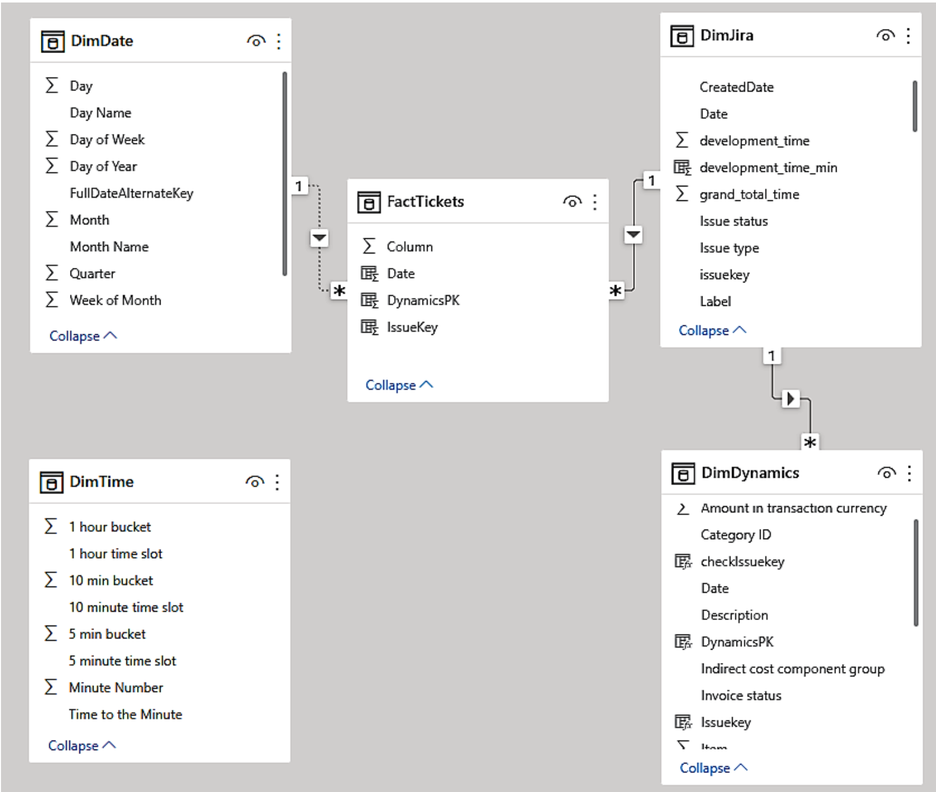

Figure 16. Hybrid schema between star schema and snowflake schema used in the artifact.

Creating a hybrid-like schema for the data model felt appropriate. Current tables are extracted from the data sources as they are, as big tables, while solutions using data warehousing usually use more time in dividing the data into smaller tables. For example, DimJira table could be divided into different categories that we saw earlier in Jira’s example ticket in Figure 14. If the case company had data warehousing solutions, using just a star schema would have been the proper way to approach the data modelling used in the artifact.

4.3.3 Tool-specific design

In preparation for increased user count, certain things needed to be addressed when designing reports in Power BI. Increasing user count emphasizes the importance of usability requirements. This is pursued by creating a more uncluttered report design, while adding functionality, such as interactive buttons for the user. Different types of charts and cards used in the report need to have clearly defined titles, to explain to the users what they are currently seeing. The visualization is clear, when the viewer can understand what it shows, and finds answers to their questions or gains insights about the data's features (Koponen & Hildén, 2019). While upcoming users do not yet have the possibility to make their own reports, the meaning of slicers used to filter the data plays a big role when helping users to get the data they need. Overall, the report's pages, titles, charts, and different visualizations used should be self-explanatory. This can be done by giving pages and different elements descriptive names that what is happening on them.

As mentioned in Subchapter 4.2, performance requirements are important for the current generation's artifact. Slow artifact gives bad impressions to the users and makes the artifact unusable. The quality of the data can make or break the artifact, as the reliability of the tools depends on the quality. Steps to improve performance has been taken, in the form of removing the automatic date table and creating a custom one to replace it. This was done for both performance and modeling reasons. Redundant measures, calculated columns, and pages have been removed, to increase the load speed of the report. The report's data model has been reassessed to display relationships more clearly. These actions and the absence of problematic many-to-many relationships in the data model allow the report's pages and visualizations to load faster than in other generations. Monitoring performance by using Power BI's Performance Analyzer was also done to identify potential bottlenecks in the report.

Connecting the data sources to the BI tool to build reports requires additional ways to calculate measures or columns. These types of measures can be done by using Power BI's quick measures, which support mathematical operations, aggregating by categories, filtering, time intelligence, and totals. Calculating measures using quick measures allows users to do these types of calculations using the graphical user interface, by generating data analysis expressions (DAX) behind the scenes. These quick measures provided by Power BI can be useful for common calculations, but when data analysis is based on text fields or require more logic behind calculations, the user needs to write their own DAX statements. In the artifact, tens of different measures and calculated columns use DAX. Take Dynamics as a data source, where employees report their working hours by copying the issue key of the ticket and the title paste it on the working hour reporting software. By adding the calculated column "checkIssueKey" to DimDynamics, which prints a boolean value based on the description of the reported hour. Should this value begin with three letters symbolizing the project code of the team's Jira project, it either prints true or false, to signal if this row is related to some Jira ticket. The same kind of logic is used to gather issue keys that, which signals that these many hours have been reported for certain tickets. In the DimJira table, calculated columns are used to convert seconds to minutes and then to hours, to track how many hours the ticket has stayed in certain statuses. To detect SLA breaches, Jira calculates a certain duration based on the priority and type of ticket, which is then compared in Power BI to the total sum of time. If the total sum of time surpasses Jira's calculated duration, the ticket is due. In addition to these calculations, additional measures and calculated columns have been created, to change data types, create dynamic URLs for tickets, and create time intelligence functions.

Finally, to understand the decision-making behind making reports interacting, we must explain the parts of Power BI. Power BI includes three different basic elements: Power BI Desktop, Power BI Service, and Power BI Mobile. As the name suggests, Power BI Desktop is a desktop application, which is used to connect data, create relationships for the data, and create reports. These reports can then be published online, through Power BI Service, which is an online SaaS used to browse these reports. Power BI Service also offers ways to create reports from existing dataflows, and edit existing reports, but with limited functionality. The last of the elements is Power BI Mobile, which is a mobile application, which is not used in this thesis. Should the artifact be successful at what it aims to do, these reports can be published to Power BI Service, where they can be used by the employees in the near future. Providing interactive buttons for these employees is vital, as they might not possess the same permissions as the current developer does. This means that they need to be able to filter the data from the interactive elements of the reports while utilizing buttons for page navigation.

However, certain limitations have emerged during the development phase. The case company's current license for Power BI is "Pro". This means that there are currently a limited number of licenses that can be distributed in the case company. The problem comes when users, even with read-only permissions, must possess the same level of license to access the reports. A higher-level license, Premium, would allow access for every employee in the company to read reports, but this solution is mostly used by bigger organizations. Buying a Premium level license for Power BI for the case company would cost approximately the same amount of money as buying 500 Pro level licenses (Meltlake, 2022). This requires exploring potential ways to get access for users in the upcoming generations.

4.4 Demonstration

In this subchapter, the artifact's functionality is demonstrated by showcasing parts of the report and by providing illustrative scenarios. The following screenshots seen in this subchapter are taken from the built artifact's CO team's report. The functionality will be compared and demonstrated against the detected issues from interview results while highlighting the unique benefits that BI can offer. Certain parts of the screenshots have been blurred, to hide information either from customer companies, or employees of the case company.

4.4.1 Analyzing historical trends

BI tools excel at categorizing large volumes of data, which can help in extracting meaningful insights. Giving access to the right employees with an exploratory mindset can help companies recognize phenomena that are currently affecting the situation.

In Figure 17 a glimpse of an opening page called the "Front page" is shown where the users access the artifact. The front page gives an overview of the current ticket situation based on the Jira data. From the left side of the report, it can be observed what kinds of tickets have been completed the most during the year 2022. Below the pie graph and the table, average and median ticket durations are given. Should the user want to observe the situation of the specific customer company, a slicer called "Customer organization" is offered, which opens a drop-down list of all available customer companies. When the slicers are applied, the visualizations of all pages are filtered based on the selected slicer. The visualizations of the Front page display the values related to tickets, based on the timeline slicer, which can be used from the top of the visualizations. The area chart below the timeline slicer demonstrates the cumulative sum of the tickets by showing a comparison between resolved and open tickets. Based on the area chart, users can see what number of tickets are not being solved monthly. Below the area chart, bar graph visualization shows us similar information, but it is easier to distinguish the monthly amount of ticket that is being solved or has been left open. The line graph at the bottom demonstrates how that what have been average ticket durations during each month. Currently, the year 2022 is selected, which has filtered the information of the page to that year's data only. The bottom toolbar shows all available pages that can be accessed in the report.

Figure 17. Screenshot from CO team's report's front page.

To observe where the service hours are spent in the TSO team, "Service hours" are displayed on the next page as shown in, which is displayed in Figure 18. From the Service hours page, more filters are available in the rounded rectangle on the left side. From here the users can search for specific ticket information, service hours that are used by a certain employee, service hours used by customer companies, information based on ticket priority, and information based on issue types. Clicking certain slicer opens a search window and a drop-down list based on available values. When the user uses these slicers by selecting different filters to filter the data, the visualizations, and the table on the page react to these filters in real-time, by changing the visualizations. Under the timeline filter, a similar line graph is presented on the front page, however this time with service hours instead of the average duration of tickets. These service hours consist of working hours reported to certain project codes of customer companies. Under the line graph, the table of the hours shows how many hours are reported for each issue. Currently, the table is ordered by descending values, starting from the ticket that has the most hours reported with current filters. In the table's row quantity of the service hours used for a ticket, the issue's identification key, the link to the Jira page of the ticket, and the current status of the key are displayed. Below the table, visualizations of most service hours reported for customer companies are shown, in addition to visualization of most service hours used to ticket.

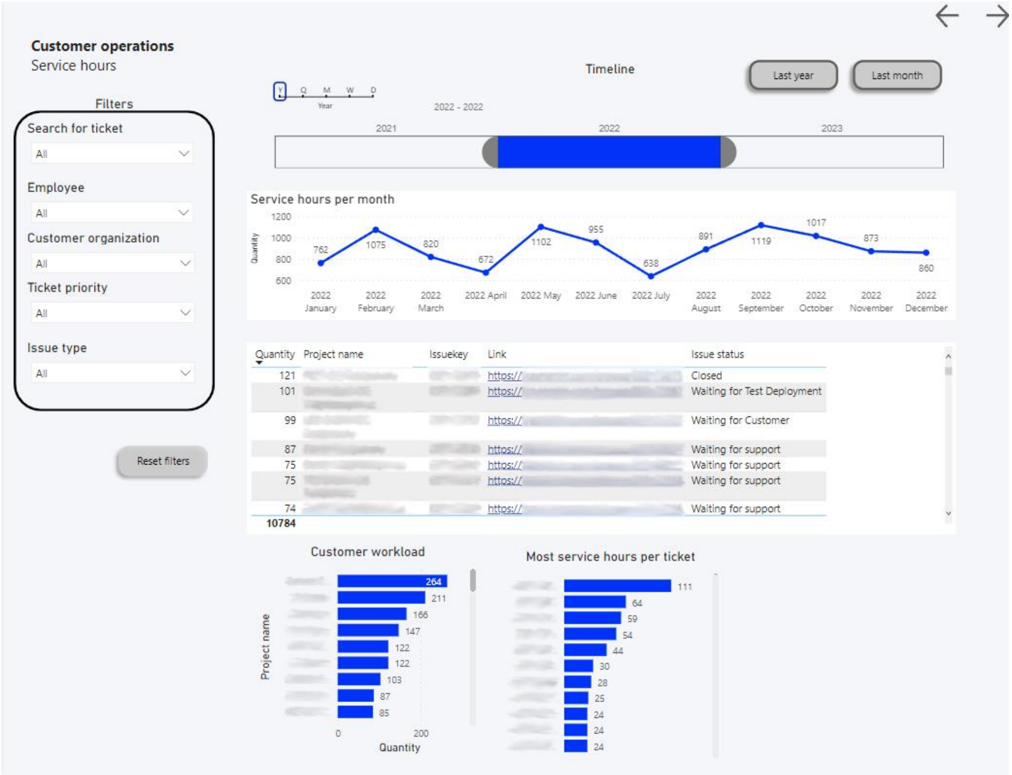

Figure 18. Screenshot from Service hours page.

Analyzing historical trends like this could not have been done in Jira without external tools. Members of the stakeholder teams could have utilized Excel to draw similar kinds of data visualizations, but investing time in these types of tasks would be highly unlikely as stakeholders already spend a lot of time in reporting-related tasks. The artifact in this setting combines multiple data sources while providing capabilities to perform data visualization.

4.4.2 Interactive features

Power BI itself is quite interactive already when users are aware of its possibilities, as visualizations and tables update based on when users click on a specific month or customer company. To give users an even better experience, buttons were added to the artifact. Every page includes small interactive arrows on the top right corner to enable navigating to the previous or next page. The date timeline slicer was also supplemented with quick buttons to filter data from the previous year, or previous month. These buttons can be seen in Figure 19.

Figure 19. Timeline slicer and buttons for page navigation and date modification.

Timeline slicer operates by the user simply highlighting the years, quarters, months, or weeks from when data is needed. The date's granularity can be adjusted by selecting Y, Q, M, or W from the top left corner of the picture's timeline slicer. To clarify the buttons' responsiveness, the button was set to get borders when it was active as seen in Figure 19 from the button "Last year".

Occasionally users can end up filtering too much data with slicers. As different pages include different types of slicers, the user might forget to reset the slicer on the previous page, meaning that the data is filtered by that slicer on every page. This was noticed to be an infuriating issue, which was not so easy to notice as the number of pages in reports grew. To solve this problem, a "Reset filters" button was added under the slicers, as can be seen in Figure 20. Another solution could have been to add a display to show current filters affecting the visualizations.

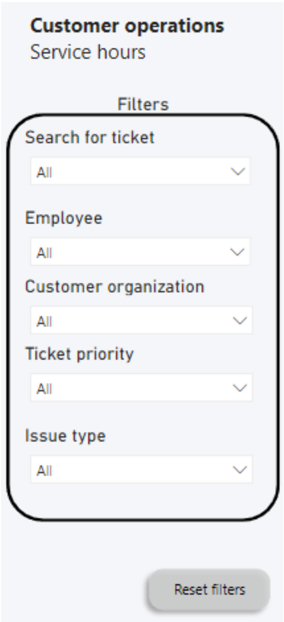

Figure 20. Reset filters button.

Filtering data does not always need to be done from the slicer. Users can click the visualizations to filter the data as well. From below we can observe how the user wants to search for incidents that were not solved in time, meaning they breached their SLA. While having issue type slicer as incident, the user decides to want to only filter these kinds of tickets that have been priority high or blocker. This can easily be done by clicking priority visualization on the page. Figures 21 and 22 show how visualization reacts to this.

Figure 21. SLA page.

Figure 22. SLA page filtered by the user.

When the section of the visualization is clicked, the data is filtered further from the existing visualizations. For example, Classification and Organization bar graphs highlight the amount of high or blocker priority tickets in darker blue and the line graph shows when these ticket breaches have happened.

These features and functionalities have been introduced or made for the 3rd generation's artifact when considering earlier set usability requirements. Users should be able to operate with reports whether they used them on a web page or embedded in some tools. These currently implemented ways to make the artifact more interactive are a great start to introduce users to how to use reports and Power BI. After users have utilized the artifact in reporting, they probably will have suggestions and more requirements that can be used to improve future generations of the artifact.

4.4.3 Analyzing ticket-specific data

During interviews, service managers expressed their frustrations about gathering data from Jira. Jira was seen as a potentially great data source, but writing queries with JQL complicated the use of the tool. Invoicing-related tasks were also considered to be time-consuming, as this meant exporting Excel files from Dynamics and then going through them. This ended up being one of the issues which were mentioned to need some automatization.

To help service managers with these issues, the artifact was designed to show how many service hours have been reported to be used for specific tickets. This information can be accessed from the "Resources used in tickets" page of the report. A view of this page can be seen in Figure 23.

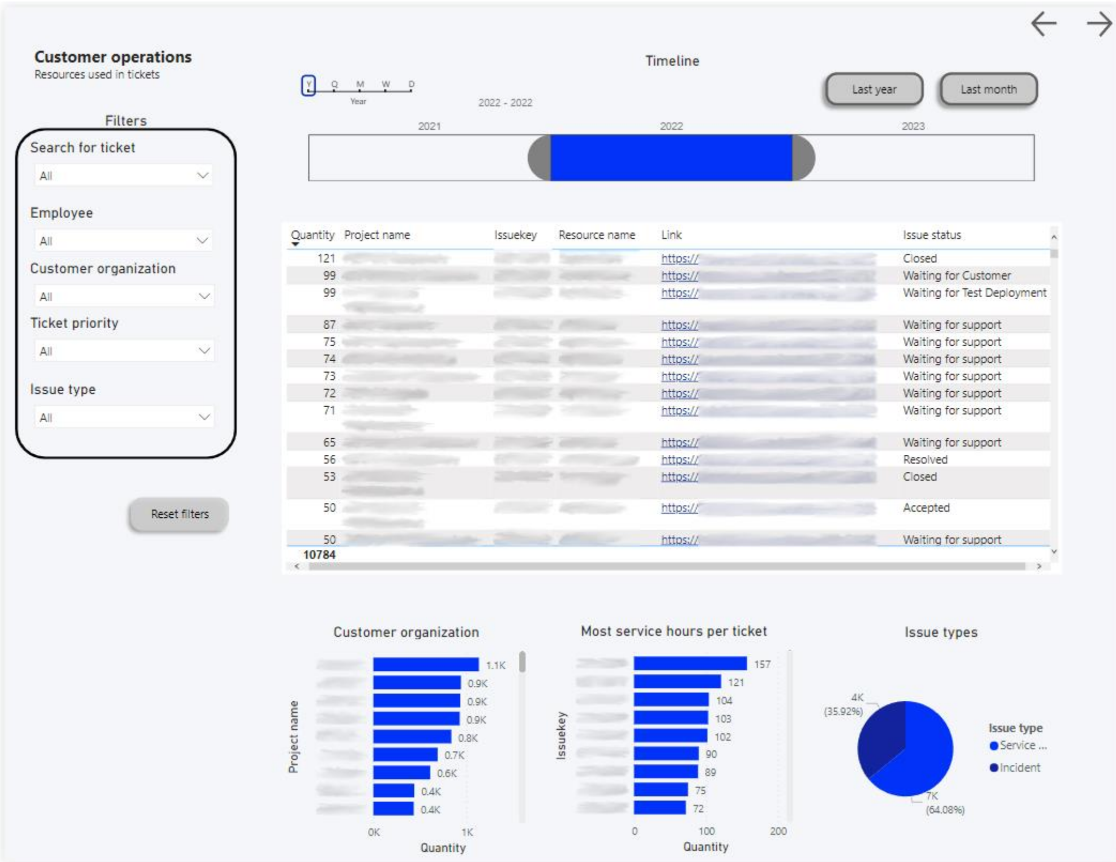

Figure 23. Resources used in the tickets page.

On this page, service managers can filter information from their own customer companies and see information on how many service hours has been reported to certain projects. To see how many hours have been reported for a certain ticket, service managers can use the "Search for ticket" slicer from the top left rounded rectangle. When slicers are set according to their wishes, the table in the middle of the page shows how many hours have been reported to the chosen ticket. The table displays the quantity of the hours, the project name where service hours were reported, the ticket's issue key, who reported these hours, the link to the ticket itself, and this ticket's status. The artifact can also be used for cross-checking the data or in monthly reporting itself, as service manager can filter their customer companies from the slicer and set the date of service hours to the last month from the timeline slicer at the top. Additionally, the "Last month" button can be used to set the timeline slicer to only include the previous month's reported hours. Contents of the table can be exported to Excel, which can provide easier access to service hours than exporting files from Dynamics.

4.4.4 Differences in team-based reports

The current difference between the technical service operation team's report and the customer operation team's report is that the technical service operation team's report has limited access to the data. This is done because service managers have wider access to data, such as service hours that support specialists have reported based on the project codes. Giving TSO team members access to each other's reported working hours would conflict with the currently set accesses they have with data.

This also sparks new discussions that have not been addressed yet. Would it be okay to inform members of the TSO team about how their working hours have been distributed between customer companies and their project codes? Current tools that this team uses cannot display the data, as they don't have the right to access the working hours data from Dynamics. In Figure 24, the artifact's "Service hours" page is shown where hours used in tickets are displayed.

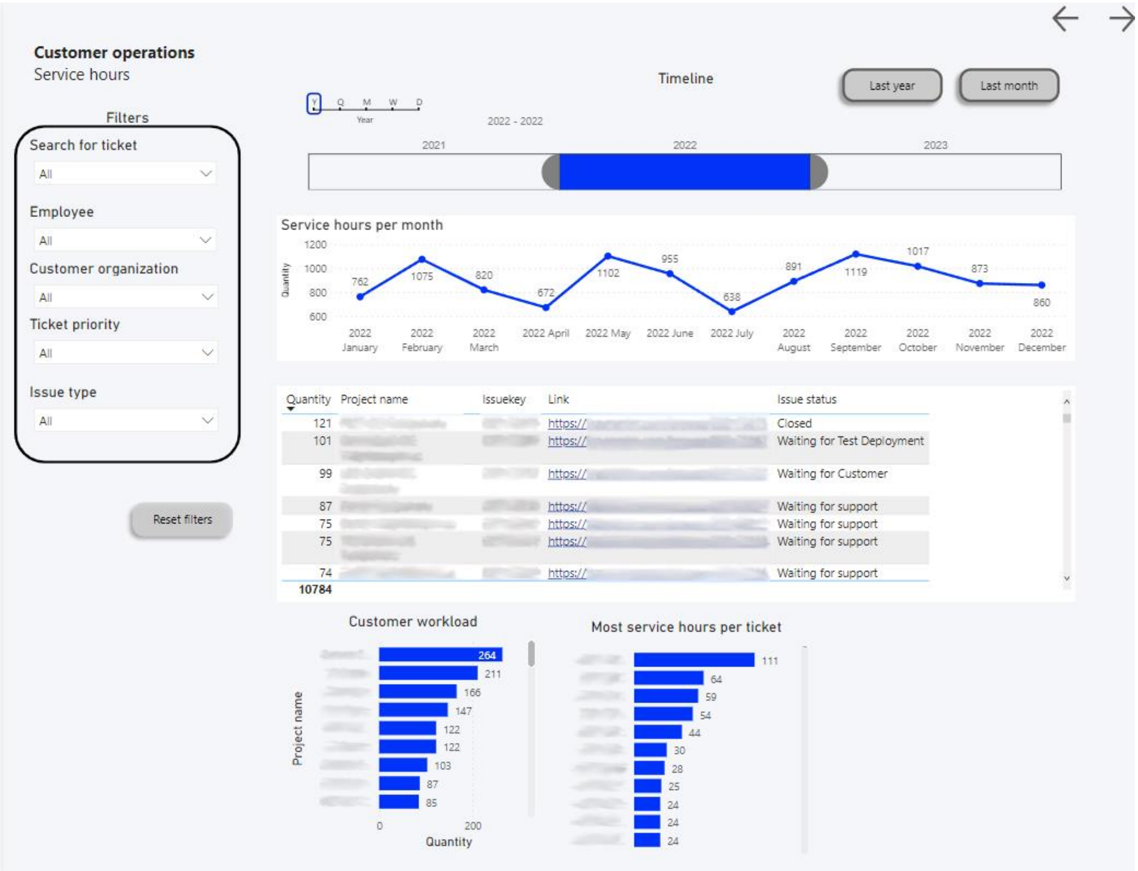

Figure 24. Service hours page in the report.

Giving the TSO team members access to see this page could potentially help them get insights about which kind of tickets usually are most time-consuming, but members of the team could figure that who has used a certain number of hours in those tickets. This is one of the examples of how inadequate data governance can harm analytical initiatives, at the cost of innovation in this case.

4.5 Evaluation

Evaluation of the artifact is done by comparing how requirements and issues that emerged from the business environment are handled by the artifact. In the previous demonstration chapter, we demonstrated how the built artifact can provide value for the stakeholders via illustrative scenarios. Using illustrative scenarios to demonstrate the artifact's utility is the second most used evaluation method used in DSR (Peffers et al., 2012). While illustrative scenarios have been mentioned to provide less strong evidence of efficacy than the most popular evaluation method of using case studies (Peffers et al., 2012), it is important to note that requirements are based on the issues that were discovered during gathering empirical evidence from interviews. Similarly, data for case studies can be gathered from interviews (Hancock et al., 2020).

New limitations that have emerged during the designing of the artifact show that additional iteration of the DSRM is needed. This was found in Subchapter 4.3.3, where tool specific design of the artifact was described. The limitation was that the case company currently has limited access to Power BI Pro licenses. The case company has distributed these licenses to selected users of the tool, but to view these reports created during the thesis, even the readers would need to possess a Power BI Pro license. This delays the possible implementation, as the artifact cannot be used right away. More research is required to find out other possible ways to use these reports, such as embedding them into other tools. Nevertheless, the study managed to produce a working implementation of the artifact, and it can be developed further by gathering feedback via demonstrations, or locally.

To evaluate the artifact, we compare how this study's artifact can help stakeholders with issues that were detected from interviews. These issues and the artifact's functionality that can be used to solve the issue are displayed in Table 7. Issues are color coded based on how well the artifact can support the detected issue. Green means that the artifact can be utilized to solve the issue. The yellow color indicates that the artifact can be utilized partly to solve the issue. The red color is used to show that the artifact could not be utilized for the issue.

Table 7. Evaluation of the artifact based on the issues revealed during the interview.

Subject	ID	Issue description	Artifact's functionality that helps with the issue
Reporting	1	Accessing data from Jira can be complicated	The artifact offers ways to browse, visualize, and explore data from Jira with simple graphical user interface
	2	Limited experience from other reporting solutions	BI tools are commonly used as reporting tools. The artifact can be used alternatively to some existing tools, or it even can replace some of the tools used.
	3	More effortless ways to integrate data, and monitor it	The artifact currently supports only data from some of the data sources that stakeholders usually use. These data sources are Jira and Dynamics. This can be partly observed from Subchapter 4.4.1.
	4	Eliminating manual work, especially tasks done with PRTG, and Excel	Service managers have the possibility to use the artifact's Service hours page, as demonstrated in Subchapter 4.4.3. This allows gathering Dynamics data easier than it is currently done with current tools used in reporting.
	5	Capability to visualize data for reports	The artifacts current report templates provide simple data visualizations based on the information gained from the interviews. Data from the reports can be filtered which makes it possible for stakeholders to take screenshots of the visualizations for their own reporting needs.
	6	Jira is huge data source, but full potential is hard to capitalize	The artifact currently accesses every field used in the case company's Jira. Jira can fully be used as a data source in the artifact and utilized to the utmost.
	7	Data integration is problematic with currently available tools	The artifact as a BI tool allows the integration of multiple different data sources into the system.
Data	8	Cross-checking data from multiple different sources is difficult	Current templates allow browsing the data at a limited level with provided lists.
	9	Commonly needed data is found easily, but queries done in an exploratory mindset are rarely successful	The artifact allows stakeholders to browse the data in ways it has not been used before. This can generate new insights and help detect problematic parts of the product. This is discussed in Subchapter 4.4.4.
	10	Data requires manual cleaning and transformation	The artifact required data modelling and used ETL tools to prepare the data for the reports. This data can now be accessed from the artifact and can potentially be prepared to give out the required data for stakeholders easily.
	11	The granularity of the data varies	Some of the data can be accessed with high granularity in the artifact. For example, data can be filtered to show yearly, quarterly, monthly, and weekly. This can be seen in Subchapter 4.4.2.
Key figures	12	Key figures are not always easily available	The current state of the artifact allows easy access to some of the key figures. Such as the number of breaches, and the current situation between open vs. closed tickets. This can be observed in Subchapter 4.4.1.
	13	Key figures require manual calculations, and data transformations to monitor	Measures and calculations have been made in the artifact to observe key figures more easily.
Business intelligence	14	Detecting trends is hard with existing tools	The artifact offers multiple ways to observe historical trends, like in Subchapter 4.4.1.
	15	Requires well-designed templates with specific measures and data visualization	The artifact currently consists of two separate reports, that can be used as templates to build better, and more tailored reports, based on the stakeholders' needs

5. Discussion

This chapter aims to discuss the findings of the thesis. The chapter also utilizes existing background literature of the field to relate these findings to this thesis. The role of the artifact and its potential opportunities in the future for the case company is reviewed. In total, this chapter aims to provide answers to the main research question RQ1: "*How can business intelligence be effectively utilized at the operational level of the case company?*"

The artifact in its current state has the potential to generate value for its stakeholders. However, to build sustainable value, the artifact must be further developed based on stakeholders' needs. Current functionality shows potential in how it can be used alternatively in reporting tasks, but to generate value, not only the data refreshments are needed, but the artifact itself must be improved based on the feedback it requires. For example, should the service managers want to export data from the artifact's lists to help them with their invoicing tasks, additional fields to the tables should be added. This activity would normally be part of the DSR process as a *Demonstration* activity. However, limitations and time constraints caused this part to be left out of this thesis, and it will be done later.

Development of the third-generation artifact started by defining the problem, which was done by interviewing the members of the stakeholder teams. This was done in order to detect what are the current issues in reporting that affect operational-level employees. However, during the interviews, issues relating to reporting emerged on a wider level that the artifact itself could influence. These kinds of issues were introduced in Subchapter 4.1, which were shown in Table 6, and they were referred to as "organizational issues" as the artifact could not directly have an impact on these issues. In addition to the developed artifact, I believe that these current issues can provide valuable information for the case company to consider. Some of these issues and suggestions on how the current situation can be improved are introduced in the next paragraph. The interview included all four service managers from the case company, as well as three senior support specialists out of five available. This information could help current decision-makers of the case company to gain insight into how operational level's experienced employees see the current reporting solutions. Subchapter 4.1, and this paragraph answers the RQ2: "*What are the current challenges faced by the case company's employees in performing reporting related tasks?*"

Many of the organizational issues that were detected reflected the absence of data and analytics strategy. These issues were issue 16, "*General policies for reporting are missing*", issue 18, "*Absence of commonly used general templates*", and issue 20, "*More transparency in information sharing and data usage between teams is required*", from Table 6. As information and data increases in companies, data and analytics strategies should be introduced. One of the ways to measure a company's analytical level is presented in the thesis by Davenport et al. (2017), in Subchapter 2.3. If the company wants to pursue developing its analytical capabilities, a road map for this process has also been introduced in Subchapter 2.3.1 (Davenport et al., 2017). This could help the company identify the ownership of the data, which allows different teams to hone their data handling regarding specific types of data. A successful data strategy could help employees to handle data better, as general guidelines and policies are introduced, and instruct how the data should be used and reported. In addition to this, employees should be guided to use certain general templates, to promote and train them to use similar reporting policies. Table 6 issues 17, "*Tool-specific training is insufficient*", and 22 "*Data input by humans is often inconsistent*", could also be affected by designing data and analytics plan. However, designing data and analytics strategy needs to be done by executive managers of the company to be effective. It is the only way to sustainably transform the company, but it requires active sponsorship from one or multiple members of the executive level, as analytical initiatives need to actively be included in the company's strategy. If the analytical initiatives are not pursued, the company's analytical development is hindered, and the company has a risk of falling behind its competitors. This is how the case company can enhance its current analytical maturity level if the support comes from the executive management level, and it provides an answer to research question RQ3: "*How can the case company enhance its current level of analytical maturity?"*

Utilization of BI tools is currently happening in the case company, but only on a limited level. Sectors that BI tools are used in are the financial department, HR, and executive level of management. Data and analytics strategy is non-existent, or it has not been informed to all levels of the company. Executive-level initiatives are not made for data or analytics, but instead, the sponsorship comes from the managerial level. This causes the use of analytics to be localized, and the use of data is not discussed between different teams. These points indicate that the use of data and analytics is on the lower levels of analytical maturity models in multiple elements. The current situation of the case company from the analytical perspective creates a possibility to prove the value of analytics in smaller-scale projects with modest targets. Gathering a string of successful smaller-scale projects can be documented for stakeholders about the value gained from these initiatives, which can lead to raising awareness about the use of data and analytics, which can finally attract the attention of the executive leadership. This is how the case company can enhance its current level of analytical maturity from the situation where only managerial sponsorship is supportive towards analytical initiatives and provides an answer to research question RQ3.

Non-existing data and analytics strategies also caused issues during the development of the artifact. If the artifact were implemented currently as it is, the amount of benefit gained for the TSO team would be relatively low. This is because the case company has not properly clarified the current data governance. By allowing employees access to sources that they currently can access themselves, senior support specialists can only get access to Jira and its ticket-related data. This leaves out information such as service hours used per ticket, which can be an important factor to monitor and gain an understanding of why certain types of tickets take longer to complete than others. This matter requires decision-making from the current management.

To answer the main research question RQ1, "*How can business intelligence be effectively utilized at the operational level of the case company?*", interviews were held with the employees working at the operational level. This was done to gain insight into current solutions used in reporting tasks, while the subjects discussed were related to BI. The interview's main subjects were reporting, data, key figures, and previous experience from BI. After interviews were done, the results were analyzed in Subchapter 4., to detect potential issues which could be solved with BI tools. Some of these potential issues could be viewed as requirements themselves, while other additional requirements were made to ensure the functionality of the artifact in Subchapter 4.2. To demonstrate the use of BI, the artifact in the form of multiple Power BI report templates was designed and developed. Subchapter 4.4 introduces some of the possibilities of how BI can be utilized in the case company's operational level, such as observing time series data about the number of tickets received between certain intervals. BI also allowed easier access to analyzing data from multiple data sources than current reporting tools, as seen in chapter 4.4.3, while eliminating potential manual work done by users who had to export the data from Dynamics. Other ways that the BI tool's functionality can be utilized were giving stakeholders the capability to visualize data easily, filter this data either by using slicers or interactive buttons and give easier access to key figures used in reporting. These key figures included showing the current amount of open vs. closed tickets, showing the amount of SLA breaches that happened in tickets because they were not solved in the proposed time, and showing the total amount of tickets received from certain companies. To be able to continue utilizing BI effectively, the case company must include analytical initiatives in their strategy and aim to continuously strive towards utilizing data more in their decision-making.

5.1 Limitations

One of the current major limitations was discovered during the design activity of the artifact in Subchapter 4.3.3. This concerns the availability of the BI tool, as currently the number of Power BI Pro licenses is limited. Users require a Pro license to access Power BI Service from the web to view report templates done as the artifact. This current situation compromises the artifact, as it was designed according to Imhoff and White's (2011) suggestion to provide a self-service BI tool for the users. This requires additional solutions to give users access to the report. One of the potential solutions could be that these reports could be embedded into Confluence, where most employees access product-related information. This limitation was one of the reasons why DSR's process needs to be iterated again, as the current third-generation artifact cannot be utilized properly in the current state.

Another major limitation was that sharing data from the contents of the TSO team's report might not be allowed according to current data governance principles. Support specialists do not have access to Dynamic's data by themselves, so additional clarifications need to be made before it can be released for them. Leaving the data out of the report could harm the BI tool's potential for innovation, as the amount and variety of the data are significantly lower. This limitation could be solved by making the data anonymous, by only showing how many service hours are reported for each ticket. This solution, however, might still conflict with current data governance principles, as tickets are usually assigned to a single person, and other employees could easily guess who has reported the hours for specific tickets. This limitation is easier to solve than the license limitation, but the time constraints of the thesis caused this limitation to be left unsolved.

5.2 Future research

This study provides a starting point for the case company to pursue the use of BA. As BI mostly deals with descriptive analytics, the further development of these analytical applications could potentially help case company to predict upcoming events, in the form of predictive analytics. However, to pursue more sophisticated form of analytics, the BI and data it uses must be refined further. As more complicated methods are being developed, the data's quality and velocity need to be at a higher level. Potential future research subjects are developing the current BI reports to include more data sources and making the artifact suitable for other teams of the case company. Including more data sources, such as PRTG monitor, could help stakeholder team members to gain more insights into why incidents happen in certain customer companies and help them identify causes for these incidents. Should the artifact be successful and provide value for stakeholders, other teams of the case company might also be interested in the artifact. As the artifact already has data integrations to Jira and Dynamics, developing the artifact further to serve other teams' purposes would not be difficult, as it would only require editing current queries that gather the data from the systems. Once data from other teams' project codes has been gathered, data visualizations and related key figures of the team can be easily visualized and presented.

Other future research could concern how other Finnish companies utilize their data. While BA's methods can be difficult to utilize without proper dedication, I am sure that Finnish companies of varying sizes have accomplished implementing BI tools into their arsenal. Examples of successful use of BA, like utilizing AI or big data, could inspire other Finnish companies to pursue the use of BA.

6. Conclusions

This research was conducted with the aim of assisting the case company utilize business intelligence at their operational level. The artifact, in the form of Power BI report templates, was made based on principles of design science research. The artifact was able to provide additional functionalities for its potential users. The research problem was finding out how business intelligence could be utilized effectively at the operational level of the company. The Background literature on business intelligence was utilized as a theoretical foundation to offer potential solutions for this problem. Empirical research in the form of interviews was conducted to gain insights into the current challenges of the reporting solutions that could be addressed by business intelligence.

The main finding of the thesis was that the artifact in its current state can serve as an efficient addition to the reporting tools currently used in the case company. The artifact can offer functionalities that are currently unavailable in the case company's other reporting tools. These included providing a streamlined way to access data from multiple data sources, as well as capabilities to visualize data, filter data, and track key performance indicators.

However, its implementation and evaluation were impeded by two major limitations identified during the design and development phase. The first major limitation that emerged during the study was the requirement for stakeholders to possess a Power BI Pro license to access the reports in their current form. The second major limitation was the unclear data governance policies of the case company, which resulted in partial contents within the reports of the stakeholder team. These limitations, coupled with time constraints of the thesis writing process, led to the inability to conduct more in-depth evaluation of the artifact with stakeholders. As a result, the initial plans to test the utility of the artifact with stakeholders had to be abandoned. Instead, an alternative evaluation method was chosen, which proved lesser evidence to evaluate the effectiveness of the artifact.

Enabling employees at the operational level of the case company to utilize business intelligence is crucial as it provides a broader perspective on the current situation of the customer companies. It allows for a more comprehensive understanding of the data, trends, and insights relevant to the company's operations and customer interactions. Having access to real-time data from various types of tickets empowers employees to identify potential faulty parts of the product. It enables them to make data-driven decisions, leveraging the insights derived from the data. Additionally, this capability eliminates the delay in decision-making by enabling employees to make immediate decisions instead of having to rely on inquiring information from other employees who may have access to that specific data. Raising awareness about business intelligence can have a transformative effect, leading to the adoption of more sophisticated analytical methods. These advanced methods can include predictive analytics to anticipate incidents that may cause outages, as well as the automation of manual tasks.

It is crucial to gather stakeholders' feedback on the artifact once the current major limitations have been solved. This means that its design science research process cycle needs to be iterated again. Once the necessary iteration has been done, it can be evaluated accordingly to assess its efficacy to stakeholders, and it can potentially be implemented for wider use.

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Appendix A. Interview questionnaire

1. **Background**
    - What is your job title?
    - How long have you worked in current position?
    - How would you describe your job? What are your main responsibilities?
    - Can you give estimate your hours used in reporting...
        - ... Weekly?
        - ... Monthly?

2. **Reporting**

1. What kind of reporting you currently do in your job?
2. Who are the stakeholders included in this reporting?
3. What kind of tools or techniques you utilize in reporting?
4. Have you been told to use certain specific tools?
5. Have you been trained to use these tools?
6. Does current tools suit your needs in reporting?
7. Are the current tools sufficient for reporting?
    - No: What could be improved in current tools?
8. Are the current processes sufficient for reporting?
    - No: What could be improved in current processes?
9. What kind of improvements would help you reach your goals in reporting in the future?
10. Is reporting signifigant part of your job?

3. **Data**

11. Are you aware where you can find the data you need?
12. Is the data easily accessible?
13. Is the data good quality?
14. Is manual labor required to be done to data before it is usable?
15. Do you require data from multiple different systems when doing reporting?
16. Do you need to transform data from multiple different systems when doing reporting?

4. **Key figures**

17. Are the any statistics or KPIs you are required to follow?
18. What are these statistics or KPIs?
19. How frequently these KPIs need to be accessed?
20. What are the effects to the business in these KPIs?
21. Is it clear to you, that where you can access these KPIs?

5. **Business intelligence**

22. Have you hear about business intelligence (BI) before? Are you aware what it means?

23. Have you used BI-tools before, or been in environment they have been used frequently? (Power BI, Tableau...)
    - Yes: Did you find the use of these tools useful?
24. Would you find these BI-tools to be useful in your work?