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THE IMPACT OF BUSINESS INTELLIGENCE FOR DATA-FACILITATED DECISION-MAKING IN SOFTWARE ENGINEERING

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Thesis abstract

Digital Business Management
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Digital transformation significantly impacts business operations, compelling organizations to leverage digital data to maintain competitiveness, responsiveness, and operational efficiency. Business Intelligence encompasses various methodologies designed to support data-facilitated decision-making. However, its optimal application, especially within the software engineering domain, is an understudied area.

This thesis research conducts an exploratory literature review to define the concept of Business Intelligence, identify its primary goals and challenges, and relate these aspects specifically to the domain of software engineering. The thesis research presents a single case study of Webstar Csoport Kft., a Hungarian software engineering agency, which previously relied heavily on decision-making processes based on intuition and prior experience. The thesis research examines how the implementation of Business Intelligence methods improved decision-making processes, resulting in more structured, data-facilitated operations.

Initial expectations and qualitative insights regarding this problem-oriented research were obtained in a semi-structured interview with key informants at the case organization. Further quantitative data was collected through a survey and analysis of system data across two strategic focus areas: Team Happiness and Software Delivery Performance, covering a period of 1.5 years. Analytical methods including pattern matching, time series analysis and exploratory data analysis were used to examine the obtained data.

The research findings indicate that effectively applied Business Intelligence methods allowed setting baselines to enhance decision-making quality and organizational responsiveness at Webstar Csoport Kft. The thesis research highlights critical challenges, such as technological complexity, data management and ongoing employee training faced during the development work, that must be systematically addressed to fully capitalize on the benefits of the developed tools. By adopting the proposed DevOps metrics, Webstar Csoport Kft. can bridge existing gaps between Business Intelligence capabilities, decision-making processes, and strategic organizational goals.

Keywords business intelligence, decision-making, software engineering

CONTENTS

SYMBOLS AND ABBREVIATIONS USED

BI	Business Intelligence
CEO	Chief Executive Officer
CTO	Chief Technology Officer
DSS	Decision Support System
IT	Information Technology
SME	Small and medium-sized enterprise

1 INTRODUCTION

Digitization has an impact on numerous aspects of the everyday activities of individuals and organizations alike. More and more innovation possibilities open because of the conversion from analogue to digital data on various levels and areas, such as optimizing resource allocation, cutting costs, optimizing processes, delivering better service to customers, or increasing efficiency. (Rachinger, Rauter, Ropposch, Vorraber & Schirgi 2018; Schmarzo 2016, 15.) Porter and Heppelmann (2014) name multiple areas (such as manufacturing, logistics, sales and marketing) as potential beneficiaries of the digital transformation process in the hope of deeper insights via analysis of digital data using smart and connected devices. Brynjolfsson, Hitt and Kim (2011) support this statement by naming numerous ways in which digital data can be collected, specifically pointing out customer and user-generated data through mobile phones and web applications. When the potential offered by the digital transformation process is seized appropriately, organizations go through radical changes and business model innovation with the goal of achieving success and competitive advantage. (Rachinger et al. 2018.)

Digital transformation is rapidly evolving, forcing all businesses to make faster, more accurate decisions to react appropriately to customer needs and to remain competitive in the market (Brijs 2013; Hans & Mnkandla 2013; Larson & Chang 2016; Schmarzo 2016; Tang, Deng & Huang 2022). To succeed, to remain competitive, organizations need to overcome these challenges and adopt better decision-making practices supported by data (Tang et al. 2022). The well-defined goal of data usage can make a difference between becoming a leading organization, because it is the only way of maximizing the potential of digital data in the transformation process (PricewaterhouseCoopers 2019; Schmarzo 2016, 15).

One essential part of the analogue to digital transformation is the collection and analysis of digital data. In comparison to traditional, paper-based data and documents, digital data can be easily visualized and analyzed, which can help businesses in their critical thinking and decision-making processes. In the context of digitization's far-reaching impact on organizational operations, Business Intelligence (hereinafter BI) systems emerge as pivotal tools for leveraging the potential of digital data. When utilized appropriately, BI systems built on top of digital data become assets and sources of information, based on which more established business decisions can be made. (Rachinger et al. 2018; PricewaterhouseCoopers 2019; Baruti 2023; Cuellar 2020; Zdraveski 2009.)

Despite recognizing its importance, organizations often do not to develop an appropriate business strategy in advance about the usage of data, in which case they end up having a large amount without any added value (PricewaterhouseCoopers 2019; Davenport 2014, 193). Leveraging data in an effective way can be a catalyst for more impactful decision making, which raises the organization above average performance in the market in all business sectors (Baruti 2023; Hans & Mnkandla 2013). The ultimate purpose of BI utilization is to gain market advantage compared to competitors, to improve quality of services provided to customers or to improve overall organizational performance (Cuellar 2020; Hans & Mnkandla 2013; Rachinger et al. 2018; PricewaterhouseCoopers 2019).

Although digital data offers valuable insights, its potential is not exploited by most organizations, and the way digital data can create value is different, unique, and often is not evident (Mulligan & Taylor 2019, 5; Schmarzo 2016, 15; Davenport 2014, 2). Davenport (2014, 6) referring to Harvard Business Review states that only 3.5% of the surveyed firms leveraged digital data in making strategic business decisions. Davenport (2014) suggests instead of being dazzled by digital data, it is wiser to think critically what insights can be learned and converted into business value. Based on these claims it can be inferred, there is a research gap to be addressed in how digital data can be used for strategic decision-making purposes to create value and for businesses (Shollo & Kautz 2010).

1.1 Background and motivation

Software engineering businesses are a subset of organizations influenced by the digital transformation and BI. Being a considerably fast-phased industry, the timely discovery of problems, followed by the informed decision-making in the software engineering team can have a crucial impact on the prevention and the resolution for various situations, ultimately pointing towards gaining organizational-level productivity and competitive advantage in the market. (Hans &

Mnkandla 2013; Forsgren, Humble & Kim 2018.) Yeoh and Koronios (2010) support this claim, by stating how fast strategic decision-making is an essential attitude in fast-phased environments, such as IT.

Hans and Mnkandla (2013) conducted research with the specific focus on the BI implication of managing software engineering projects. Their findings emphasize that the clever application of BI in this sector can be a critical success factor for any software project, when the project manager takes not only tracking the needs of the project (e.g., efficiency, tasking, progression, quality) into consideration, but also put emphasis on the needs of team members, such as well-being, communication barriers, bottlenecks, lacking competences, team culture (Hans & Mnkandla 2013). BI in the context of software engineering refers to the process designed around the team's everyday workflows to quantify various metrics (e.g., efficiency, performance, quality) with the aim to extract meaningful business information from the data (Forsgren et al. 2018).

This thesis research specifically focuses on the utilization of BI and discovering its value in the decision-making process in software engineering teams. At the beginning of the research, the management of the case company (Webstar Csoport Kft.) just started thinking about how to utilize their own workplace data in the decision-making process. There was a gap between strategic goals and operational activities at the case organization, which could be addressed by the introduction of appropriate metrics using BI, so that useful information is extracted on a day-to-day basis. There was a clear need to leverage the available digital data, as it offered the possibility to support the upper management – the Chief Executive Officer (CEO) and the Chief Technology Officer (CTO) – in aligning strategic objectives with day-to-day operational processes within the company.

Parmenter (2020) explains this phenomenon as a common behavioral misalignment between strategic organizational goals and the teams' directions, which is a result of insufficient communication of critical success factors. This fact makes the research appropriate and timely at the case organization, so that the impact of the invested resources in a system that supports decision-making are maximized. The thesis research focuses implementing BI at the case organization with specific focus on two areas: Software Delivery Performance and Team Happiness. This choice is driven by the desire to address the misalignment and to maximize the impact of decision-making resources within the organization.

Figure 1 displays an overview of the topical areas in this thesis research. BI is the main area of research which is generally a widely studied topic by numerous disciplines, however this thesis research approaches its applicability from the business and management perspective. In the software engineering context, various aspects of BI are explored from the managerial point of view, such as the choice of appropriate metrics, reporting, data visualization, and their impact on the decision-making processes. The thesis presents specific metrics and frameworks relevant to BI in this context. The studied frameworks (DORA and SPACE) serve guiding principles for assessing two focus areas selected by the case organization. These frameworks are analyzed due to their potential alignment with the case organization's requirements and existing situation, making them ideal starting points for the introduction of BI within the company.

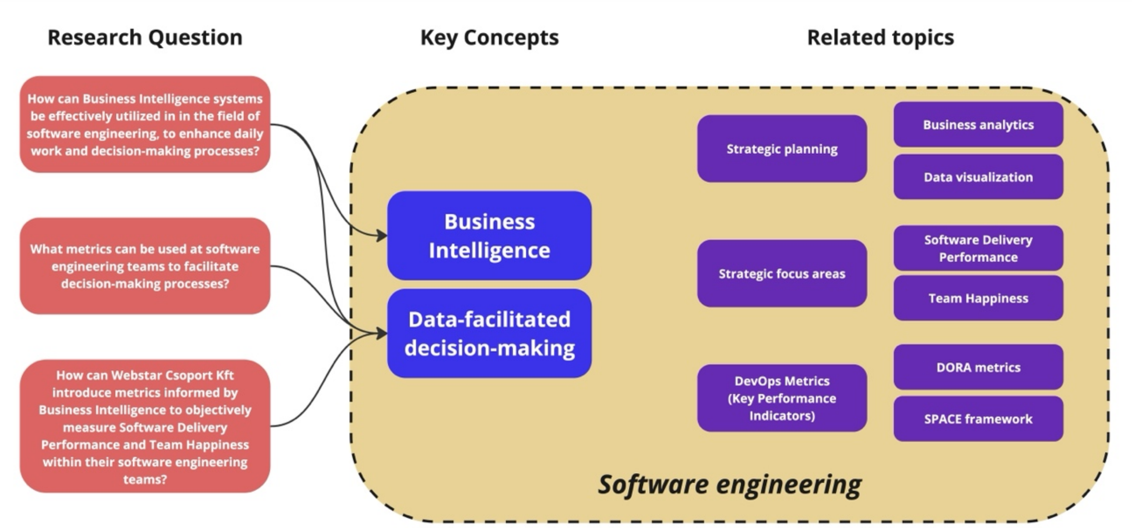

Figure 1. Overview of the research questions, key concepts and related topics studied in the thesis research in the context of Software Engineering.

The main motivation for conducting this research emerges from the fact that every software business must deal with challenges of digital data and strategic planning. The author's personal interest and involvement in the daily decision-making process at the case organization is another motivation towards this work. Being a decision maker at the company, the author can analyze and present insights regarding the impact of the process. Peers at the case organization are also keen to learn about further exploiting the potential of BI methodologies.

Yeoh and Koronios (2010) found motivation for their research in the fact that implementing a BI system for supporting the decision-making process is a long journey and a complex task. BI requires adequate infrastructural planning, human resources and restructuring organizational processes over the course of the system's introduction (Yeoh & Koronios 2010). This thesis research was also motivated by similar aspects and aims to find critical success factors for the case organization by the introduction of BI. Forsgren et al. (2018) extensively study how to measure organizational efficiency in software engineering firms. Their research found several connections between software delivery performance, organizational revenue, customer satisfaction, and employee satisfaction, all tied to digitized processes and their measurement (Forsgren et al. 2018). Researching the impact of the above areas via proper application of BI in software engineering is another motivation towards this thesis, because the findings may provide inspiration and directions for future practitioners and researchers in this area.

The main challenge is that there is no standard way, or single metric which would universally be suitable to support the case organization's strategic goals. Another challenge is the intangible and abstract nature of the software industry, which is a commonly known issue among researchers in this area (Forsgren et al. 2018, 146-155; El-Den, Schneider, Mirzaei & Carter 2020). In this thesis, the introduction of BI presents an opportunity to close this gap by measuring the right metrics across the organization.

1.2 Knowledge base

This subchapter introduces knowledge base for this thesis research and outlines the foundational concepts and goals of BI as they relate to this thesis. The subchapters to follow review key literature in the main topics to establish the knowledge base that informs the development task and define relevant concepts. The foundation of the thesis's knowledge base is built upon a selection of significant scientific and academic works, enriched by the author's own expertise developed through university education and a career spanning more than ten years in the field of Information Technology (hereinafter IT) and software engineering.

A significant portion of the theoretical data is drawn from contemporary literature, primarily scientific journals, articles, books, and online sources published in the recent years. To emphasize the enduring significance of some ideas, literature from past is occasionally cited.

Most of the literature was identified through extensive searches of electronic articles through the Lapland University Consortium Library, Google Scholar, ACM Digital Library, and IEEE Xplore using a variety of search terms displayed in Table 1. Furthermore, the Theseus service was used to gain access to published thesis works at Finnish universities. After the initial discovery of relevant articles, the snowballing technique was used to further expand the research base. Following the cited references in the initial secondary sources allowed for gathering relevant literature, ensuring a detailed review of the topic.

Table 1. The list of keywords used during the literature review.

Business Intelligence	Software engineering	Software development	DevOps
Data facilitated decision making	Software quality	Software delivery performance	Strategic planning
Metrics	Culture	Performance management	Business analytics

1.2.1 Business Intelligence and Business Intelligence systems

By integrating technologies and data into reports or visual dashboards, BI empowers organizations to extract actionable insights from raw data, enabling informed decision-making across all levels of the enterprise instead of relying on intuition (Baruti 2023, 10-11). BI is an enabler of data-facilitated decision-making, forming a symbiotic relationship that underpins effective organizational strategies (De Mauro, Greco & Grimaldi 2014). BI exceeds being merely a collection of tools: it represents a vital business process that creates the basis of data-facilitated decision-making. Through BI methodologies, organizations gain access to tools and processes to collect, process, analyze, and interpret data from various sources. (Baruti 2023; De Mauro et al. 2014; Hans & Mnkandla 2013.)

In the contemporary business landscape, where data has become the new currency, BI systems serve as the cornerstone for organizations as tools to enable extracting information and knowledge from digital data (Cuellar 2020; Yeoh & Koronios 2010). BI systems are software products that incorporate numerous tools and techniques to process, integrate and visualize digital data to enable decision makers to obtain relevant information to overview their own business (Cuellar 2020, Yeoh & Koronios 2010). By leveraging a BI system to transform raw data into actionable insights, managers gain access to valuable information that facilitates more informed analysis, enhances the performance of daily operations, and ultimately helps in gaining a competitive advantage (Cuellar 2020; Porter & Heppelmann 2014; Schmarzo 2016, 20-21; Davenport 2014).

At the heart of BI lies the convergence of data management, analytics, and visualization capabilities, which collectively enable organizations to derive value from their data sources (Brijs 2013; Davenport 2014). Through advanced data processing techniques such as data mining, statistical analysis, and predictive modelling, BI uncovers hidden patterns and correlations within the data, offering valuable insights into past performance and possibly even future trends (Brijs 2013; Cebotarean 2011; Sharda, Delen & Turban 2014). By presenting these insights in intuitive and interactive formats through dashboards, reports, and data visualizations, BI systems offer actionable information across all organizational levels, from frontline employees to top executives (Brijs 2013; Cuellar 2020).

1.2.2 Data-facilitated decision-making

Data-facilitated decision-making relies heavily on BI systems to provide timely, accurate, and relevant information to decision-makers. Data-facilitated decision-making is the process of using systematically collected and analyzed data to guide business actions, reducing reliance on intuition or past experience (Schildkamp, Lai & Earl 2013; Watson 2012). It supports strategic and operational improvements by enabling more objective and informed decisions that align with organizational goals, ultimately enhancing performance and competitiveness (Brynjolfsson et al. 2011; Baruti 2023; Bara & Knežević 2013).

In essence, BI serves as the catalyst for data-facilitated decision-making by transforming raw data into meaningful insights that drive strategic actions and outcomes. By embracing BI methodologies and technologies, organizations can unlock the full potential of their data assets, gaining a competitive edge in contemporary fast-paced business environments. Recognizing BI as a dynamic process underscores its pivotal role in driving strategic initiatives and maintaining competitiveness in the contemporary data-driven business landscape. (Brijs 2013; Hans & Mnkandla 2013; Rachinger et al. 2018; Sharda et al. 2014; Cuellar 2020.)

1.2.3 Business Intelligence in software engineering

Being one of the fastest-phased industries, organizations and managers in software engineering must be innovative and transformative to remain successful in the market (Forsgren et al. 2018; Farley 2021). The ability to objectively measure daily operations is critical, because this way offers the possibility to benchmark efficiency, level of quality and financial metrics more objectively. Without the capability to do so, leaders of such organizations risk losing sight of important information, hence making suboptimal decisions. (Forsgren et al. 2018, 5-6; Hans & Mnkandla 2013; Yeoh & Koronios 2010; Farley 2021.) Despite its importance, Forsgren et al. (2018, 5) citing Stroud et.al (2017) report that only 31% of the software industry uses none of the widely accepted practices (such as continuous integration, Lean and DevOps practices, and collaborative culture) to accelerate their daily software engineering processes and technology transformations. Amaro, Pereira and da Silva (2024) support this claim, by stating that many companies claim to be data-driven, however only a small portion use their data for informed decision-making, raising concerns about critical thinking.

In their four-year research called “The State of DevOps Report”, Forsgren et al. (2018) surveyed over 23,000 respondents from over 2,000 organizations of all sizes that are involved in software engineering and delivery. Their research fundamentally aims to identify areas and causational relations, which contribute to effective software delivery and high performance of software engineering business. The outcome of their research suggests that top performing teams excel at maximizing performance and quality leading to better results across the board. Their research suggests that engineering teams do not tend to take advantage of following metrics of daily operations, they are often stuck in a reactive state of mind. (Forsgren et al. 2018; Kim, Humble, Debois, Willis, & Forsgren 2021.)

Long-term success of software engineering teams is often the result of critical business decisions, that are made after the careful analysis of daily operations and interconnected aspects of business. Software engineering teams face daily challenges regardless of BI utilization, such as reliance on empirical decision-making, limited operational visibility, slow adoption of digital assets, the abstract nature of performance evaluation and misalignment with strategic goals (Forsgren et al. 2018; Farley 2021). Objectively evaluating performance and well-being of software engineering teams are nontrivial tasks, because of the abstract nature of these areas and the unique needs and processes of the teams and their members. In other words, there are no obvious answers and off-the-shelf solutions in how a software engineering team's performance could be measured that would not mislead decision-making processes by managers.

In the context of software engineering, the capabilities of BI offer unprecedented advantages, yet it is an understudied area (Amaro et al. 2024). The ability to analyze historical and current data allows software engineering teams to not only understand and learn from what has happened but also anticipate future trends and outcomes (Hans & Mnkandla 2013). This shift from reactive decision-making to a proactive approach aligns seamlessly with the demands and challenges of the software engineering industry (Amaro et al. 2024; Farley 2021; Forsgren et al. 2018; Hans & Mnkandla 2013).

The exploration of BI in software engineering uncovers transformative potential, particularly in an industry characterized by rapid changes and innovation. The challenge lies in the inherent difficulty of quantifying certain crucial aspects of software engineering teams, such as performance, quality, and team culture, unlike economic measures such as financial results. The former aspects are more abstract in nature which makes them more difficult to measure objectively yet are essential part of achieving success in the field software engineering. Furthermore, the context in which engineering teams operate can also have an impact on how BI could create business value, therefore there is no single answer to the challenges of all software engineering teams. (Farley 2021; Forsgren et al. 2018; Hans & Mnkandla 2013.) This complexity and the case organization's specific needs add another layer to the research gap, because the characteristics of the software engineering field demand tailored approaches for the effective integration of BI practices.

1.3 Purpose, objectives and thesis question framing

The main research problem identified in the research is the underutilization and limited research in the growing field of BI within software engineering teams. The goal of this thesis research is to gather insights from the scientific literature in the domain of BI and software engineering. The literature review in this thesis is carried out to seek the connection between and the applicability of BI systems in software engineering teams. The insights gained through the literature review provide great examples in the introduction of a BI system at software engineering teams.

At the time of conducting this research, most of the business decisions were made in an empirical manner at Webstar Csoport Kft. There is a common agreement among the managers, that the existing practices were suboptimal, and the daily work should be supported by digital data to achieve the strategic goals. The upper management has recognized the issues with this way of working already years ago, but still the organization utilizes only limited number of tools to collect digital data and back up any decisions. The main reason behind this slow development is that the organization first had to go through a transformation process before utilizing digital assets, the observation of which is supported by Rachinger et al. (2018) in their research as a common step in the process.

This thesis is focused on this business area to explore the specific applications of BI within the domain of software engineering, shedding light on its critical role in continuous learning and experimentation and improving overall organizational performance. The thesis aims to address the case organization's challenges by exploring the applicability of BI and proposes quantifiable metrics to enhance decision-making processes and organizational performance.

The main objective of this thesis research is to develop a BI system for Webstar Csoport Kft. to facilitate decision-making processes and enhance overall organizational performance by providing reports on the results of teams and projects. This objective is triggered by the strategic goal of the organization, which is to

> *"Become the most recognized Hungarian software engineering firm based outside of the capital Budapest, providing the highest quality service, having the best financial outcomes, the most satisfied employees and customers"* (Board of Directors, Webstar Csoport Kft.).

The reason for the implementation of BI at the case organization is to support decision-making processes, especially at the level of the upper management, who have limited visibility into operational processes at the beginning of the study (Appendix 1). The strategic goal of the case organization above suggests numerous business areas, that are all relevant in the context of the business but are too wide for the scope of this thesis. Deriving from the challenges identified in the literature review part of this thesis research, the scope is reduced to the areas where the research gap is widest and interesting. As a result, the thesis focuses on implementing BI at the case organization with specific focus on two areas: Software Delivery Performance and Team Happiness. The strategic goal of Webstar Csoport Kft. also incorporates customer satisfaction and financial success, but these areas are intentionally left out of this thesis' scope.

The main challenge in measuring these areas is that there is no standard way, or single metric which is universally suitable to support the strategic goals. Another challenge is the intangible and abstract nature of these areas, which is a commonly known issue among researchers in this area. (Forsgren et al. 2018, 146-155; El-Den et.al. 2020.) For this reason, quantifiable metrics (performance and result indicators) are identified in both areas which can be used to provide insights to the members of the organization to enhance their internal processes. Addressing challenges like the lack of standardized metrics, this research introduces quantifiable indicators to enhance internal processes.

Due to the short timeframe of this research, only a limited number of metrics are introduced in both areas respectively. Even though predictive outputs by the application of data science methods could be interesting for the management, at this stage it is not required to include such metrics in the system to be developed. However, the management of the organization can see the potential of these methods, hence it can be an interesting direction for future research to investigate how the company can create additional value by their utilization.

The research questions for this thesis are as follows:

1. How can Business Intelligence be effectively utilized in the field of software engineering, to enhance daily work and decision-making processes?

   This research question aims to discover the best ways to use Business Intelligence (BI) in organizations, especially in software engineering teams. It explores how BI is understood and applied by professionals to uncover its impact and industry challenges.

2. What metrics can be used at software engineering teams to facilitate decision-making processes?

   This question investigates specific metrics for software engineering teams, aiming to provide practical solutions for measuring important aspects in software engineering, leading to more informed and effective business decisions. The results of other studies are analyzed and carried forward to the empirical part of this thesis.

3. How can Webstar Csoport Kft. introduce metrics informed by Business Intelligence to objectively measure Software Delivery Performance and Team Happiness within their software engineering teams?

   Drawing from the findings of the literature review and in reflection to the case organization’s internal structure and processes, this research question addresses the core task for the practical part of this thesis. Based on the obtained insights, this question critically assesses how BI can introduce metrics within the organizational context. The analysis involves thoroughly reviewing recommendations from previous studies and assessing the case organization's existing structure, workflow and business domain in order to find the fit of the BI system within the company. The goal is to enhance Software Delivery Performance and Team Happiness across the organization, that align with the organization's overall strategic objectives.

1.4 Methodological implementation

The research methodology of this thesis adopts a mixed-method approach, combining qualitative and quantitative techniques to pragmatically explore the implementation of BI within software engineering teams and address the specific needs of the case organization. The thesis aims to enhance decision-making and daily operations by analyzing BI adoption within the case organization. It primarily seeks to answer why and how BI is a relevant methodology in the chosen context, providing evidence through the examination of the organization's challenges.

This thesis research establishes the theoretical basis through an extensive literature review focusing on the core concepts of BI and data-facilitated decision-making. The literature review is primarily based on texts from scientific journals and books, however in rare cases Internet resources have proven to have beneficial insights and contributions to the topic. Furthermore, a semi-structured interview with key stakeholders (CEO and CTO) was conducted highlighting the challenges and goals at the beginning of this research (Appendix 1). Finally, quantitative survey data was designed to measure Team Happiness, and system data from internal software tools is used to assess Software Delivery Performance. The obtained results are analyzed in relation to the organizational goals and presented alongside with development recommendations.

In this thesis, the writing process was supported by artificial intelligence tools. Specifically, ChatGPT's GPT-4o model was used for proofreading, improving readability, and reducing redundancies. The language and structure of the content were refined to ensure clarity and coherence of the text.

1.5 Ethical foundations and reliability

From ethical perspective, concerns of two parties involved in this thesis research are addressed: Webstar Csoport Kft. as the case organization, and their employees. To avoid any conflicts of interests and risks of exposing confidential information, the commissioner of the thesis is involved in how the context and findings are presented. Furthermore, data related to the case organization's employees and customers are anonymized in a way, that the research context and findings remain understandable to the reader, but the details of trade secrets remain on a level which is required in the context of the research. This allows the reader to understand the flow of the thesis and to remain inspired in how the techniques and theoretical means are used in the practical part, without exposing the case organization’s confidential information.

On the other hand, the personal data of the employees working at the case organization is to be considered from ethical perspective. In order to protect personal data and the possible identification of individuals, all survey data was collected anonymously, so that respondents cannot be identified directly. The case organization is not interested in analyzing these results as single data points individually, rather the results are interesting on the level of teams and projects. For this reason, the data collected in all focus areas was aggregated and presented in this manner, thereby eliminating the risk of possibly exposing any personal data concerning the involved parties.

1.6 General structure of the thesis

The thesis is divided into seven chapters. A brief introduction, the background, the motivation, the research purpose, scope, objectives, and questions followed by the methodology and ethical were described in this chapter. A general overview of BI and decision-making facilitated by digital data is presented in the Chapters 2 and 3. Chapter 4 investigates BI’s relationship and its applicability to the field of software engineering. These chapters are dedicated to summarizing the theory that establishes the empirical part of the thesis research.

In the empirical part of the thesis, Chapter 5 introduces the research design. Alongside the practical utilization of the chosen research and data collection methods, the case organization is introduced and the goals and expectations from the development work are presented. Chapter 6 presents the results obtained by the implementation of the BI system at the case organization. Finally, Chapter 7 discusses the findings and pinpoints development suggestions for the case organization and directions for further research.

2 BUSINESS INTELLIGENCE AND BUSINESS INTELLIGENCE SYSTEMS

Contemporary organizations generate massive amounts of data at incredible speed in their daily operations (Davenport 2014, 1-3). The appropriate usage of data in any industry can have a positive impact on various aspects of the business. However, multiple studies have proven that only a few organizations and leaders exploit its potential. (Amaro et al. 2024; Mulligan & Taylor 2019, 5; Schmarzo 2016, 15; Davenport 2014, 2.) Such businesses are potential beneficiaries of BI, which offers the possibility to enhance overall performance and help to achieve strategic business goals, regardless of company size and industry.

The subchapters to follow explore the history, core concepts and theory around BI as well as the goals and challenges of utilizing BI in a business context, drawing on scientific literature. The final subchapter presents some real-world examples when BI was reportedly utilized. The discussion aims to provide insights into how organizations can effectively harness the power of data to inform strategic decisions and optimize overall performance.

2.1 Conceptual definitions

The concept of BI is widely used by researchers and practitioners alike, however there are various views about its meaning in the literature. To have a clear understanding on the perception and usage of BI and BI systems, it is worth looking at the history and evolution. This overview not only reveals the origins of this research area but also highlights its potential to modern organizational contexts.

Baruti (2023), Elliott (2007), Bara and Knežević (2013) report that the concept of BI was first used by Luhn (1958), whose article outlines several approaches to addressing business challenges that remain relevant in the contemporary landscape. Luhn (1958) identified various areas as potential use cases, such as obtaining and visualizing information on-demand by processing business documents. Being a visionary at his time, Luhn’s ideas were not popularized back then, only about 40 years later (Elliott 2007; Power 2007).

Multiple researchers (Power 2007; Sharda et al. 2014, Shollo & Kautz 2010; Cebotarean 2011) report differently, stating that the concept of BI was first introduced by Howard Dresner in a Gartner Group report in 1989, who explained it as fact-based decision support system – in other words a set of tools based on (digital) data – which assists executives in making important business decisions. Such computer-aided reporting tools and expert systems were already present back in those days, often referred to as a Decision Support System (hereinafter DSS) or a Management/Executive Information System (M/EIS) (Baruti 2023, 8; Brijs 2013, 5; Cebotarean 2011; Watson 2009).

DSSs gained popularity during the 1970s and 1980s, primarily within larger organizations utilizing mainframe systems. Over time, with the evolution of the IT industry and the advent of the Internet, their usage expanded to smaller enterprises and personal computers. (Baruti 2023; Power 2007; Wixom & Watson 2010.) Natural to this development, related concepts and decision-support frameworks incorporating the new technology emerged, forming the basis of the modern business jargon (Baruti 2023; Watson 2009). Power (2007) classifies the evolution of such applications into seven main categories. Among these, Data-Driven DSS stands out, focusing on the systematic analysis of both internal and external data over time through an integrated data warehouse. This approach supports decision makers, usually management teams or company executives, with fact-based insights. This area of DSSs serve as the basis for the development of popular BI systems. (Power 2007; Watson 2009; Bara & Knežević 2013.)

The shift during the 1990s into BI began (Cuellar 2020, 24; Elliott 2007; Power 2007), when more and more vendors started to offer integration of multiple data sources into the DSSs. This new era of software not only could report what has happened but also provide predictive behavior of future data points on business operations (Cebotarean 2011; Sharda et al. 2014). The key differentiator compared to DSS is to leverage advanced analytics of multiple data sources and visualization techniques to empower organizations with actionable insights in a continuous, day-to-day fashion (Baruti 2023). As a result, BI is still focused on the enterprise ecosystem of the organization, however the application area and the stakeholders of the available digital data started to evolve and expand (Baruti 2023; Cuellar 2020; Cebotarean 2011; Power 2007). Unsurprisingly, the concept of BI started to spread among researchers and industry professionals.

Despite its ever-increasing popularity, multiple understandings and definitions of BI started to appear in scientific literature (Shollo & Kautz 2010). Having explored the historical development, it is now imperative to explore the diverse definitions and perspectives that shape our understanding of this crucial concept. Appendix 4. lists the definitions of BI found in scientific literature. The paragraphs to follow explore these definitions and the interconnections between them.

While the literature offers various interpretations of BI, a common thread is the use of data to enhance strategic decision-making. Larson and Chang (2016) explain BI as a data-driven decision-making process, which requires proper IT infrastructure, data processing and knowledge management as the enablers to gain successful insights about the organization. Davenport (2014, 10) defines BI similarly, listing the concept as set of tools that can be used for data-driven decisions and generation of reports. These authors approach the definition from the perspective of the use-case, which leverages digital data for the purpose of more sophisticated decision-making with support of computer-based, digital means.

Sharda et al. (2014) see the concept slightly differently, stating that BI is an umbrella term, which incorporates the architecture, tooling, integration, analysis, and methodological questions of decision-making based on digital data. The goal to support business decision-making remains the same, however BI is seen more as a complex process, rather than just individual tools (Sharda et al. 2014). Shollo and Kautz (2010) agree by explaining how BI has evolved over the years from being only a software product into a process and a set of technological tools with the goal of extracting valuable information and knowledge from (transactional) digital data. Watson (2009), Wixom and Watson (2010) include a range of applications and data operations in their definition aimed at facilitating decision-making processes within businesses. Brijs (2013, 6) agree that BI also deals with the methodological concerns how data should be structured and collected in alignment with business-critical processes and information on all hierarchical levels to maximize performance and achieving strategic goals. This approach is aligned with the findings of Sharda et al. (2014), suggesting that BI begins at the design of business processes and architecture of various data sources, and concludes in an action derived from the perceived results. Cebotarean (2011) goes one step further, arguing that BI refers to computer-based techniques used in spotting, digging-out, and analyzing business data, which provides historical, current, and predictive views of business operations.

The definitions in Appendix 4. do not convey, but numerous researchers (Boto, Correia & Borges 2024; Baruti 2023; Cuellar 2020; Watson 2009) argue that executives wish to have "at a glance" reports and descriptive analysis on what is happening in their organization. This requirement reflects the shift from traditional reporting to a more dynamic, data-driven approach to decision-making and strategic management. Furthermore, in the era of data-driven business, the true value of data lies not in its volume, but in how effectively it is analyzed and leveraged for strategic purposes. Typically, the main differentiator of success is not how large quantities of data is gathered, rather how it is analyzed and what it is used for. (Boto et al. 2024; Baruti 2023, 6; Cuellar 2020; Mulligan & Taylor 2019; Watson 2009; Hans & Mnkandla 2013; Williams & Williams 2003.)

From the above findings it can be seen that BI includes both methodological and technical aspects. For this reason, it is wise to make a distinction and look at BI separately when discussing about the methodologies and the software systems that make the practical implementation possible. From this perspective, BI systems provide tools to support the conscious collection, usage, and processing of digital data in any organization. Table 2 lists definitions of BI systems by other researchers.

Table 2. Definitions of Business Intelligence systems in the studied literature.

Source	**Definition of a BI system**
Boto, Correia and Borges (2024)	The „(...) BI system is one of the components of the company's digital transformation. It allows us to move from the manual calculation of business indicators, with greater probability of occurrence of failures, to the repeated automation of the business processes."
Al-Okaily, Ping and Al-Okaily (2021)	„The concept of BIS is known as an integrated set of tools, technologies and programmed products that are used to collect, integrate, analyze and make data available (...) an umbrella term that covers a wide range of techniques, tools, concepts, processes and methods used to consolidate, analyze and provide information access in order to improve business decision-making"
Stasieńko (2011)	Business Intelligence Systems „use data warehousing, analytic tools (OLAP and Data Mining), and presentation techniques.

BI systems are software applications, which are specifically designed to allow implementation of BI practices. They serve as the operational backbone of BI, making it possible for organizations to automate data collection, reporting, integration of multiple data sources and visualize processed data. (Boto, Correia & Borges 2024.) Depending on the business need, this may require the capability of processing and presentation of multidimensional data in real time relying on technologies such as Online Analytical Processing (OLAP) (Paredes 2024; Stasieńko 2011). These systems empower businesses to implement BI methodologies efficiently, making it possible to reveal accurate, timely, and actionable insights (Al-Okaily, Ping & Al-Okaily 2021). Features provided by in BI systems can range from data warehousing, automated reports, defining Key Performance Indicators to data mining and machine learning techniques – or even artificial intelligence. Researchers agree that business decision-makers should ensure they consider the BI mindset and not rely solely on the tools provided by BI systems. (Mulligan & Taylor 2019; Hans & Mnkandla 2013; Williams & Williams 2003.)

This thesis refers to the BI and BI systems in the following way, deriving from the definitions listed in Appendix 4 and Table 2 and the studied literature (Paredes 2024; Baruti 2023; Cuellar 2020; Sharda, Larson & Chang 2016; Delen & Turban 2014; Davenport 2014; Brijs 2013; Cebotarean 2011; Stasieńko 2011; Shollo & Kautz 2010; Wixom & Watson 2010; Watson 2009). BI is a systematic process through which organizations collect digital data and apply analytical tools to generate reports that inform critical business decisions. BI refers to the process and mindset, that enables extracting insights from digital data, transforming it to actionable information to facilitate making business decisions. It provides approaches, methodologies, and strategies towards how to collect, transform and analyze raw business data to derive actionable insights. BI systems, on the other hand, are specific software tools that are specifically designed to implement BI in practice. BI systems provide means to efficiently analyze historical data central to an organization's primary operations. BI systems can be of assistance in analyzing digital data at organizations by providing tools for data integration and analysis, such as customizable dashboards, automated reports. BI reports and dashboards are crucial as they provide fresh insights by visualizing operational data, revealing patterns and trends that might otherwise remain hidden. The key decision-makers (managers, executives), rely on BI systems to allow making objective choices driven by data, enhancing the credibility and effectiveness of the decision-making process.

2.2 Goals

To better understand the goal behind utilizing BI and BI systems, it is important to elaborate on the purposes for which it can be used. In modern business environments, the utilization of BI serves several key goals aimed at enhancing organizational performance and strategic decision-making by gaining an at-glance overview of what is currently happening in an organization (Cuellar 2020; Yeoh & Koronios 2010; Boto, Correia & Borges 2024). By integrating and extracting key information from sparsely located digital data, BI systems enhance the reliability and accuracy of decision-making processes, which in turn improves organizational efficiency, performance, future planning, and cost-effectiveness (Baruti 2023, 5; Cuellar 2020; Zdraveski 2009; Hans & Mnkandla 2013; Bara & Knežević 2013; Porter & Heppelmann 2014; Schmarzo 2016; Davenport 2014; Cebotarean 2011; Sharda et al. 2014).

BI can be useful in teams and organizations, where the operations or decision points are too widespread for executives to oversee solely based on previous experience, which makes empirical decision-making suboptimal. By allowing leaders to investigate fact-based (historical or predictive) data points, business processes can be improved, and competitive advantage can be gained. (Cuellar 2020, 10; Baruti 2023, 10-11). Zdraveski (2009), Cuellar (2020, 9-10), Bara and Knežević (2013) emphasize, that BI systems process daily business data to valuable information accessible to employees at all levels of the organization. This statement suggests that its potential to be much more than solely a performance management tool. BI systems offer the capability to create objective reports and forecast trends, that allow processing data more objectively compared to intuition (Cuellar 2020, 10). This kind of automated trend forecasting allow extracting insights and identify patterns more easily in a visual manner at the right time for the right parties (Baruti 2023, 48; Zdraveski 2009; Brijs 2013; Davenport 2014; Bara & Knežević 2013).

Small and medium-sized enterprises (hereinafter SMEs) often face the issue that much of their information is digital, but located in numerous spreadsheets, documents, or software systems. This scattered data presents a significant challenge in effectively harnessing valuable insights for decision-making especially when the organization is growing rapidly. (Cuellar 2020.) Baruti (2023, 5, 10-11) and Paredes (2024) also point out, that not only large organizations, but SMEs invest in the development of BI systems and competences also for the sake of performance evaluation and monitoring operations, which is an emerging trend in the rapidly evolving business ecosystems. However, Cuellar (2020, 23) states that management at SMEs is often done on a tactical level based on intuitive decisions which often are suboptimal – a BI system can have transformative impact on the management practices of such companies to make them truly strategic in nature and achieve better results. Cuellar (2020, 23) interestingly also reports that the potential side-effect of a utilizing a BI system is the possible simplification of business processes in context of SMEs. The structural nature of digital data offered by BI systems enables a better overview of the business on all organizational levels, therefore allowing a more elaborate analysis and decision-making process (Boto, Correia & Borges 2024; Cuellar 2020, 22-23; Zdraveski 2009).

Regardless of the company size and targeted level of utilization, organizational learning is another important goal of utilizing BI systems. In dynamic and competitive business environments, the ability to absorb knowledge and adapt to changes is essential for achieving success. Organizational learning and change management require changing human behavior in a positive direction, which in turn leads to changes in organizational culture. To facilitate this process, it is important to deliver information at the right time and in the right format. BI systems are instrumental in this regard, as they enable organizations and individuals to access and analyze relevant data about their operations. (Bara & Knežević 2013.)

According to Cuellar (2020, 23) and Baruti (2023, 59), by utilizing a BI system, the approach to organizational and individual performance management can be looked at from a new perspective, which is more reliable and less exposed to risks. By incorporating the BI systems into an organization's daily operations, access to information becomes not only more convenient, but also the communication among the parties can be improved due to the structured nature of the data (Cuellar 2020, 10; Baruti 2023, 23; Bara & Knežević 2013). Baruti (2023, 60) states that BI systems serve as platforms that enable discussion between the involved parties, fostering a collaborative environment. Sharda et al. (2014) sum up the main goals behind BI as *“Organizations are being compelled to capture, understand, and harness their data to support decision making to improve business operations. Because of the continuously changing, fast-phased business environments, managers need the right information at the right time and in the right place”*. This means that the success of managing a contemporary business is strongly dependent on how well managers can utilize their organizational data at critical decision points (Nyblom, Behrami, Nikkilä & Søilen 2012; Baruti 2023). The above claims underscore the broad applicability of BI systems across companies of varying sizes and hierarchical levels within organizations.

The findings above outline 7 category of goals as drivers behind BI utilization, which are displayed in Appendix 5. These goals highlight BI’s capability to empower leaders with an overview of their business operations and enable them to approach their business ecosystem from a more fact-based perspective. This facilitates organizational learning and has the potential to provide the basis for innovative discussions. Risk management becomes easier by considering data-facilitated facts rather than past experiences, which reduces uncertainty and improves reliability of decisions. BI can also reduce the need for manual work by providing automated reports, thereby saving valuable work hours as well as providing insights about key metrics and indicators. By integrating scattered data from multiple data sources, BI systems can reveal and visualize previously unseen trends and even forecast upcoming challenges or opportunities, enabling businesses to stay proactive and competitive.

It can be concluded that the most important goal of BI is to have a positive impact on the strategic decision-making processes which drives organizational success and results. Even though the goals of BI utilization highlight its transformative potential, achieving them is not without challenges.

2.3 Challenges

BI and BI systems pose various challenges to organizations that seek to implement them effectively. Shollo and Kautz (2010) report in a comprehensive literature review, that researchers and practitioners tend to focus on the technical perspective (data and information) and often neglect analyzing the impact of BI on knowledge and decision-making. The definitions and goals presented in the previous subchapters help to recognize the fact, that the introduction of BI is not solely a task of introducing computational/IT tools at the desired application area for digital data analysis purposes. As with many areas in business field, the success depends on how well the involved stakeholders interpret the data and how they enrich the information within the context of their organization. (Baruti 2023; Davenport 2014; Schmarzo 2016.) Schmarzo (2016, 32-33) argue that leaders must be ready to transform their own mindset to think as data scientists in matters related to business to take advantage of BI. Research shows that fact-based, data-driven mindset among users is often lacking, thereby limiting the potential values of BI systems (Schmarzo 2016, 32-33; Davenport 2014, 15-20). Watson (2012), Shollo and Kautz (2010), Wixom and Watson (2010) suggest that a fact-based culture requires strong commitment and engagement from parties on all levels of hierarchy to achieve success.

Researchers agree that BI must be embedded in the strategic, business development process at the organization, because many processes and workflows must be continuously aligned to provide appropriate digital data which is ready for analyses (Forsgren et al. 2018, 3-10; Dewett & Jones 2001). This strategic nature and transformative aspect of BI makes its application challenging, because it demands both new IT infrastructure and internal expertise within organizations, while also reshaping existing tools and processes (Dewett & Jones 2001). Yeoh and Koronios (2010) emphasize that having a clear business objective and strategy for using BI is a crucial success factor, more significant than the technical infrastructure. Davenport (2014, 128-129) echoes this sentiment, warning that investing in BI without clear goals can be costly and lack business value. However, integrating and unifying the data by better practices is insufficient, because the daily business processes often must be redesigned and aligned continuously to support data-facilitated operations (Forsgren et al. 2018, 3-10; Dewett & Jones 2001; Schmarzo 2016, 32-33; Davenport 2014, 15-20). In other words, shifting towards a mindset that incorporates BI also requires the necessary alignment of business operations and workflows, which can be a complex endeavor requiring strategic planning and organizational commitment (Schmarzo 2016; Davenport 2014).

BI demands strong commitment and engagement of the business domain during its introduction, as well as deep practical knowledge, critical thinking, good presentation skills and data-driven mindset from the analysts during its usage. Users of BI systems must be able to ask the right questions and engage in the conversation with the decision makers. (Brijs 2013, 3-7.) Schmarzo (2016) argues that leveraging on the potential of data can only be a success, when the organization understand the economic and business transformation possibilities this process offers. This means that any organization must be self-aware in respect to where they stand in terms of maturity and what consequences data-oriented solutions might have (Baruti 2023; Cuellar 2020; Schmarzo 2016; Dewett & Jones 2001).

Cuellar (2020, 6) reports, that even though all employees could see the potential impact what such system has on the business operations, only 58% of users demonstrated usage of the BI system during their research. The reasons behind this observation are unclear, most likely resistance to change, lack of understanding about the benefits of BI, and fear of technology can be the root causes behind the lack of user adoption (Cuellar 2020; Watson 2012; Forsgren et al. 2018). These facts point out the importance of raising awareness of the value provided by the BI system, but also elevate the need to educate and engage the involved parties in its usage and adoption (Cuellar 2020, 27-28, 49-53). Stated differently, ensuring widespread adoption of the tools is a common challenge in integrating a BI system into an organization (Schmarzo 2016, 32-33; Davenport 2014, 15-20). These findings once again emphasize the necessity for both managerial and operational-level employees to understand the strategic goals and embrace the value of data usage as mentioned by other researchers (Brijs 2013; Sharda et al. 2014; Williams & Williams 2003).

Finding the right data management practices is clearly another challenge in incorporating BI system into any organization (Baruti 2023; Cuellar 2020; Davenport 2014; Brijs 2013). Baruti (2023) argues that the BI architecture must be designed in a way that it supports the goals of all involved parties, whether their focus is technical or business-oriented in nature. To maximize the benefits of BI, studies propose first to think about how data will provide value and become an asset before its collection (PricewaterhouseCoopers 2019, Davenport 2014).

A data warehouse is typically the answer to this problem, which incorporates structured data from multiple data sources into an integral database as the source of BI analyses (Baruti 2023, 32; Schmarzo 2016; Davenport 2014, 128-130). According to Davenport (2014, 15-20), the mindset regarding data management practices (collection, organization, utilization, and innovation) holds greater significance than the surrounding IT infrastructure. This suggests that building BI systems successfully is an interdisciplinary effort that combines expertise in engineering and business development, because both sides must have clear understanding of the other's roles, goals and business ecosystem (Davenport 2014; Schmarzo 2016; Brijs 2013; Wixom & Watson 2010; Watson 2012). Cuellar (2020) in their research provides a great example to this, pointing out that the studied case organization utilized poor data management practices by using low quality data and loosely structured spreadsheets. Before the BI project, critical analysis of the available data and careful architectural design had to be done before the actual implementation of BI, which also included the nurturing of the company's digital data (Cuellar 2020; Schmarzo 2016).

Data quality is another significant challenge in incorporating BI systems into an organization (Baruti 2023). To derive meaningful insights for decision-making purposes from BI reports, validity, reliability, and consistency of the underlying data are essential factors. Poor data quality, characterized by inaccuracies, incompleteness, inconsistency, or outdated information, can lead to unreliable analysis and erroneous conclusions. This is typically addressed by incorporating data integration practices (such as cleansing, extraction, transformation) supported by audit and validation done by experts before loading data into the data warehouse. (Baruti 2023 25-26, 45-47; Yeoh & Koronios 2010; Paredes 2024.) Furthermore, addressing data quality issues requires implementing robust data governance practices, establishing data quality standards, investing in data cleansing and validation processes (Baruti 2023; Rachinger et al. 2018; Watson 2009; Paredes 2024). Cuellar (2020, 52-53) specifically states that cleansing and preparing the data took 80% of the resources in their BI project and even though some information could not even be recovered due to previous human mistakes, the value added by the BI system is still significant. Without adequate attention to data quality, BI initiatives may yield misleading results and fail to realize their full potential in driving strategical decisions and organizational performance (Baruti 2023; Zdraveski 2009; Watson 2009; Paredes 2024).

Specific to SMEs, Cuellar (2020, 6) reports that many companies suffer from limitations (such as human and technical resources, know-how and budget), when a BI system is being introduced, which can be another challenge. Wixom & Watson (2010) point out the complexity of BI architecture can differ based on the size and requirements of a business, ranging from modest implementations to extensive multi-million-dollar enterprise data warehouses. They identify three targets (levels of utilization) for BI, which support the findings of the abovementioned studies.

The first level is when a single or a few (BI) applications are utilized. In this case, an organization utilizes BI to solve the specific need(s) of a single business unit. The scope and boundaries of the targets are well defined. The business unit is responsible for defining governance rules. The level of commitment, business impact and required resources to implementation are relatively low. (Wixom & Watson 2010). In the second level, a BI infrastructure is built. In this scenario, the BI system is available to all hierarchical levels across an organization. This target requires more elaborate data governance and higher commitment, as certain standards must be agreed upon by the involved business departments. Naturally, the scope and required resources are higher, as well as the impact of the BI system. (Wixom & Watson 2010). The third level is the most complete organizational transformation when fundamental changes are introduced, and the BI mindset is adopted. It requires the highest level of commitment and strategic vision of C-level executives, who support the transformation of the work processes, jobs and culture to a more analytical, fact-based approach. (Wixom and Watson 2010).

Depending on the needs and commitment of an organization, some organizations may find value even in the smallest utilization of BI for a specific purpose, which is certainly more cost-efficient than an organization-wide transformation. For this reason, organizations and decision makers must be conscious to align the level of BI utilization to the business needs. (Wixom & Watson 2010.)

The paragraphs above highlight 8 challenges that are summarized in Appendix 6. One of the often-recurring themes in the literature is the clear identification of goals and strategy in advance of BI implementation. Business owners and managers need to clearly define their goals for implementing BI and how it will help solving their existing problems. The lack of such analysis is risky because the provided tools and solutions might not be the right answers to the challenges the business is facing. Alongside the strategic alignment, commitment and wide engagement is required from all stakeholders in the organization, because this change has an impact on multiple levels of daily operations. The involved parties must understand the transformation in cultural and methodological aspects of BI, break existing habits and possibly even redesign organizational processes. Based on the studied literature, success fundamentally depends on the maturity of the organization and the individuals, who often exhibit resistance. Organizations that overcome the resistance to change and engage employees will be able to benefit completely from the new processes and tools.

Clearly, BI poses challenges in the vision development and engagement. However, it is equally challenging from the technical perspective for numerous reasons. One reason that stands out is the establishment of data management practices in advance and along the way. Similarly, paying attention to the quality of the data is equally important. Neglecting the planning and quality assurance process can lead to inaccurate or inconsistent reports, that cause incorrect or suboptimal results. In other words, proper data governance and quality eliminates serious risks, therefore should be a crucial point to consider in BI initiatives.

The final challenge identified focuses on the financial and intellectual resource constraints. Organizations must be able to evaluate the depth of BI and fit its outcomes into their processes. For instance, the complexity certainly differs in case of an SME counting a couple of employees in comparison to an international company counting thousands. Likewise, the constraints regarding budget and human resources are certainly different, yet important aspects to consider. In conclusion, aligning strategy, cultural aspects and the technical challenges combined is probably the most crucial factor of all, ensuring successful value creation by the better outcome of business decisions. Being its most influential goal and challenge, strategic decision-making is explored in more detail in the Chapter 3 with respect to BI as a methodology and tool supporting this area.

2.4 Examples

Numerous examples in the literature highlight the wide application areas of BI systems at all managerial levels and organization sizes. Cuellar (2020) in their thesis introduced BI to a Latin-American SME which had 30-35 employees and a product portfolio of 257 items at the beginning of the research. The case company in their research is selling various type of beverages and dietary products, many of which are popular only during the summer season. The main goal of introducing BI in this context was to allow managers to become more aware of sales trends and optimize the business strategy and processes. By structuring, cleansing, reporting, and visualizing the company’s day-to-day sales data, the company’s sales process and data has become more reliable and transparent, which facilitates strategic planning to this day. (Cuellar 2020, 27-28, 49-53.)

In their thesis, Baruti (2023) presents another example in the field of logistics and procurement management, where the introduction of BI has helped making a step forward in optimizing processes. The international case organization, which manufactures cable harnesses and other components for the automotive industry in four countries, faced various challenges due to the shortage of supplies and the dependencies with suppliers. The management identified that to optimize and be more efficient in the production line, a BI system which can create reports and forecasts can be an appropriate solution in response to the continuously changing supply market. During the COVID pandemic, visual representations of the inventories were using the BI system, which allowed decision-makers to identify the shortage of supplies ahead of the curve, allowing proactive reaction and flexibility for the organization. Later on, the same system was used to track supplier and customer value chains, which all contributed to better organizational performance. Overall, the introduction of BI resulted in tangible improvements in efficiency, monitoring, customer service, and collaboration. (Baruti 2023.)

The study conducted by Nyblom et al. (2012) showcases multiple application areas by analyzing BI system usage by eight Swedish SMEs in various sectors, such as printing, manufacturing, construction and communications. Even though the case organizations in their study are completely different in many respects such as business domain, portfolio, size or processes, all of them utilize BI systems successfully for various purposes along their daily operations. (Nyblom et al. 2012).

Brijs (2013, 2-3), Williams and Williams (2003) highlight that BI has been proven in various sectors such as banking, finance, industrial environments, logistics and retail. Zdraveski (2009) and Rachinger et al. (2018) support this finding by stating that BI systems can have numerous application areas, highlighting sales, production, internal operations, or customer management. By leveraging on the transformative potential of BI, these business areas can achieve optimized resource allocation, cut costs, deliver better service to customers, or increase efficiency in general (Schmarzo 2016, 15). Sharda et al. (2014) present a case in telecommunication where BI is utilized for diverse purposes, ranging from strategic planning, innovation, restricting business processes, production, or customer relationship management.

The broad range of sources underscore the growing recognition of BI’s potential across industries, regardless of company size or complexity. These case studies showcase the flexibility offered by BI that can enhance decision-making processes, streamline operations, and provide valuable insights that drive strategic goals. Evidently, BI systems can be tailored to meet the specific needs of different business environments, whether it's a small SME in Latin America or a large international company in the automotive industry. Building on the diverse examples from various industries, it becomes clear that BI systems can be adapted to address the unique challenges of organizations of different sizes and across multiple sectors.

3 DATA-FACILITATED DECISION-MAKING

Data-facilitated decision-making, as highlighted by Schildkamp, Lai and Earl (2013, 1), is the process of basing decisions on a broad range of evidence rather than relying solely on individual opinions, impressions or past experience. Instead, the emphasis is put on the systematic collection, analysis, and interpretation of descriptive reports to inform decisions. This approach underlines the use of quantitative data, trends, patterns, and insights derived and concluded from descriptive reports to guide decision-making processes by analyzing data. (Watson 2012; Bara & Knežević 2013.) On an advanced level, the process involves the usage of advanced analytics techniques, such as predictive and prescriptive modeling to uncover hidden insights and forecast outcomes (Watson 2012). Bara and Knežević (2013) highlight even if the organizational culture incorporates a data-facilitated approach in the process, it is difficult (and should not be a goal) to eliminate intuition, especially on the strategic levels.

In the contemporary business environment, data-facilitated decision-making plays a pivotal role in driving organizational performance. Researchers argue that as tasks become more complex, there is a greater need for high quality, processed information. The fact-based process supports organizations in the information processing with technology to lower costs and improve performance. (Baruti 2023; Davenport 2014; Schmarzo 2016; Brynjolfsson et al. 2011; Watson 2012.) Brynjolfsson et al. (2011) support this claim by suggesting that having better information helps to identify outcomes and risks more accurately.

Data-facilitated decision-making differs from traditional decision-making processes in several key aspects. Firstly, it offers the capability to remove biases, such as politics and ideology from decisions, allowing for a more focused approach to any problem (Schildkamp, Lai & Earl 2013). Its fact-based nature reduces risks and adds objectivity to the decision-making process compared to traditional methods (Wixom & Watson 2010; Watson 2012; Paredes 2024). By basing decisions on empirical data, organizations can improve their performance significantly, as insights provide a clear path for reducing biases and enhancing outcomes as pointed out by Schildkamp, Lai and Earl (2013). Moreover, this approach facilitates continuous improvement within organizations by outlining learning paths and goals, fostering practices to address individual needs (Bara &

Knežević 2013; Farley 2021). In other words, data-facilitated decision-making strongly contributes to organizational learning and development, that can be a significant improvement in comparison to traditional decision-making paradigms (Bara & Knežević 2013; Farley 2021; Forsgren et al. 2018).

Wixom and Watson (2010) report several success stories from various companies in the gaming, health care and travel sectors, showcasing significant advantages gained through data-facilitated, fact-based decision-making processes. Paredes (2024) extends that list with various industries and examples, where decision-making in this way plays a pivotal role in enhancing operations and customer experiences. Reportedly, e-commerce giants like Amazon utilize data analysis to tailor product recommendations, while manufacturing industries leverage predictive analytics to forecast equipment failures. The transportation sector optimizes routes and delivery times using real-time data from GPS trackers and weather forecasts. (Paredes 2024). Schildkamp, Lai and Earl (2013) report evidence in how this approach adds value in educational contexts, such as evaluating pupil's past performance and achievements compared to traditional decision-making practices.

According to previous studies (Baruti 2023; Cuellar 2020; Shollo & Kautz 2010; Nyblom et al. 2012), even smaller organizations in rapidly evolving business environments should put emphasis on learning how to leverage information that hinders in their organizational data. Incorporating these practices into daily workflows and processes allow organizations to remain competitive in the market. Research conducted by Brynjolfsson et al. (2011) based on many firms suggest a direct correlation between data-facilitated decision-making and productivity, market value, and profitability. Investors recognize the importance of this intangible cultural asset, which adds confidence to the strategic management of the firm besides enhancing output and profitability (Brynjolfsson et al. 2011). Brynjolfsson et al. (2011) report that adopting data-facilitated decision-making can lead to a 5-6% increase in productivity, which underscores the viability of this approach in professional business management.

Promoting data-facilitated decision-making within an organization poses several challenges and limitations. Most importantly, there is a need for a cultural shift, requiring changes in organizational processes and the transformation of old habits and mindsets (Cuellar 2020; Watson 2012). This shift towards an analytical, fact-based way of thinking demands changes not only in culture and habits, but organizational structure, hierarchy, and competencies as well (Wixom & Watson 2010; Paredes 2024). Additionally, businesses must establish robust data governance roles and frameworks. Such frameworks define foundational rules and policies governing the collection, storage, processing, and use of data as part of the decision-making process. (Wixom & Watson 2010). Moreover, converting information into knowledge is an essential skill which must be developed thorough the organization. Without proper skill development, stakeholders may fail to realize the potential gains from their data-facilitated initiatives. (Bara & Knežević 2013.)

Relying too heavily on data in decision-making processes can introduce several risks that organizations need to be aware of. These risks include the potential for inaccurate or incomplete data, and ethical concerns such as algorithmic bias or the misuse of personal information (Paredes 2024). To mitigate these risks, it is crucial to thoroughly analyze and validate the data, as well as involve diverse perspectives in the decision-making process. Misinterpretation of data due to a lack of knowledge or manipulation can also lead to false conclusions. Similarly, relying solely on previous experience and personal opinions without critical evaluation can pose risks. (Paredes 2024; Schildkamp, Lai & Earl 2013, 193-203.) Therefore, it is essential for decision-makers to be educated and be critical about all aspects of data when making decisions – it should be seen as a valuable source of information, rather than the single source of truth. (Paredes 2024; Watson 2012; Shollo & Kautz 2010; Wixom & Watson 2010.)

In conclusion, while data-facilitated decision-making presents challenges and risks, its importance in enhancing organizational performance, promoting continuous learning, and fostering innovation cannot be emphasized enough. By leveraging data effectively and responsibly, organizations can gain valuable insights to make informed decisions and ultimately achieve their strategic objectives faster in the ever dynamic and competitive business environment.

As explained in Chapter 2, BI can positively influence business operations in various areas and organizational levels. By the computational transformation, processing, and presentation of digital data, the stakeholders on all hierarchical levels can obtain visual representation from various angles, which is then a useful input of a business decision (Cuellar 2023; Sharda et al. 2014; Brijs 2013). BI methodologies are enablers of data-facilitated decision-making and play a key role in extracting information from raw data. Essentially, BI systems enable organizations to harness the power of data to make informed decisions, optimize processes, and drive business growth. (Bara & Knežević 2013.) They serve as catalysts for expediting decision-making processes within organizations, fostering information transparency essential for maintaining competitiveness (Bara & Knežević 2013). Based on the above claims it can be surmised, that the connection between BI and data-facilitated decision-making lies in their synergy to empower organizations with the necessary tools and insights to make business decisions more effectively.

Williams and Williams (2003) agree on this observation, listing two major application areas which can be positively impacted by the proper usage of BI during decision-making processes. On one hand, BI attempts to *"Improve management processes - such as planning, controlling, measuring, monitoring, and/or changing - so that management can increase revenues, reduce costs, or both"* (Williams & Williams 2003). On the other hand, BI aims to *"improve operational processes – such as fraud detection, sales campaign execution, customer order processing, purchasing, and/or accounts payable processing – so that the business can increase revenues, reduce costs or both"* (Williams and Williams 2003). On the operational level, BI can have impact short-term as being able to create a visual representation of the processes, which allows a more in-depth understanding on what is happening on a day-to-day basis (Baruti 2023; Brijs 2013; Sharda et al. 2014; Williams & Williams 2003). On a strategic level, Williams & Williams (2003) argue to look at this topic as an investment to create revenue by uncovering previously unknown knowledge, or by making better decisions which have positive impact on day-to-day operations.

All in all, BI in helps decision makers in making better decisions, however it has a broader scope with the transformative potential that has an impact on any organization (Wixom & Watson 2010). Undoubtedly, such fundamental transformation can rarely happen overnight, and it requires stakeholders to shift their mindset towards fact-based, analytical way of thinking (Watson 2012). From this perspective, BI systems and data-facilitated decision-making combined can be seen as tools for business model innovation, that allow companies to undergo significant process changes and rethink their way of working to achieve the next level of organizational maturity (Wixom & Watson 2010).

The remainder of this thesis focuses on the role of BI and strategic decision-making in the field of software engineering. The upcoming chapter further explore examples and methodologies illustrating how software engineering organizations can be beneficiaries of the research areas discussed earlier.

4 BUSINESS INTELLIGENCE IN SOFTWARE ENGINEERING

Software engineering is the application of empirical practices to solve practical problems and business needs using computational software tools (Farley 2021). Despite the common belief that the focus is primarily on programming and the development of software source code, Farley (2021) and Martin (2011) argue that this profession is much more about applying pragmatic tools and principles to enable continuous learning and effectively manage complexity. Software engineering is a creative profession that can greatly impact business outcomes. Aligning business and technical goals is a challenge for software engineering teams due to the need to balance strategy with the complexities of building software systems. (Farley 2021; Forsgen et al. 2018; Kim et al. 2021).

Based on the findings presented in Chapter 2, BI could offer valuable practices in the realm of software engineering by providing a comprehensive overview of daily operations from various aspects. Software engineering teams can benefit significantly from the actionable insights revealed by BI, such as identifying areas for improvement and enabling data-facilitated decision-making. The appropriate adoption of BI practices can lead to significant benefits, including improved productivity, higher product quality, and increased customer satisfaction. BI empowers teams to analyze trends, detect patterns, and uncover hidden inefficiencies, thereby fostering innovation and management of complexity – key areas emphasized by Farley (2021) in software engineering.

Interestingly, the studied literature rarely mentions BI and software engineering together. However, multiple authors (Kim et al. 2021; Amaro et al. 2024; Farley 2021; Forsgren et al. 2021; Forsgren et al. 2018) discuss the DevOps movement, which captures similar ideas as BI in terms of measurements and outcomes in this domain. During the literature review for this thesis, the ideas, practices, and metrics associated with the DevOps movement frequently emerged in this context even though the primary focus of this research was to explore BI applications. Given these overlaps, exploring DevOps provides valuable insights into BI's role in the field of software engineering.

4.1 The DevOps movement

DevOps is a collaborative approach that bridges development (Dev) and operations (Ops) teams to work towards a common goal of building reliable, quality software. The movement evolved from agile methodologies, focusing on cultural changes and technology-enabled strategies for automated deployment, quality assurance, and stable, rapid software delivery, even in unpredictable environments. (Amaro et al. 2024; Mishra & Otaiwi 2020; Kim et al. 2021). DevOps puts high emphasis on continuous improvement and learning as well as the management of complexity, meanwhile providing numerous metrics (Amaro et al. 2024; Mishra & Otaiwi 2020; Kim et al. 2018; Forsgren et al. 2021; Forsgren et al. 2018). DevOps also offers a cultural shift for software engineering teams to view their profession in novel ways with emphasis on communication, collaboration and the continuous deployment of production software (Amaro et al. 2024; Forsgren et al. 2018; Mishra & Otaiwi 2020; Kim et al. 2021). For this reason, Mishra & Otaiwi (2020) suggest that DevOps deals with a broader area than the close collaboration between development and operations, expanding the concept to the key dimensions of culture, collaboration, automation, measurements and monitoring.

According to previous studies, high performing teams and organizations reportedly implement DevOps practices to quantify and measure performance and success of their processes (Amaro et al. 2024; Farley 2021; Forsgren et al. 2021; Forsgren et al. 2018). The DevOps methodologies and metrics can be considered as starting points to the empirical part of this thesis and for any software team planning to introduce measurement techniques in daily operations. Amaro et al. (2024) highlight that both academia and practitioners recognize the practical benefits and value of this approach to software engineering, as it effectively connects theoretical research with real-world applications.

The similarities between BI and DevOps are notable, particularly in their shared focus on data-facilitated decision-making, and continuous improvement. The systematic literature review by Amaro et al. (2024) and the ideas presented by Kim et al. (2018) pinpoint multiple application areas where DevOps practices and metrics have proven beneficial in the past, that are essential for strategic management of and the creation of high-trust culture in software engineering teams.

These findings are closely aligned with the findings presented in Chapter 2, which captures BI's goals and values.

Scientific literature in this area – such as the work done by Forsgren et al. (2018) – argues for measuring certain dimensions of software engineering teams, however only a few studies demonstrate how to obtain this kind of data on a regular fashion in a single company. The introduction of a BI system, which is an integral part of the daily operations, can become an essential piece in this puzzle for organization involved in software engineering. A well-positioned BI system that is in close connection with the team members' daily tools (such as development environments, task management system, customer management system, source control system etc.) has the capability to automatically extract information whenever required from the underlying databases and present the relevant information to managers of the team.

From the findings above it can be surmised, that DevOps is an approach, which aims at solving similar goals as BI in the software engineering context. This connection suggests that integrating DevOps ideas and practices could enrich the application of BI within software engineering, offering methods to achieve the same objectives. This statement confirms the relevance of studying DevOps in the selected context. The following subchapters focus on the application areas and metrics, as well as the specific challenges regarding the introduction of BI and DevOps practices in the context of software engineering teams.

4.2 Application areas

In "The State of DevOps Report", Forsgren et al. (2018) surveyed over 23,000 respondents from over 2,000 software engineering organizations of all sizes that are involved in software development and delivery. Their research aimed to identify measurable factors that distinguish high-performing software engineering organizations from their low-performing counterparts. Their groundbreaking research identifies numerous areas and causational relations, which contribute to effective software delivery and high performance of software engineering businesses (Amaro et al. 2024; Farley 2021; Forsgren et al. 2018).

Forsgren et al. (2018) suggest focusing on capabilities to drive continuous improvement and adapt to the ever-changing landscape of IT. Their research identified 24 key capabilities in total (listed in Appendix 3) which reportedly have statistically significant impact on the success of software engineering teams. These capabilities are classified into five categories. The first category is Continuous Delivery, which focuses on practices, that enable effortless, automated deliver software to a production environment, directly to end-users securely, reliably and with minimal interventions. The second is Architecture, that suggests loosely coupled software architecture between applications, thereby providing flexibility and independence of software engineers in their tooling and workflows. The third is Product and Process, which emphasizes the close collaboration with customers and regular feedback to foster innovation, enabling the free flow of creative solutions to the business problems addressed by the developed software solutions. The fourth is Lean Management and Monitoring, which puts emphasis on a lightweight change approval process and the visual monitoring of workflows alongside with system performance to inform business decisions. The final category captures Cultural aspects of the team, encouraging close collaboration, fluent information flow and high trust between team members, enabling individuals to create meaningful work, improvement of job satisfaction, and reduction of burnout. (Forsgren et al. 2018, 199-205).

The survey-based research demonstrated that efficient software delivery performance not only drives an organization’s financial success but also significantly improves team well-being, reducing burnout and fostering job satisfaction (Amaro et al. 2024; Mishra & Otaiwi 2020; Forsgren et al. 2018; Kim et al. 2021). In essence, the findings prove that software engineering teams do not need to make compromises between quality and speed, because high performing organizations achieve both at the same time. In other words, some teams achieve exceptional performance across all dimensions, while others tend to struggle in multiple of the studied areas. (Forsgren et al. 2018). The literature review conducted by Amaro et al. (2024) suggest similar application areas of DevOps. Researchers behind the studied articles generally state that DevOps practices positively influence software delivery, system uptime and reliability, while also enhancing customer experience and cultural dynamics of the engineering team. Amaro et al. (2024) identify the 22 most used metrics and categorize them into four categories.

Business metrics focus on the alignment between software development and overall business objectives. Change metrics assess the efficiency and effectiveness of modifications made to software or services. Operational metrics evaluate system stability, reliability, and overall performance. Lastly, Cultural metrics measure aspects such as collaboration and trust, emphasizing psychological safety, meaningful work, and long-term job satisfaction. (Amaro et al. 2024).

The findings from Amaro et al. (2024) and Forsgren et al. (2018) combined highlight a fundamental shift in how to approach the assessment of performance in software engineering. The results suggest that relying solely on technical skills and making decisions based on past experiences on the managerial level is insufficient. Instead of skills, organizations should put more emphasis on technical, cultural, and operational capabilities. Authors agree that these application areas are closely interconnected and mutually reinforce eachother at every software engineering team and organization (Amaro et al. 2024; Kim et al. 2021; Forsgren & Kersten 2017; Forsgren et al. 2018).

Emphasizing and measuring the above areas in software engineering teams, while adopting DevOps practices reportedly leads to better performance, faster delivery of quality software and higher satisfaction of team members. (Amaro et al. 2024; Mishra & Otaiwi 2020; Forsgren et al. 2018). However, implementing these measurement strategies is not without its difficulties. The next subchapter explores the specific challenges software engineering organizations face in applying BI and DevOps metrics effectively.

4.3 Specific challenges

Effective measurements are essential to drive change and improve overall outcomes in software engineering teams. However, choosing the right metrics and measurement techniques is less evident, because of the nature of this domain (Farley 2021; Forsgren et al. 2018; Forsgren & Kersten 2017; Kim et al. 2021). Forsgren et al. (2018, 11-13) propose that being critical about the validity and reliability of the chosen metrics is a crucial factor, as many of the easily accessible metrics might lead to false conclusions and misinterpretations.

At first glance measuring output-based metrics, such as the lines of source written by a developer, might seem like a good indicator for developer productivity. Often developers prefer shorter, more compact solutions, which results in fewer lines of code, which is another reason against choosing this as a productivity metric (Forsgren et al. 2018; 12-13). However, a shorter piece of source code can be much harder to understand and less maintainable in many situations, because it might lack clarity, proper documentation, or thoughtful structure, leading to technical debt (Farley, 2021; Forsgren et al. 2018; 12-13; Martin 2011). Instead, Forsgren et al. (2018; 12) suggest that developers should be rewarded for solving business problems effectively, which can mean not writing a single line of code at all. Another way to achieve tackle this is by focusing on outcome-based metrics instead of output-based metrics. Outcome-based metrics assess how a developers' contributions align with and drive broader business goals. These might include metrics such as customer satisfaction, feature adoption rates or the amount of mistakes, bugs and rework hours. (Amaro 2024; Kim et al. 2021; Forsgren et al. 2018). In another article, Forsgren et al. (2021) warn that choosing a single metric for evaluating developer productivity is not sufficient or accurate, as productivity is multidimensional and influenced by satisfaction, collaboration, efficiency, and performance.

Forsgren et al. (2021) suggest choosing metrics across multiple dimensions and measurement techniques, so that tension between the numbers is created a balanced result is achieved at the end of the day. Moreover, Forsgren & Kersten (2017) argue that metrics should be validated through triangulation and continuously revisited to ensure their relevance and effectiveness in driving improvement. (Amaro et al. 2024; Forsgren et al. 2018 157-158; Forsgren & Kersten 2017). To address these challenges, Forsgren & Kersten (2017) suggest the adoption of a measurement strategy that integrates both system-based and survey-based metrics. This approach ensures a more accurate reflection of software delivery performance by combining quantitative precision with qualitative insights (Forsgren et al. 2018 157-158; Forsgren & Kersten 2017).

Some psychosocial areas, such as well-being of team members, culture, or inclusivity, can hardly be quantified or measured automatically via system data. Therefore, the easiest way to feed digital data about these dimensions into a BI system is by asking the involved individuals about their feelings in a quantitative manner, for instance by classifying or rating statements on a Likert-scale (Forsgren et al. 2018, 32). The challenge with this is that many can be resistant in contributing as such matters are not closely related to their daily work, or some might have difficulties in expressing their opinions in such abstract matters (Forsgren & Kersten 2017). System data, while providing real-time tracking and granularity, lacks the ability to capture personal experience of team members, cultural factors, and unstructured work processes. Conversely, survey data can reveal the perception of individuals quickly but is prone to biases and lacks real-time continuity. (Amaro et al. 2024; Forsgren & Kersten 2017).

Another issue is that measuring individual impact can lead to unintended consequences, such as promoting competition instead of collaboration or some might exploit the metrics in their own favor. Forsgren et al. (2021) explain this by stating that *“metrics shape behavior”* – in other words, team members will inevitably try to align the numbers in their favor. To address this, Forsgren et al. (2018) and Amaro et al. (2024) highlight the importance of prioritizing team-level metrics, which foster a sense of collective responsibility toward achieving business objectives. To mitigate this challenge, studies suggest reflecting on the shared contributions of the entire team instead of individual performance (Amaro et al. 2024; Kim et al. 2021; Forsgren et al. 2018).

Furthermore, quantifying dimensions such as team culture or quality of software is a complex task and often depends on the goals of the organization. Amaro et al. (2024) and Forsgren & Kersten (2017) highlight that there is always the matter of subjectivity and possible misinterpretation of the metrics. Managers must carefully consider the desired goals and outcomes when choosing the measurement metrics and dimensions. This is particularly important while designing surveys, because the wording and phrasing can be misinterpreted by individuals differently, possibly leading to biased results. (Amaro et al. 2024). To address this issue, Amaro et al. (2024) and Forsgren et al. (2018) recommend clear, well-defined, strong statements in surveys (e.g., measuring culture and perceived efficiency), which employees understand the same way with high certainty. Similarly, survey-based insights should be complemented with system-based data, which provides a more objective and continuous measurement of software delivery performance (Forsgren et.al. 2021; Parmenter 2020; Forsgren & Kersten 2017; Hans & Mnkandla 2013). When designed appropriately, this way of operation facilitates decision-making from operational to strategic levels, because it allows monitoring the business efficiency, and its ups and downs over time with more certainty.

Despite the above challenges, Forsgren & Kersten (2017) propose establishing a baseline and the initiation of the measurements across the relevant dimensions as early as possible. This recommendation has two key reasons. First, as organizations grow, it gets increasingly more difficult to identify and fine-tune the right metrics, requiring significant amount of time. Second, the earlier managers get to see some visualization and patterns of the chosen metrics (even if they are not perfect), the earlier improvements can be made within the team. (Forsgren & Kersten 2017). This approach aligns with Farley (2021) and Kim et al. (2021), who emphasize continuously seeking opportunities for self-improvement even in early stages of the software development lifecycle.

Software engineering organizations must understand these challenges to drive improvements and maturity. To successfully implement and refine these practices, businesses need clear metrics and structured frameworks that offer quantifiable insights into the desired areas. The following subchapter introduces alternative starting points and discusses their potential usage.

4.4 Recognized DevOps metrics and frameworks

The Multivocal Literature Review conducted by Amaro et al. (2024) specifically focused on exploring and identifying the most relevant DevOps metrics in the IT landscape. Their analysis of 139 documents (academic and industry reports) revealed and prioritized 22 metrics in total. In their context, DevOps metrics are business-relevant, actionable indicators that enable teams and organizations improving their outcomes by optimizing the adoption of DevOps practices. The identified metrics are quantifiable, impactful, and widely recognized in the industry, serving as a valuable starting point for software engineering teams looking to implement measurement strategies. (Amaro et al. 2024). The results presented by Amaro et al. (2024) pinpoint the relevance of DevOps metrics in data-facilitated decision making emphasizing their role in software delivery performance and business alignment. Their results highlight that leveraging a combination of system-based Key Performance Indicators, cultural insights and best practices, organizations can enhance software delivery, reliability, and team collaboration (Amaro et al. 2024), which finding is well-aligned with findings by other scholars in the past (Forsgren & Kersten 2017; Forsgren et al. 2018).

Specifically, Amaro et al. (2024) identify four key DevOps metrics that stand out significantly in the studied literature. First, Mean Time to Recover (MTTR) measures the average time required to restore service after a failure, with lower values indicating better incident response and system resilience, ultimately reducing downtime and improving service reliability. Second, Mean Lead Time for Changes (MLT) measures the between code commit to production deployment, where shorter times indicate a more efficient software delivery, enabling faster feedback loops. Third, Deployment Frequency (DF) reflects how often a team successfully releases code to production, with higher frequencies associated with continuous delivery and better agility. Finally, Change Failure Rate (CFR) represents the percentage of deployments that result in production failures, with lower rates indicating higher deployment quality and stability, reducing service disruptions and operational risks. (Amaro et al. 2024).

Among the 22 metrics identified by Amaro et al. (2024) there are many other numerical metrics that can be convenient starting points for many organizations. For instance, Defect Escape rate captures the percentage of bugs/issues that are discovered in a production environment in comparison to those discovered earlier, during development and quality assurance stages. This metric is straightforward to track, provided the engineering team can segment the source of reported issues. Another key metric is Work In Progress (WIP), which quantifies the number of open tasks an engineering team is handling simultaneously (Amaro et al. 2024). Kim et al. (2021) extensively discuss the impact of excessive Work In Progress value, drawing a parallel between software development and factory production lines. They argue that accumulating unfinished products is harmful, as they take up space and provide no immediate value – like unfinished tasks in software engineering. However, in the engineering domain, the burden is not physical but cognitive, as excessive task-switching increases mental load and reduces efficiency. (Amaro et al. 2024; Kim et al. 2021)

In addition to quantitative metrics, Amaro et al. (2024) agree and suggest that gathering qualitative insights through developer surveys and team retrospectives are equally vital for understanding the cultural and human factors influencing DevOps success. To be exact, the authors suggest using the Westrum's Organizational Culture Measures (Amaro et al. 2024; Westrum 2004), which is the same method proposed by Forsgren et al. (2018, 32-39) and Kim et al. (2021, 46-50). Forsgren et al. (2018) specifically suggest that Likert-type survey questions in this area work very well with worded clearly and strongly formulated statements about how the respondent perceives a certain area of the team's culture. This holistic approach ensures that metrics evaluate multiple aspects of the organizational processes and outcomes by triangulating various data sources.

Beyond proving the relevance and popularity and presenting the application areas and categories of DevOps metrics (presented in subchapter 4.2), Amaro et al. (2024) aimed to capture how to put them into practice, despite implying that there is little research conducted in this area. Nevertheless, they suggest an infinity loop in which organizations continuously monitor and refine metrics and practices after their introduction. The findings also raise awareness for vanity metrics which may appear useful at first sight but can be misleading or misinterpreted in the long run (Amaro et al. 2024). The creative nature of software engineering pointed out by Farley (2021) further complicates metric interpretation, as desired outcomes often depend on specific business needs.

Previous studies in the field of DevOps already presented several standardized frameworks that integrate similar metrics. The most widely recognized frameworks are DORA (Forsgren et al. 2018; Circei 2023) and SPACE (Forsgren et.al. 2021). These frameworks share a common objective, their focus and approach differ, making it worthwhile to explore these distinctions. While DORA primarily focuses on software delivery performance on the team level based on system data, SPACE offers a broader perspective by extending the scope of metrics beyond technical measurements assessing individual well-being and perceptions.

The core idea behind DORA metrics is that effective software engineering teams excel essentially in two areas: speed and quality. Speed reflects to the throughput of the team, meaning how quickly a team can deliver to the end-users after a feature request is identified. Quality means the stability and reliability of the system. Namely, how often a team makes a mistake or introduces a bug, and once that happens, how quickly they can recover the system into a stable state.

(Forsgren et al. 2018; Circei 2023). To quantify these areas, DORA uses the same four metrics that Amaro et al. (2024) marked as outstanding during their literature review (presented in the preceding paragraphs). The reason these four metrics stand out is likely due to the growing popularity of the DORA framework, which has been widely used in the industry and academia for several years.

The SPACE framework designed by Forsgren et al. (2021) offers an alternative, multidimensional approach to productivity assessment, ensuring that decision-makers consider both technical performance and human factors when analyzing software development processes. Unlike traditional productivity assessments, which often rely on singular activity-based metrics (e.g., lines of code, commit counts), SPACE acknowledges the complexity of software engineering and emphasizes a holistic perspective. SPACE defines five dimensions of developer productivity: Satisfaction and well-being, Performance, Activity, Communication and Collaboration, and Efficiency and Flow. Furthermore, SPACE divides each dimension into three levels: Individual, Team or group and System, ensuring a comprehensive overview of productivity from multiple perspectives. The framework also suggests example metrics at the intersection of each dimension and level, offering 35 potential metrics in total. (Forsgren et.al. 2021.)

Forsgren et.al. (2021) propose using the SPACE framework such that the evaluated performance of individuals or teams are measured from multiple angles. Specifically, the suggestion is to use at least metrics from 3 distinct dimensions for crucial business processes (such as code reviews). By using this approach, no single metric dominates the evaluation, reducing the risk of misleading conclusions or unintended trade-offs. (Forsgren et.al. 2021.) This hybrid approach provides a more comprehensive view of software engineering effectiveness, guiding strategic decisions that balance efficiency, quality, and team health.

SPACE is designed in a way that software engineering teams have flexibility and freedom to adapt it to their own workflows and processes. By offering a structured yet adaptable framework, it enables teams to select and refine metrics that align with their specific workflows, challenges and objectives. SPACE framework provides a comprehensive overview and concrete metrics; therefore, it serves as an excellent starting point for software engineering teams looking to implement BI and DevOps metrics effectively. (Forsgren et al. 2021.)

4.5 Summary

In the field of software engineering, a complex and creative profession, output-based performance metrics often fail to capture the full scope of productivity and success. Unlike other industries, software teams require a unique approach to measurement, balancing business impact, collaboration, and team culture. BI methodologies offer structured ways to gather and analyze data, providing insights into numerous areas. However, identifying the right metrics that truly reflect the performance of a software engineering team remains a challenge, and defining success in this context is not straightforward. Although BI is relevant, its discussion in software engineering literature is limited – even though its principles align closely with DevOps methodologies.

DevOps methodologies put high emphasis on continuous improvement, collaboration and data-facilitated decision-making while managing a software engineering team – key principles that mirror BI's objectives. This alignment suggests that DevOps can serve as an effective approach for implementing BI practices in software engineering. Established frameworks, such as DORA and SPACE, provide well-defined metrics and methodologies to capture both technical and cultural dimensions of team performance. However, relying solely on DevOps metrics presents risks due to the inherent subjectivity of productivity assessments, potential misinterpretation of data, and the risk of unintended consequences when measuring individual performance. To address these challenges, a combination of system-based and survey-based data collection is recommended across multiple dimensions, ensuring a holistic view over business outcomes and team dynamics.

The utilization of DevOps methodologies reportedly leads to a more structured, mature and insightful way of working. The measurement of team culture using survey-based data alongside the system metrics empowers software engineering teams to elevate their performance and improve their results. The successful implementation of DevOps principles indicates a higher level of operational maturity and greater adaptability, aligning with the rapid evolution of the IT industry. These findings suggest that DevOps is not merely a tool for integrating BI into software engineering but represents a revolutionary, comprehensive approach to the field.

5 RESEARCH DESIGN

This chapter presents the research design conducted in this thesis. First, the research approach is presented, followed by the research methodology. Then the rationale behind the case selection is discussed, along with a brief introduction of the selected company, Webstar Csoport Kft. Further, the data collection and analysis methods are presented. Finally, the aspects regarding the reliability and validity of the research are discussed.

5.1 Research approach

This research adopts a constructive research approach to investigate the phenomena related to the effective implementation of BI systems in organizations, particularly focusing on the context of software engineering. Ojala & Hilmola (2003) define constructive research as a sub-method of the case study methodology where the researcher has the intention to understand a real-world phenomenon and solve the identified research problems of the case organization, and thereby to make contributions towards theory in applied research. The purpose of this research approach is to innovate and develop something new, rather than to purely experiment with an already existing methodology or procedure and report the results. (Ojala & Hilmola 2003, 83-84.)

The reason to choose this approach is that the case organization has a well-defined strategic goal, with interesting application areas not solely on engineering but business development and psychosocial aspects of work. The case organization, facing difficulties in decision-making practices due to its recent growth, requires a shift towards more data-facilitated decision-making to align with its strategic goals. Deriving from this research problem, this thesis is a problem-oriented, constructive research where the case organization’s problem is solved as explained by Ojala and Hilmola (2003 83-101). The challenges faced by the case organization make the research relevant and interesting in various fields.

5.2 Research method

The research methodology of this thesis uses a literature review followed by a single case study approach. In the preceding chapters, in the theoretical part the related concepts and frameworks were addressed based on relevant scientific literature, books and online sources. The exploratory and descriptive literature review aimed at uncovering the understanding, feasibility, application areas, and challenges of BI systems, with a particular emphasis on data-facilitated decision-making within software engineering teams. Potential metrics were discovered which can provide the basis of the empirical part of the thesis research.

Eisenhardt and Graebner (2007) point out the importance of the strong basis of established literature in empirical research, because it outlines the related key concepts and helps to confirm the relevance of and identify the research gap, meanwhile setting the scene for the development work. Yin (2009, 3) supports this statement by arguing how literature review at the beginning of a case study research contributes towards understanding the context and framing the research questions or objectives. The secondary sources were acquired from established scientific electronic libraries, which form the essential basis of the literature review conducted and addressing the research questions in this thesis.

The empirical part delves into the specifics of the case organization, introducing challenges related to the management of digital data and decision-making processes. These challenges include addressing issues such as reliance on empirical decision-making, limited operational visibility, and objectively quantifying performance of business processes. By utilizing BI and quantified metrics across the strategic focus areas, the management of the company aims for growth and enhanced business leverage, seeking an improvement over its state and maturity at the time of the research. The empirical part of the research is a single-case study where the phenomena and the potential utilization of a BI solution is explored via a development work. A single case study is a research design that involves the in-depth investigation of one case to validate, challenge, or apply theoretical propositions and generate significant insights specific to the case (Yin 2009, 85). Yin (2009, 3-5) points out that the case study research methodology is relevant mostly when the researcher seeks to find answers to “how” and “why” type of questions, therefore is relevant for the purposes of the thesis research. In a single-case study, the researcher analyzes the case organization’s internal structure and processes building on top of the theoretical foundations (Yin 2009).

The case organization, Webstar Csoport Kft., is analyzed in-depth considering the existing and desired future state of decision-making processes in two key focus areas (Software Delivery Performance and Team Happiness). The insights are compared with existing literature and theoretical frameworks, allowing the researcher to draw meaningful conclusions and recommendations for the case organization. By triangulating data from multiple sources and perspectives, the empirical part of the research aims to provide a comprehensive understanding of how BI can be leveraged to enhance Software Delivery Performance and Team Happiness within the software engineering teams at Webstar Csoport Kft. These areas are particularly emphasized as the case organization has explicitly identified them as key priorities for improvement and measurement. The metrics used by previous studies are evaluated in the case organization's context as the potential inputs of decision-making processes.

Yin (2009) explains that single case studies are often used in research and theory building, because the in-depth analysis of a single case of a certain area of research highlights specific problems or challenges and their potential solution for the case organization. Furthermore, this approach allows the author to gather and analyze both qualitative and quantitative data from primary sources, put the findings in relation to findings of secondary sources and make suggestions or improvements at the case organization (Eisenhardt & Graebner 2007; Yin 2009).

5.3 Case selection and description company - Webstar Csoport Kft.

Webstar Csoport Kft. is a 29-year-old Hungarian software agency, employing 65 people at the beginning of the research. The business model of the firm is to plan, develop, deliver, and maintain custom-built software systems on unique terms depending on the needs of the customer. Most of the software developed by the company are web-based or mobile applications with the purpose to support daily workflow specifically tailored to the customers' needs and internal processes. The case company develops a wide range applications for customers (e.g., content management systems, customer service portals and webshops, among others), with integration to other software systems (e.g., Enterprise Resource Planning, financial/invoicing, or any domain-specific software). The customers can be grouped into two types of categories: governmental/civil organizations (majority of customers) and companies present in the domestic and international market (minority of customers). The former group of customers has been with the case company for over two decades and contributes significantly to its revenue. Most of the software development projects are conducted in the fashion of the waterfall model of software development, which is typically preferred (in some cases required) by both group of customers. However, the teams internally use iterative agile methodologies, because they support the internal workflows and processes better. This means that the company operates in a hybrid model of software development that is a combination of waterfall and agile.

The company's structure is organized preliminarily around projects. Every software development project at the company requires multiple disciplinaries in the daily work: Project Managers (PM), Software Engineers and Quality Assurance Engineers (QA). The company structure is presented on Figure 2.

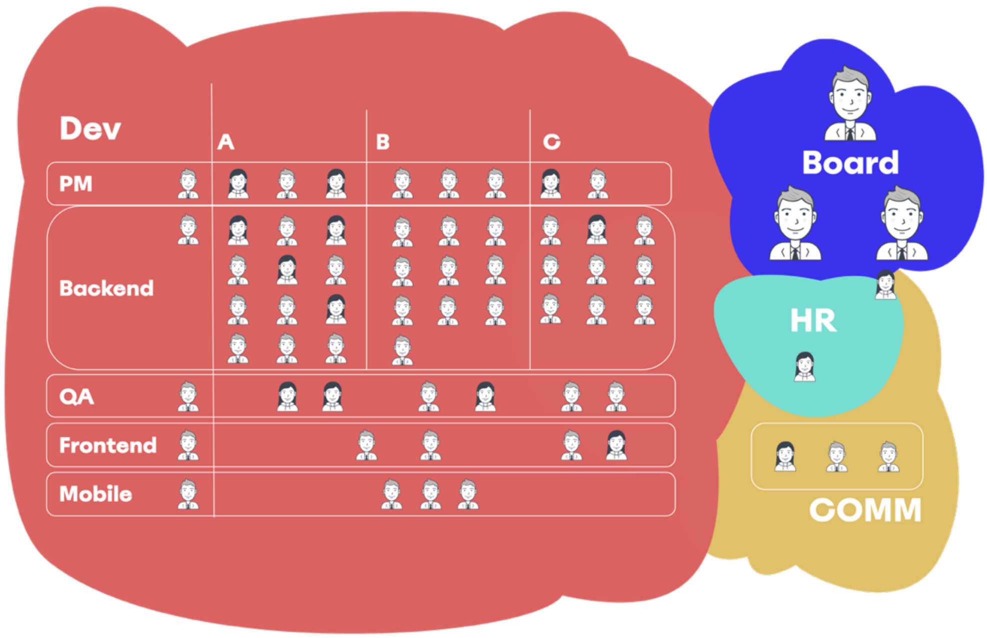

Figure 2. The organizational structure by teams at Webstar Csoport Kft. (names are anonymized).

Software Engineers are the largest group of professionals at the company. They can be further divided by technological platforms into three vertical teams (also called divisions): Backend, Frontend and Mobile. Each vertical team has one dedicated Team Lead, who is responsible for that particular platform in terms of professional perspectives such as quality, processes and standards. Quality Assurance Engineers (QA) and Project Managers (PM) also have their own delegated Team Lead, responsible for similar matters in their own field of expertise.

Historically, projects were driving composition of the teams. The company has cherry-picked project members in the past depending on their availability, which meant that the same group of professionals was rarely assigned to multiple projects. In other words, engineers seldom collaborated with the same group of colleagues on two separate projects. This approach proved ineffective, because every team had to establish their own way of, build up team spirit and learn about how to work with others effectively, thereby influencing the outcome of the projects.

Instead, horizontal teams (also called project teams, labelled A, B, C on Figure 2) were established, which consist of at least one representative from every discipline. When a project begins, it is assigned to one of the three horizontal teams depending on the scope, the timeframe, and the customer, as well as the availability and competence of the team members. On a general level, this way members of the team compositions are not changing, however there are some exceptions when employees are rotated temporarily between teams (e.g., certain competence is needed elsewhere for a short amount of time). The core business is conducted by the combination of horizontal and vertical teams labelled as “Dev” on the left side Figure 2. On the right side of Figure 2 are supportive roles which function alongside of the core business, labelled as “Board”, “HR” (Human Resources) and “COMM” (Communication and Marketing). Members of these functions are not essential part of the daily production work: their roles are focused on strategic matters and the facilitation of the core business by the division of supportive activities. These functions do not take part in any software engineering projects but support the daily work and well-being of the employees in one way or another.

On top of the structure above, the company can be divided into three layers from the point of view of organizational hierarchy (displayed on Figure 3): C-level executives/Board – 3 employees; Middle managers (Project Managers, Team Leads, Lead Developers) – 14 employees; Production workers (Software Engineers, Quality Assurance Engineers) 43 employees; Support personnel (Human Resources, Marketing, Communications), 5 employees.

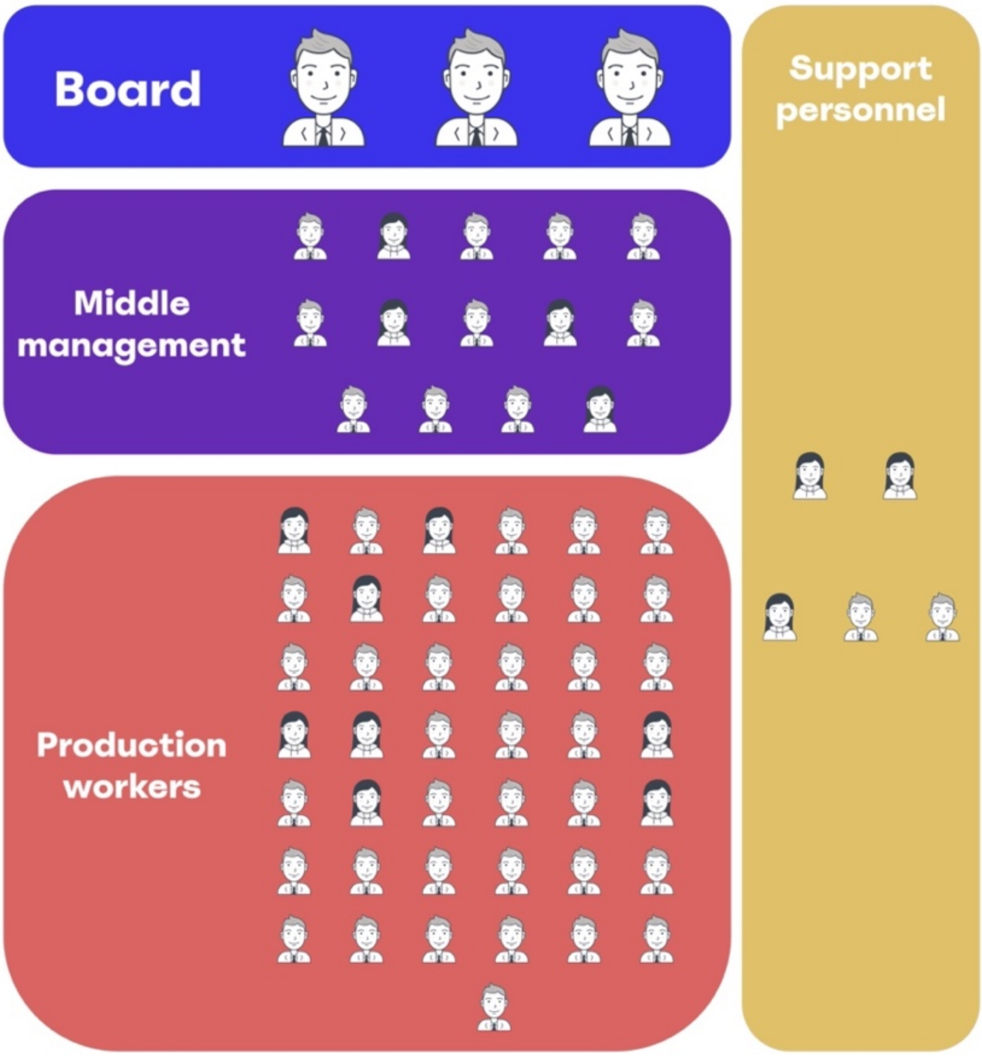

Figure 3. The hierarchical structure at Webstar Csoport Kft.

Despite having a 3-layer hierarchy at the company, in practice the everyday work is done in a fashion that the organizational hierarchy can be considered flat. This means that every production worker (e.g., a software engineer) can be part of the decision-making process done on the middle-managerial level, anybody can express their viewpoint and opinions on matters related to the organization. This culture facilitates collaborative work and is well-aligned with one of the company's core values to establish mutual trust between employees and to bring joy, team happiness to the workdays.

The main stakeholders of BI at the case company are the Board members and Middle Managers (Project Managers, Team Leads), because they can directly observe and monitor health of the teams by looking at the metrics provided by BI. By measuring the same metrics over time, the same stakeholders can track and follow the health and development progress of their teams. Indirect stakeholders of the introduction of BI are the production workers because their daily work will be indirectly influenced by the decisions made based on the measured metrics. A potential side-effect of an improved decision-making process will impact the engagement and motivation towards daily work of all employees, which is one of the goals during this research. Customers of the case company are external stakeholders in this development process and focusing on their perspectives is out of the scope in this thesis. However, the introduction of the BI system developed in this research is expected to positively influence the satisfaction on the customer side. In other words, the acceleration of performance and employee well-being at the case company leads to higher employee satisfaction, motivation, and engagement, which increases overall service quality, hence to customer satisfaction (Forsgren et al. 2018, 24; Mulligan & Taylor 2019, 4, 24, 31).

The management of the case organization demands to produce an arbitrary number of metrics in both focus areas, which metrics can be investigated for each team and project separately, joined together into a single value reflecting on the performance of the focus area in the unit (Appendix 1). Furthermore, by calculating metrics for all teams, the achieved numbers can be projected onto the organization as a whole. By doing so, the possibility opens to measure and investigate performance of the teams over time and reflect on how their work contributes to the organization altogether. Even though, it would be beneficial to define and see metrics even individual employees over all departments at the company, the research focuses on the core business. In practice this means that only the teams labelled as “Dev” presented in Figure 2 and Figure 3 are involved in this research and the development of the BI system. Stated differently, the employees who fulfill supportive roles (teams Board, HR, and COMM) are excluded from this research for the sake of focus and scope reduction. This decision is made so that the outcome of this research influences majority of the employees at the case company, thereby making the biggest possible impact at the present stage of the firm.

5.4 Collection of data

Primary sources include a combination of methods. The empirical phase involves a semi-structured interview at the beginning of the research with key stakeholders at Webstar Csoport Kft. The semi-structured interview is a qualitative data collection method in which the interviewer follows a flexible, conversational approach rather than a fixed script, allowing for open-ended questions and two-way interactions that adapt to the context and the responses (Yin 2011, 134). As Yin (2011, 134) suggests, interviews enable researchers to gain insights into respondents' perceptions and gather a substantial amount of qualitative data, which is essential component is case studies like this thesis. The CEO and CTO of the case organization were interviewed as key informants based on their relevant roles in strategic decision-making. The aim of the discussion was uncovering insights about the desired goals and understand the expectations from BI development project and the potential challenges in the industry. The transcript of the interview is displayed in Appendix 1.

To assess the focus area of Team Happiness, quantitative data is gathered through employee surveys. The survey includes Likert-scale questions that allow respondents to express their views on various statements related to their overall well-being within project teams. The survey questions and response scales are provided in Appendix 2, while a summary of the collected data can be found in subchapter 6.2.1.

The case organization already utilizes various software systems in the daily work for the administrative purposes of employees' time tracking, cost and expense calculations, source code versioning, deployment automations and continuous integrations. The digital data available in the databases behind these systems can be obtained and utilized for the purposes of this research. The focus area of Software Delivery Performance (introduced in subchapter 1.3) is a great candidate to be based on the underlying data in these databases. This kind of data is referred to as system data (Forsgren et al. 2018, 157-158, 160-162; Forsgren & Kersten 2017) and is viable in the present research, because there is wide availability of historical data at the case company's premises. However, the raw data certainly must go through some preprocessing to be usable for the purposes of this thesis, which means data transformation, filtering and potentially error corrections, which is a typical part of similar projects (Tan, Steinbach & Kumar 2005, 44-65). The obtained data for this focus area is displayed in detail in subchapter 6.2.4.

5.5 Data analysis

The insights gathered during the semi-structured interview with the key informants of Webstar Csoport Kft. is analyzed using pattern matching technique. As Yin (2009) explains, pattern matching is one of the most desirable techniques for case study analysis because it strengthens internal validity by comparing empirically observed data with theoretically patterns derived from prior literature. In this thesis, the goals and challenges related to BI and DevOps are compared with the specific context of the case organization.

This thesis utilizes time-series analysis to examine how key performance metrics in the chosen focus areas evolve over the observed time period. According to Yin (2009), time-series analysis is particularly useful in single-case studies when the goal is to analyze change over time or to compare trends with theoretical expectations. This technique is well-suited for the present research, as it enables setting the baselines for each area respectively, alongside the identification of patterns, anomalies, and basic correlations in the context of the case organization. Furthermore, exploratory data analysis is conducted to explore the collected data. Tan, Steinbach, and Kumar (2005) explain that exploratory data analysis as the process of analyzing datasets to summarize their main characteristics, often using visual methods. This approach helps uncovering patterns, trends, and anomalies in the data without prior assumptions, offering intuitive insights into the underlying structure of the selected metrics through basic statistical measures and graphics.

5.6 Reliability and validity of the research

The reliability and the validity of this thesis is supported by the used primary and secondary sources which both reinforce its relevance and findings alike. The case organization has hands-on knowledge and daily connections to the research area. Furthermore, the company’s management can evaluate the viability of the developer practices quickly in its daily operations. This feedback loop and close connection to industry experts reinforces the validity, especially when secondary sources report similar findings in related industries in other areas of research.

The unique context of the case organization poses a potential threat to the validity and reliability of this research. Since this thesis is a single case study, the results are also specific and tailored to the case organization’s profile, ecosystem and business environment. Therefore, any future researcher who wishes to generalize findings and build on top of this research, should take into consideration that the cultural, geographical, and unique attributes of the IT industry and the case organizations are all strong factors in the results of this thesis. In other words, despite the results achieved in this thesis, the techniques and methods might not be applicable in other contexts. For this reason, future researchers must be critical and careful about investigating the overlapping attributes in their respective fields of research.

6 CASE STUDY: WEBSTAR CSOPORT KFT.

This chapter presents the analysis of the empirical observations at Webstar Csoport Kft. First, the strategic goals behind the introduction of BI at the case organization are presented, considering the initial conditions of the research. This is followed by the steps towards designing the measurements of the two chosen strategic focus areas in their respective subchapters. Finally, the collected data is analyzed, and the relevant findings are presented.

6.1 Strategic goals behind the introduction of Business Intelligence

The leadership of Webstar Csoport Kft. recognized years ago that several decisions concerning resource planning, scheduling, team dynamics and team alignments were made in an empirical manner, solely based on intuitions. While this approach was sufficient for a time, the company's rapid growth in recent years has demanded organizational changes, as managers have increasingly felt that the company has outgrown its organically developed processes. Managers at all levels, including Board members and Middle Managers, agree that relying on empirical decision-making remains common but is limiting the potential of the organization. The daily operations should be supported by the available digital data in some way to make progression towards the strategic goals presented in subchapters 1.3 and 5.3 (Appendix 1).

A key milestone in this process was the introduction of timesheets in 2020, requiring employees to log their work hours and activities on the running projects. This change made it possible to monitor time spent on each project and put the recorded time in relation to what was estimated and allocated previously during the resource planning and estimation. This shift has enabled the comparison of initial project plans (allocated human resources and budget) with actual results (work hours and money spent). This helps to assess project efficiency, identify misalignments, and improve future planning and resource allocation. Encouraged by this positive outcome, the company has high expectations for BI to provide solutions in other areas, further driving progress toward strategic goals.

The strategic expectations from BI were outlined in a semi structured interview (transcript displayed in Appendix 1) at the beginning of the research jointly with

Attila Bertók, the CEO of the firm and the commissioner of this thesis and Tibor Bodai, CTO of the organization. The interview highlighted that by the introduction of the BI methods in the selected key focus areas, the Board expects more objectivity in how and why changes, improvements and business development is made at the organization (Appendix 1). Bertók clearly states that by looking at data from teams and projects, the biases derived from prior experience can be reduced, and the gradual improvements can be tracked in much better ways compared to the current practices (Appendix 1). Furthermore, this development work will support the monitoring if the chosen areas are moving towards the right direction, as well as provide more insights to improve daily workflows in the teams. In the long run, BI methods should be designed to quantify various aspects of the organization in a standardized, numerical format across teams and projects. This flexibility ensures comprehensive insights, supporting continuous improvement and strategy. (Appendix 1.)

The uncovered expectations and goals during the initial discussions (Appendix 1) are well-aligned with the findings of the literature review throughout Chapters 2 and 3, as well as Appendix 5. It seems evident, that BI is a tool that the case organization in its current state needs. However, as the case organization faces similar challenges to those discussed in the literature, addressing data management practices and standardizing workflows will be critical next steps.

The interviewed informants noted that Middle Managers tend to focus on daily tasks rather than aligning with broader strategic goals. Addressing these misalignments requires middle managers to collaborate more closely, establish common standards, and integrate strategic alignment into their daily responsibilities. Team Leads and Project Managers often evaluate their teams' performance differently and manage daily operations individually, leading to inconsistencies in underlying data. (Appendix 1.) This variation makes it difficult to choose universal metrics and conduct standardized analyses across multiple teams. The introduction of BI is expected to close the gap between middle management and strategic objectives. This shift contributes to the organization’s maturity and foster a data-facilitated approach to decision-making.

Bodai emphasized also that the chosen strategic goals are too abstract in nature, therefore it is hard to grasp what they mean and aim at (Appendix 1). Experience shows that employees have difficulties in making a personal connection to the strategic goals for the same reason. By the introduction of BI, Bodai expects to provide measurable indicators in the upcoming years, to which employees can relate better. This shift facilitates the general understanding of how daily work contributes to broader organizational objectives. (Appendix 1.) By translating abstract goals into concrete, quantifiable metrics, employees can see the direct impact of their efforts, fostering a stronger sense of ownership and alignment with strategic priorities. Overall, a positive impact is anticipated on the continuous development of individuals and teams in reaching their goals, while also enhancing the company's growth and competitiveness.

The BI pilot in the two strategic focus areas chosen for this research provides an opportunity to test methodologies and systems as a foundation for future development. The active involvement and commitment of Board members in fostering a fact-based mindset are expected to ease user adoption and support long-term success. Furthermore, the chosen focus areas are relevant to the middle management layer (Team Leads and Project Managers), because they are expected to be beneficiaries of the gained insights and applied metrics.

During the initial interview (Appendix 1) at the beginning of the research with the CEO and CTO as informants, the consensus was made to keep the above goals and expectations in mind. This was an important step in the research as Kumar, Stern and Anderson (1993) point out that in qualitative data collection from multiple key informants poses the potential risk that the involved parties perceive the topic differently. By clarifying the expectations in the beginning of the research, this risk was addressed and minimized.

6.2 Measuring strategic focus areas

At the beginning of the research, the available data was limited to system data, automatically collected by software tools during daily operations. The primary sources include the task management system (Redmine) and the version control system (GitLab), both of which are integral to the workflow of software engineering teams at the case organization. Even though this data is rich and easily available, the lack of standardized usage across teams poses a challenge. Inconsistent data entry and varying workflows make it difficult to design reliable analyses and derive meaningful insights. Establishing uniform data management practices is essential to ensure the accuracy and comparability of BI-driven evaluations. Additionally, the company conducts online surveys using Typeform for various purposes. However, these surveys do not address strategic goals or objectives at the initial stage of the research. This thesis provides an opportunity to leverage the survey tool in a more structured way, aligning it with the company's strategic focus areas. The case organization uses Metabase as its BI system, where various project management-related analyses are already conducted at the project level using data from the task management system. The capabilities of Metabase are fully leveraged in to measure metrics in the selected focus areas.

At the beginning of the research, a key challenge in data management was the lack of structured organization within the task management system. Projects were recorded as an unstructured list without any categorization, making it impossible to determine which projects belonged to specific customers or internal teams (labelled A, B, C on Figure 2). To address this, the database of the task management system was extended to enable project grouping. These newly defined project groups categorize projects within the same business domain. Each project group was then assigned to an internal team, with this information also stored at the database level. Establishing this structure was a crucial prerequisite for designing meaningful measurements and building the BI system.

In addition to these database enhancements, significant data management efforts were done, including data cleansing, labeling, and organizing records related to employees, projects, and project groups. Most of this preparatory work falls outside the core focus of this research, therefore details are omitted. The charts presented in the following subchapters are compiled into a single dashboard, which, along with the outlined findings, represents the key results and outcomes of the empirical research and development work.

The following subchapters outline how these strategic focus areas are measured and implemented within the BI system at the case organization. First, the measurement design choices for Team Happiness are presented, followed by an analysis of Software Delivery Performance.

6.2.1 Measuring Team Happiness

The primary goal of measuring Team Happiness among employees is to gather feedback on their well-being and overall satisfaction with daily work at Webstar Csoport Kft. The Board aims to quantify and track this area to ensure effective progress toward the strategic goal of having the most satisfied employees. Another objective behind this is to receive feedback about the overall well-being and perceptions of the employees about daily work at the organization. Since this is a broad and intangible area with no existing data that can be extracted from existing systems, an employee satisfaction survey was designed to capture the key aspects of employee satisfaction as defined by the Board. The choice for this approach was made due to the literature findings presented in subchapter 4.4, as this area is closest to team culture in DevOps methodologies. In other words, Team Happiness can be measured by similar means as culture in the DevOps methods. The survey questions were originally stated and submitted to respondents in Hungarian but were later translated to English. Appendix 2 displays the translated version of the employee satisfaction survey.

10 survey questions were composed for the survey, all of them requiring the respondent to answer on a scale between 1-6. An even number of scale numbers what chosen intentionally, to avoid respondents marking the middle number, aligning either to positive or negative direction in their answers. Eight of the survey questions are statements regarding how the respondent feels during the daily work about certain aspects, such as engagement, teamwork, collaboration and trust. The final three questions are formulated as questions regarding feedback, motivation and task distribution. The questions are stated in a way that the choice of words describe one particular area clearly and the statements are formulated strongly, so that respondents can strongly agree or disagree with the discussed area. The intent behind this choice is to have clear feedback on each area specifically and to enhance the relevance of the results.

The survey is distributed by project managers to all production workers involved in a specific project. This setup enables responses to be linked to a particular project, making it possible to analyze answers at the project, project group, or organizational level. This flexibility is important, as Middle Management and Board members wish to analyze the data from multiple perspectives.

An agreement was made with Project Managers to ensure the surveys are distributed at milestones of active projects. In cases where projects do not have milestones (e.g., support projects have this attribute), surveys are distributed once every three months. In both cases, team members working on a project receive a link to the Typeform survey, which includes the identifier and name of the project. For closed projects, no Team Happiness survey submissions are expected. The survey is anonymous in all cases, thereby fostering honesty and clarity from respondents. The instructions at the beginning of the survey highlight that the respondent is expected to provide answers to a single project only and neglect their experiences in the others, in case they are working on multiple projects simultaneously. All answers are optional, allowing respondents the freedom to skip questions if they feel they are not relevant to their role or situation.

This survey design ensures a structured and measurable approach to assessing Team Happiness, which is generally a subjective and intangible area. By linking responses to specific projects while maintaining anonymity, it allows the Board and Middle Management to track trends, identify areas for improvement in culture and employee satisfaction, meanwhile maintaining privacy of and honesty from respondents. Involving Project Managers in the design and distribution of surveys increases their engagement and reduces resistance to collaboration. This inclusion of Middle Management is important, as they receive structured, quantitative feedback from their teams firsthand, ensuring clearer insights and informed decision-making processes during the daily work.

6.2.2 Collection and analysis of Team Happiness data

Data collection took place from May 2023 to December 2024, resulting in 108 survey submissions across 15 projects. Although all survey questions were optional to answer, only one submission had two unanswered questions (specifically, questions 4 and 5). In all other cases, respondents answered every question. This high response rate indicates strong employee engagement and a willingness to provide thoughtful feedback. This positive finding suggests that employees are engaged and take the time to contribute.

During the time the questionnaire, there were 92 projects on which employees logged more than one week of work hours (40 hours) according to the task management system. From this observation it can be concluded, that in the given time approximately 20% of the running projects were rated. Some projects had only one or two employees logging time, making survey impractical. Despite these exceptions, a higher level of participation across the organization was expected over the course of more than a year. This finding suggests potential issues with the survey distribution process or a lack of engagement from middle management in ensuring that surveys are consistently submitted to the team members. The fact that the participation in this strategic initiative is lower than expected impacts the completeness and reliability of the data.

The data collected via the Typeform submissions were initially stored in a Google Sheet, which later was migrated to the same database that the task management and BI systems are using. This data migration process, though seemingly minor, required extensive planning to ensure proper data management, and long-term maintainability. By integrating survey data into the same database as the task management system, the BI system can enrich survey responses with additional project data, enabling comprehensive querying and analysis. Strategically this is critical, because the case organization can incorporate all the BI metrics and outputs into a single tool, eliminating the need for multiple platforms and streamlining data analysis across various project areas. After the migration process, multiple queries and a dashboard was built in Metabase to visualize the collected data.

The results displayed on Figure 4 indicate an overall positive reaction among employees, with an average happiness score of 5.04. It can be concluded in general, that employees feel relatively satisfied with their work environment and project involvement. Over time, the average values in the company level remain stable, showing minimal fluctuations, which indicates consistency in employee experiences across the analyzed period. Among the individual survey questions, Question 10 received the highest score, averaging 5.31. This shows that employees generally feel motivated to work on their assigned projects, which is a strong indicator of engagement and alignment with their tasks. This high motivation level contribute towards productivity and job satisfaction, reinforcing the success and results of the case organization.

Figure 4. Team Happiness metrics at Webstar Csoport Kft.

However, the lowest-rated questions were Question 4 (4.68) and Question 9 (4.46), which ask about the feeling cared for within the team and the frequency of feedback received, respectively. These aspects are closely related, as feedback and personal support from leadership contribute significantly to employees' sense of belonging and professional growth. The lower scores in these areas indicate that Project Managers and Team Leads may not be providing enough regular feedback or personal engagement with their team members. These results indicate that some respondents might feel isolated or disconnected from their team, hence risking the success of the project and potential burnout of the employee on the long run. This finding also suggest that teams tend to operate in a task-driven manner, where focus is placed on work execution and personal interaction or support is sometimes secondary.

The data displayed on Figure 4 shows that there were no survey submissions between 2023 November and 2024 November. The reasons for this are unclear, but one likely factor is that some projects lack dedicated Project Managers, leading to a gap in survey distribution and submission responsibilities. This suggests that the number of obtained results could have been higher if the distribution process had been designed differently, as the chosen approach relies too heavily on project-specific workflows and Project Managerial involvement, which may have led to inconsistencies in the delivery of the surveys.

Overall, the results indicate a good baseline of employee satisfaction on the company level, with motivation levels remaining high across projects. However, the findings also highlight areas for improvement in leadership engagement, feedback culture, and team support, which could be enhanced through targeted changes in management practices and survey refinements. The team-level breakdown of the Team Happiness survey results are displayed on Figure 5. The collected data reveals variations between teams.

Figure 5. Team Happiness metrics by teams at Webstar Csoport Kft.

Team A reports the highest overall satisfaction, with an average score of 5.4, outperforming the other teams in nearly all survey questions. Team B and Team C display lower, but similar overall scores, averaging 4.76 and 4.84, respectively. The bottom-left chart represents the breakdown of the ten survey questions by teams. The consistently higher results from Team A suggest that this team benefits from strong cohesion, balanced workload, or well-aligned internal processes. However, the underlying reasons remain unclear and call for further investigation. One possible explanation is that Team A is typically working on novel, innovative projects, whereas Teams B and C work more on legacy projects, which might shape the general work environment and leave its mark on job satisfaction and motivation levels.

One notable observation from the bottom right chart is that Team C did not participate in the survey after September 2023, which could indicate a misalignment in the survey process or a lack of engagement in contributing to this initiative. This team may require targeted intervention to encourage participation and ensure their perspectives are represented in future assessments. Furthermore, Team C reports the lowest average scores for Questions 4 and 9, which assess sense of belonging (4.47) and feedback frequency (3.67), respectively. Given that these aspects are crucial for engagement and productivity, special attention could be given to improving team cohesion, feedback culture and communication within Team C.

Regarding response distribution, Team B provided the highest number of responses (48 total), despite being smaller than Team A. This is likely due to the team's intense workload in 2023, which required conflict resolution and restructuring. Specifically, a key example of how this survey provided actionable insights comes from a project executed by Team B between late 2023 and early 2024. During this period, the workload was heavily concentrated on one individual, causing stress and inefficiencies. While the upper management had already identified this issue based on direct feedback from the Project Manager and observed delays in the project's budget and timeline, the Team Happiness survey confirmed the problem, yielding the lowest average score recorded for any project (3.97). In response to resolve the bottleneck, the management expanded the project team by two additional members and changed task distribution to clarify responsibilities and balance workloads more effectively. Six months later, the survey was conducted again, showing a significant improvement in the average score (5.11), along with generally positive feedback from the team. This crisis situation alongside with the involvement of leadership have increased engagement with the survey process, as team members had concerns to share.

Although these particular results on the project level are not displayed on the dashboards, this case demonstrates how Team Happiness metrics can serve as both an early warning for organizational issues and a method for tracking the impact of decisions. Although, the problem was already known through other empirical channels, the survey results provide quantitative validation of employee concerns and help assessing the effectiveness of decisions over time.

6.2.3 Measuring Software Delivery Performance

One of Webstar Csoport Kft.'s strategic goal is to provide the highest quality software engineering services within its market segment and business ecosystem. As discussed in the literature review (Chapter 4), achieving this goal requires shifting the focus from software quality to Software Delivery Performance, which offers clearer metrics for tracking for driving improvements.The aim of measuring Software Delivery Performance at Webstar Csoport Kft. is to assess and improve the efficiency, stability, and effectiveness of its software engineering processes. The Board wants to track these aspects to ensure continuous progress toward delivering high-quality software with optimal speed and reliability. Given the complexity of software delivery, with its dependencies across teams and systems, a structured approach is necessary to define success in this area. The DORA and SPACE frameworks provide useful starting points, but the organization must consider its specific circumstances and business processes to choose the most suitable metrics and data collection methods.

As outlined in subchapter 5.3, most customers of Webstar Csoport Kft. are governmental and civil organizations, which typically operate in highly regulated environments. These projects often follow a waterfall approach, with extensive analysis and planning before development and testing, which shapes the competencies and processes of the software engineering teams. For example, the teams are rarely responsible for managing production systems at the infrastructure level. Instead, external partners handle production deployments. While engineering teams provide a deployable package, the responsibility for monitoring and ongoing operations after deployment falls outside their scope. Thus, the teams focus mainly on development and application-level support, with production operations managed externally.

This model does not align with DevOps principles, where development and operations are shared within the same team. While the partnership with external parties has been effective, this division of responsibilities limits the applicability of DevOps metrics. Adapting DevOps methodologies to measure Software Delivery Performance in a way that suits the case company presents a unique challenge.

However, the ideas and categories introduced by the DORA and SPACE frameworks, along with the metrics identified in the literature review, can inspire the teams to find metrics for measuring Software Delivery Performance.

Lead Time for Changes is a key metric in the DORA framework which measures the time between identifying a feature request and deploying it to production. However, given the case organization's internal processes, applying this metric in its standard form would reflect the speed of business decision-making or the customer's capabilities rather than the engineering team's delivery performance. Therefore, this metric is accommodated to better fit the organization's needs. The organization's task management system allows for tracking completed tasks by measuring the time between their start and completion. This can be seen as Delivery Time for each task, reflecting how quickly the software engineering teams at Webstar Csoport Kft. plan, develop, and test their work. By extracting milestones from the issue tracking system, Delivery Time in hours can be calculated for each task. Averaging this value across completed tasks provides a meaningful representation of the team's actual delivery performance. Ideally, this value should be as small as possible, reflecting on the quick development processes and rapid, agile way of working in the team.

Deployment Frequency is another popular metric proposed by the DORA framework to quantify speed/throughput, reflecting how often production deployments occur. At the case organization, this metric is not applicable for similar reasons as the previous standard metric. Instead, measuring deployments to development and staging environments seems to be a more reasonable approach. Since these deployments are controlled by the engineering teams, their frequency provides an objective measure of speed and throughput. However, no simple and uniform method was found to measure these deployments consistently. The challenge lies in the fact that different teams use various tools (e.g., Jenkins and GitLab CI) to automate deployments, and some deployments occur outside of these tools, manually. Accurately measuring Deployment Frequency would require standardizing processes and integrating existing tools, which falls outside the scope and timeframe of this thesis. Nonetheless, this limitation highlights an opportunity for further research and development in this area to elevate the organization's maturity in this regard.

In terms of measuring stability of work performed by an engineering team, the literature review suggests using Change Failure Rate and Mean Time to Restore as metrics. These indicators require a high level of engineering maturity, including robust test automation, continuous delivery practices, and observability tools in production environment. These tools help detect system failures, track resolution times, and confirm when the system has returned to a stable state. Engineering teams of Webstar Csoport Kft. do not yet widely use such tools, therefore these metrics are not practical at this stage. Similar to the previous metrics, relying on external partners for this process would not provide meaningful insights into the engineering team's actual performance either.

As a more practical alternative, Defect Escape Rate was selected as the primary metric for evaluating software quality. Unlike other metrics, it does not require advanced tools or methodologies, making it a better fit given the organization's engineering maturity. Quality Assurance Engineers' responsibilities were updated to ensure that all production-identified issues are properly recorded with appropriate meta data in the task management system. This small but effective process change allows defects discovered in production to be systematically recorded, enabling accurate tracking of the Defect Escape Rate. A high value of this metric indicates that Software Engineers and Quality Assurance Engineers miss some of the discovered issues during the development and testing phases, which can be an indicator of internal misalignments or different usage of the developed software in comparison to the actual end-users. Naturally, the aim is to minimize this value and discover all issues before releasing to production.

Finally, the average number of Work In Progress per employee is chosen as a metric to evaluate efficiency and flow, as proposed by the SPACE framework. This metric helps assess how effectively tasks are distributed among team members and whether task management practices support a sustainable and productive engineering process. This metric can be easily integrated into the daily workflow and requires no process redesign, external tools, or complex data management practices. The value is calculated by recording the number of in-progress tasks for all active projects and dividing the total by the number of production workers on a daily basis. The result represents the average number of tasks an individual employee is working on at the end of each day. A high Work In Progress value suggests that employees are managing multiple tasks simultaneously, leading to context switching, cognitive overload, and potential delays in delivery. Conversely, a low value indicates that tasks are well-managed, allowing employees to focus on completing work efficiently with minimal interruptions. Monitoring Work In Progress levels help Project Managers and Board members identify bottlenecks and optimize task allocation.

Table 3 sums up the chosen metrics and their descriptions in the focus area of Software Delivery Performance. These were chosen based on their practicality, alignment with business processes, and feasibility within the engineering environment of the case organization. By using these metrics, the Board aims to take meaningful steps toward achieving its strategic goals in this area.

Table 3. The chosen metrics for evaluating Software Delivery Performance at Webstar Csoport Kft.

Metric	**Description**
Daily Work In Progress per Employee	The number of tasks that are in progress state, divided by the total number of production workers.
Average Delivery Time	The average number of hours it takes for software engineering teams to complete a task, including planning, development, and testing (quality assurance) cycles.
Defect Escape Rate	The percentage of defects that go undetected during testing and were discovered in the production environment.

6.2.4 Collection and analysis of Software Delivery Performance data

To collect relevant data for measuring the identified metrics, an automated script was developed in May 2023 to log data at the end of each day. Using this automation, the required data for calculating Daily Work In Progress per Employee and Average Delivery Time is obtained at the end of each day by project. This script runs nightly, extracting necessary information from the task management system to calculate the metrics outlined in Table 3. The results are then stored in a dedicated table within the same database as the task management system, which has been integrated with Metabase to enable seamless querying and visualization of the obtained data. Automating data collection ensures consistency, minimizes manual effort and reduces the risk of errors, making the analysis more reliable and actionable for the analysis and decision-making. This data is collected only for active projects, as generating it for closed projects would be unnecessary. The data collection is still ongoing, but for this research the utilized data was filtered until the end of 2024.

To measure Defect Escape Rate, the issue tracker database already offers categories for the recorded tasks (e.g., development tasks, user stories, errors), which can be queried easily. During this research, a new custom meta data field was introduced in the task management system, allowing Quality Assurance Engineers and Project Managers to mark any of the issues as customer-reported. This field was introduced in March 2024 and was a prerequisite of determining Defect Escape Rate. To do so, the number of customer-reported issues are divided by the number of internally identified issues, yielding a ratio. This ratio is calculated over time across the teams and the organization.

Table 4 displays the number of data points, involved projects and the time periods of the data collection for each metric. Defect Escape Rate has significantly less amount of data because the data collection to calculate this metric covers a shorter period and less projects. The collected data is first presented and analyzed on the company level and then broken down to the level of teams.

Table 4. Summary of Software Delivery Performance metrics, data sources and measurement periods.

Metric	Number of records used for calculation	Number of projects	Time period
Daily Work In Progress per Employee	26 980	123	1 May 2023 – 31 December 2024
Average Delivery Time	10 298	79	1 May 2023 – 31 December 2024
Defect Escape Rate	3 620	7	17 June 2024 – 31 December 2024

Through exploratory data analysis, 200 records related to Average Delivery Time were removed during data sanitization due to abnormally large values. These anomalies occurred when tasks within certain projects were closed in bulk, making the average delivery time appear irracionally higher. Figure 6 displays the visual dashboard of the collected data on the company level. There is a noticeable misalignment in the number of projects recorded for Daily Work In Progress (123 projects) compared to Average Delivery Time (79 projects). The reason for this is that some projects remain open without any activity. This means that at least one task within these projects are incorrectly marked as in progress and some often tasks are neglected and left incomplete. This is not a significant concern at this stage since the primary goal is trend analysis, however, enhancing data quality would yield more accurate and reliable results.

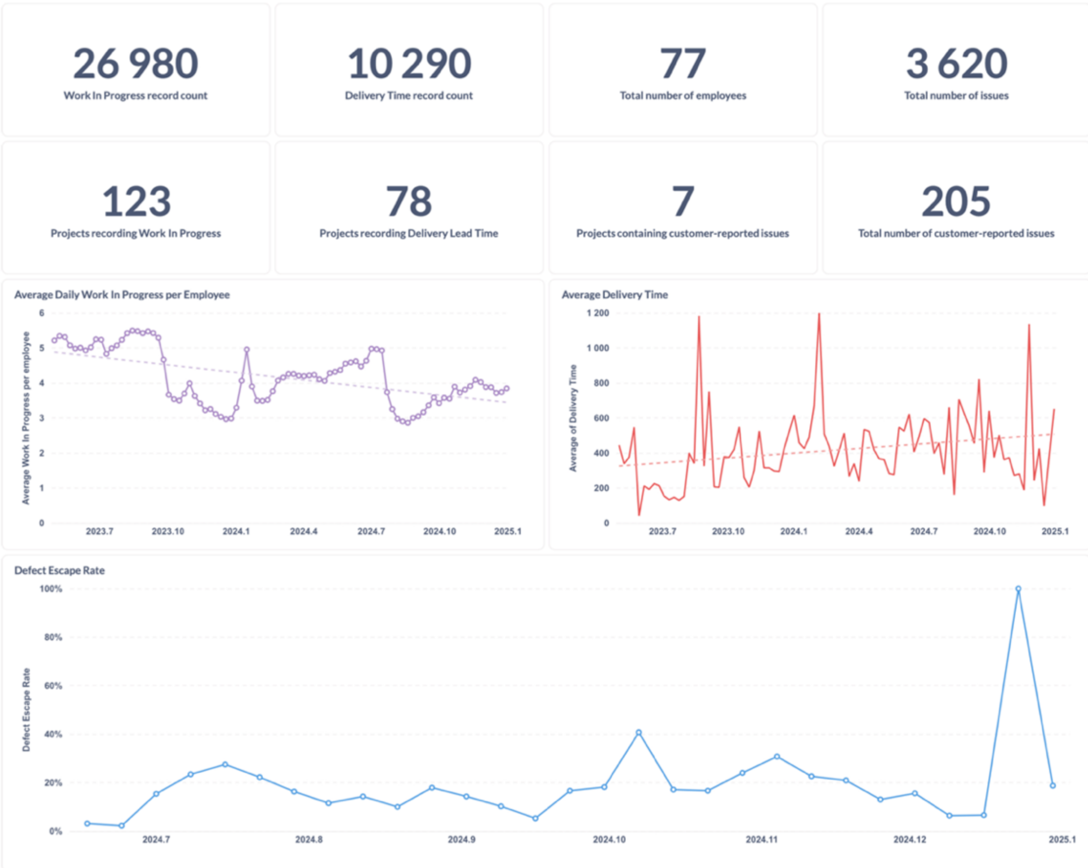

Figure 6. Software Delivery Performance metrics at Webstar Csoport Kft.

Examining the trend for Average Daily Work In Progress per Employee, there is a steady decline over the observed 1.5 years. This positive finding is aligned with DevOps principles promoting task management efficiency. However, at the end of the observed period the metric shows an upward trajectory, suggesting the need to reinforce DevOps practices to ensure this number remains consistently low, thus avoiding task overload and improving productivity. Despite the decline, the average remains around 3–4 tasks per employee, indicating that employees are typically working on multiple tasks simultaneously. During daily work, engineers frequently express concerns about this issue, particularly those with additional middle-management responsibilities. This organizational-level challenge can now be numerically demonstrated through these dashboards, validating and supporting the experiences shared by this group.

Average Delivery Time shows a generally increasing trend over the analysed period, with notable spikes occurring periodically. These spikes are likely due to the start and end phases of projects, where tasks initially take longer due to project setup and coordination requirements. However, the average range of 400-500 hours per task (over two weeks) is considerably high. The Defect Escape Rate, averaging between 10-20%, falls within acceptable limits and reflects effective quality assurance practices. This value indicates that the engineering team detects over 80% of issues before they reach customers, which is a solid baseline that can be improved over time. Compared to other performance metrics, this measure has relatively strong baseline. There is a notable spike to 100% at the end of December 2024, which was caused by reduced staffing during holiday periods. During this time, only critical on-call issues were addressed, primarily from Team C, which were all customer-reported. This fact highlights the need for careful planning during peak holiday periods to ensure service quality, despite the lower staffing levels.

Overall, the metrics indicate effective baseline performance across all dimensions. The data also highlights opportunities for targeted improvements in managing delivery times and workload distribution across teams. At the company level, Work In Progress and Delivery Time metrics show room for improvement, whereas the Defect Escape Rate remains on an acceptable level. Figure 7 presents the visual dashboard of the collected data, broken down by the three teams. It is evident that most data originate from Team A, except for Delivery Time records and customer-reported issues. This aligns with expectations, as Team A has the highest number of team members (counting 17 team members on Figure 2, Quality Assurance Engineers included). The reason Team B has the highest number of Delivery Time records is that, during the initial phase of data collection (March–August 2023), no data was recorded for Teams B and C. The exact cause of this gap is unclear, but it was likely due to data management and labelling errors at the time. Differences in work organization among project managers in these teams may have led to certain configuration oversights, preventing proper data collection.

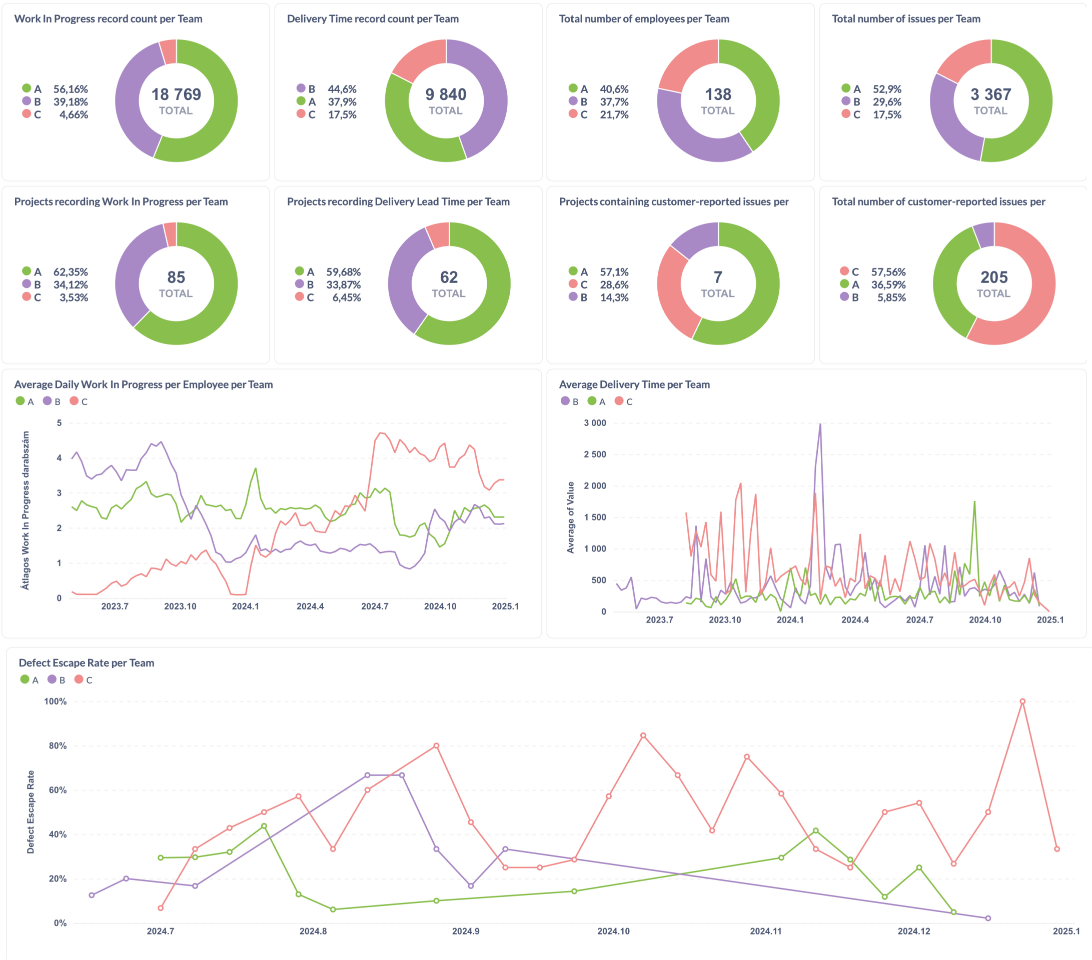

Figure 7. Software Delivery Performance metrics by teams at Webstar Csoport Kft.

This issue was identified and resolved in August 2023, ensuring more accurate tracking moving forward. However, this observation highlights a critical challenge within the case organization: teams often structure their processes differently, and standardized practices are not consistently followed across teams. Such inconsistencies lead to misalignments in data collection, making it difficult to objectively compare metrics across teams that do not adhere to the same workflows. Strategically, this inconsistency poses a significant limitation, as achieving organization-wide strategic goals requires a degree of process uniformity. Without standardized workflows, data inconsistencies hinder meaningful performance assessments and decision-making. Implementing change management was particularly challenging, as it required engaging a large number of employees in modifying their daily routines.

A more in-depth analysis of Average Delivery Time at the team level reveals that, apart from occasional spikes, the three teams perform at a relatively similar level. A notable spike is observed for Team A, likely due to a particularly hectic period. Interestingly, while the company-wide trend for this metric appears to be increasing, the team-level trends remain relatively stable or even decreasing, particularly in Team C. This suggests that, by the end of the observed period, there are no significant performance differences between teams in terms of Delivery Time. However, periodic spikes across all teams indicate fluctuations in workload, likely driven by project cycles or sudden increases in task volume.

When comparing team-level Work In Progress values, it can be observed that Team C is on an upward trajectory, despite a steady decrease in Delivery Time. This continuous increase of Wirk In Progress is not present in Teams A and B, suggesting that that Team C is getting more and more tasks started, but not finished. This trend may indicate potential issues with task prioritization, capacity planning, or resource allocation within Team C. While the reduction in Delivery Time suggests that completed tasks are being handled efficiently, the growing backlog of in-progress items could lead to future bottlenecks or quality concerns if not addressed.

The Defect Escape Rate presents another important insight worth investigating. Team C consistently shows a significantly higher ratio throughout the observed period, aligning with the earlier finding that most customer-reported issues originate from this team. Additionally, the graph reveals that Teams A and B have missing values for certain months, suggesting two possible explanations. One is that Quality Assurance engineers in these teams are not consistently following the designed process of marking issues appropriately in the system. Another explanation could be that there are genuinely no customer-reported issues for these teams during those months, which would be an unexpected finding, as software development inherently involves some level of defects, especially over an extended timeframe. This observation highlights a potential inconsistency in process adherence across teams.

7 DISCUSSION

This chapter summarizes the key findings of the thesis research and offers suggestions for Webstar Csoport Kft. on how to further develop its BI solution. The chapter concludes with final remarks and outlines potential directions for future research.

7.1 Summary of the results

While the overall value of BI has been extensively explored in business literature, its strategic integration within software engineering teams remains relatively understudied. This thesis addressed that gap by investigating the practical application of BI in a software engineering context through a single case study of Webstar Csoport Kft. The thesis illustrated how data-facilitated decision-making can replace intuition-driven practices, contributing to better alignment between day-to-day operations and long-term strategic objectives. A key contribution lies in the adapted use of DevOps methodologies – specifically the DORA and SPACE metrics (Forsgren et al. 2018; Forsgren et al. 2021) – which were adapted to the case organization's needs and implemented to measure Software Delivery Performance and Team Happiness. This extends the scope of BI beyond conventional financial and productivity metrics into more abstract and human-centric domains (Shollo & Kautz 2010). Additionally, this thesis highlighted the organizational challenges encountered during the implementation process, offering insights for practitioners and researchers studying similar contexts.

The effective application of BI in software engineering through DevOps methodologies offers organizations valuable opportunities for growth and performance enhancement. This approach enables management to gain deeper visibility into daily operations and supports more data-facilitated, strategic decision-making. When tailored to a software engineering organization's unique needs, BI and DevOps together provide actionable insights that drive improvements in efficiency, employee well-being, and overall organizational maturity (Davenport 2014; Yeoh & Koronios 2010).

The case study of Webstar Csoport Kft. illustrated how the thoughtful implementation of BI tools helps to bridge the gap between strategic goals and operational activities. By adopting DevOps-based methodologies and metrics and visualizing them in the selected BI system (Metabase), the case organization was able to objectively evaluate key focus areas such as Software Delivery Performance and Team Happiness. This thesis research supported the organization in developing a structured employee survey and automating system data collection, enabling a clearer view of internal workflows, employee satisfaction, and key performance indicators.

Throughout the development of this thesis research, Webstar Csoport Kft. encountered challenges commonly described in the literature regarding the introduction of BI. Among these, issues related to data management, process redesign, and employee engagement proved particularly significant. Notably, the middle management layer appeared somewhat passive at the necessary stages (also observed by Brijs (2013) in another context), whereas production-level employees demonstrated greater involvement. This observation highlights the organization's relatively flat hierarchy and collaborative culture, suggesting that strong employee engagement will be essential for the continued success and growth of similar initiatives.

By implementing customized DevOps metrics and optimizing data analysis processes, Webstar Csoport Kft. significantly improved its ability to monitor team dynamics and delivery performance. This approach not only contributed to a culture of continuous improvement but also provided leadership with reliable data to support strategic decision-making. Over the course of the 1.5-year data collection period, visualizing and analyzing performance metrics established clear baselines at both the company as well as team levels and helped to improve organizational processes. This shift enabled management to evaluate the utilized practices and implement targeted improvements. Early outcomes already led to data-facilitated decisions around team structure and workflow adjustments, demonstrating the value of the approach and underscoring the need for further development.

The research findings offer a model and example for BI adoption tailored to the realities of software development agencies and SMEs, highlighting both the transformative potential and practical challenges of implementation. It uncovers critical success factors such as stakeholder engagement, clear strategic alignment, and the importance of data quality and management practices. These findings contribute the research fields of BI and DevOps by illustrating that the value lies not only in the tools and systems themselves, but in the cultural and organizational capabilities they enable – similar to the SME context studied by Cuellar (2020) and Hans & Mnkandla (2013). As such, this thesis provides both theoretical enrichment and practical guidance for software engineering firms seeking to leverage BI as a driver of performance, learning and strategic awareness.

7.2 Development suggestions for Webstar Csoport Kft.

In terms of Team Happiness, the results indicate a solid baseline both at the organization and team levels, providing strong foundations. However, there are specific areas where refinement could enhance the depth and quality of insights. One suggestion is to revise the wording of Question 9, which asks respondents how often they receive feedback without considering individual preferences. This can lead to misleadingly low scores from employees who may not require frequent feedback, such as experienced team members who are already confident in their roles. Rephrasing the question to reflect whether the amount of feedback received meets the employee’s personal expectations would likely produce more accurate and insightful responses.

To address the lower scores observed in the areas of feedback and sense of belonging, additional qualitative data could be gathered. Incorporating open-ended questions into the survey could allow employees to express their expectations and experiences in their own words, offering deeper insight into the reasons behind the numerical scores. This would be especially useful in identifying insights that might not be evident from quantitative data alone.

The research also encountered issues in the survey distribution process. Gaps in response data – spanning several months in some cases – indicate that relying on Project Managers to manually distribute the survey during project milestones is not effective. Automating the distribution on a regular basis (e.g., monthly, bimonthly, or quarterly) would likely increase consistency and participation. This improvement would ensure more systematic and reliable data collection, while also reducing the mental load on Project Managers.

The analysis of Software Delivery Performance revealed that while Webstar Csoport Kft. maintains a relatively low Defect Escape Rate, the overall Delivery Time remains high. This suggests that although the quality of work is high, the speed at which it is delivered to customers could be significantly improved. One possible cause is the high Work In Progress value across teams, which likely contributes to longer delivery cycles. To enhance delivery performance, teams could be encouraged to reduce the amount of in-progress work by focusing on completing existing tasks before starting new ones. Optimizing task completion in this way would minimize context switching and improve flow efficiency, both of which are closely aligned with the company's strategic goals to provide high-quality software with greater speed and reliability. To address the high Delivery Time values, the organization might consider adopting practices that shorten iteration cycles and reduce delays. These could include breaking down tasks into smaller, more manageable units, limiting the number of handoffs between team members, and encouraging more agile planning practices.

Finally, inconsistencies in the Defect Escape Rate data between teams suggest that not all teams are following the designed process to mark customer-reported issues. In particular, Teams A and B show several months with missing data, which may either indicate a lack of customer-reported issues (an unlikely scenario) or a breakdown in the tracking process. Conducting interviews with Quality Assurance Engineers and Project Managers in these teams would help to clarify whether the inconsistencies derive from non-compliance with the established procedures or from other organizational factors. Addressing this issue is critical to ensuring the accuracy of quality-related metrics and maintaining trust in the BI system's outputs.

At the managerial and Board levels, it is recommended to incorporate the developed dashboards into daily workflows to ensure continuous visibility of team well-being and project health. Regularly reviewing these dashboards before making decisions can help align leadership intentions with actual operational data, fostering more informed and objective decision-making. Finally, expanding the scope of the BI solution to include additional areas incorporated in the organization's strategy (such as financial performance and customer satisfaction) would provide a more comprehensive view of progress towards strategic goals.

7.3 Conclusions and future research directions

This thesis research demonstrated how BI, when tailored to the specific needs of software engineering teams, can become a powerful enabler of strategic alignment and data-facilitated decision-making. Through the integration of customized DevOps metrics, automated data collection, and structured employee feedback mechanisms, Webstar Csoport Kft. made significant progress in bridging the gap between abstract strategic goals and measurable team-level performance indicators. The findings underscore how Software Delivery Performance and Team Happiness dimensions can be monitored, analyzed, and improved using a cohesive BI framework, contributing to a data-facilitated organizational culture.

While the initial results and implemented solutions mark a successful first step, the research also revealed areas for improvement and further exploration. Future research could extend the findings by incorporating additional focus areas to gain a more holistic view of the organizational maturity. Additionally, investigating how BI adoption affects middle-management behavior and culture may yield insights into better engagement in future initiatives.

As this thesis demonstrated, the successful implementation of BI is highly context-dependent. Therefore, it is essential to critically assess the unique characteristics of the business ecosystem and the operational domain before designing technical solutions. Without a careful understanding of organizational workflows and team dynamics even the most advanced BI tools may fail to deliver meaningful insights. It is essential for researchers in this field to recognize that adapting BI methods to an organization's specific needs, maturity level and cultural context is key to ensuring their relevance, effectiveness, and sustainable adoption. As BI systems and practices continue to evolve, Webstar Csoport Kft. is now well-positioned to expand its efforts and become a more insight-driven organization.

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APPENDICES

Appendix 1 1(2). Interview transcript with A. Bertók (CEO) & T. Bodai (CTO) of Webstar Csoport Kft. Conducted on 19th November 2022.

Interviewer: Why do you think the introduction of a Business Intelligence solution and Key Performance Indicators would improve processes at Webstar Csoport Kft?

A.B.: We aim to become more objective during the daily work. By this I mean we can see in a more tangible way, by looking at numbers, if our processes and achieved results are improving or not. I would also hope that by doing this we can become more focused and progress to the same direction with the colleagues in middle management and operative levels.

T.B.: The current objectives and key results are not entirely clear. By introducing Key Performance Indicators I would expect to present these in a way that the other colleagues can relate to them much better in comparison to the abstract goals, to “become the most established Hungarian software engineering firm”. I would like to see the impact in terms of numbers behind the changes we are carrying out by reshaping teams and standardizing the ways how we work together.

Interviewer: What are the strategic goals behind all of this?

A.B.: On the strategic level the introduction of BI is important because this is the approach to quantify and showcase our improvements as a company. By looking at numerical data about daily operations, we can showcase the improvement of teams and the company. This will help us seeing if we are making the right step towards our strategic goals. Another goal is that the upper management will get a better understanding what is happening “in the field” or the operational level, which we currently see only by talking to people and inferring what they say. This way of working is certainly inefficient as and biased in many cases, which is a problem we must solve.

Appendix 1 2(2). Interview transcript with A. Bertók (CEO) & T. Bodai (CTO) of Webstar Csoport Kft. Conducted on 19th November 2022.

Interviewer: What do we wish to achieve with this shift towards utilizing Business Intelligence?

A.B.: I would like to have at one number in each of the strategic focus areas (Software Delivery Performance, Team Happiness, Financial Performance, Customer Satisfaction) both on the organizational and team level, which gives me more insights about how things are going and what areas should we improve. By visualizing and keeping a close eye on these metrics, I would like to have a grasp on the impact of the changes we are making and see if the direction we are going towards is aligned with our organizational strategy. I wish to incorporate these metrics in the evaluation of strategic changes in the long run, so that we make more elaborate decisions in comparison to our current way of working. In a broader scope, I would like to have better results and more engaged atmosphere among colleagues as the result of this shift.

Interviewer: How the daily work will be impacted by facilitating our decision-making process with data? What difference will it make in comparison to the current way of working?

A.B.: In our current operations, we rely on emotions and empirical experiences alongside efficiency and well-being in many areas. At present, we do not have visibility into the pace of progress toward our strategic goals or whether we are even moving in the right direction. When we change a method or tool within a team, we only receive feedback on its results based on emotions. By introducing Business Intelligence, we hope that this improvement process will become much more objective and successful.

T.B.: The main goal in this project is to change the current ways by introducing objectively interpretable Key Performance Indicators. This will support the teams' operations and decision-making processes. As a result, we can strengthen methods that positively impact the numbers while rejecting, improving, or approaching differently those that move in the opposite direction.

Appendix 2 1(2). Team Happiness survey questions – Webstar Csoport Kft.

Please complete the following short survey regarding the {PROJECT_NAME} project. We are currently interested in how you feel about working on the {PROJECT_NAME} project at this moment, today.

If you are working on multiple projects simultaneously, please focus solely on this one and disregard the others.

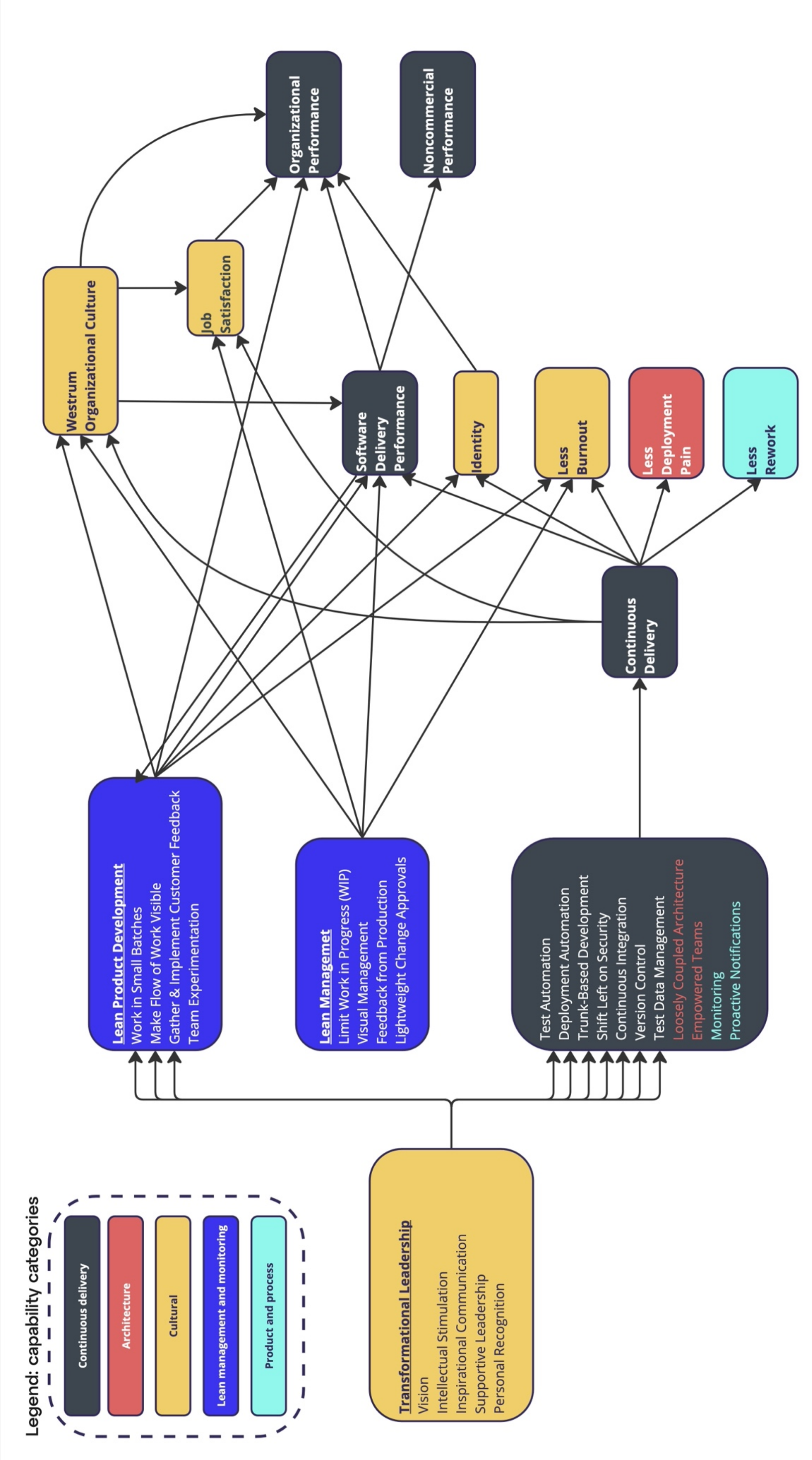
The survey is anonymous. Answering the questions take approximately 3-5 minutes.

1. I know what is expected of me in the project.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
2. I have enough knowledge to do a good job in the project.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
3. In the project, I have the opportunity to work on what I am best at.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
4. I feel that I am cared for in this team.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
5. There is someone in the project who supports my development.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
6. My opinion matters in the project.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true

Appendix 2 2(2). Team Happiness survey questions – Webstar Csoport Kft.

7. I feel that my work is useful and important for the project.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
8. My colleagues working on the project are committed to quality work.
   1 = Not at all true
   2 = Not true
   3 = Rather not true
   4 = Rather true
   5 = True
   6 = Completely true
9. How often have you received feedback on your work in the past month?
   1 = Not at all
   2 = Once a month
   3 = Twice a month
   4 = Weekly
   5 = Multiple times a week
   6 = Daily
10. How motivated are you to work on this project?
   1 = Not at all
   2 = No
   3 = Rather not
   4 = Rather yes
   5 = Yes
   6 = Completely

Appendix 3. DevOps capabilities and capability categories (adopted from Forsgren et al. (2018)).



Appendix 4 Conceptual definitions of Business Intelligence in the studied literature.

Source	**Definition of BI**
Niu et al. (2021)	„A firm's potential to effectively use the information gathered during day-to-day activities (...) BI is an enterprise's ability to leverage the available data meaningfully.”
Torres & Sidorova (2019)	„a broad class of IT-based applications for data management, analytics and information delivery, which are positioned as specialized solutions to the aforementioned problem” [translating volumes of diverse organizational data into successful action]
Davenport (2014, 10)	„Tools to support data-driven decisions, with emphasis on reporting”
Sharda, Delen and Turban (2014)	„BI is an umbrella term that combines architectures, tools, databases, analytical tools, applications, and methodologies.”
Brijs (2013, 6)	„the systematic collection and preparation of data to provide management, employees, and other stakeholders with meaningful information, that combined with the context-rich knowledge of the organization, improves the effectiveness of the organization’s strategy”
Cebotarean (2011)	„computer-based techniques used in spotting, digging-out, and analyzing business data (...). BI technologies provide historical, current, and predictive views of business operations.”
Shollo and Kautz (2010)	„a process where data are gathered, stored and transformed into information through analysis, and where information is transformed into knowledge which is used when acting (making decisions).”
Watson (2009); Wixom and Watson (2010)	„a broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions. ”
Noble (2006) as cited in Larson and Chang (2016)	„...the ability to provide the business an information advantage; business doing what it has always done, but more efficient.”
Negash and Gray (2008) as cited in Larson and Chang (2016)	„a data driven process that combines data storage and gathering with knowledge management to provide input into the business decision-making process”
Signer (2001) as cited in Larson and Chang (2016)	„BI (...) helps organizations tap into decision-making information that regular reporting does not provide. (...) BI requires tools, applications, and technologies focused on enhanced decision-making and is commonly used in supply chain, sales, finance, and marketing.”

Appendix 5 1(2). Summary of goals behind utilizing Business Intelligence in the studied literature.

Goal(s) behind BI utilization	Sources
1. Enhance strategic outcomes by improving the reliability and accuracy of decision-making process	1. Boto, Correia & Borges (2024) 2. Baruti (2023) 3. Cuellar (2020) 4. Schmarzo (2016) 5. Porter & Heppelmann (2014) 6. Davenport (2014) 7. Sharda, Delen & Turban (2014) 8. Hans & Mnkandla (2013) 9. Bara & Knežević (2013) 10. Cebotarean (2011) 11. Yeoh & Koronios (2010) 12. Shollo and Kautz (2010) 13. Zdraveski (2009)
2. Improve organizational performance and efficiency (simplify and optimize processes), change management	1. Baruti (2023) 2. Cuellar (2020) 3. Schmarzo (2016) 4. Davenport (2014) 5. Porter & Heppelmann (2014) 6. Sharda, Delen & Turban (2014) 7. Bara & Knežević (2013) 8. Hans & Mnkandla (2013) 9. Cebotarean (2011) 10. Stasieńko (2011) 11. Yeoh & Koronios (2010) 12. Shollo and Kautz (2010) 13. Zdraveski (2009)
3. Automated reporting and trend forecasting to identify patterns and extract insights	1. Boto, Correia & Borges (2024) 2. Baruti (2023) 3. Cuellar (2020) 4. Davenport (2014) 5. Bara & Knežević (2013) 6. Brijs (2013) 7. Zdraveski (2009)

Appendix 5 2(2). List of sources mentioning goals behind utilizing Business Intelligence in the studied literature.

Goal(s) behind BI utilization	**Sources**
4. Provide an overview (to executives) about business operations, performance monitoring	1. Boto, Correia & Borges (2024) 2. Cuellar (2020) 3. Baruti (2023) 4. Yeoh & Koronios (2010) 5. Shollo and Kautz (2010) 6. Zdraveski (2009) 7. Zdraveski (2009)
5. Data transformation and knowledge creation	1. Cuellar (2020) 2. Yeoh & Koronios (2010) 3. Shollo and Kautz (2010) 4. Sharda, Delen and Turban (2014) 5. Bara & Knežević (2013)
6. Organizational learning	1. Bara & Knežević (2013) 2. Stasieńko (2011)
7. Provide new perspectives to enable discussions for collaboration and communication	1. Baruti (2023) 2. Cuellar (2020) 3. Bara & Knežević (2013)

Appendix 6 1(2). Summary of challenges behind utilizing Business Intelligence in the studied literature.

Challenge(s) of BI utilization	**Sources**
1. Strategic alignment to organizational goals	1. Baruti (2023) 2. Schmarzo (2016) 3. Davenport (2014) 4. Shollo and Kautz (2010)
2. Commitment and engagement	1. Schmarzo (2016) 2. Davenport (2014) 3. Brijs (2013) 4. Watson (2012) 5. Wixom & Watson (2010) 6. Yeoh and Koronios (2010) 7. Dewett & Jones (2001)
3. Lack of maturity or resistance against fact-based mindset	1. Baruti (2023) 2. Cuellar (2020) 3. Forsgren, Humble & Kim (2018) 4. Schmarzo (2016) 5. Davenport (2014) 6. Brijs (2013) 7. Watson (2012) 8. Shollo and Kautz (2010) 9. Wixom and Watson (2010) 10. Dewett & Jones (2001)
4. Interdisciplinary collaboration	1. Schmarzo (2016) 2. Davenport (2014) 3. Brijs (2013) 4. Watson (2012) 5. Wixom & Watson (2010)

Appendix 6 2(2). Summary of challenges behind utilizing Business Intelligence in the studied literature.

Challenge(s) of BI utilization	**Sources**
5. User adoption and resistance to change	1. Forsgren et al. (2018) 2. Schmarzo (2016) 3. Davenport (2014) 4. Dewett & Jones (2001)
6. Establishing data management practices	1. Baruti (2023) 2. Cuellar (2020) 3. Schmarzo (2016) 4. Davenport (2014) 5. Brijs (2013)
7. Ensuring data quality	1. Paredes (2024) 2. Baruti (2023) 3. Cuellar (2020) 4. Rachinger et al. (2018) 5. Yeoh & Koronios (2010) 6. Watson (2009)
8. Resource constraints	1. Cuellar (2020) 2. Wixom & Watson (2010)