

Data-Driven Decision-Making in Finland's Public Social and Healthcare Sector

Information Systems Science

Master's thesis

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This thesis examines the implementation of data-driven decision-making (DDDM) in Finland's public social and healthcare sector, focusing particularly on the integration of Business Intelligence (BI) and Knowledge Management (KM) to improve organizational efficiency and strategic outcomes. The sector is currently facing increasing organizational complexity, resource limitations, and rising demands for quality and accountability, which traditional decision-making practices struggle to address effectively. Fragmented information systems, siloed knowledge, and inconsistent data use have hindered efforts to optimize operations and improve service delivery.

To address these challenges, this study explores DDDM as a systematic approach that replaces intuition-based practices with evidence-based insights. In this framework, BI is seen as a critical enabler of timely and accessible data, while KM provides the organizational processes needed to capture, share, and use knowledge effectively. By combining these elements, the study outlines a coherent framework for improving operational efficiency, strategic alignment, and the overall quality of care in the public social and healthcare sector.

The research applies a qualitative method based on semi-structured interviews conducted with the information services team of one of the newly established Finnish wellbeing services counties. Using grounded theory and the Gioia method in the data analysis process, the study identifies key drivers and barriers to DDDM implementation, such as technological infrastructure, cross-departmental collaboration, and organizational culture. The results reveal that while strategic commitment to data-driven models is evident, successful implementation requires aligned practices, knowledge-sharing frameworks, and clear communication across departments and professional boundaries.

The study contributes to existing literature by providing current views on DDDM practices in the context of the Finnish social and healthcare reform of 2023, as the topic is still relatively unexplored. By combining BI and KM within a coherent DDDM framework, this thesis demonstrates how these tools can support better decision-making, transparency, and collaboration in public social and healthcare sector. The findings highlight that DDDM is not just a technological upgrade, but an organizational and cultural transformation that needs to be implemented at all levels of an organization to realize its full potential.

Key words: Data-Driven Decision-Making, Knowledge Management, Business Intelligence, Public Social and Healthcare

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Glossary of terms

Data-Driven Decision-making (DDDM): DDDM can be seen as an ideology, where data is seen as a strategic resource rather than an assumption and experience, and where decision-makers and managers are required to promote a data-driven culture of innovation and to take information into account at all stages of decision-making (Brynjolfsson et al., 2011, 2).

Business Intelligence (BI): BI is seen as a method that allows an organization to explore, utilize, and analyze data from its data warehouse to generate insights that support better decision-making (Nylund, 1999).

Knowledge Management (KM): KM is a systematic process that involves discovering, selecting, organizing, refining, and presenting information in a manner that enhances an employee's understanding in a specific area (Herschel & Jones, 2005).

Artificial Intelligence (AI): AI refers to computer systems capable of learning and making decisions based on their own experience. Unlike systems that rely solely on human expertise, predefined rules, or decision-support frameworks, AI systems use their learning to improve and adapt over time. (Koski & Murphy, 2021.)

Social and Healthcare reform 2023: A major restructuring of Finland's healthcare and social welfare systems, which came into effect on January 1, 2023. Responsibility shifted from municipalities to 21 wellbeing services counties and the City of Helsinki, covering healthcare, social services, and emergency services. The reform aims to streamline service delivery and promote public health through collaboration with private providers and NGOs. (Sosiaali- ja terveystieteiden ministeriö, 2023.)

1 Introduction

1.1 Background

We live in a digital age where information is both a tool and a commodity. As a result, data-driven decision-making (DDDM) has become a prominent phenomenon in various fields of study, such as information systems science, law, or medicine. Today, we see information overload almost everywhere. As technology advances, more and more data are being made available to people and organizations. Data-driven decision-making refers to the process of analyzing and using the information collected to support decision making (Shafiq, 2024; Brynjolfsson et al., 2011; Troisi et al., 2020). The core idea behind this approach is that decisions are based on objective, data driven analysis, not just intuition or personal experience. (Provost & Fawcett, 2013.)

The constant and fast-paced development of information and communication technologies means that organizations are processing more information, leading to information overload (Yigitbasioglu & Velcu, 2012). The expanding volume of data in businesses and the multiple information systems they use have made it increasingly difficult to distinguish between essential and irrelevant data. As a result, producing timely, sufficient, and reliable data has proven to be quite challenging in many industries (Kinnunen et al., 2018). Although information is filtered, enhanced, and analyzed to satisfy demands, using it in an organization in a way that adds value is not always simple. Information management frequently faces both internal and external problems, and organizations usually have either too little or too much data use, both causing issues. It is possible that insufficient awareness of the demands, changes, and requirements in the business setting would undermine decision-making (Laihonen et al., 2013, 15). To address these challenges and improve decision-making, organizations are increasingly turning to structured approaches such as knowledge management (KM) and business intelligence (BI).

The general conception of KM is that it is an organized process for producing, obtaining, sharing, using, and capitalizing on information to maintain competitive advantage and accomplish organizational goals (Rolland, 2004). KM and BI are frequently used synonymously, if not interchangeably. The goals of knowledge management and business intelligence are to facilitate understanding, learning, and decision-making. KM and BI are two different ideas; KM aims to promote understanding and insight inside an organization, while BI focuses primarily on accurate and unambiguous data. BI can be seen as part of KM, which covers both explicit and tacit knowledge in an organization. (Herschel & Jones, 2005.)

Today, a lot of data is being generated through various digital technologies, which can be utilized through different data products to improve decision making in an organization. In the social and healthcare sector in particular, decision that are traditionally based on experience can be enhanced by BI. While significant progress has been made in integrating BI methods into the social and health care, current studies have mainly focused on clinical and technical systems. The potential of BI from an organizational perspective, particularly in improving the management and coordination of healthcare processes, is still relatively unexplored. (Basile et al., 2023.)

Ratia (2022) highlights that optimizing administrative and managerial processes through data-driven decision-making can lead to more cost-effective operations. With the increasing competition among public and private healthcare operators, there has been a growing interest among managers and executives in utilizing advanced methods and data technologies such as KM, BI, and Artificial Intelligence (AI) to harness siloed organizational data. These tools allow healthcare organizations to unlock value from their existing operational systems. While prior literature offers a framework for understanding the value creation potential of business analytics, there is still limited research focusing on the public social and healthcare sector. This creates an opportunity to explore how these data-driven approaches could benefit public social and healthcare organizations in Finland.

The number of elderly people is increasing, and there is pressure to reduce costs, which provide complicated difficulties for the Finnish healthcare system. More generally, one of the common challenges in many nations is the requirement for performance improvements. From the perspective of organizational and management practices, this calls for the effective use of knowledge resources and proactive sharing of knowledge, among many other things. The knowledge needs for healthcare professionals have changed and grown. For example, as they increasingly serve as managers in addition to medical specialists, new types of knowledge are needed. (Myllärniemi et al., 2012.)

To conclude, although the concepts of data-driven decision-making, BI, and KM have received increasing scientific attention, there is still a significant gap in understanding of how these practices are implemented and developed in Finnish public and social healthcare sector. Furthermore, as the wellbeing services counties in Finland were established in 2023, there is limited empirical evidence on how these organizations utilize data for strategic and operational decision making. This study aims to address this gap by investigating how data-driven decision-making supported by BI and KM practices is currently used in one Finnish wellbeing services county, and what organizational and technological factors enable or hinder its implementation.

1.2 Research goals and research question

This study aims to explore how data-driven decision making (DDDM) is utilized in the Finnish public social and healthcare sector to improve organizational performance and decision-making. It aims to contribute to a deeper understanding of how data can be leveraged not only to optimize resource allocation and improve service delivery but also to promote strategic alignment and collaboration across complex healthcare systems. Given the rising costs and increasing complexity of healthcare, DDDM offers a valuable framework for supporting evidence-based decisions, improving patient outcomes, and fostering operational efficiency. Through a combination of literature review and empirical findings from one Finnish wellbeing services county, this study contributes to the ongoing development of DDDM practices in the public sector. To address the objectives of this thesis, the following research question has been formulated:

RQ1: How do public social and healthcare sector in Finland utilize data-driven decision-making to improve operational efficiency?

The following sub-research questions has been established to compliment the main research question:

RQ2: What roles do knowledge management and business intelligence play in facilitating data-driven decision-making within Finnish public social and healthcare organizations?

RQ3: What challenges does the Finnish public social and healthcare sector face in implementing data-driven decision-making processes?

The aim of the study is to provide an improved understanding of how knowledge-based strategy can improve management and operational efficiency in such a challenging environment as the public social and healthcare sector in Finland. It also aims to provide insights into how structural and cultural barriers can be overcome to support the effective use of data to improve health outcomes.

1.3 Motivation

The motivation for this research stems from my interest in the digital age and the exponential growth of data. With the increasing adoption of business analytics, knowledge management has become a critical strategy for improving organizational performance across industries. However, despite proven benefits in sectors such as finance and retail, the healthcare sector has been slower to embrace these innovations. The reason for this delay is the sector's hierarchical structures, reliance on traditional practices and the complexity of healthcare systems.

Furthermore, the 2023 reform of the healthcare sector in Finland also led to extensive changes in the way the public sector operates, its organizational structures and the greater utilization of data. Finnish Innovation Fund (Sitra) emphasized in their research that the success of this kind of healthcare reform is heavily dependent on an open-minded attitude toward embracing new technologies and utilizing data effectively (Lehto, 2023). Therefore, exploring the role of data-driven decision-making in the context of this reform offers a compelling opportunity for this thesis. It will allow me to delve deeper into the intersection of organizational structures, data utilization, and management in public healthcare, offering a more comprehensive view of how these elements collectively drive efficiency and effectiveness in the sector.

In my previous bachelor's studies, I explored data-driven methodologies within the field of management accounting. Combining this background with my work experience in the social and healthcare sector and my current studies in information systems science, it was a natural choice to integrate these areas into the focus of this research. Recently, I also had the opportunity to participate in a research seminar on work informatics at the University of Turku, where we explored topics such as the challenges of management in the public healthcare sector and the impact of hierarchical structures. These discussions sparked the idea that this could be a fascinating area for further research. This experience provided additional motivation and clarity for pursuing my research in data-driven decision-making in healthcare.

1.4 Thesis structure

This thesis is divided into six main chapters. The first chapter explains the background to the thesis and its importance to the research. This section also explains the author's motivation for the topic, formulates the research questions and briefly explains the structure of the thesis.

In the second chapter, the principles of data-driven decision-making, business intelligence and knowledge management within healthcare are explored, highlighting their interrelationship. It also examines the current situation and challenges of public social and healthcare sector in Finland. Lastly, this section also briefly describes the use of technologies such as artificial intelligence in healthcare management.

In the third chapter, the study presents the research methodology, data collection and analysis. It explains why a qualitative approach is suitable for conducting research and how grounded theory can be applied in a semi-structured interview method.

The fourth chapter reviews the findings of the semi-structured interviews and the factors influencing data-driven methods in public social and healthcare sector will be discussed.

The fifth chapter discusses and reflects the key findings in the light of literature review and empirical findings. The section highlights the growing significance of DDDM in wellbeing services counties and outlines the cultural and structural barriers that may hinder its successful implementation.

Finally, the sixth chapter summarizes the main findings and presents the theoretical contributions. It also presents the managerial implications of the study and discusses the limitations and directions for future research.

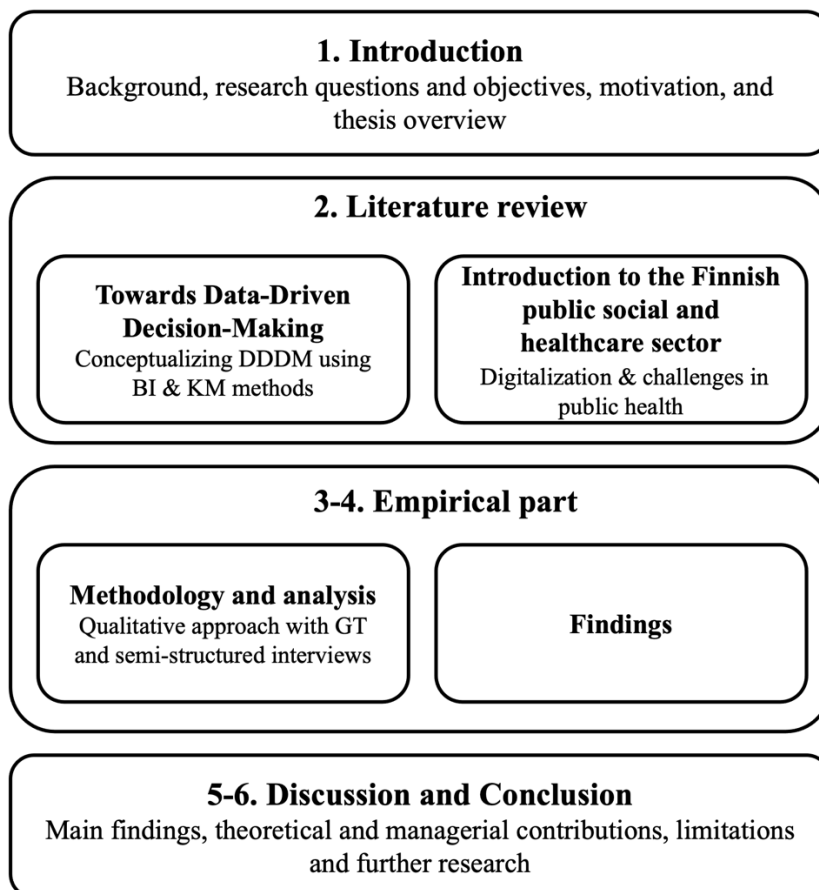


Figure 1 Thesis outline

2 Literature review

This section introduces different aspects of data-driven decision-making (DDDM) and its relevance in the public social and healthcare sector. It explores key frameworks, such as the DDDM process, BI, and KM as critical enablers for improved decision-making. Secondly, the chapter examines the current situation and challenges of the Finnish public social and healthcare sector, and the role of BI and KM to addressing these challenges. The literature review also briefly discusses the role of digital platforms and AI in transforming healthcare management.

2.1 Towards Data-Driven Decision-Making

Rapid technical breakthroughs, heightened competition, and changing customer demands define the current business environment and force organizations to always strive for increased performance and efficiency. The significance of utilizing data-driven ways to improve organizational performance has gained increasing attention, as highlighted in recent research by Prakash (2024). A strategic method known as “data-driven decision-making” uses data to guide organizational choices and actions. This method’s fundamental steps include gathering, processing, and analyzing huge volumes of data to generate relevant insights to improve the functioning of the organization (Shafiq, 2024). According to Sarioguz & Miser (2024), organizations in this modern digital age are currently navigating a vast amount of data, which holds the potential to fundamentally transform how decisions are made. This shift is not just a technological advancement but represents a fundamental rethinking of how organizations operate and make strategic decisions in an increasingly complex environment. Traditional decision-making methods that rely on gut feeling and past performance have not been able to fully utilize the enormous amounts of data that are available to us. More informed approach involves shifting away from gut feeling in favor of an organized, evidence-based approach to managerial decision-making. To put it in simple terms, making informed decisions involves gathering, analyzing, and comprehending data to draw conclusions and guide practical and strategic decisions.

Researchers have long recognized that decisions based only on an individual’s knowledge are vulnerable to inaccuracies and that data by itself is useless (Lamba & Dubey, 2015; Korherr et al., 2022). Based on these findings, different analytical methods have emerged over the last decades as a distinguishing factor in the competitive environment of organizations (Korherr et al, 2022). According to Troisi et al. (2020), the data-driven approach to management studies is a result of the acknowledged necessity to develop innovative business models that can identify how to use data in

each stage of organization decision-making incrementally and how to turn data into knowledge and competitive advantage.

On the other hand, Brynjolfsson et al. (2011) highlight data-driven decision-making (DDDM) as an ideology, where data is seen as a strategic resource rather than an assumption and experience, and where decision-makers and managers are required to promote a data-driven culture of innovation and to take information into account at all stages of decision-making. Thus, hiring data scientists to gain analytical capabilities cannot be the only way to usher in the age of data-driven business. Rather, business analytics must be established in the organizational culture and understood by all employees, but especially by those who make decisions. (Carillo et al., 2019.)

2.1.1 DDDM Framework

Nijzink (2020) has developed a causal model for DDDM in his research conducted at the University of Twente, aiming to illustrate the key methods and processes involved in DDDM (Figure 1). Despite being a Master thesis, Nijzink's framework is conceptually strong and builds on a solid theoretical foundation. The model brings together insights from several well-regarded sources on data quality, data management, and decision-making, including Moreno (2017), Kleindienst (2017), and Mazurek (2015). Based on this literature, Nijzink has built a comprehensive model that illustrates the dynamic relationships between data sources, processing mechanisms, knowledge, and their role in organizational decision-making. Therefore, the model serves as a valuable framework in this thesis for analyzing the dimensions and enablers of DDDM in public social and healthcare. The framework presented in Figure 2 consists of dimensions (blue) and variables that affect these dimensions (grey).

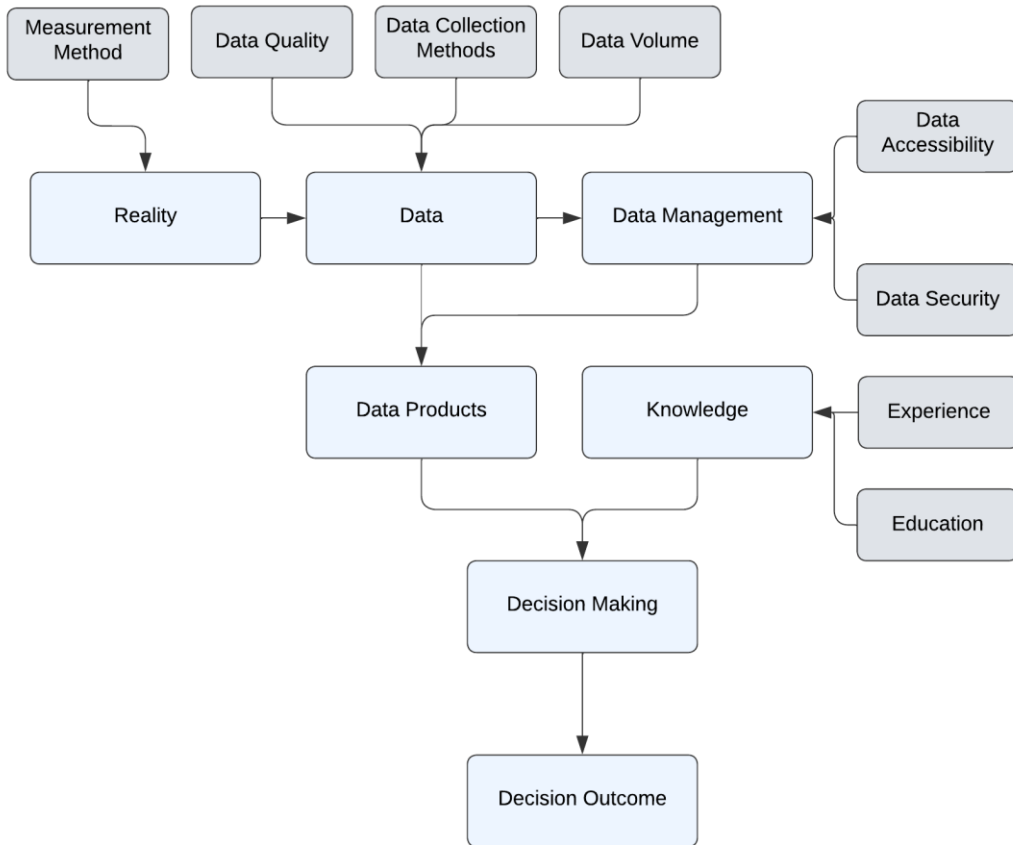


Figure 2 Causal model of DDDM (Modified from Nijzink, 2020)

The entire process begins with the current reality, which serves as the foundation for decision-making. This dimension exists within every organization, though the specific circumstances can vary. Analyzing the present situation generates new insights, making reality the starting point for any new idea or processes. It also presents an opportunity to collect data through various measurement methods. (Nijzink, 2020.)

According to Nijzink (2020), the nature of the data and the way it is collected is important. The author mentions three important variables in the process that affect the dimension of the data:

- Data quality
- Data collection methods
- Data volume

With the exponential increase in data generation globally, maintaining high data quality has become an increasingly significant challenge for organizations. Data must meet several criteria, including being timely, complete, consistent, valid, and accessible. This is particularly crucial for

organizations because information and communication technologies have given rise to new data-driven business models, which significantly increase interaction between businesses and customers through data. The criteria mentioned above are essential for improving the quality of these interactions, and given these challenges, it is vital to adequately address data errors (Kleindienst, 2017). According to Redman (2004), the exponential growth of data has made it increasingly challenging for organizations to maintain high data quality, which is essential for ensuring cost-effective operations and reliable decision-making. Insufficient data quality can undermine the successful implementation of data-driven approach and destabilize decision-makers' confidence in the data (Schröer et al., 2023, 469).

In the context of business, data collection is a fundamental process that directly impacts the quality and effectiveness of DDDM. Accurate and relevant data collection is essential for enabling organizations to make informed decisions that drive strategic outcomes. Primary data collection methods, such as customer surveys, interviews with stakeholders, and direct observations of market trends, are crucial for gathering first-hand insights that are directly aligned with business objectives. These methods provide high-quality, tailored data that can enhance an organization's ability to respond to market demands, optimize operations, and improve customer satisfaction. On the other hand, secondary data collection, which involves leveraging existing data sources such as industry reports, financial records, and market analyzes, can offer valuable background information and benchmarks. As businesses increasingly rely on data to guide decisions, the selection of appropriate data collection methods has become a critical determinant of success in data-driven business strategies. (Taherdoost, 2021.)

Volume means the amount of data. What counts as a large amount of data can change over time and depends on the type of data. A dataset that seems large today might not be considered as large in the future, because advanced storage technologies will make it easier to handle much bigger datasets (Gandomi & Haider, 2015). Additionally, the type of data plays a crucial role in defining what constitutes a large dataset. For example, video or images produce lot of unstructured data, while tabular data is more structured and organized. These may require different data management technologies. Consequently, defining a specific threshold for a large volume of data is also difficult because it is usually industry specific. (Gandomi & Haider, 2015; Lee, 2017.)

Once data has been collected from different sources, it is important to store it properly in databases (Strong et al, 1997, 103). As Nizjinki (2020) states, Data management is the process of collecting, storing, organizing and maintaining collected data. The aim is to ensure that data is accessible,

reliable and up to date. In addition, it is important to protect the data so that it cannot be damaged or altered by third parties. From this stored data, valuable information is derived as data products to support organizational decision-making. (Strong et al, 1997, 103.)

After data is collected and organized, data products are utilized to create value. Collecting data offers limited value to an organization; only when users and applications access the data and use it for decision-making. Therefore, extracting and utilizing data becomes the primary focus for organizations. This process, often referred to as Business Intelligence (BI), involves business users and applications accessing data from the data management systems for reporting and analytics. (Watson & Wixom, 2007.) These products process data as input and deliver valuable insights as output (Nizijinki, 2020). Business Intelligence (BI) plays a crucial role in helping organizations manage vast amounts of data by accessing, cleaning, integrating, and analyzing it to generate valuable insights (Foley & Guillemette, 2010). These insights assist in making informed decisions and improving business efficiency and productivity. By gathering essential information from a wide range of unstructured data sources, BI tools convert raw data into actionable information that supports policy decisions and improves overall organizational performance. (Niu et al., 2021.)

As Nizijinki (2020) also mentions that data is not the sole input for decision-making. Although data is fundamental to decision-making, it alone is insufficient for guiding organizational strategies. Data merely represents objects or events, and its true value is realized when combined with the knowledge and expertise of managers (Intezari & Gressel, 2017). According to Davenport and Prusak (2000), knowledge encompasses a blend of experience, values, and contextual insights that form the basis for evaluating and incorporating new information. This type of knowledge is acquired through years of hands-on experience, reflective thinking, and judgement, making it crucial for interpreting data in alignment with the unique demands of an organization. Since knowledge is rooted in the minds of managers and evolves over time, it equips them to navigate the complexities of a rapidly evolving business landscape. The success of DDDM therefore depends not only on the availability of data, but also on the education, experience and insights of managers who can interpret and apply information effectively to make rational decisions. Figure 3 conceptualize the intersection of data and knowledge:

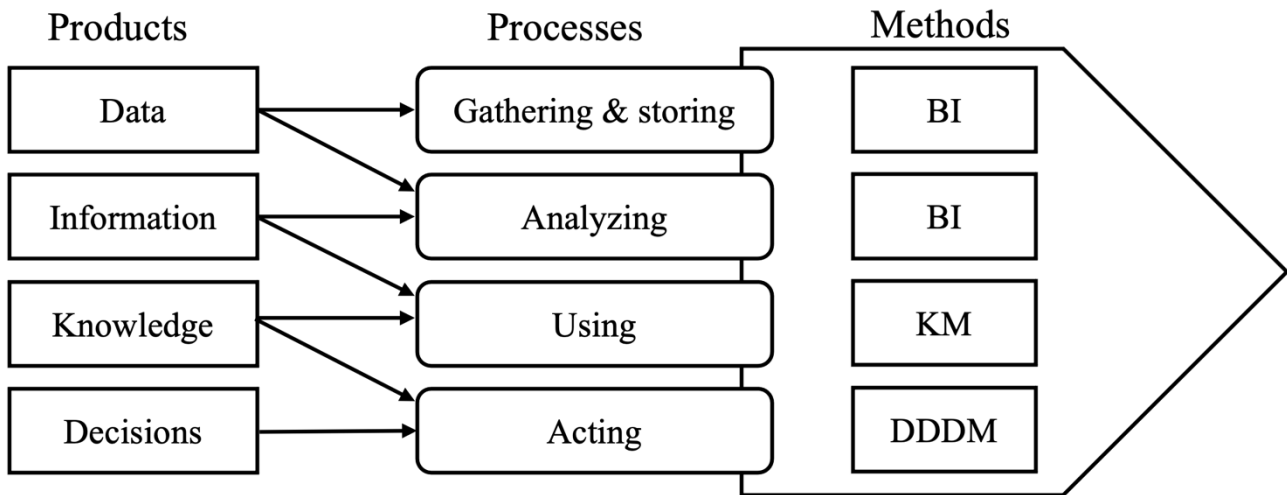


Figure 3 Conceptualizing DDDM (Modified from Shollo & Kautz, 2010)

The conceptual framework starts with gathering and storing the data. This data is analyzed and transformed into information. When action is needed in an organization, information and knowledge are used together to improve decision-making (Shollo & Kautz, 2010). However, many researchers state it is not enough for organizations to simply analyze data, produce knowledge and apply it. They must also focus on optimizing their decision-making processes to ensure that the knowledge produced is used effectively to support meaningful and strategic decisions (Shollo & Kautz, 2010; Davenport & Prusak, 2000; Intezari & Gressel, 2017). To obtain the most useful information possible, organizations should look at the structures and methods that influence their decision-making. In many examples, the information produced is not utilized right, insufficient for decision-making or ambiguous and open to different interpretations depending on the context (Shollo & Kautz, 2010; Ross et al., 2013). In conceptualizing DDDM, the decisions are made using data and knowledge, supported methods like BI and KM.

2.1.2 Data utilization challenges

Despite notable progress in adopting data-driven methods, substantial evidence suggests that many organizations have not successfully integrated these approaches into their decision-making processes (Tabesh et al., 2019). According to Adesina et al. (2024), many organizations are facing difficulties with strategic decision-making due to the lack of reliable data-driven insights. Traditional decision-making is heavily relying on past experiences, gut feelings, or incomplete data, leading to unfavorable outcomes. In addition, LaValle et al. (2011) states that ensuring data accuracy is not the primary challenge organizations encounter when adopting analytics. The most significant barriers to adoption are managerial and cultural, rather than issues related to data or

technology. The main barrier to the proper use of data analytics is the lack of understanding of how to use analytics effectively to improve business performance.

Bean and Davenport (2019) observed that despite significant investments in data and analytics, many organizations struggle to become truly data-driven and often fail to recognize data as a critical business asset. Barton and Court (2012) also mention that a lot of skepticism about the data-driven approach to decision-making is expressed by managers. Ross et al. (2013) states that the primary reason why investments in data utilization often fail to deliver returns is that many organizations struggle to effectively manage the information they already possess. They lack the ability to properly handle and analyze data in ways that improve their understanding, and they fall short in implementing changes based on new insights. Many managers tend to rely more on their past experiences rather than adopting evidence-based, data-driven decision-making processes (Tabesh et al., 2019). The challenges of data utilization are amplified by the rapidly changing and complex organizational landscape, where making timely and precise decisions is essential for success. Without adapting DDDM, organizations may miss key opportunities, struggle to predict market trends, and find themselves unprepared for disruption. (Adesina et al., 2024.)

Changing the decision-making culture in an organization is a key enabler for better use of data to make decisions, which can improve organizational performance. (McAfee & Brynjolfsson, 2012.) Barton & Court (2010) continue that organizational transformation is one of main areas in which organizations should develop strengths to fully benefit from data. Since organization culture plays a significant role in data-driven decision-making, the successful use of data often requires a broader change in the way managers think. As Sarioguz & Miser (2024) point out, building data-driven practices into organizational processes demands cultural transformation in addition to technical capacity. Managers are expected to develop a more analytical approach and promote a work environment where evidence-based decision-making is valued. Carillo et al. (2019) continue that managers need to shift away from intuition-based decisions and embrace a culture that prioritizes the analysis of data. Understanding how data-driven approaches are transforming management and organizational models is essential to realize the long-term impacts and benefits of this change (Sarioguz & Miser, 2024). McAfee & Brynjolfsson (2012) states at their research that DDDM has been shown to significantly improve organizational performance in companies that adopt these approaches. Organizations in the top third of their industry in using data-driven methods were found to be 5% more productive and 6% more profitable than their competitors, demonstrating the competitive advantage of such approaches. These measurable gains highlight why managers should prioritize data-driven strategies to enhance organizational success.

Davenport (2006) highlights the significance of cultivating an organization-wide culture that supports informed, fact-based decision-making through data-driven methods. To foster such a culture, managers must not only be skilled in transforming raw data into meaningful, actionable insights but also in effectively communicating and collaborating with business and domain experts within the organization to ensure these insights are applied appropriately (Chen et al., 2012). Laihonon et al. (2013, 28) also notes that building a data-driven culture within an organization fosters transparency and openness in operations. In this context, value is created from knowledge when available data is effectively utilized, and decisions are based on more accurate understanding of the current situation. Achieving this requires not only data from information systems but also human knowledge and intellectual capital.

2.1.3 Transforming data to insight

As earlier mentioned, BI plays a crucial role when organizations seek to transform data into valuable insights. BI is widely used to refer to various applications that enable more informed, data-driven decision-making.

Data scientists and information systems researchers have been developing and working on decision support systems (DSS) for approximately 40 years. In the early 1970s, the first model-driven DSS systems were created to support financial planning (Power, 2007). Gradually, by the late 1980s, data-driven DSS systems, commonly referred to as Business Intelligence (BI), became a widely recognized term among data scientists. Today, BI is broadly used to describe the application of analytics in real-world contexts (Watson & Wixom, 2007).

In their research, Eidizadeh et al. (2017) describe that a key characteristic of BI is the collection, processing, and storage of data so that all levels of the organization can access it according to their needs for future decision-making and to optimize their operational efficiency. Therefore, one of the primary objectives of BI is to gather and share information across the organization, ensuring that every unit has access to it and can utilize it to improve overall organizational performance. Vugec et al. (2020) defines BI as a managerial tool that integrates various applications, technologies, and processes within organizations to assist business users in addressing challenges, identifying opportunities, monitoring performance, and making more informed decisions. BI systems assist decision-makers by gathering, analyzing, and reporting both internal and external data. Various disciplines influence BI; some focus on the technical aspects, while others emphasize knowledge discovery and integration. (Ghaida, 2018.) Figure 4 illustrates the BI process using the classical mode created by Gilad & Gilad (1985):

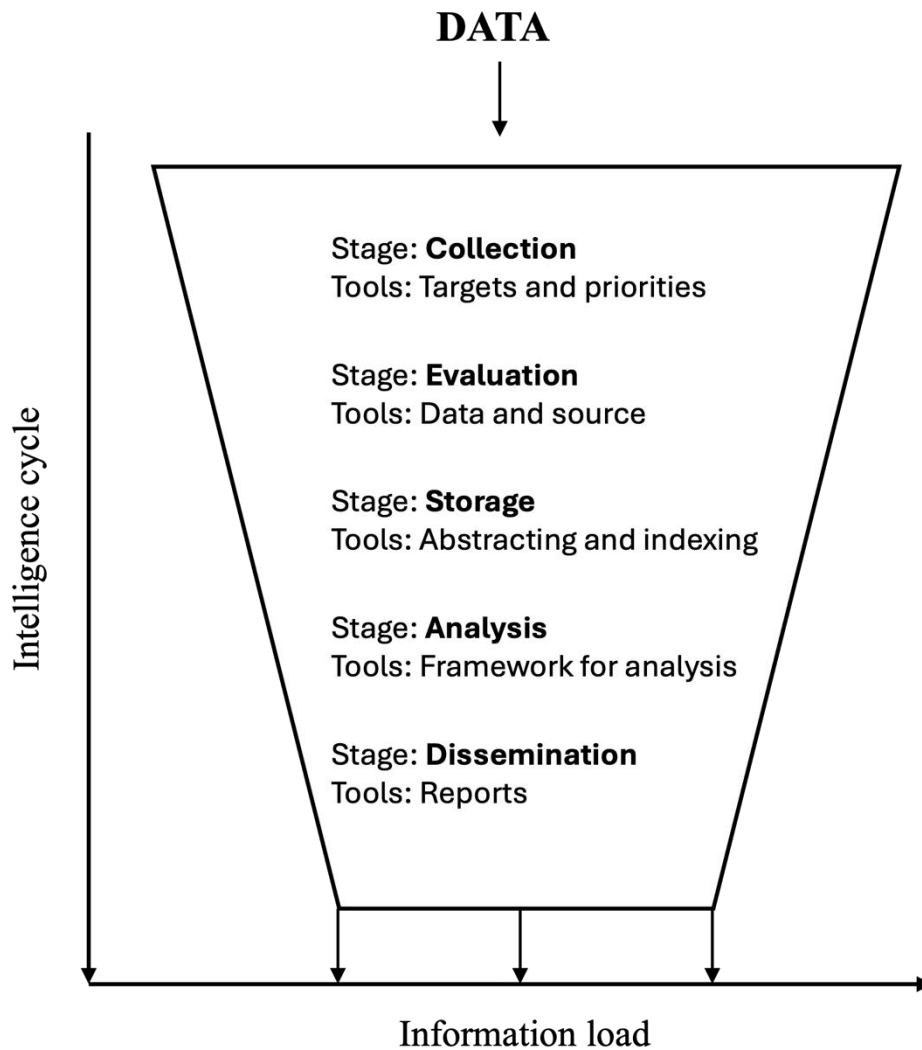


Figure 4 General BI process (Modified from Gilad & Gilad 1985, 70)

As Pirttimäki (2007) points out, collecting vast amounts of data is only valuable if the organization possesses the necessary capabilities and expertise to transform that data into actionable insight. Figure 4 demonstrates how the intelligence cycle correlates with the information load: as the volume of data is reduced through processing, the level of intelligence derived increases, highlighting the importance of efficient data management.

The BI process (Figure 4) developed by Gilad & Gilad (1985) consists of five key stages, each crucial for transforming data into actionable insights. The first stage involves collecting relevant data from different sources, including internal databases and external data points. External sources of information usually consist of specific business environment related technologies, competitors, industries, and environment. The identification phase is essential, as it starts the process by defining the priorities of the organization and identifying the specific information needed to achieve them.

Evaluation focuses on ensuring the quality and the relevance of the data collected. The data are put through a quality control process that includes an assessment of the reliability and accuracy of the data sources. This stage ensures that only high-quality data will progress to the next stages, which helps to optimize the usefulness of the stored data for decision making. Data is also indexed to simplify retrieval and analysis later in the process. The stored data is then analyzed using frameworks and different analytical models to translate it into actionable insights. These BI products can be different industry analysis, management reports, monthly business reviews and more. The analysis stage involves interpreting and clarifying ongoing events and signals to provide timely and effective insights to decision-makers. Because the quality of analysis is critical to effective decision making, this phase is generally considered one of the most essential parts of the BI process. Finally, these insights are disseminated to key decision-makers. This is typically achieved through reports, dashboards and visualization tools that present the analyzed data in a clear, actionable format. The dissemination phase ensures that insights are not only available but also ready to be used for strategic planning and operational improvement. (Gilad & Gilad, 1985.)

According to Nylund (1999) BI encompasses all the methods through which a company can explore, utilize, and analyze data from its data warehouse to generate insights that support better decision-making. Ghoshal & Kim (1986, 49-58) provided the first scientific definition of the term. They view BI as both a management philosophy and a tool that helps organizations manage and refine business information to make effective decisions. Lönnqvist & Pirttimäki (2006, 32) linked BI to two distinct concepts:

- Relevant information that provides a comprehensive view of the business environment and the organization, including its position relative to markets, customers, and competitors.
- A structured and systematic process by which organizations gather, analyze, and distribute information from both internal and external sources to support their operations and decision-making.

BI can be seen as an analytical tool that offers automated decision-making regarding operational conditions, resource allocation, service demand, and other key factors related to organizational performance. It utilizes a large data warehouse, compiled from multiple sources, and applies past organizational dynamics. BI integrates data analysis into decision-making tools to provide essential information for supporting strategic and tactical decisions across the organization. (Ghazanfari et al., 2011, 1580-1581.)

Organizations that utilize knowledge and analytics in decision-making aim to identify the right priorities and people, while promoting a culture of data-driven management. Such a culture increases transparency and openness throughout the organization. As information becomes more accessible, management practices will change accordingly, allowing decision to be made in a more informed way (Davenport, 2006). According to Laihonen et al. (2013, 44), it is essential that decision-makers build their situational understanding by interpreting available information in the context of experience, as timely and relevant insights help to identify new opportunities. In this context, both the knowledge generated by BI systems and the expertise of people are critical components of effective decision making (Davenport, 2006). In summary, the primary goal of BI is to facilitate the use of data and transform it into valuable insights for the organization. Therefore, the development of BI solutions focuses on converting raw data into actionable information. (Larson & Chang, 2016.)

In recent years, the importance of BI has grown with rapid technological development. The advanced technology has elevated BI as a key tool for organizations seeking to refine management practices, optimize performance, and improve services and outcomes. The ability of BI systems to give deeper, more strategic insights has attracted growing interest among organizational managers, particularly in sectors such as healthcare, where data-driven practices can significantly improve decision making and service quality (Alkhwaldi, 2024).

2.1.4 Knowledge Management enhances decision-making processes

Organization leaders recognize that timely and accurate knowledge can significantly enhance organizational performance. Paoloni et al. (2023) see knowledge as the main driver for business efficiency and value creation. Two methods that have been pivotal in increasing both the quantitative and qualitative value of the knowledge available to decision-makers are BI and Knowledge Management (KM) practices (Cody et al. 2002). Both BI and KM aim to promote learning, decision-making, and understanding within organizations. The key difference between the two concepts lies in their focus: KM seeks to promote insight and comprehension within the organization, while BI concentrates more on delivering clear and precise information. KM encompasses both tacit knowledge, which is often hidden within the organization, and explicit, structured information, whereas BI is a component of the broader KM framework. (Herschel & Jones, 2005.)

According to Hicks et al. (2007), explicit knowledge is codified and can be communicated through various methods, such as mathematical expressions or formal language. Tacit knowledge, however,

is more challenging to articulate in these ways. Kothari et al. (2012) describe tacit knowledge as personal knowledge developed through experience and action. It includes skills, intuition, know-how, and practical knowledge, often context-specific and deeply connected to individual expertise. Hicks et al. (2007) has developed the “EITS” metaphor to describe the knowledge hierarchy (Figure 5).

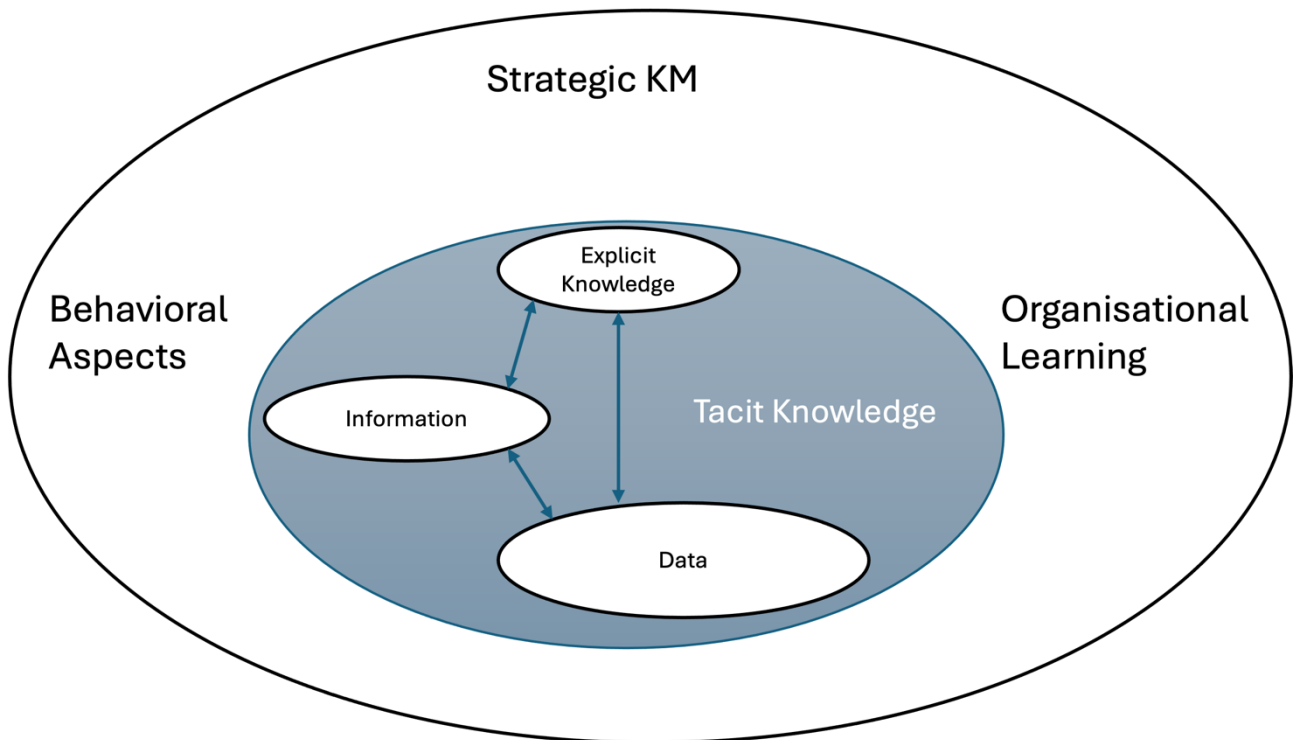


Figure 5 The EITS paradigm (Hicks et al., 2007)

Through different applications, users can access and share data, information, and explicit knowledge stored in digital environments. For instance, data is stored in databases and data warehouses, information is utilized within decision support systems, and explicit knowledge is embedded in expert systems and best practices. These factors are surrounded by tacit knowledge. This is essential for creating, using, and sustaining data, information, and explicit knowledge. It also helps in choosing the right data sets, processes, and methods of analysis. (Hicks et al., 2007.)

As Hicks et al. (2007) describes, the knowledge hierarchy is framed with three major environmental factors: Behavioral aspects, strategic KM, and organizational learning. Within this framework, several fundamental elements of behavioral aspects and organizational learning play a crucial role in supporting KM. Figurska (2012) cites cooperation, trust, and continuous learning as important

aspects of behavior and organizational learning in KM strategy. Cooperation is essential, as it allows knowledge to be shared between employees by fostering collaborative environments. Trust further facilitates this exchange by encouraging individual to share their tacit knowledge, knowing that it is respected and valued. A commitment to continuous learning promotes the ongoing development of knowledge and skills, creating a culture in which growth is supported, and expertise is constantly refined (Figurska, 2012). According to Ferreira et al. (2020), strategic KM refers to the processes and infrastructures that organization use to acquire, produce, and share knowledge for strategic decision-making and strategy development. This is strongly linked to business strategy, which is one of the most important factors for successful KM (Yeh et al., 2007).

Herschel & Jones (2005) define KM as a systematic process that involves finding and shaping information so that it can be presented in a manner that enhances an employee's understanding of a particular topic. KM enables organization transform accumulated experience into actionable insights. Through systematic collection and organization of knowledge, KM supports key activities such as strategic decision-making and continuous improvement in learning. In essence, knowledge-based value creation focuses on enhancing organizational performance. Activities and processes should not only contribute to the achievement of the organization's goals but also support the creation of value for stakeholders. While private sector organizations often prioritize profitability, public sector institutions face more complex objectives. These may range from financial sustainability to promoting national well-being or fulfilling other goals aligned with a broader public agenda. (Laihonen et al., 2013, 26.)

It is crucial that KM processes are tightly integrated with an organization's business operations; otherwise, the knowledge may not effectively support the organization's primary mission, and its potential value may go unrealized. In practice, successful KM often involves creating the right conditions for sharing, applying, and generating knowledge, alongside its systematic use. Effective KM is a comprehensive process that includes stages such as creating, collecting, organizing, refining, distributing, and maintaining knowledge. This process is further supported by key factors, including how personnel are organized, the decision-making practices of management, information and communication technology, and, most importantly, the organization's culture (see Figure 6). (Laihonen et al., 2013, 27.)

The knowledge creation process, according to Abubakar et al. (2019), is a dynamic, complex, and multifaceted stage that helps organizations utilize, shape and incorporate knowledge into their products, services, and operational processes. Organizational success depends on the efficient and

ongoing creation and use of knowledge (Mousavizadeh et al., 2015). Abubakar et al (2019) state that equally important is knowledge capture, where organizations not only generate new content but also replace outdated or irrelevant knowledge and ensure that both explicit and tacit knowledge is captured and used efficiently. Dissemination, or sharing of knowledge between individuals or groups, is vital to foster collaboration and innovation in an organization. According to Laihonon et al. (2017), the business value of knowledge is realized when knowledge is used to guide action at either individual or organizational level. Therefore, knowledge application focuses on ensuring that the knowledge is used to support decision making and problem solving, ultimately benefiting the organization through improved business processes and improved organizational outcomes (Mousavizadeh et al., 2015). As illustrated in Figure 6, this process can be described as a cycle, where applying knowledge can eventually lead to knowledge creation. The cycle continues because the created knowledge must be captured, shared, and applied (Abubakar et al, 2019; Laihonon et al. 2017).

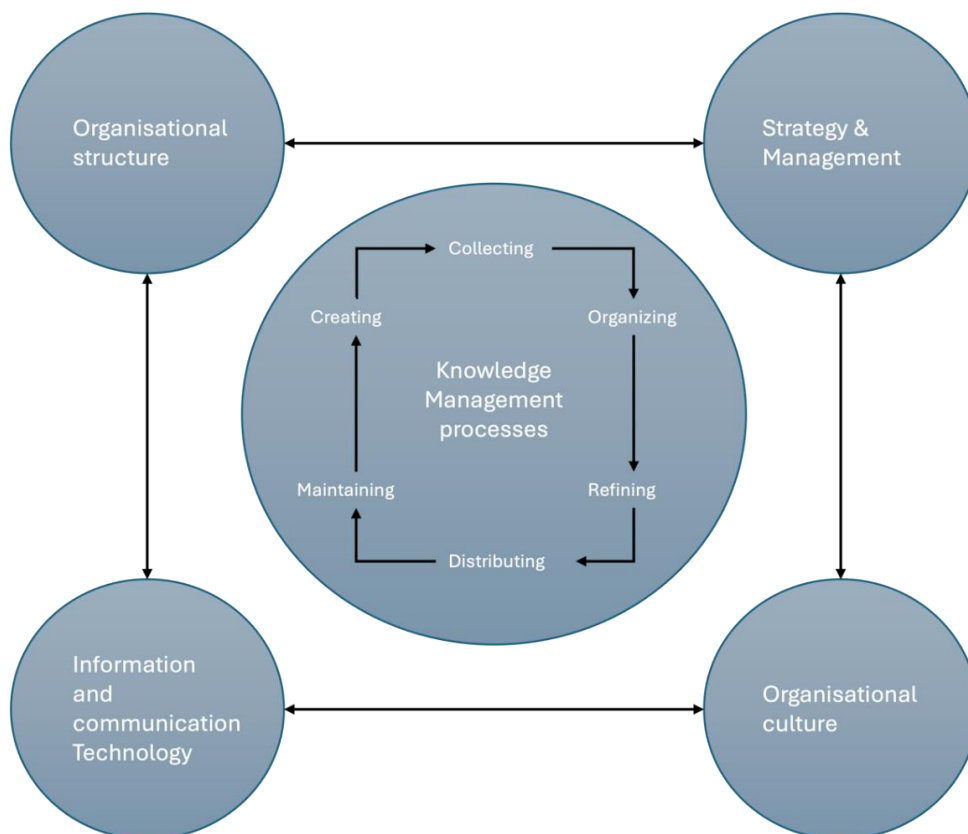


Figure 6 Knowledge Management process and enablers (Laihonon et al., 2013, 27)

Abubakar et al. (2019) describe knowledge enablers as influential factors that can accelerate and improve KM activities, such as knowledge capital accumulation and dissemination in an organization. Yeh et al. (2006) and Hujala & Laihonon et al. (2023) confirm that these enablers (see Figure 6) are systems that organizations use to develop, share and create their knowledge. However, it is good to be aware that these enablers can also act as a barrier to knowledge management. For example, technological limitations and the complexity involved, poor organizational culture and lack of management support have negative effects on employees, technology and other factors that lead to the failure to implement the KM process. (Mousavizadeh et al., 2016.)

According to Abubakar et al. (2019), effective organizational culture can have a positive impact on KM activities and sharing between individuals. Mousavizadeh et al. (2016) describes this enabler as follows:

“Organizational culture is defined as a system of meanings associated with behaviors and practices that are recognized as a distinct way of life. It is a set of shared beliefs, ideologies, rituals, myths and norms that influence organizational activities or behavior.”

Abubakar et al. (2019) confirm that an organization should have a culture where values such as sociability and trust promote knowledge sharing and interaction among the employees. This type of collaborative environment enables a culture of knowledge management, while allowing individuals to openly share their knowledge.

Information technology (IT) can also be seen as one of the critical enablers in the knowledge management process. Abubakar et al. (2019) demonstrate that investing in IT is an essential part of increasing the success of knowledge management projects and applications. According to Yeh et al. (2006), IT architecture, such as various databases, data platforms, decision support systems and other can enable rapid search, access and retrieval of data and support collaboration and communicating among employees. However, Laihonon et al. (2013, 44) point out that technologies are evolving rapidly and in complex ways. In such cases, organizations need to seek a deep understanding of the technologies and their evolution, as well as the organization’s practices and cultures.

Yeh et al (2006) summarize that business strategy is one of the most important factors that guides KM. Research by Smith et al. (2010) shows that the effectiveness of an organization is strongly influenced by the link between business strategy and KM capabilities. To be most successful, knowledge management initiatives should also be linked to organizational performance measures,

such as cost efficiency and resource utilization in the public sector. For management, this requires an integrative approach that considers the relationships between all these capabilities. (Smith et al., 2010.)

The link between strategy and KM also involves management support. Smith et al. (2010) argue that support from management is critical for successful KM implementation, as it ensures the allocation of necessary resources. This managerial support not only adds organization performance but also encourages employees to actively participate in KM initiatives. When employee engagement is strong, organizations are more likely to achieve improvements in KM performance, leading to increased organizational value. Therefore, the degree of support from management is a key factor that can determine whether KM initiatives succeed or fail. (Yeh et al., 2006.)

Organizational structure is also one of the KM enablers. Abubakar et al. (2019) states that organization can suffer from ineffective KM if the organizational structure is unclear. Varzaru & Varzaru (2013) describes that in organizations where knowledge management is a priority, the structure and division of roles must be designed to facilitate the effective sharing of both tacit and explicit knowledge. The organization's hierarchy, role definitions and responsibilities should support the open flow of knowledge through collaborative networks. For effective KM, the role of each person should evolve to include knowledge creation and management in addition to their current operational tasks. This change requires a flexible structure that promotes knowledge sharing while maintaining the core functions of the organization (Varzaru & Varzaru, 2013). The relationship between key enablers of KM and organizational effectiveness is illustrated in Figure 7.

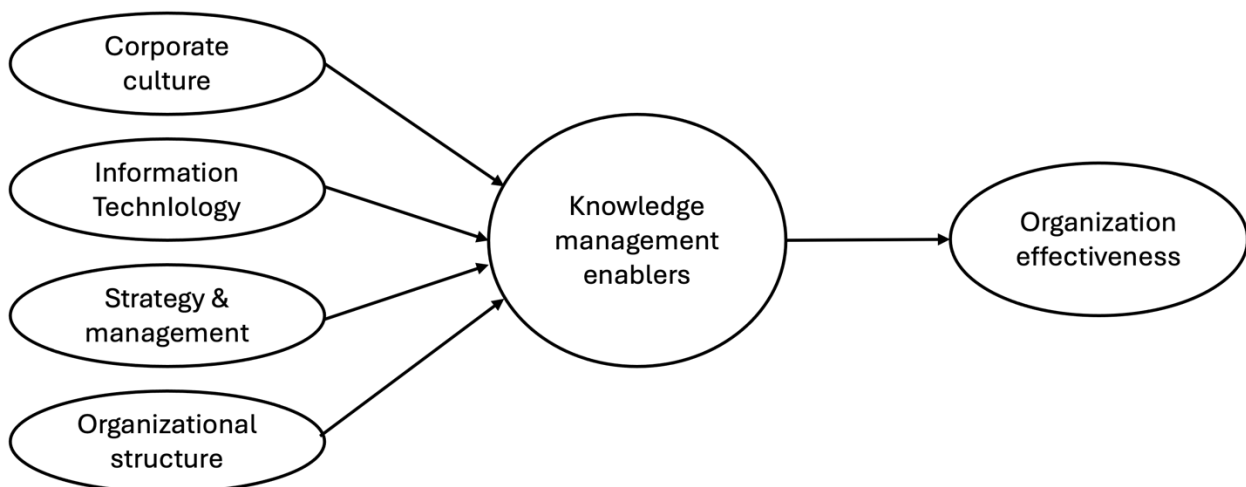


Figure 7 Relationship between KM enablers and organization effectiveness (Modified from Yeh et al., 2006)

To maximize the value of knowledge, organizations must establish effective systems that promote the seamless flow of information, supported by well-defined knowledge management initiatives. (Mousavizadeh et al., 2015.)

2.2 Introduction to the Finnish public social and healthcare sector

Integration of social and healthcare services has been associated with improvements in the effectiveness of care (Baxter et al., 2018). Hujala & Laihonen (2023) describes that successful service integration relies on the use of enabling information technology, integrated data, and a shared knowledge base that facilitates the seamless flow of information across stakeholders. They also note that certain barriers like fragmented information systems, diverse organizational cultures, and multi-professional collaboration can hinder integration efforts, limiting the development of cohesive care systems. Moreover, Hujala & Laihonen (2023) states that the differing objectives between the public and private sectors further challenge service integration, which remains a key issue in achieving holistic care.

Finland recently experienced a significant healthcare reform, transferring the responsibility for organizing healthcare, social welfare, and emergency services to new autonomous regional entities known as wellbeing services counties (Pusenius & Laihonen, 2024). This change aims to streamline and enhance service delivery across regions. Since January 1, 2023, 21 welfare regions and the Helsinki and Uusimaa Hospital District (HUS) have been responsible for organizing primary care, social services, special care, dental care, mental health and addiction services, disability services, and elderly housing services. The HUS group has a separate responsibility for organizing special healthcare services. The welfare regions serve as the main organizers and providers of social and healthcare services, working in collaboration with municipalities to promote well-being and public health. Private sector providers, along with organizations and associations, complement the public social and healthcare services. (Sosiaali- ja terveystieteiden ministeriö, 2023.)

This reform was essential to ensure equal access to services, reduce disparities in health and wellbeing, and control the rising costs of healthcare (Ministry of Social Affairs and Health, 2024). A wellbeing services county can offer services on its own or in collaboration with other counties. Services may also be outsourced to private companies and organizations or offered through customer service vouchers. The healthcare services that wellbeing services counties are required to provide are specified separately in relevant legislation. However, counties retain some discretion in

how they deliver these services, if they comply with legal requirements. As a result, there can be regional variations in the availability and delivery of healthcare services (EU-Healthcare, 2024). Tynkkynen et al. (2023) note that while the long-anticipated health system reform is being implemented, aligning service delivery with population needs, addressing long waiting times, and managing relatively high levels of cost-sharing continue to pose significant challenges.

2.2.1 Current challenges in public social and healthcare management

In Finnish healthcare, public organizations are often characterized by static and hierarchical structures, with management operating at various levels. Leadership is exercised at different tiers within the organization: top management, middle management, and frontline management. Top management typically refers to the strategic management of the organization. Middle management bridges the gap between strategic management and frontline operations, often represented by roles such as head nurses. Frontline management refers to the direct relationship between managers and employees, focusing on day-to-day leadership. Healthcare management in Finland has historically sought to break away from the traditional divisions between political and contractual management or specialized and general management. Increasingly, the focus in healthcare management is on integrating both task-oriented and people-oriented approaches, emphasizing interaction between managers and staff, and taking a more holistic view of management. (Rissanen et al., 2017, 82.)

Healthcare services are one of the most central topics in political decision-making. Management in healthcare has also become a critical issue due to the many challenges facing health services. One of the key challenges is shifting from a reactive approach to a proactive one. Greater emphasis must be placed on preventive measures to control the continuously rising costs. Digitalization is also playing a role in transforming traditional practices and will continue to challenge many conventional operating models in the future (Syväjärvi & Pietiläinen, 2016, 148). Halonen (2021) continues in his research that the motivation and skills of healthcare managers, particularly in the use of information systems, are often seen as challenges in healthcare management. The data collected should be more aligned with the management needs of healthcare organizations. The healthcare environment is perceived as complex, and the information provided by current systems is often insufficient to meet the demands of effective healthcare management.

According to Myllärniemi et al. (2012), Finland's healthcare sector also faces many complex challenges around growing elderly population and increasing pressure to reduce costs. Härkönen et

al. (2010) notes that the ageing population is putting increasing pressure on the public health sector. Alkhwaldi (2024) also mentions that social and healthcare organizations are struggling with limited resources to cope with the ongoing demands to improve outcomes. These problems are not unique to Finland, as the need to improve performance is a common concern in many countries. From an organizational and managerial perspective, meeting these challenges requires the effective use of knowledge resources and the promotion of active knowledge sharing. In addition, the knowledge requirements of health professionals have evolved as they increasingly act as both managers and medical experts, requiring a new level of expertise. (Myllärniemi et al, 2012.)

2.2.2 Digitalization and data infrastructure in Finnish healthcare

Digitalization has been viewed as a potential solution, or at least a way to address, many of the challenges faced by healthcare systems and societies. According to Parviainen et al. (2022), digitalization or digital transformation refers to changes in work processes, roles and service offerings that the introduction of digital technology brings about in an organization or its operating environment. Saranto et al. (2020) suggest that digitalization focuses on updating organizational processes and services by integrating digital technologies to improve efficiency and modernize workflows. Payne et al. (2016) also mention that digitalization has had a variety of effects on improving efficiency and quality in the health sector.

The Finnish healthcare sector has undergone significant digital transformation, supported by a robust national eHealth and eSocial strategy. Central to this shift are platforms like Kanta Services, which enable the collection, storage, and sharing of patient data across healthcare providers (Vehko, 2022). This digital infrastructure has facilitated better access to real-time data, supporting decision-making and enhancing the quality of care. According to Pietronudo et al. (2022), digital platforms support the operational efficiency of healthcare systems by managing the enormous data generated within healthcare ecosystems. However, challenges remain, particularly in ensuring the interoperability of systems and optimizing the use of collected data for data-driven decision-making. As Aula (2019) also states, data-driven approach in healthcare has also intensified the need to reform existing data infrastructures.

Finnish data infrastructure in healthcare sector is shaped by significant institutional and regulatory complexities. The Secondary Health Data Initiative was introduced to facilitate the more seamless flow of health data between various data-governing institutions, with the aim of improving healthcare services using big and open data (Aula, 2019). Secondary health data refers to the use of

personal social and health data, originally collected during health and social service activities, for purposes beyond the primary reason for which they were saved. Under Finland's act on the secondary use of health and social data (Saarikko & Niinistö, 2019), this includes scientific research, development and innovation activities, and knowledge management among others. According to Parikka (2019), the act facilitates the better utilization of health and social data for decision-making in healthcare management, supporting initiatives like data-driven innovations and knowledge management.

Vehko et al. (2018) highlight the importance of electronic health record (EHR) systems in the digitalization of healthcare in Finland. These systems allow for collection, storage, and sharing of patient data across healthcare providers in Finland. Platforms like Kanta enable patients to access their health data, fostering transparency and engagement with their healthcare. Jormanainen et al. (2019) states that by 2018, nearly 50% of the Finnish population had accessed their EHR data. The widespread use of EHR supports real-time decision making and increases operational efficiency in healthcare services.

Currently, the use of artificial intelligence (AI) is also an emerging trend in digitalization in the healthcare sector. AI applications have the potential to improve various aspects of healthcare, from improving diagnosis and treatment to optimizing hospital management and administrative workflows. According to Koski & Murphy (2021), AI systems offer significant value by reducing variability in care, improving precision, and empowering both healthcare professionals and patients. AI technologies such as machine learning and natural language processing help synthesize large volumes of medical data, from EHRs to genetic information, improving decision-making processes. However, as Secinaro et al. (2021) highlight, integrating AI into healthcare requires overcoming several challenges, including technical limitations and regulatory restrictions, as well as ensuring that AI systems are transparent and trustworthy. Saraswat et al. (2022) further emphasize the importance of explainability in AI applications, especially in complex healthcare environments, to ensure clinicians feel confident in using these tools in their everyday practices.

2.2.3 The role of BI and KM in addressing challenges

Digital platforms play a crucial role in supporting healthcare organizations' ability to innovate by effectively managing the vast amounts of data generated. Pietronudo et al. (2022) emphasize that digital platforms in healthcare facilitate not only data collection but also its analysis and integration, enabling healthcare professionals to optimize decision-making processes and improve patient outcomes. These platforms enhance capabilities, allowing healthcare systems to transition from

traditional reactive approaches to more proactive, data-driven models. Paoloni et al. (2023) address that in this domain, public social and healthcare organizations provide a unique subject for study because they usually prioritize efficiency and effectiveness rather than competition or profit.

Healthcare organizations are increasingly recognized as knowledge-based entities rich in data and information. As Ayatollahi & Zeraatkar (2020) note, effective KM processes can help these organizations manage strategic assets like knowledge, leveraging both tacit and explicit information. According to Ashok et al. (2021), KM practices in the public sector contribute to better efficiency, more informed decision-making, and the improvement of policy development, service delivery, and overall effectiveness. Knowledge serves as a strategic asset in healthcare organizations, with KM implemented as an effective approach to addressing challenges such as escalating healthcare costs and the growing demand for higher-quality care (Ayatollahi & Zeraatkar, 2020). By doing so, healthcare professionals can make more informed decisions, ultimately leading to higher quality care, reduced errors, and lower costs.

Nicolini et al. (2008) states at their research that data-driven approach have become a vital component in healthcare, driving both organizational performance and patient care quality by enabling knowledge management and sharing. However, they are also aware that implementing KM successfully requires addressing several enablers and barriers, which are particularly linked to healthcare sector due to its complexity and the interaction between clinical and managerial roles.

Table 1 Major enablers and barriers of KM success in healthcare organizations (Modified by Nicolini et al., 2008)

Enablers	Barriers
Shared common values and culture	Over-management and interference from political sphere
Minimizing concerns about power and status differences	Clinical-managerial conflict
Interdisciplinarity	Professional barriers
Close proximity (operational)	Lack of trust
Salient topics	Poor quality relationship
Political commitment	Insufficient technology skills

As illustrated in Table 1, numerous enablers support the successful implementation of KM in healthcare organizations. Shared common values and culture are pivotal, as highlighted by Nicolini et al. (2008), since a unified vision promotes collaboration across interdisciplinary teams. In healthcare, where multiple professional groups often work in different levels and departments,

common values that emphasize patient-centered care promote more effective knowledge sharing and smoother communication between departments.

Another significant enabler is minimizing concerns about power and status differences. Edmondson (2003) points out that when power dynamics are reduced, team members are more likely to share information openly, which is crucial for learning in fast-paced sectors such as healthcare. In addition, political commitment and acceptance are essential for promoting KM initiatives in the health sector. Nicolini et al. (2008) argue that political support helps embed KM practices into organizational culture and ensure their sustainability.

Finally, interdisciplinarity and close operational proximity are also enabling key factors. Tagliaventi & Mattarelli (2006) argue that when professionals from different domains work together and are physically close to each other, they exchange information more effectively. This proximity support both formal and informal information exchange, which is crucial in healthcare settings based on multi-professional collaboration.

Despite these enablers, significant barriers can hinder the success of KM in healthcare. Over-management and political interference are common challenges. Addicott et al. (2006) argue that excessive political involvement in clinical processes can distract attention from the goals of knowledge sharing, with decision-making driven by external goals rather than patient outcomes or organizational learning.

Clinical-managerial conflict is another key barrier, due to the different priorities of clinical staff and management. Guven-Uslu (2006) explains that clinicians tend to prioritize patient care, while managers often emphasize cost management and operational effectiveness, leading to tension and a reluctance to share information across professional boundaries. Additionally, professional barriers such as the rigid hierarchical structure of healthcare can complicate knowledge exchange. The traditional division between clinical and managerial professionals creates social barriers that limit the flow of information. (Ferlie et al., 2005.)

Insufficient technology skills and lack of trust among professionals are additional obstacles (Nicolini et al., 2008). In many cases, the rapid implementation of new KM related technologies, such as electronic health records or BI systems, can overwhelm staff who may lack the necessary training or confidence to use them effectively. Mistrust in these systems can lead to reluctance in adopting new technologies, which diminishes the potential benefits of KM (Guah & Currie, 2004). Guo and Chen (2023) further elaborate on the importance of data technologies by noting how

healthcare organizations can leverage these technologies to provide better, more personalized patient care. They argue that integrating these technologies into existing healthcare infrastructure will enable the use of predictive analytics to improve both operational efficiency and patient outcomes.

There has also been considerable work done in applying BI within healthcare industry, with focus on IT and clinical aspects. However, the use of BI for improving the healthcare management and operational processes remains an under-explored area (Basile et al., 2023). As Alkhwalidi (2024) explains, also in the healthcare industry, BI involves utilizing data and analytical tools to support a more informed and efficient decision-making process. Ratia (2018) notes that Finnish private healthcare organizations (HCOs) lacked the internal capabilities required for effective BI utilization, leading to a reliance on external resources. Adapting Ratia's (2018) observations to the context of the public sector, it is reasonable to infer that the Finnish public social and healthcare sector might face similar challenges as private organizations, given that both sectors share some systemic characteristics like hierarchical structures and resource limitations. To overcome this, organizations must improve internal capabilities and human capital to promote data-driven mindset. Similarly, Basile et al. (2023) demonstrates that using BI in decision-making overcomes experience-based practices by improving operational efficiency and leading to financial savings. However, they emphasize that BI complements human cognitive capabilities rather than mimicking them and highlight its importance for management in improving decision outcomes. To success, these organizations need to excel at collecting and analyzing both clinical and market data and turning it into actionable insights for decision making. Proper management and dissemination of this information are critical to ensure the future sustainability and success of organizations and to improve their ability to deliver high quality care while improving overall outcomes. (Paoloni et al., 2023.)

Although there is still relatively limited research on DDDM in healthcare, particularly in public health systems such as Finland's, recent studies have begun to address some of the key challenges and opportunities associated with implementing DDDM in healthcare. Freitas (2024) highlights several obstacles, such as concerns around data privacy, the need for robust data infrastructures, and the potential of emerging technologies like AI to revolutionize healthcare management. Rehman et al. (2022) emphasize the transformative potential of big data analytics, noting its capacity to significantly improve healthcare delivery. However, this also brings challenges, including managing unstructured data, ensuring data interoperability, and effectively integrating new technologies into existing systems. Moreover, data-driven technologies are often mistakenly seen as being the same

as AI. Di Nucci (2019) points out that data-driven technologies are designed to improve human cognitive and computational abilities, whereas AI is intended to replicate or mimic them. These differences are important, as despite their differing objectives, both data-driven technologies and AI play complementary roles in healthcare decision-making and can contribute to improved outcomes.

3 Methodology and analysis

One of the most important factors in conducting successful research is choosing the right research method. There are different scientific, and research approaches available, and the choice depends largely on the research topic, the specific research questions and the overall objectives of the study. (Hirsjärvi & Hurme, 2022)

The research method for this thesis adopts a qualitative study approach, with empirical data gathered through semi-structured interviews conducted with employees responsible for the development of KM and BI initiatives within one of the wellbeing services counties in Finland. This method allows for more in-depth insights to be obtained from each participant, enabling a comprehensive exploration of DDDM practices. The interview data was analyzed using grounded theory methodology, which facilitates the identification of emerging patterns and themes. The specific research methods employed include semi-structured interviews and the Gioia method for data analysis.

3.1 Qualitative approach

The empirical research conducted for this thesis studies the role of data-driven decision-making improving management and operational efficiency in the public social and healthcare sector in Finland. A qualitative research method fits well because it allows for in-depth insights into participants' experiences, perspectives, and practices (Agius, 2013). Granero-Molina et al. (2024) also cite that due to these insights, qualitative research has found increasing attention as an essential tool in contemporary health sciences. Similarly, Adeoye-Olatunde et al. (2021) highlights that qualitative research has gained growing recognition for its value and relevance in health and pharmacy services research. This approach aligns well with the objectives of this thesis, which seeks to understand how public social and healthcare sector engages with DDDM processes. By focusing on the experiences and practices of specialists involved in KM and BI development, qualitative research provides rich, contextual insights that help to capture the complexities of healthcare operations.

Qualitative research is rooted in the traditions of social sciences and is commonly applied to explore social dynamics and cultural contexts. It provides researchers with the opportunity to develop a deeper understanding of the environment in which action and decision-making take place and to gain insight into the context that shapes these processes. (Agius, 2013). Additionally, qualitative methods are especially valuable in situations where sociocultural contexts play a critical role in

decision-making and problem-solving. When traditional quantitative approaches may not fully address the complexities of human behaviors and organizational dynamics, qualitative research is instrumental in uncovering deeper layers of meaning (Granero-Molina et al., 2024). This further supports the use of qualitative methods in studying DDDM in public social and healthcare sector, where human factors and organizational practices are pivotal to success.

According to Eriksson & Kovalainen (2008), quantitative research is explained as a structured and standardized approach, often used for hypothesis testing and statistical analysis. This method typically deals with numerical data and focuses on explaining and quantifying relationships between variables (Basias & Pollalis, 2018). Quantitative approaches have been described as dominant in business and social sciences due to their ability to provide accuracy through a controlled and systematic approach. However, Eriksson & Kovalainen (2008) also recognize that this emphasis often overshadows the value of qualitative methods, which seek to interpret and understand social realities and complexities that quantitative methods may not fully capture. While quantitative methods are valuable for testing hypotheses and producing accurate, measurable results, they are less suitable for studying the nuanced and context-specific aspects of public health decision-making.

Basias & Pollalis (2018) highlight that qualitative research methods are particularly effective in new areas of research because they provide insights into complex, evolving situations that cannot be easily quantified. As Eriksson & Kovalainen (2011) point out, qualitative approaches are exploratory by nature, aiming to explore ongoing phenomena, identify new patterns and support the development of future research directions. In this thesis, the literature review provides a basis for understanding how organizations are prepared for DDDM and how organizational characteristics influence this awareness. The aim of the empirical study is to explore and refine this framework in practice and to understand the subjective experiences, organizational dynamics and human factors that influence informed decision-making. These complexities are difficult to measure quantitatively, which is why a qualitative approach is more appropriate, as it allows a deeper exploration of the experiences and perspectives of healthcare professionals that a quantitative method would likely miss. The purpose of this study is not only to identify the factors that influence organizational capacity, but also to explore the underlying causal relationships in the context of the public social and healthcare sector.

3.2 Grounded Theory

Developed in 1967 by Glaser and Strauss, grounded theory methodology is a systematic, yet flexible methodology that allows researchers to generate theory based on empirical data (Charmaz, 2006). Rather than beginning with a set hypothesis, the researcher collects data and continuously engages in a process of coding, categorization, and conceptualization to build theory from the beginning (Eriksson & Kovalainen 2011). Charmaz (2014) describes the nature of grounded theory methods as following:

“Stated simply, grounded theory methods consist of systematic, yet flexible guidelines for collecting and analyzing qualitative data to construct theories “grounded” in the data themselves. [...] Grounded theory methods foster seeing your data in fresh ways and exploring your ideas about the data through analytical writing.”

Eriksson & Kovalainen (2011) states that grounded theory is both a research method and the result of a research process. It involves a series of steps to develop a theory directly from the data collected, so that the theory emerges naturally from the research. This approach uses both inductive reasoning, in which conclusions are drawn from observations, and deductive reasoning, in which these conclusions are tested and refined. In addition, revising the theory throughout its development is considered an essential part of the process to ensure that the emerging theory is based on the data. Wiesche and Krcmar (2017) further emphasize that the grounded theory method is highly flexible and adaptable to different research contexts. It allows researchers to refine data collection and analysis iteratively, which is crucial when dealing with complex and dynamic environments such as healthcare. The process involves open coding to identify themes, then selective coding to link these themes to a core category, and finally theoretical coding to determine the relationships between these categories. This systematic approach ensures that the theory developed is deeply grounded in the empirical evidence and is flexible enough to incorporate new findings or categories as the research progresses. (Wiesche and Krcmar, 2017.)

Grounded theory methodology has expanded significantly beyond its origins, finding application in various fields such as business management, education, and public health (Tan, 2008). This adaptability is due to its suitability for exploring emerging and dynamic social phenomena where there is little established theoretical framework (Charmaz 2014). Grounded theory is suitable for this thesis because it enables the development of theory directly from the data collected, without relying on pre-existing assumptions. This approach is ideal for exploring the complex, evolving nature of DDDM in public social and healthcare sector, as it allows for a flexible and iterative analysis of the data. This is particularly useful in studies of this kind, where there is little previous

research on how public social and healthcare organizations use data to make decisions. By continuously refining the data throughout the research process, grounded theory helps uncover insights into improving decision-making processes and enhancing operational efficiency.

3.3 Data collection and analysis

3.3.1 Semi-structured interview

This study used semi-structured interviews to collect empirical data, which provide a balance between flexibility and structure throughout the interview process. While it provides a framework for gathering in-depth information on specific topics, it also enables the interviewer to steer the conversation and explore areas that may not be easily accessible through other data collection methods. The goal is to foster an open, comfortable atmosphere for the interviewees, encouraging a discussion-like interaction rather than a rigid question-and-answer session. This method ensures that key themes are covered while allowing room for the interviewee's experiences and insights to guide the flow of conversation.

According to Hirsjärvi & Hurme (2022), The semi-structured interview method does not have a single method, but is characterized by its flexibility in use when a particular aspect is locked in. The questions are predetermined, but the answers are not tied to specific response options, allowing the interviewees to respond in their own words. The method is based on the work of Merton, Fiske, and Kendall (1956) in their publication *The Focused Interview*, where the authors describe their approach as one that specifically targets individuals who have experienced a particular situation. The interview process is carefully structured around preliminary analyzes of the phenomenon, allowing the interviewer to guide the discussion towards significant aspects and participants' subjective experiences, which the researcher has anticipated through prior content or situational analysis. (Merton et al., 1956.)

Semi-structured interviewing is particularly well suited to qualitative research when the aim is to capture the unique perspective of the participant rather than to produce a generalized understanding of the phenomenon (Adeoye-Olatunde et al., 2021). One of its main advantages is the balance it achieves between structure and flexibility, allowing the researcher to address predefined themes while responding to new, relevant ideas that emerge during the conversation. The method encourages discovery by providing a guided framework, while leaving room for unplanned themes to emerge as the interview progresses (Magaldi & Berger, 2020). By combining a clear focus and

openness to exploration, semi-structured interviews allow for a deeper understanding of complex issues, making them highly valuable in gathering rich and varied data.

Hirsjärvi & Hurme (2022) highlight that semi-structured thematic interviews offer the advantage of not being strictly tied to either qualitative or quantitative paradigms. Instead, they focus on the flow of discussion around central themes, allowing the conversation to evolve naturally based on the interviewee's responses. This method is particularly well-suited to this study on data-driven decision-making in the public social and healthcare sector because it allows for capturing the nuances and complexities of managerial practices in real-world settings. The semi-structured format enables a deep exploration of how healthcare managers engage with data, how they perceive its impact on decision-making, and the challenges they face in operational environments. As this method allows for both guided questioning and flexibility, it ensures that the interviews provide a wide range of insights that reflect participants' different experiences and perspectives, which are crucial to understanding the complexity of informed decision-making in a complex and evolving field such as public health. (Hirsjärvi & Hurme, 2022.)

3.3.2 Applying grounded theory to the semi-structured interview method

According to Airaksinen (2021), Grounded theory can be viewed both broadly as an overall research approach or more narrowly as a systematic method for data collection and analysis. It is particularly well-suited for studies that lack extensive prior research or where new perspectives are sought. This methodology offers a structured framework for gathering and interpreting data, making it versatile for various types of qualitative research. Utilizing grounded theory and semi-structured interview method to collect and analyze the data allows emerging themes to be explored without rigid question structures. The researcher can explore participants' perspectives in depth and adapt the questions for the next interviews based on the initial findings (Duffy et al., 2024). Adeoye-Olatunde et al. (2021) also emphasizes the use of grounded theory as part of semi-structured interview process.

After significant healthcare reform in Finland, KM and BI have become increasingly important in managing the healthcare sector (Sosiaali- ja terveystieteiden ministeriö, 2023). However, there has been a lack of research examining how these practices are implemented in public social and healthcare sector. By using grounded theory as a systematic method alongside semi-structured interviews, it is possible to delve into the unique experiences of interviewees while remaining adaptable to new insights that emerge during the research process.

3.3.3 Data collection

Before the interviews started, it was explained to the participants that their interview responses would only be used to generate and discuss the empirical evidence for this study. Interviewees were also given the opportunity to review their interview responses in writing before the data were analyzed and discussed. For a more in-depth description of research data management can be found in Appendix 2, which was also sent to the case organization when applying for the research permit. The plan contains information on data handling, permissions, rights, documentation and data preservation.

The concepts relevant to the interviews were explained to the participants before the actual questioning began. Initially, the interviewees were briefly asked about their job description, followed by the main interview questions. The interviews questions started with straightforward questions and moved on to more open questions towards the end. At the end, there was also time for open discussion in case any additional topics came up.

The structure of the interviews:

1. The initialization of the interview
 - a. the purpose of the interview explained
 - b. the concepts used in the interview explained
 - i. Data-Driven Decision-Making
 - ii. Business Intelligence
 - iii. Knowledge Management
2. Questions about job description details
3. Planned interview questions
4. Open discussion

The detailed interview questions are presented in the Appendix 1: *The interview questions for the semi-structured interview*. These questions were divided into four thematic sections. Section 1 (questions 1-2) focused on understanding the current state of DDDM in the case organization and aimed to find out how data-driven practices have already been implemented. Section 2 (questions 3-5) examined how the organization collects and utilizes data, including the technological solutions involved, such as BI tools. Section 3 (questions 6-8) addressed the organizational and cultural factors that influence data utilization and knowledge management. Finally, section 4 (questions 9-

10) aimed to assess how DDDM has impacted the organization's performance and efficiency and to gather interviewees views on how DDDM could develop in the future in the Finnish public social and healthcare sector.

All interviews were recorded and transcribed to prevent any bias in interpretation. According to Adeoye-Olatunde et al. (2021), recording is recommended to maximize the use of data for analysis. It also allows the interviewee to be more present in the interview situation, making the conversation feel more natural to the participants. In terms of data collection, interviews were conducted with the information services team of a wellbeing services county, as they are responsible for the development and implementation of DDDM practices in the organization. Each interview began with an introduction, some announcements, and requests for permission. The goal was to maintain an informal atmosphere and clarify that there were no wrong answers, encouraging interviewees to respond openly and confidently. Additionally, all interviews were conducted in Finnish, the native language of the participants, which facilitated a broader range of responses to the questions.

Table 2 The semi-structured interviews overview

Participants	Position and job description	Date of interview	language	Length of the interview
A	Head of Information Services	20.12.2024	Finnish	1:06:35
B	Information Services Manager	21.1.2025	Finnish	1:04:19
C	Specialist, Information Services	28.1.2025	Finnish	0:40:04
D	Specialist, Information Services	31.1.2025	Finnish	0:36:01
E	Specialist, Information Services	7.2.2025	Finnish	1:01:58
F	Specialist, Information Services	11.2.2025	Finnish	1:03:10

3.3.4 Data analysis

Adeoye-Olatunde et al. (2021) note that qualitative data analysis usually begins with assigning codes to the content of transcribed interviews. This thesis uses the Gioia method to analyze the data, which provides a structured approach and increases the transparency of the analysis process. The method is designed to support the development of grounded theory by identifying theories that emerge from the data. It aims to uncover new concepts or reveal relationships between them, thus providing deeper insights into the phenomenon under study. (Gioia et al., 2012; Eriksson & Kovalainen, 2008.)

Eriksson and Kovalainen (2008) point out that a key element of grounded theory is the systematic classification of data, known as coding. This process takes place in three stages: open, axial, and selective coding. Charmaz (2006) explains that coding involves categorizing segments of data with short, descriptive labels that simultaneously summarize and explain each data point. Coding allows researchers to select, separate and organize data in a systematic way to facilitate analytical interpretation. Ultimately, the aim is to identify a small set of core categories that combine the most relevant concepts and form a theoretical foundation grounded in the data. (Eriksson and Kovalainen, 2008.)

As described by Gioia et al. (2012), qualitative analysis follows a structured coding process to systematically develop theoretical insights. In the first step (often referred to as open coding), the data are divided into several first-order categories that closely reflect the language and terms used by informants. At this stage, the researcher focuses on identifying a broad set of emergent themes without imposing predefined theoretical frameworks. In the second stage (often referred to as axial coding), these categories are refined by identifying relationships and patterns between them, resulting in the development of second-order themes that represent a more abstract level of interpretation. In the last stage (often referred to as selective coding), the second level themes are combined into aggregate dimensions that serve as the basis for theory development.

Table 3 Summary of data analysis

Analysis steps	Description
First-order analysis (i.e., open coding)	The initial phase involves breaking down the data into distinct first-order categories based on recordings and transcriptions.
Second-order analysis (i.e., axial coding)	First-order categories are refined into second-order themes by identifying patterns and relationships among them.
Aggregate dimension analysis (i.e., selective coding)	Second-order themes are integrated into aggregate dimensions, forming the basis for theoretical development.

This process allows researchers to move systematically from raw data to conceptual insights and ultimately build a data structure that visually illustrates the development of the themes and their theoretical meaning (Gioia et al., 2012).

4 Findings

This section presents and discusses the empirical findings based on the analysis of semi-structured interviews with six employees working in the information services team of a wellbeing services county in Finland. The interviews were conducted in Finnish, as it was the interviewees' native language. The citations included in this chapter are translations of the original responses.

4.1 The current role of DDDM in public social and healthcare

The first set of interview questions (see questions 1-2 for more detail in Appendix 1) aimed to explore the current role of DDDM in public social and health care by asking participants to describe their professional status and reflect on the organization's current focus and progress in developing DDDM practices. The aim was to encourage interviewees to think about the role of DDDM holistically rather than as a tool for a single function in their organization. Overall, interviewees acknowledged that data plays a crucial role in decision-making processes. However, they also highlighted various challenges in making effective use of it. The following are selected responses that illustrate the common themes that emerged from the interviews: the increasing integration of KM into decision-making processes, and the persistent issues of timeliness, availability, and manual handling of data. These examples from interviewees C and D were selected since they represent the most typical and recurring views expressed by participants on the progress and ongoing difficulties in implementing DDDM.

C: "Knowledge management is already an established part of decision-making, but the challenge remains the timeliness and availability of data."

D: "We have already made progress in integrating lot of systems, which has improved data-driven decision-making. However, a significant amount of data is still processed manually. Nevertheless, we are clearly moving in the right direction."

The participants generally agreed that DDDM has become an integral part of the public social healthcare management. At the same time, they recognized that its implementation remains a work in progress and its effectiveness varies across departments. While some units have successfully integrated data-driven processes, others still face challenges related to accessibility, interoperability and manual data processing. They mentioned that although most information systems are integrated on a data platform, data is not always readily available in a usable format, making real-time decision-making difficult. Another data related challenge has been the fragmentation of information systems.

D: “There have been an overwhelming number of client and patient information systems in use. Even when the same systems were used, they operated in separate instances, preventing seamless data transfer. As a result, data remains fragmented, lacking consistency and coherence. Additionally, some systems still lack proper integration, and manual data collection is often required, further complicating the process.”

When the wellbeing services counties were established as part of the social and healthcare reform, multiple municipalities were merged under a single organization. The various information systems previously used by individual municipalities did not easily synchronize, leading to fragmented data and significant challenges in data integration and processing. Interviewee A highlighted that data from different systems cannot always be seamlessly combined into a unified format. Even when some municipalities used the same systems, the data structures were inconsistent, making integration challenging. For example, within the same services, data may not be standardized across systems. The same concept may be recorded differently in each system, making it difficult to extract relevant information.

All the six interviewees confirmed also that knowledge management and utilization of data has been a long-term strategic priority for the organization even before the establishment of the wellbeing services counties. They stressed that DDDM is embraced at all levels of the organization and its importance is commonly understood.

E: “It has been identified as a strategic priority and remains an active area of development. We continuously monitor progress in fostering a data-driven culture.”

Participants F and A agreed strongly with the previous answer and highlighted the organization’s long-standing commitment to integrating DDDM:

F: “Our goal has long been to integrate data-driven decision-making at all levels and to exploit its full potential. We have developed a comprehensive action plan for knowledge management at the organizational level.”

A: “Knowledge management is one of the priorities in our organizational strategy. We are actively developing the knowledge base and investing in ensuring that everyone understands how their work relates to the core mission of the organization, while at the same time monitoring the achievement of the objectives set.”

While knowledge management and data-driven solutions are becoming increasingly important at middle management level, their integration into the organization is taking place through a top-down approach. The need to enable the use of data stems from the organization’s strategy and financial and operational planning. However, in an organization of this scale, fully implementing strategy at all levels, or ensuring that what is identified at operational level reaches management, remains a challenge. Different levels of management deal with very different types of issues and these

perspectives are not always consistent. The basic approach is that DDDM strategy is developed at the top and then translated into operational models at different levels of the organization.

Overall, the results suggest that while DDDM is increasingly recognized as a valuable tool as well as a strategic guide, its full implementation is still hampered by challenges related to data quality, system integration, organizational culture and analytical maturity. In the following sections, specific challenges and organizational factors that affect the effective use of data for decision making will be examined in more detail.

4.2 Factors influencing the collection and use of data for decision-making

After examining the current role of DDDM in the case organization, the interviews shifted focus to how data is collected and utilized for decision-making purposes. Participants were asked to describe the tools used to process data, to reflect on data quality and governance practices, and to describe the development and use of BI tools (see questions 3-5 for more detail in Appendix 1). The aim was to uncover both current practices and possible challenges in data utilization. The data structure for factors influencing the utilization of data in decision-making are illustrated in Figure 8 below. The analysis identified three aggregate dimensions: 1) *Data infrastructure and integration*, 2) *Institutionalizing data-driven decision-making*, and 3) *Technology adoption and capabilities*. The dimensions consist of five second-order codes, which are i) *Fragmentation of data sources*, ii) *Data quality and standardization issues*, iii) *Operational barriers to data utilization*, iv) *Organizational readiness and adoption*, and v) *Advancing BI tools*. A detailed analysis of the data structure follows in sections 4.2.1, 4.2.2, and 4.2.3.

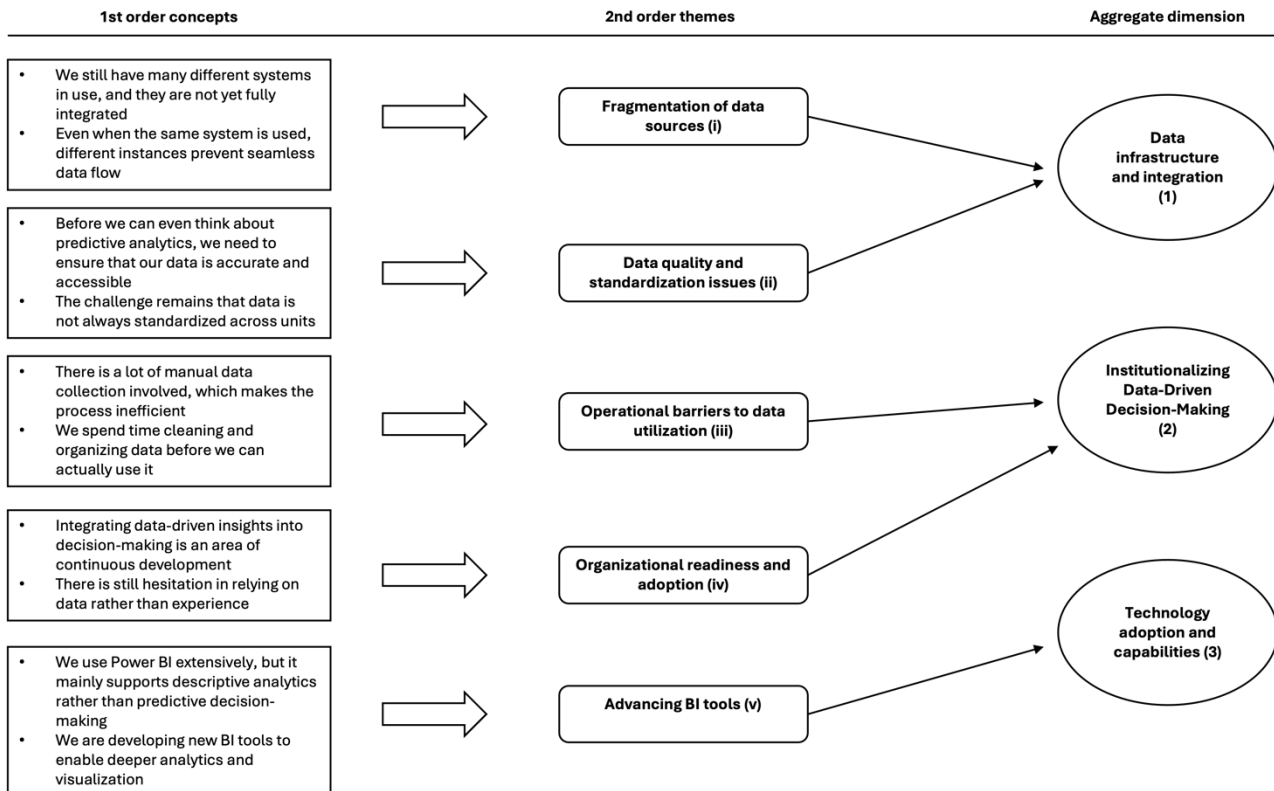


Figure 8 Data structure for factors influencing the collection and use of data for decision-making

4.2.1 Data infrastructure and integration

Data infrastructure and integration (1) is aggregated from the second order themes which are *i) Fragmentation of data sources and ii) Data quality and standardization issues*. As stated in section 4.1, fragmented data sources have been a challenge in the target organization due to the mergers of municipalities.

A: “One of the main challenges remains the standardization of data across systems. Although we have addressed the integration between patient and client information systems, linking this data to financial data is still complex. Financial data is essential for cost-effectiveness and productivity monitoring, but it is not directly aligned with the technical environment. [...] The lack of coherent core data structure has been a major challenge, and we are actively working to address this problem through guidance and data management improvements.”

With the reform of the social and health care system, the information systems used by the municipalities were integrated into the new organization. The interviews revealed that the integration of these systems has been challenging, as the data is not standardized and the same services are recorded in different ways in different systems, leading to inconsistencies. Even with individual municipalities, the same data has been entered in different ways across systems, making

standardization a complex task. This has required double the effort in data collection, management, and analysis. Another major challenge has been ensuring the accuracy of data due to the fragmented information systems. The issue is particularly evident in national data collection efforts, such as required by institutions like the Finnish Institute for Health and Welfare (THL). Interviewee A highlighted that data is regularly transferred to national authorities, but there is limited visibility into what information is being sent until it is received back as processed dataset. Ensuring that all nationally reported data is accurate and aligned with regulatory requirements has been a key priority in the organization. However, due to the complexities of data standardization, ensuring the accuracy and consistency of legally mandated reports has required significant effort.

Although these challenges have been significant following the social and healthcare reform, the organization has addressed them through effective and professional knowledge management.

B: “The goal is to establish a unified data platform that would provide access to comprehensive, organization-wide data. This would significantly improve both the quality and reliability of the data available. [...] We have developed temporary, more manual and labor-intensive data management solution as an interim measure. While the system is not highly automated, it allows for necessary data processing until the new integrated systems are fully deployed.”

A: “We are already at the point where more efficient data management methods will soon be in place, allowing seamless integration of data across platforms.”

Building a cohesive data platform is a robust and effective solution for improving the mobility and reliability of data in an organization. According to the case organization, one of the main strategic initiatives has been the integration of different data sources, which is being implemented through management pilots at different levels of the organization. From the interviewees’ perspective, the information services team is seen as essential function for organizations to ensure that data solutions are effectively integrated into both business and financial systems. In addition to strategic initiatives, knowledge management projects have also been launched at the unit level, allowing active involvement of operational management in knowledge-based initiatives. This alignment is crucial to strengthen both operational and strategic decision-making through data-driven insights.

4.2.2 Institutionalizing data-driven decision-making

Institutionalizing data-driven decision-making (2) emerged as another aggregate dimension from the analysis of the empirical data. This dimension is based on the second-order themes of *iii) operational barriers to data utilization* and *iv) organizational readiness and adoption* (see Figure 8). The operational barriers stem from the manual nature of data processing. As noted in section

4.2.1, interviewees highlighted that the fragmented data infrastructure has to some extent led to manual processing, which in turn has slowed down data-driven decision-making processes. In some cases, data had to be extracted from several different systems into Excel files and manually converted to ensure compatibility between data platforms.

F: “Initially, the data had to be manually extracted from several systems and compiled into Excel files for reporting. As the data formats were not directly compatible with the reporting systems, the standardization and processing of the data required considerable manual work, making the workflow very laborious.”

E: “Although we have been able to produce data to support decision-making, the process is still partly manual. As our data warehouse is not yet mature enough to follow full automation, data still must be collected manually, which introduces uncertainties and potential errors that affect the consistency and accuracy of the data.”

Fragmented data sources are problematic not only for systems integration but also by increasing the need for manual data processing. The case organization has identified that manually extracting dozens of reports from different systems and further processing them just to obtain a few key data points is inefficient. To address this, it has prioritized the automation of manual data retrieval processes with the aim of improving the efficiency and productivity of knowledge management. According to the interviews, temporary data warehouses have been created to reduce dependence on manual workflows. In addition, interviewee F mentioned having developed automated software solutions that have helped streamline data processing and minimize manual steps, which has improved the efficiency of DDDM.

Organizational readiness and adoption of DDDM depend on the organization’s ability to change its thinking towards a more data-centric approach. As organizations increasingly generate data to support their operations, the effective use of this data will improve efficiency and decision-making processes at all levels. In the case organization, Interviewee B illustrated this development process by noting that the early stages of KM initiatives were particularly difficult. Although management had a strong need for information, they initially struggled to articulate their precise needs. However, as more and more data products became available, management was better able to define their requirements, which refined the focus of knowledge management efforts. Over time, the adoption of DDDM has grown exponentially and has become an integral part of the organization. Currently, data is better understood within management and communication between decision-makers and data teams has significantly improved, ensuring that data solutions are more closely aligned with strategic needs.

4.2.3 Technology adoption and capabilities

Technology adoption and capabilities (3) is the third and final aggregate dimension, derived from the second order theme “Advancing BI tools” (v). This dimension is independent, as it focuses on the BI environment as one of the enabling tools for DDDM. In the literature review, the DDDM causal model framework refers to “data products”, which in this context correspond to BI tools used for reporting and analytics in the case organization.

The adoption of BI tools plays a significant role in the case organization’s DDDM efforts. The interviews highlighted that BI development and reporting is managed in-house, which allows for greater efficiency and cost-effectiveness compared to outsourcing. The information management team is responsible for the production of data products and ensures that reporting is in line with strategic performance indicators. The organization has also emphasized user acceptance of BI tools and promoted direct engagement with power BI dashboards rather than static reports. To support this, training and communication activities have been implemented to encourage independent use of BI tools by employees.

In addition, collaborative BI development processes have been implemented, involving clinicians and operational staff in defining reporting needs and ensuring that these data products meet relevant requirements. While the current BI environment primarily facilitates descriptive analytics, the case organization is currently exploring advanced tools to improve predictive and prescriptive capabilities to further integrate data-driven insights into decision-making processes.

4.3 Organizational factors influencing DDDM

Organizational factors influencing the use of DDDM, alongside the utilization of the data, were a key aspect of the analysis of the empirical data. To explore these themes, participants were asked about organizational and cultural barriers, collaboration, and the integration of KM to decision-making (see questions 6-8 for more detail in Appendix 1). Every interviewee recognized that in a large organization like the wellbeing services county, where multiple smaller entities (formerly individual municipalities) have merged into a single system, creating a strong culture of DDDM is a significant challenge. The empirical data also reveals that the organization considers cross-departmental collaboration to be essential of effective DDDM. Ensuring organization-wide commitment to DDDM and promoting continuous collaboration between departments are key to successfully implementing data-driven practices in an organization of more than 20 000 employees. Two aggregate dimensions were identified from interview questions 6-8: *Transforming*

organizational practices for DDDM (4) and *Cross-departmental collaboration for DDDM (5)*. A detailed analysis of the data structure is presented in sections 4.3.1 and 4.3.2.

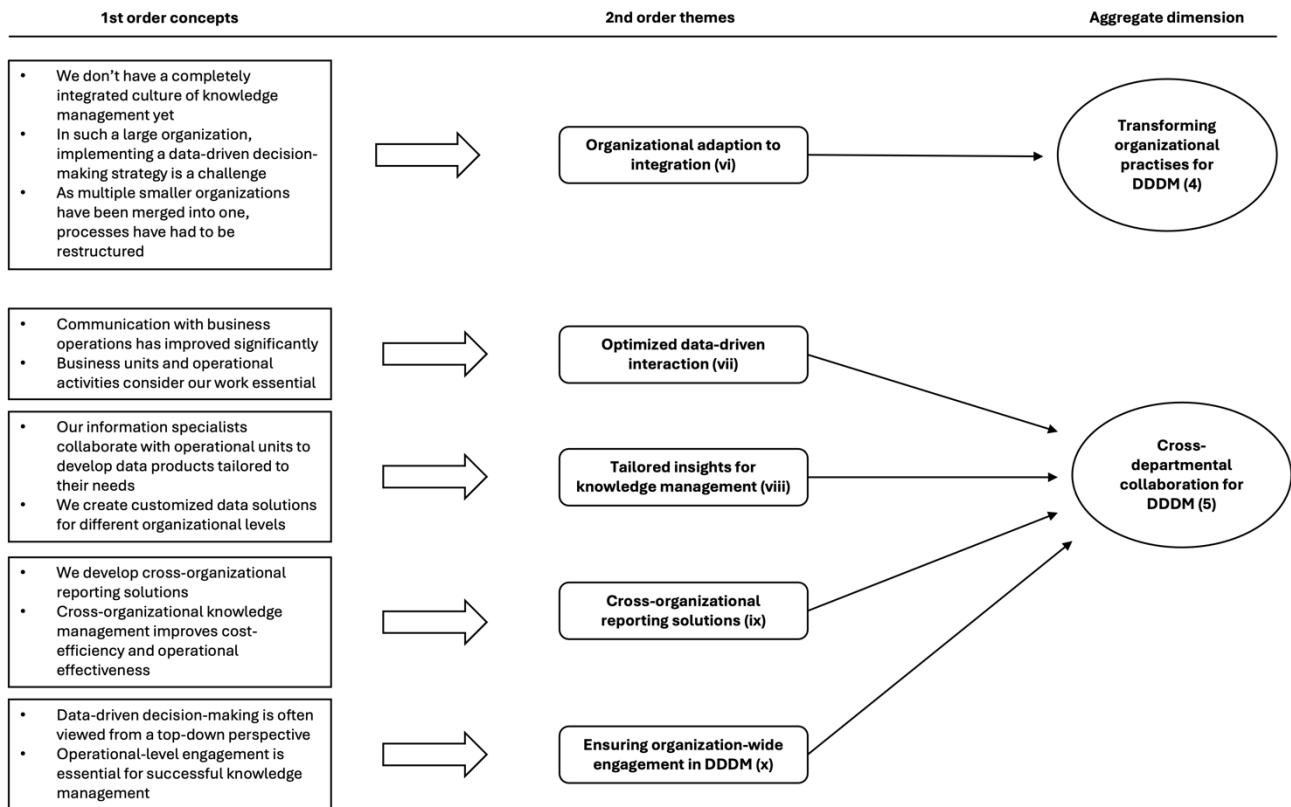


Figure 9 Data structure for organizational factors influencing the DDDM

4.3.1 Transforming organizational practices for DDDM

The first of these two aggregate dimensions resulted from the second order theme “Organizational adaption to integration” (vi). In the case organization, this refers to the integration of multiple municipalities into a single wellbeing services county, which led to significant organizational and cultural changes. Interviewee C noted that more than 20 municipalities were merged into a single organization, covering hospital services, social services, primary care and special care, among others. Each of these entities had its own organizational structures and cultural practices, functioning somewhat independently before the integration.

As noted in sections 4.1 and 4.2, this merger presented challenges not only in integrating different information systems but also in harmonizing organizational cultures and decision-making processes, particularly in the context of knowledge management. Every interviewee stressed the

importance of understanding the wellbeing services county as a whole and promoting a unified organizational culture.

A: “Employee satisfaction and sense of belonging to the organizational culture are measured through various surveys. In one survey, employees are asked whether they feel like they are part of the organization.”

B: “In such a large organization, implementing the knowledge management strategy at the operational level – or bringing challenges from the operational field to the management – remains a challenge. Different management levels deal with different matters, and they do not always yet align with each other. [...] this is still a young organization, and we are still in a transitional phase.”

One organizational and cultural challenge in advancing DDDM has also been the differences how various units within the organization have become accustomed to using data. For example, some units have a long-established culture of data utilization and have always had access to mature reporting systems. However, with the transition to a new system, the development of the old data infrastructure has been put on hold, and the new system is still being implemented. In addition to the establishment of the wellbeing services county, the organization has recently gone through significant changes. As a result, the reporting and data systems have struggled to keep up with these transformations. Due to this, not all units have fully understood the broader complexities, partly due to cultural differences in how data is utilized.

Although these changes have created pressures, such as keeping the data infrastructure aligned with organizational transformations, interviewee B emphasized that there is strong willingness across the organization to develop DDDM processes. The organization is very positive to knowledge management initiatives and is excited to adopt more data products developed by the information services team. All interviewees also stressed that a successful data-driven based culture requires its integration into a coherent management model, where data-driven decision-making and management of the whole organization are seen in the same framework. In addition, interviewee F highlighted the importance of cross-functional communication. The information services team considers this as one of the key enablers for successful DDDM, ensuring comprehensive communication across the different parts of the organization.

4.3.2 Cross-departmental collaboration for DDDM

As mentioned in the last section, communication between different departments is crucial for effective DDDM. Such communication is a necessary precondition for cross-departmental collaboration, which enhances data-driven approach across the organization. From the empirical

data, four second order themes were identified under the aggregate dimension “*Cross-departmental collaboration for DDDM*” (5): *Optimized data-driven interaction* (vii), *cross-organizational reporting solutions* (viii), *tailored insights for knowledge management* (ix), and *ensuring organizational-wide engagement in DDDM* (x).

The case organization’s information services team actively promotes data products and implements them across different levels of management to ensure that insights gained through DDDM are effectively integrated into both strategic and operational decision-making.

A: “We are actively developing our database and making sure that everyone understands how their work is linked to the core mission of the organization and that the achievement of objectives is tracked. [...] With data, we can provide the organization with opportunities to improve its performance.”

B: “We aim to be present in the decision-making forums where key decisions are taken and to ensure that data is considered in these discussions. But we cannot be sure that the data we produce will always be used. [...] We are trying actively to promote our data products to decision makers.”

One of the key reasons the organization has its own information services team is to ensure that each employee has a specific area of responsibility in developing DDDM. The development of data products follows a need-based approach, ensuring that the data provided is relevant and actionable. According to the interviewee E, a key priority is to maintain an ongoing communication with different units to determine which insights are most valuable for decision-making. While management may track long-term trends, operational units need more immediate and responsive data to guide their day-to-day operations.

To ensure consistency while meeting the individual needs of different departments, the organization aims to create a structured but flexible data products. Instead of creating separate, highly specialized BI reports for each department, the organization develops standardized reporting tools that allow users to filter and analyze relevant information according to their specific needs. However, interviewee F also stressed that tailored data products for different departments have significantly improved the adoption of DDDM. As departments and service areas have become more familiar with the use of available data, they have started to integrate it into their daily activities. This has also led to a two-way exchange of information, with departments actively requesting specific information, which has further improved communication between the information services team and operational services. This continuous feedback loop strengthens data-driven decision-making at all levels of the organization.

One organizational factor influencing DDDM that emerged from the empirical data was the need for *cross-organizational reporting solutions (ix)*. As a large organization, the wellbeing services county consists of multiple sectors, such as hospital services, social services, and emergency care, each with their own roles and responsibilities, as mentioned in section 4.3.1. The treatment path of an individual patient may cross several of these sectors. Through cross-departmental data solutions, organization can gain insights that support cost-effective decisions and improved resource allocation.

D: “We utilize knowledge management in cross-departmental reporting solutions, which provide valuable insights into various aspects, such as patient treatment paths. This highlights the need for collaboration and communication between different departments.”

F: “We are increasingly able to examine patients’ treatment paths more comprehensively thanks to the improved availability of data. This will allow us to better understand the effectiveness of care and evaluate it across organizations.”

DDDM across departments in the case organization can increase cost-effectiveness and improve resource allocation. This approach provides insights on the need for collaboration between departments and can help staff better understand treatment effectiveness and patient movement between services. Waiting times within the wellbeing services county have at times increased, making cross-functional data analysis a valuable tool for identifying the causes of bottlenecks and developing strategies to reduce them. By using data, the organization can improve the transparency of treatment paths, allowing for more accurate identification of potential challenges. From the patient’s perspective, this is crucial to ensure timely access to the necessary care, ultimately resulting in cost savings for both the organization and the patient themselves.

The second order theme “*ensuring organization-wide engagement in DDDM*” (x) also emerged as an important theme from the empirical data. Interviewee D highlighted the importance of embedding a data-driven culture across the organization and in particular extending this to the frontline of patient and client care.

D: “It is important to recognize that while a knowledge management strategy is established at the top level, its implementation among employees is one of its most essential aspects. It is important for employees to understand why patient data is recorded in the system in a specific way. [...] There must be an understanding that knowledge management belongs to all employees, not just a few dozen managers.”

Proper documentation of data is a crucial part of successful DDDM. Interviewee D highlighted that knowledge management should not be limited to management but should be integrated into daily

operations across all units. Employees need to recognize how their data entries to the information system impact on decision-making, resource allocation, and even organizational funding. By increasing awareness of the practical implications of data, the organization can make sure that data is not just collected but actively used to improve operations and patient care. Insights stem from information, and information comes from data, making accurate data entry into the system essential.

4.4 Impacts and the next steps

Towards the end of the interviews, participants were asked about the impact of DDDM on social and healthcare outcomes, as well as their perspectives on its future development in Finland's public social and healthcare system, including key opportunities and innovations in the field (see questions 9-10 for more detail in Appendix 1). Interviewees A and B stated that DDDM has had a positive impact on the case organization, both in terms of resource allocation and operational efficiency. They pointed out that when an organization improves its ability to generate and use data, it improves its capacity to develop more accurate scenarios and analyzes. In the future, as information systems and data infrastructures become more integrated, the organization will be able to use data more effectively, leading to better decision-making and improved outcomes. Interviewee D confirmed this perspective, noting that a data becomes more transparent in the future, it will allow for more targeted actions to increase efficiency.

Knowledge management and data have played a crucial role in ensuring an equitable distribution of health services across regions. Continuous data monitoring helps to identify regional differences in access to services, allowing targeted action to improve access and efficiency. Addressing these gaps is in line with the wider objective of ensuring equal access to health services for all citizens. By identifying and addressing service gaps, the organization has been able to make more informed decisions on resource allocation, ultimately increasing efficiency and equity of services.

The case organization viewed the future of knowledge management and data utilization in a positive light. All six interviewees believed that AI will, in some form, improve DDDM, particularly by automating data processing, improving predictive analytics and enabling more efficient allocation of resources.

B: "AI is developing rapidly, and I see significant opportunities in its ability to accelerate data analysis and provide new perspectives for decision making. I am genuinely looking forward to working with AI and exploring its potential."

C: "AI offers significant opportunities, specifically in the automation of documentation processes. For example, AI or robotic automation could streamline data entry by

ensuring that information stored in one system is automatically transferred to another. In the healthcare sector, where patient and client information systems operate separately, AI could identify relevant entries and integrate them across platforms, reducing manual work and improving data consistency.”

The public social and healthcare sector produces huge datasets containing millions of data records, providing a significant opportunity for AI to improve data analysis and innovation. The organization has recognized that AI could and should be used to analyze patient data, enabling the identification of outliers and trends that may not yet be detectable using traditional methods. Interviewee D cited an example of how AI-powered speech recognition systems could streamline documentation processes and improve data classification, which would significantly reduce manual workload. However, all interviewees stressed that AI is not intended to replace human-based work in patient encounters, but rather to optimize resources and improve operational efficiency.

Beyond the role of AI, interviewees A, C, and F also pointed out that the future of DDDM in public social and health care depends on better integration of national data, more benchmarking capabilities and standardization of information systems. As Finland’s healthcare landscape continues to evolve, participants highlighted the need for a more integrated and structured approach to data use, enabling decision-makers to make more informed choices at both regional and national levels.

D: “With the consolidation of municipalities, we now have a better opportunity to analyze healthcare effectiveness on a national level and develop more efficient care pathways.”

E: “Now that reform has been implemented, we have a stronger foundation for evaluating healthcare impact across different areas and using that data to improve services.”

A key priority for the future is the development of standardized, nationally comparable data, which would enable better coordination between wellbeing services counties and more precise evaluation of healthcare outcomes. By ensuring data compatibility across different regions and service providers, DDDM can facilitate more effective resource planning, reduce inefficiencies, and improve patient care.

5 Discussion

This study aimed to explore how DDDM can be utilized in social and health care to improve operational efficiency and decision-making. The research specifically examined one of the wellbeing services counties in the Finnish public social and healthcare sector, where the increasing adoption of data-driven methods is crucial for optimizing resource allocation, improving patient outcomes, and supporting evidence-based policy development. To achieve these objectives, the research was guided by following research questions:

RQ1: How do public social and healthcare sector in Finland utilize data-driven decision-making to improve operational efficiency?

RQ2: What roles do knowledge management and business intelligence play in facilitating data-driven decision-making within Finnish public social and healthcare organizations?

RQ3: What challenges does the Finnish public social and healthcare sector face in implementing data-driven decision-making processes?

Through a qualitative research approach utilizing semi-structured interviews, this study explored how data is currently collected, managed, and applied to decision-making within the case organization. The findings from interviews with six participants reveal both the potential of DDDM in improving healthcare operations and the structural and cultural barriers that need to be addressed for successful implementation.

5.1 The growing significance of DDDM in public social and healthcare sector

The findings from the empirical data confirm what has already been noted in previous literature. Data has become a vital resource for improving organizational performance and operations (Brynjolfsson et al., 2011; Korherr et al., 2022). In the case organization, data is increasingly used not only to improve performance monitoring but also support real-time decision making to allocate resources more efficiently and improve treatment paths for patients. This change reflects a broader organizational approach where data is no longer seen as a by-product of operations, but as a key driver of strategic and operational development (Shafiq, 2024). As Davenport (2006) and Laihonon et al. (2013) suggest, such a culture increases transparency and supports better matching of information systems and employee knowledge. Particularly in healthcare organizations, knowledge is a strategic asset, and KM is an effective approach to address challenges such as rising healthcare costs and increasing demand for better quality care (Ayatollahi & Zeraatkar, 2020). The case

organization demonstrates increasing integration of data into decision making at different levels of management, which contributes to both operational improvements and strategic alignment. This is consistent with the view that knowledge-based strategies not only increase efficiency but also allow for more data-driven and responsible governance in complex health systems (Sarioguz & Miser, 2024; Myllärniemi et al., 2012). The growing emphasis on data utilization at all levels of the organization points to an emerging culture of knowledge management, recognizing the value of data-driven insights in decision-making.

The case organization also sees significant future potential in using AI to enhance DDDM. AI and Big data analytics are expected to transform healthcare management by improving predictive analytics, automating documentation, and supporting more efficient resource allocation (Freitas, 2024; Rehman et al., 2022). Empirical findings showed that AI could streamline manual processes such as data entry and classification, while improving data accuracy and timing, which are core requirements for effective DDDM. The understanding of case organization is in line with Di Nucci's (2019) view that data-driven technologies are not intended to mimic human reasoning, but rather to extend cognitive and analytical capabilities. It is essential that an organization doesn't view AI as a substitute for human expertise in patient interactions, but rather as complementary tool for knowledge management to support DDDM across the organization.

While the case organization shows a strong commitment to DDDM and to the increasing integration of data into decision-making processes, the empirical findings also highlight areas where further development is needed to fully leverage the potential of DDDM. The strategic direction and growing awareness of data have laid a strong foundation, but challenges remain, particularly in ensuring consistent implementation across all departments and overcoming existing structural and technological difficulties. These findings don't undermine the progress made but rather point to important opportunities for further development. The next section will discuss these challenges in more detail, focusing on the cultural and structural factors that influence an organization's path towards fully data-driven decision-making.

5.2 Cultural and structural barriers to DDDM implementation

Transforming an organization into a data-driven environment requires both a technological infrastructure and a change in organizational culture (Abubakar et al., 2019). This was particularly evident in case organization, where the merging of several municipalities into a single wellbeing services county showed that cultural and structural integration challenges were the primary obstacles. The literature suggests that successful DDDM implementation requires a harmonized

data culture and common goals across departments (Troisi et al., 2020). In the case organization, interviewees highlighted that there were several difficulties in integrating data-driven practices between previously independent municipal units. Differences in organizational cultures, decision-making processes and KM traditions caused friction in developing a coherent approach to DDDM. For example, some units were more accustomed to using data for strategic decision-making, while others lacked the experience or tools to use it effectively. While management commitment exists, transforming strategy into daily operations across such a large and complex organization is still a work in progress. Figure 10 illustrates the key barriers, improvement actions, and outcomes identified in the empirical data related to the implementation of DDDM in the case organization.

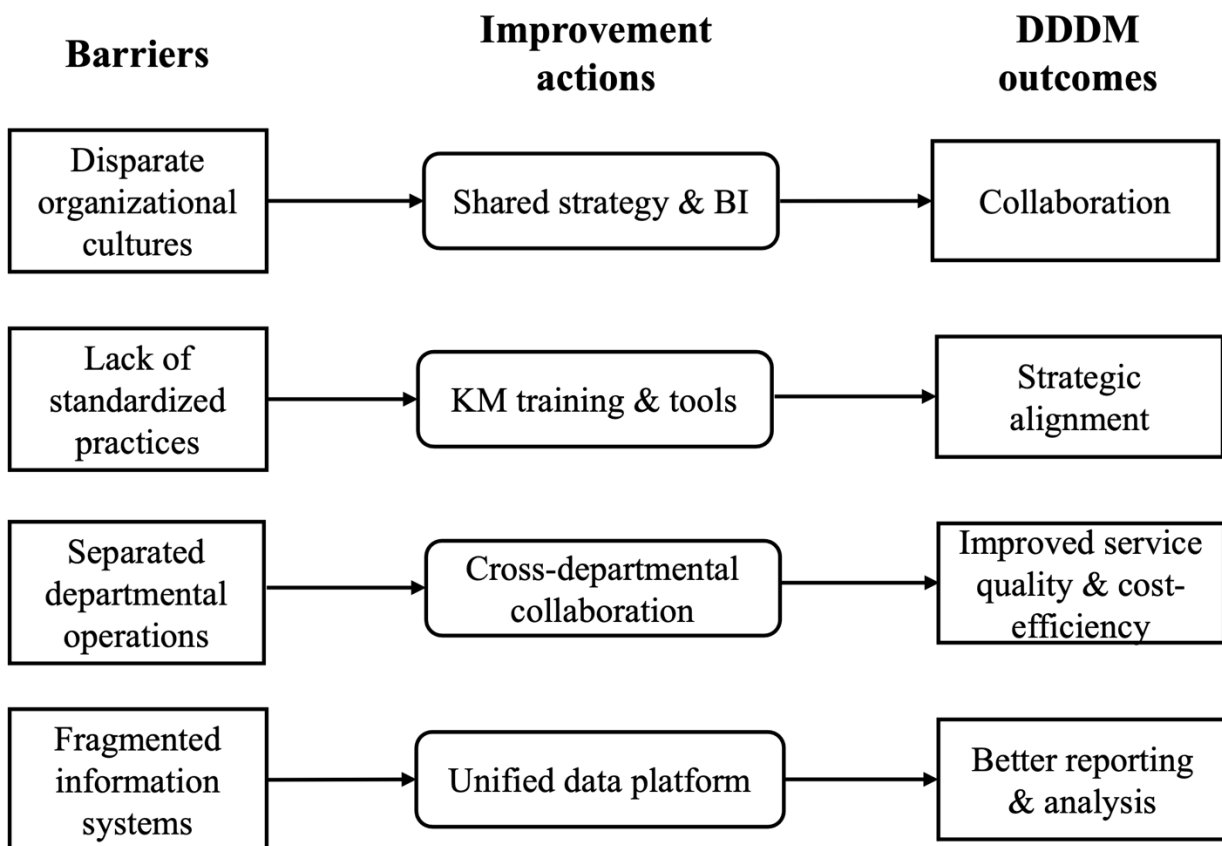


Figure 10 Barriers, improvement actions, and resulting outcomes in implementing DDDM in the case organization

The figure summarizes the organizational and technological challenges that were identified in the interviews, such as fragmented information systems, separate departmental functions and different organizational cultures. These barriers have been addressed through targeted improvement actions, such as investment in a unified data platform, development of BI tools and an increased focus on

cross-departmental collaboration, which together have supported DDDM progress by improving reporting, harmonization, and service quality.

According to the empirical findings, the main areas for development in fostering DDDM in the case organization were related to the harmonization of organizational culture, the strengthening of cross-departmental collaboration, and the systematic implementation of KM practices at all levels of organization. These findings reflect key factors also identified in previous literature, particularly the importance of aligning organizational practices, management approaches, and organization's culture to support data-driven transformation (Laihonen et al., 2013).

The establishment of wellbeing services counties brought together diverse organizational cultures, decision-making traditions, and levels of digital maturity. This has made it challenging to create a coherent data-driven culture where common goals and consistent practices are applied across the organization. As Abubakar et al. (2019) point out, organizational culture can either enable or hinder knowledge sharing. A culture that promotes openness, sociability, and trust is essential to foster collaboration across units and roles. Furthermore, Varzaru et al. (2015) emphasize that in organizations where KM is a priority, roles and responsibilities must be structured in a way that supports the flow of both tacit and explicit knowledge.

Strengthening cross-departmental collaboration and communication was also considered essential, particularly as patient's treatment paths often span several departments, including primary care, special care, and social services. Without strong collaboration and information sharing between these units, information will remain fragmented and its potential for improving care and operational efficiency will be missed. According to Nicolini et al. (2008), promoting shared values and a collective focus on patient-centered care is crucial to fostering effective collaboration across professional and departmental boundaries. Laihonen et al. (2017) argue that the business value of knowledge is realized only when it guides action. This highlights the importance of cross-departmental collaboration to find effective insights and improve decision-making outcomes.

While there is a major strategic commitment to DDDM, consistent implementation of KM practices at all levels of the organization is still a work in progress. Mousavizadeh et al. (2015) state that knowledge must be actively used to support problem-solving and performance improvement, which requires organizational practices to be aligned with knowledge goals. Smith et al. (2010) also stress that managerial support is essential for KM success, as it facilitates resource allocation and encourages employee engagement. Empirical findings highlighted the need for a better understanding of the purpose and impact of data documentation and utilization across the entire

staff, but particularly at the operational level. As Abubakar et al. (2019) and Yeh et al. (2006) point out, effective KM requires not only structural readiness but also cultural adaption and management support. This cultural shift is essential to ensure that data is not only collected accurately but also used meaningfully to guide operational and strategic decisions.

One major barrier related to the lack of integration across information systems. From the days of the municipalities' own operational activities, the organization was left with many fragmented information systems, which have been challenging to integrate into a single, standardized data platform. Mousavizadeh et al (2016) stated that technological limitations and its complexity can have a negative impact on the effectiveness on KM. The complexity of technology, in this case the data contained in many different information systems and their lack of standardization, has led to manual work with data and challenges in developing data products, which has slowed down the development of DDDM in the organization. Abubakar et al. (2019) and Yeh et al. (2006) emphasize that investing in IT infrastructure, such as unified databases, decision support systems and collaborative platforms, is critical for effective KM and can improve access, integration and use of data across an organization. To address these challenges, the organization has prioritized investment in a unified data platform and implemented temporary data warehouse solutions to harmonize fragmented data sources. These efforts are designed to reduce manual workload, improve data quality and accelerate the development of standardized data products that support more effective decision-making.

While creating a coherent technological infrastructure has been a challenge, the organization has managed to deliver valuable data products to different levels of the organization. By developing BI tools, the information services team has been able to transform partly fragmented data into accessible, user-oriented reports. These tools support both strategic and operational decision-making by providing relevant metrics and visualizations aligned with the organization's goals. Eidizadeh et al. (2017) describe BI as a process that ensures data is collected, processed, and made accessible at all organizational levels to improve operational efficiency and support DDDM. Similarly, Lönnqvist and Pirttimäki (2006) view BI both as relevant information and as a systematic process of collecting and distributing insights across internal and external sources. The empirical findings revealed that tailoring data products to the need of end-users has increased the adoption and usefulness of these tools. Increasing number of departments in the case organization are becoming more familiar with data use and have started to request specific tailored insights. This has strengthened cross-departmental communication and encouraged continuous feedback. This collaborative development approach, where end-users such as clinicians are involved in defining

reporting needs, ensures that data products are both technically accurate and operationally relevant. As Figurska (2012) highlights, open communication, mutual trust, and continuous learning are key behavioral aspects that enable effective knowledge sharing and support the broader goals of KM strategies. Furthermore, the decision to maintain BI development in-house has improved responsiveness and ensured that the information produced is contextual and actionable. While technical limitations remain, the proactive use of BI solutions in the organization demonstrates that even in limited circumstances, strategic focus and organizational commitment can be effective in promoting data-driven capabilities.

The findings of this study underline that sustainable development of DDDM in the public social and healthcare sector requires a transformation that starts at the grassroots level. Although strategic commitment and investment in technological infrastructure are necessary requirements for successful DDDM implementation, empirical findings suggest that the active involvement of employees, such as end users of data products and clinicians, is crucial for making the change into everyday practice. Engaging end-users in the development and validation of BI tools and KM activities will increase the operational relevance of these tools and strengthen the organization's commitment to a data-driven culture. Without validation and involvement at the operational level, strategies derived from management risk remaining disconnected from practical implementation. Therefore, it can be concluded that recognizing and prioritizing the grassroots level is essential not only as a starting point but also as a key objective in the DDDM transformation process. Sustainable change requires a bottom-up approach, where the development of a data-driven culture is developed through continuous interaction between strategic management and operational staff.

6 Conclusion

The final chapter concludes the study by summarizing the main findings and theoretical contributions. It also explores the managerial implications, addresses the study's limitations, and suggests directions for future research.

6.1 Main findings

Over the past decade, the importance of data-driven decision-making (DDDM) has grown significantly across sectors, influenced by the development of data technologies and the increasing integration of business intelligence (BI) and knowledge management (KM) systems. Particularly in public social and healthcare, the growing complexity of service delivery, rising costs, and demand for higher quality care have led to a need for more evidence-based decision-making processes. As healthcare organizations collect increasing volumes of operational, clinical, and administrative data, the ability to use this information effectively has become a strategic necessity. In this evolving environment, BI and KM have become key enablers for transforming raw data into actionable insights that foster informed decisions, better resource allocation, and improved patient outcomes.

This study examined the implementation of DDDM in one of Finland's recently established wellbeing services counties. The study focused on understanding how the organization perceives and utilizes data as a basis for decision-making and what challenges it faces in promoting a data-driven organizational culture. Through semi-structured interviews, this thesis explored not only the current state of DDDM but also the structural, cultural, and technological dynamics shaping its development. The study provided empirical insight into the public sector context, which is still underrepresented in the academic literature, particularly in the context of Finland's 2023 health and social services reform.

The findings show that while the organization made considerable progress in integrating DDDM into various levels of decision-making, there are still a few challenges that remain. Fragmented information systems from previous pre-reform municipal structures have made data integration difficult and delayed the development of standardized data products. In response to this challenge, the organization has invested in the implementation of a unified data platform and developed BI tools to improve access to and use of data. As previously the information systems were often closely managed by their user groups, maintaining a sense of ownership and practical usability in the new, coherent environment also requires the active involvement of end-users in the development of data products. These methods have enabled the transformation of fragmented data into more

user-oriented and actionable reports. Collaboration with end-users, such as clinicians, has further strengthened the adoption of these data products, which has improved their practical relevance and implementation at different levels of the organization. To ensure effective data utilization, it is essential that the information services team and end-users have functional and ongoing communication channels through which feedback can be shared and applied. Together, these actions can also strengthen the organization's ability to leverage data both strategically and operationally. These findings highlight the importance of contextualized BI development and end-user involvement in promoting successful DDDM adoption.

Furthermore, another significant finding is that organizational culture and managerial alignment play a key role in supporting the systematic implementation of DDDM. While strategic commitment to data utilization was evident across the organization, the study revealed in how well DDDM practices were adopted at operational levels. However, efforts such as KM training, clarifying data responsibilities, and promoting a culture of trust and learning were identified as key drivers of transformation. The findings highlight that DDDM is not just a technological upgrade, but a broader cultural shift that requires active support from management, consistent communication and alignment between strategy, information systems, and human behaviors.

Ultimately, as the empirical findings also suggest, data-driven decision-making belongs to everyone, which means that the true potential of DDDM is realized when it is adopted at all levels and roles in the organization. Although the strategic commitment provides direction, the actual implementation and effectiveness of the DDDM depends heavily on the involvement and feedback of operational staff. The findings highlight that while end-users are the main recipients of data products, they are also active participants in their development and refinement. When the employees at the grassroots level are involved in shaping DDDM practices, the resulting solutions become more relevant, usable, and integrated into everyday work. This bottom-up perspective is crucial to ensure that DDDM does not remain only a top-down initiative, but becomes a collaborative, evolving practice that is shared and embedded across the organization.

6.2 Theoretical contributions

This study contributes to the existing literature on DDDM by offering new insights into its implementation in the Finnish public social and healthcare sector. While the theoretical frameworks of DDDM and KM have recently been extensively studied in broader organizational contexts, empirical research focusing on wellbeing services counties established in 2023 has been limited. By exploring how DDDM is practiced in one of these newly established regional organizations, this

thesis provides timely empirical evidence on the cultural, structural, and technological challenges of building data-driven decision-making model in public health.

In addition to addressing this geographical and contextual research gap, the study also contributes to the theoretical literature by linking KM and BI to the broader DDDM framework. Although KM and BI are often studied together, but partially as separate components, this study shows how they can be conceptually and practically integrated to enable more effective decision making, particularly in complex public sector environments. By highlighting their interdependence, the study contributes to the theoretical understanding of how organizations can develop comprehensive DDDM practices that are both technically solid and strategically aligned.

6.3 Managerial implications

The findings of the study highlight several important managerial insights that can support public social and healthcare organizations to develop their DDDM practices. Firstly, building a unified data platform and developing a technological infrastructure is a key element for effective knowledge management. Fragmented and non-standardized information systems increase manual work and slow down the development of data products to support decision-making. Secondly, managers should pay attention to building a common culture of knowledge management, particularly in situations where the organization is formed by several previously independent units. Third, embedding DDDM practices across the organization, up to the operational level and the customer interface, is essential to ensure that the reliability of data pipeline remains valid from the very beginning, so that it can be used appropriately in decision making.

The importance of cross-departmental collaboration is also highlighted in the context of public social and health care, where patient treatment paths often cross departmental boundaries. Managers should support structures and practices that enable information sharing and reporting across these boundaries. The findings revealed for example that waiting times are sometimes extended in the case organization and that cross-sectional data analysis can provide crucial insights into the causes of bottlenecks. Such collaboration allows employees to better understand patient movement between different services in the healthcare organization and the effectiveness of care, ultimately supporting more timely access to care. From a management perspective, strengthening collaboration between departments is about improving efficiency for the organization, which also has a direct impact on improving patient-centered care. When departments share information and work towards aligned goals, the organization is better equipped to make data-driven decisions, improve

transparency of patient treatment paths and achieve cost savings for both the organization and patients.

6.4 Limitations & suggestions for future research

The limitations of this study can be evaluated through the four criteria of trustworthiness proposed by Lincoln and Guba (1985): *credibility*, *transferability*, *dependability*, and *confirmability*. In terms of credibility, although the saturation point was at least partially reached through the six semi-structured interviews, a larger sample size could have increased the credibility of the empirical findings. However, as the study focused on a single wellbeing services county, the expert interviews provided comprehensive but different perspectives on the same topic. Increasing the number of interviews might have led to too similar responses within the same organization, potentially limiting the added value of the empirical findings. The study interviewed different employees from the organization's information services team, which is responsible for developing DDDM practices. It is therefore considered that the study provided enough evidence to support the qualitative findings.

The conclusions from the empirical data align well with previous studies and academic literature, which supports the reliability of the study in terms of transferability. However, this study focused on a single wellbeing services county out of the total of 22 in Finland (including Helsinki). As each wellbeing services county operates as an independent organization, it is reasonable to assume that applying these results to other regions may present certain challenges, even though their operational structures are mostly similar.

The dependability and confirmability of this study may be limited by the fact that all interpretations and conclusions were made by a single researcher. In a study conducted by several researchers, the ability to reflect, question and refine each other's interpretations often supports consistency and a more robust analytical process. While qualitative research allows for an in-depth understanding of the subject matter, the interpretive nature of interview analysis introduces a degree of subjectivity that can affect the reliability of conclusions. In addition, the researcher's own preconceptions may influence how empirical data are interpreted. However, to strengthen the dependability and confirmability of the study, the findings were reviewed and discussed with representatives of the case organization before finalizing the thesis, ensuring that the interpretations remained as valid as possible and reflective of the reality of the organization.

Suggestions for future research include incorporating the perspectives of different levels of stakeholders and examining DDDM across multiple wellbeing services counties. This study focused

on data-driven decision-making in a single wellbeing services county from the perspective of the information services team. Including the perspectives of different levels of stakeholders, such as operational managers, clinical staff, and representatives from service units, could provide a more comprehensive understanding of how data-driven decision-making is implemented in everyday practice in the public social and healthcare sector. Furthermore, examining the topic of across multiple wellbeing services counties would improve the transferability of the findings. Comparing several counties could reveal structural and cultural differences that influence the implementation of DDDM. This could lead to national solutions to make the public social and healthcare sector more data-driven and thus more efficient.

References

- Abubakar, M. – Elrehail, H. – Alatailat, M. (2019) Knowledge Management, Decision-Making Style and Organizational Performance. *Journal of Innovation & Knowledge*, Vol. 4 (2), 104–114.
- Addicott, R. – McGiven, G. – Ferlie, E. (2006) Networks, organizational learning and knowledge management: the case off NHS cancer networks. *Public Money and Management*, Vol. 26 (2), 87–94.
- Adeoye-Olatunde, O. A. – Olenik, N. L. (2021) Research and scholarly methods: Semi-structured interviews. *Journal of the American College of Clinical Pharmacy*, Vol. 4 (10), 1358–1367.
- Adesina, A. – Iyelolu, T. – Paul, P. (2024) Leveraging predictive analytics for strategic decision-making: Enhancing business performance through data-driven insights. *World Journal of Advanced Research and Reviews*, Vol. 22 (3), 1927–1934.
- Agius SJ. (2013) Qualitative research: its value and applicability. *The Psychiatrist*, Vol. 37 (6), 204–206.
- Airaksinen, J. (2021) Grounded Theory. Laadullisen tutkimuksen verkkokäsikirja. Tampere: Yhteiskuntatieteellinen tietoaarkisto. <https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/>, retrieved 10.10.2024.
- Alkhwaldi, A. (2024) Understanding the acceptance of business intelligence from healthcare professionals’ perspective: an empirical study of healthcare organizations. *International Journal of Organizational Analysis*, Vol. 32 (9), 2135–2163.
- Ashok, M. – Al Badi Al Dhaheri, M.S.M. – Madan, R. – Dzandu, M.D. (2021) How to counter organisational inertia to enable knowledge management practices adoption in public sector organisations. *Journal of Knowledge Management*, Vol 25 (9), 2245–2273.
- Aula, V. (2019) Institutions, infrastructures, and data friction – Reforming secondary use of health data in Finland. *Big Data & Society*, Vol. 6 (2).
- Ayatollahi, H. – Zeraatkar, K. (2019) Factors influencing the success of knowledge management process in health care organisations: A literature review. *Health Information and Libraries Journal*, Vol. 37 (2), 98–111.
- Barton, D. – Court, D. (2012) Making Advanced Analytics Work for You. A practical guide to capitalizing on big data. *Harvard Business Review*, Vol. 90 (10), 78–83.
- Basias, N. – Pollalis, Y. (2018) Quantitative and Qualitative Research in Business & Technology: Justifying a Suitable Research Methodology. *Review of Integrative Business and Economics Research*, Vol. 7 (1), 91–105.

- Basile, L.J. – Carbonara, N. – Pellegrino, R. – Panniello, U. (2023) Business intelligence in the healthcare industry: the utilization of a data-driven approach to support clinical decision making, *Technovation*, Vol. 120.
- Baxter, S. – Johnson, M. – Chambers, D. (2018) The effects of integrated care: a systematic review of UK and international evidence. *BMC Health Serv Res*, Vol 8 (350), 1–13.
- Bean, R. – Davenport, T. H. (2019) Companies Are Failing in Their Efforts to Become Data-Driven. *Harvard Business Review* 05.02.2019. <<https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven>>, retrieved 30.08.2024.
- Brynjolfsson, E. – Hitt, L. M. – Kim, H. H. (2011) Strength in numbers: How Does Data-Driven Decision-Making Affect Firm Performance? *S&P Global* 22.04.2011. <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1819486#paper-citations-widget>, retrieved 11.09.2024.
- Carillo, K. – Galy, N. – Guthrie, C. – Vanhems, A. (2019) How to turn managers into data-driven decision makers. Measuring attitudes towards business analytics. *Business Process Management Journal*, Vol. 25 (3), 553–578.
- Charmaz, K. (2006) *Constructing grounded theory: a practical guide through qualitative analysis*. London: SAGE Publications, Inc.
- Charmaz, K. (2014) Grounded Theory in Global Perspective: Reviews by International Researchers. *Qualitative Inquiry*, Vol. 20 (9).
- Chen, H. – Chiang, R. H. – Storey, V. C. (2012) Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, Vol. 36 (4), 1165–1188.
- Cody, W. F. – Kreulen, J. T. – Krishna, V. – Spangler, W. S. (2002) The integration of business intelligence and knowledge management. *IBM Systems Journal*, Vol. 41 (4), 697–713.
- Davenport, T. H. (2006) Competing on Analytics. *Harvard Business Review*, Vol. 84 (1), 98–107.
- Davenport, T. H. (2014) How strategists use "big data" to support internal business decisions, discovery, and production. *Strategy & Leadership*, Vol. 42 (4), 45–50.
- Davenport, T.H. – Prusak, L. (2000) Working Knowledge: How Organizations Manage What They Know, *Harvard Business Review Press*, Boston, MA. <https://www.researchgate.net/publication/229099904_Working_Knowledge_How_Organizations_Manage_What_They_Know>, retrieved 01.12.2024.
- Di Nucci, E. (2019) Should we be afraid of Medical AI? *Journal of Medical Ethics*, Vol. 45(8), 556–558.
- Duffy, K. – Ferguson, C. – Watson, H. (2004) Data collecting in grounded theory - some practical issues. *Nurse Researcher*, Vol. 11 (4), 67–78.

- Edmondson, A. (2003) Speaking up in the operating room: How team leaders promote learning in interdisciplinary Action Teams. *Journal of Management*, Vol. 40 (6), 1419–1452.
- Eidizadeh, R. – Salehzadeh, R. – Esfahani, A. C. (2017) Analysing the role of business intelligence, knowledge sharing and organizational innovation on gaining competitive advantage. *Journal of Workplace Learning*, Vol. 29 (4), 250–267.
- Eriksson, P. – Kovalainen, A. (2008) *Qualitative Methods in Business Research*. SAGE Publications Ltd.
- EU-Healthcare (2024). Healthcare system in Finland. *Contact point For Cross-Border Health Care*. <<https://www.eu-healthcare.fi/healthcare-in-finland/healthcare-system-in-finland/>>, Retrieved 12.09.2024.
- Ferlie, E. – Fitzgerald, L. – Wood, M. – Hawkins, C. (2005) The nonspread of innovations: the mediating role of professionals. *Academy of Management Journal*, Vol. 48 (1), 117–134.
- Ferreira, J. – Mueller, J. – Pipa, A. (2020) Strategic Knowledge Management: Theory, Practice, and Future Challenges. *Journal of Knowledge Management*, Vol. 24 (2), 121–126.
- Figurska, I. (2012) Cultural Aspects of Knowledge Management. *Human Resource Management & Ergonomics*, 66–77.
- Foley, E. – Guillemette, M.G. (2010) What is Business Intelligence? *International Journal of Business Intelligence Reserach*, Vol. 1 (4), 1–28.
- Freitas, A.T. (2024) Data-driven approaches in Healthcare: Challenges and Emerging Trends. *Multidisciplinary Perspectives on Artificial Intelligence and the Law*, 58. Springer, Cham.
- Gandomi, A. – Haider, M. (2015) Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, Vol. 35 (2), 137–144.
- Ghaida, D.A. (2018) The influence of organisational and technological factors of BI adoption in the telecommunication industry across the Middle East and Africa, *Journal of Global Business Advancement*, Vol. 11 (3), 332–350.
- Ghazanfari, M. – Jafari, M. – Rouhani, S. (2011) A tool to evaluate the business intelligence of enterprise systems. *Scientica Iranica*, Vol. 18 (6), 1579–1590.
- Ghoshal, S. – Kim, S. (1986) Building effective intelligence systems for competitive advantage. *Sloan Management Review*, Vol. 28 (1), 49–58.
- Gilad, B. – Gilad, T. (1985) A systems approach to business intelligence. *Business Horizons*, Vol. 28 (5), 65–70.
- Gioia, D.A. – Corley, K.G. – Hamilton, A.L. (2012) Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, Vol. 16 (1), 15–31.

- Granero-Molina, J. – Ruiz-Fernández, M. D. – Fernández-Medina, I. M. – Núñez-Nagy, S. – Suazo Galdames, I. C. (2024) Editorial: Qualitative research applied to public health: new topics and insight. *Frontiers in Public Health*.
- Guah, M.W. – Currie, W.L. (2004) Factors affecting IT-based knowledge management strategy in the UK health care system. *Journal of Information and Knowledge Management*, Vol. 3 (4), 279–290.
- Guo, C. – Chen, J. (2023) Big data analytics in healthcare. *Knowledge Technology and Systems: Translational Systems Science*, 34. Springer, Singapore.
- Guyen-Ussu, P. (2006) Uses of performance metrics in clinical and managerial networks. *Public Money and Management*, Vol. 26 (2), 95–100.
- Halonen, T. (2021) Tiedolla johtamisen hyödyt ja haasteet terveydenhuollon strategisessa johtamisessa. Pro gradu -tutkielma. *Vaasan yliopisto*.
- Härkönen, K. – Ulkuniemi, P. – Tähtinen, J. (2010) Managing competitive bidding in the Finnish healthcare sector. *Management Research Review*, Vol. 33 (2), 145–160.
- Herschel, R. T. – Jones, N. E. (2005) Knowledge management and business intelligence: The importance of integration. *Journal of Knowledge Management*, Vol. 9 (4), 45–55.
- Hicks, R. – Dattero, R. – Galup, S. (2007) A metaphor for knowledge management: explicit islands in a tacit sea. *Journal of Knowledge Management*, Vol. 11 (1), 5–16.
- Hirsjärvi, S. – Hurme, H. (2022) Tutkimushaastattelu: *teemahaastattelun teoria ja käytäntö* ([2. painos]). Helsinki: Gaudeamus.
- Hujala, T. – Laihonen, H. (2023) Knowledge management in a regional integrated health and social care system. *Journal of Integrated Care*, Vol. 31 (5), 15–28.
- Intezari, A. – Gressel, S. (2016) Information and reformation in KM systems: big data and strategic decision-making. *Journal of Knowledge Management*, Vol. 21 (1), 71–91.
- Jormanainen, V. – Parhiala, K. – Niemi, A. – Erhola, M. – Keskimäki, I. – Kaila, M. (2019) Half of the Finnish population accessed their own data: comprehensive access to personal health information online is a cornerstone of digital revolution in Finnish health and social care. *Finnish Journal of EHealth and EWelfare*, Vol. 11 (4), 298–310.
- Kleindienst, D. (2017) The data quality improvement plan: deciding on choice and sequence of data quality improvements. *Electronic Markets*, Vol 27 (4), 387–398.
- Korherr, P. – Kanbach, D. K. – Kraus, S. – Mikalef, P. (2022) From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes. *Digital Business*, Vol. 2 (2).
- Koski, E. – Murphy, J. (2021) AI in Healthcare. *Nurses and Midwives in the Digital Age*.

- Kothari, A. – Rudman, D. – Dobbins, M. – Rouse, M. – Sibbald, S. – Edwards, N. (2012) The use of tacit and explicit knowledge in public health: a qualitative study. *Implementation Sci*, Vol. 7 (20), 1–12.
- Laihonen, H., Hannula, M., Helander, N., Ilvonen, I., Jussila, J., Kukko, M., Kärkkäinen, H., Lönnqvist, A., Myllärniemi J., Pekkola, S., Virtanen, P., Vuori, V. & Yliniemi, T. (2013) Tietojohtaminen. Tampere, Tampereen teknillinen yliopisto, Tiedonhallinnan ja logistiikanlaitos.
- Lamba, H. S. – Dubey, S. K. (2015) Analysis of requirements for Big Data Adoption to maximize IT Business Value, *2015 4th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO) (Trends and Future Directions)*.
- Larson, D. – Chang, V. (2016) A review and future direction of agile, business intelligence, analytics, and data science. *International Journal of Information Management*, Vol. 36 (5), 700–710.
- LaValle, S. – Lesser, E. – Shockley, R. – Hopkins, M. S. – Kruschwitz, N. (2011) Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, Vol. 52 (2), 21–32.
- Lee, I. (2017) Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, Vol. 60 (3), 293–303.
- Lehto, P. – Malkamäki, S. (2023) The Finnish health sector growth and competitiveness vision 2030. Sitra working paper. Sitra 2030. <<https://www.sitra.fi/wp/wp-content/uploads/2023/05/sitra-the-finnish-health-sector-growth-and-competitiveness-vision-2030.pdf>>, Retrieved 15.10.2024.
- Lincoln, Y. S. – Guba, E. G. (1985) *Naturalistic inquiry*. Sage, Newbury Park, California, United States.
- Lönnqvist, A. – Pirttimäki, V. (2006) The Measurement of Business Intelligence. *Information Systems Management*, vol. 23 (1), 32–40.
- Magaldi, D. – Berler, M. (2020) Semi-structured Interviews. *Encyclopedia of Personality and Individual Differences*. Springer, Charm.
- Mazurek, J. (2015) On a preference analysis in a group decision making. *Silesian University in Opava*.
- McAfee, A. – Brynjolfsson, E. (2012) Big data: The Management Revolution. *Harvard Business Review*, Vol. 90 (10), 60–68.
- Merton, R. K. – Fiske, M. – Kendall, P. L. (1956) The focused interview. A manual of problems and procedures. *Glencoe, IL: Free Press*.

- Ministry of Social Affairs and Health (2024). Wellbeing services counties will be responsible for organising health, social and rescue services. <https://stm.fi/en/wellbeing-services-counties>, Retrieved 12.09.2024.
- Moreno, H. (2017) The Importance of Data Quality – Good, Bad or Ugly. <<https://www.forbes.com/sites/forbesinsights/2017/06/05/the-importance-of-data-quality-good-bad-or-ugly/>>, retrieved 10.09.2024.
- Mousavizadeh, M. – Ryan, S. – Harden, G. – Windsor, J. (2015) Knowledge Management and the Creation of Business Value. *Journal of Computer Information Systems*, Vol. 55 (4), 35–45.
- Myllärniemi, J. – Laihonon, H. – Karppinen, H. – Seppänen, K. (2012) Knowledge management practices in healthcare services. *Measuring business excellence*, Vol. 16 (4), 54–65.
- Nicolini, D. – Powell, J. – Conville, P. – Martines-Solano, L. (2008) Managing knowledge in the healthcare sector. A review. *International Journal of Management Reviews*, Vol. 10 (3), 245–263.
- Nijzink, H.J. (2020) Data-Driven Decision-Making Maturity. Master's thesis. University of Twente, Netherlands.
- Niu, Y. – Ying, L. – Yang, J. – Bao, M. – Sivaparthipan, C. B. (2021) Organizational business intelligence and decision making using big data analytics. *Information Processing & Management*, Vol. 58 (6).
- Nylund, A. (1999) Tracing the BI Family Tree. Knowledge Management.
- Paoloni, P. – Cosentino, A. – Arduini, A. – Manzo, M. (2023) Intellectual capital and knowledge management for overcoming social and economic barriers in the health-care sector. *Journal of Knowledge Management*, Vol. 27 (8), 2058–2089.
- Parikka, H. (2019) A Finnish model for the secure and effective use of data. Sitra studies 153. <<https://www.sitra.fi/app/uploads/2019/05/a-finnish-model-for-the-secure-and-effective-use-of-data.pdf>>, retrieved 20.11.2024.
- Parviainen, P. – Tihinen, M. – Kääriäinen, J. – Teppola, S. (2022) Tackling the digitalization challenge: how to benefit from digitalization in practice. *International Journal of Information Systems and Project Management*, Vol. 5 (1), 63–77.
- Payne, P.R.O. – Lussier, Y. – Foraker, R.E. – Embi, P.J. (2016) Rethinking the role and impact of health information technology: informatics as an interventional discipline. *BMC Medical Informatics and Decision Making*, Vol. 16 (40).
- Pietronudo, M.C. – Zhou, F. – Caporuscio, A. (2022) New Emerging Capabilities for Managing Data-Driven Innovation in Healthcare: The Role of Digital Platforms. *European journal of innovation management*, Vol. 25 (6), 867–891.

- Pirttimäki, V. (2007) Business Intelligence as a Managerial Tool in Large Finnish Companies. Tampere University of Technology.
- Power, D. (2007) A Brief History of Decision Support Systems. DSSresources. <<http://dssresources.com/history/dsshistoryv28.html>>, retrieved 16.10.2024.
- Prakash, D. (2024) Data-driven management: The impact of big data analytics on organizational performance. *International Journal for Global Academic & Scientific Research*, Vol. 3 (2), 12–23.
- Provost, F. – Fawcett, T. (2013) Data science and its relationship to big data and data-driven decision making. *Big Data*, Vol 1 (1), 1–70.
- Pusenius, P. – Laihonen, H. (2024) Navigating organizational success: Knowledge management capabilities in public healthcare. *Proceedings of the 25th European Conference on Knowledge Management*, Vol. 25 (1).
- Ratia, M. (2022) Business Analytics Creating Value in the Private Healthcare Sector. *Faculty of Management and Business, Tampere University*.
- Redman, T. C. (2004). Data: An unfolding quality disaster. *DM Review*.
- Rissanen, S. – Lammintakanen, J. – Hujala, A. (2017) Sosiaali- ja terveystoiminta (3. uudistettu painos.). Sanoma Pro Oy.
- Rolland, N. (2004) Knowledge management impacts on decision making process, *Journal of Knowledge Management*, Vol. 8 (1), 20–31.
- Ross, J. W. – Beath, C. M. – Quaadgras, A. (2013) You may not need big data after all. *Harvard Business Review*, Vol. 91 (12), 90–98.
- Saarikko, A. – Niinistö, S. (2019) Act on the Secondary Use of Health and Social Data. *Ministry of Social Affairs and Health*. <<https://stm.fi/en/secondary-use-of-health-and-social-data>>, retrieved 12.12.2024.
- Saranto, K. – Kinnunen, U.M. – Jylhä, V. – Kivekäs, E. (2020) Digitalisaatio ja sähköiset palvelut uudistuvassa sosiaali- ja terveydenhuollossa. Tampere University.
- Saraswat, D. – Bhattacharya, P. – Verma, A. – Prasad, V.K. – Tanwar, S. – Sharma, G. (2024) Explainable AI for Healthcare 5.0: Opportunities and Challenges. *IEEE Xplore*, Vol. 10, 84486–84517.
- Sarioguz, O. – Miser, E. (2024) Data-driven decision-making: Revolutionizing management in the information era. *International Research Journal of Modernization in Engineering Technology and Science*, Vol 6 (2).
- Schröer, T. – Janben, J. – Schuh, G. – Stich, V. (2023) Systemation approach: Handling insufficient data quality. In *Proceedings of the Conference on Production Systems and Logistics*.

- Secinaro, S. – Calandra, D. – Secinaro, A. – Muthurangu, V. – Biancone, P. (2021) The role of artificial intelligence in healthcare: A structured literature review. *BMC Medical Informatics and Decision Making*, Vol. 21 (125).
- Shafiq, W. (2024) Optimizing organizational performance: A Data-driven approach in management science. *Bulletin of Management Reviews*, Vol 2 (1), 1–11.
- Shollo, A. – Kautz, K. (2010) Towards an understanding of business intelligence. *In proceedings of the 21st Australasian Conference on Information Systems*.
- Smith, T. – Annette, M. – Paul, D. (2010) Linking Business Strategy and Knowledge Management Capabilities for Organizational Effectiveness. *International Journal of Knowledge Management*, Vol. 6 (3), 22–43.
- Sosiaali- ja terveysministeriö (2022) Hyvinvointialueiden uusi aika alkaa tiedolla johtaen. <<https://stm.fi/-/16650278/hyvinvointialueiden-uusi-aika-alkaa-tiedolla-johtaen>>, retrieved 5.4.2025.
- Sosiaali- ja terveysministeriö (2023) Sosiaali- ja terveydenhuollon järjestelmä ja vastuut. <<https://stm.fi/sotepalvelut/jarjestelma-vastuut>>, retrieved 12.9.2024.
- Strong, D. M. – Lee, Y. W. – Wang, R. Y. (1997) Data Quality in Context. *Communications of the ACM*, Vol. 40 (5), 103–110.
- Syväjärvi, A. – Pietiläinen, V. (2016) Inhimillinen ja tehokas sosiaali- ja terveysjohtaminen. Tampere University Press 2016.
- Tabesh, P. – Mousavidin, E. – Hasani, S. (2019) Implementing big data strategies: A managerial perspective. *Business Horizons*, Vol. 62 (3), 347–358.
- Tagliaventi, M.R. – Mattarelli, E. (2006) The role of networks of practice, value sharing, and operational proximity in knowledge flows between professional groups. *Human Relations*, Vol. 59 (3), 291–319.
- Taherdoost, H. (2021) Data Collection Methods and Tools for Research; A Step-by-Step Guide to Choose Data Collection Technique for Academic and Business Research Projects. *International Journal of Academic Research in Management*, Vol. 10 (1), 1–38.
- Tan, K. H. (2008) Grounded theory in practice: Issues and discussion for new qualitative researchers. *Journal of Documentation*, Vol. 64 (4), 487–510.
- Troisi, O. – Maione, G. – Grimaldi, M. – Loia, F. (2020) Growth hacking: Insights on data-driven decision-making from three firms. *Industrial Marketing Management*, Vol. 90, 538–557.
- Tynkkynen, L. – Keskimäki, I. – Karanikolos, M. – Litvinova, Y. – Maresso, A. (2023) Finland Health system summary 2023. World Health Organization.

- Varzaru, M. – Varzaru, A. (2013) Knowledge Management and Organizational Structure Design Process. *Annales Universitatis Apulensis Series Oeconomica*, Vol. 15 (2), 716–724.
- Vehko, T. – Ruotsalainen, S. – Hyppönen, H. (2018) E-health and e-welfare of Finland. Check point 2018. *National Institute for Health and Welfare (THL)*. Helsinki, Finland 2019.
- Vehko, T. (2022) E-health and e-welfare of Finland. Check point 2022. *National Institute for Health and Welfare (THL)*. Helsinki, Finland 2022.
- Vucegic, D. S. – Vukšić, V. B. – Bach, M. P. – Jaklič, J. – Štemberger, M. I. (2020) Business intelligence and organizational performance: The role of alignment with business process management. *Business Process Management Journal*, Vol. 26 (6), 1–25.
- Watson, H. J. – Wixom, B. H. (2007) The Current State of Business Intelligence. *IT systems perspectives*, Vol. 40 (9), 96–99.
- Wiesche, M. – Krcmar, H. (2017) Grounded theory methodology in information systems research. *MIS quarterly*, Vol. 41 (3), 685–701.
- Xu, X. (2024) *Data-Driven Decision Making in Business Intelligence*. Scientific Programming, Special Issue. Wiley Online Library.
<https://onlinelibrary.wiley.com/doi/toc/10.1155/5192.si.370320>, retrieved 02.12.2024.
- Yeh, Y. – Lai, S. – Ho, C. (2006) Knowledge Management Enablers: A Case Study. *Industrial Management & Data Systems*, Vol. 106 (6), 793–810.
- Yigitbasioglu, O. M. – Velcu, O. (2012) A review of dashboard in performance management: Implications for design and research. *International Journal of Accounting Information Systems*, Vol. 13 (1), 41–59.

Appendices

Appendix 1 The interview questions for semi-structured interview

The aim of this interview is to explore the conditions for data-driven decision-making within one of the wellbeing services counties in Finland. In this interview, data-driven decision making refers to the use of knowledge management and business intelligence to support organizational activities. Interviews are conducted with employees of county's information services team, whose role is to develop and support the adoption of DDDM practices across the organization.

Definitions of concepts used in the interviews:

Business intelligence: BI is seen as a method that allows an organization to explore, utilize, and analyze data from its data warehouse to generate insights that support better decision-making (Nylund, 1999).

Knowledge management: KM is a systematic process that involves discovering, selecting, organizing, refining, and presenting information in a manner that enhances an employee's understanding in a specific area (Herschel & Jones, 2005).

Data-driven decision-making: DDDM can be seen as an ideology, where data is seen as a strategic resource rather than an assumption and experience, and where decision-makers and managers are required to promote a data-driven culture of innovation and to take information into account at all stages of decision-making (Brynjolfsson et al., 2011, 2).

Questions about the job description:

1. How long you have been in the current role?
2. What is the size and structure of your team or department?

Actual interview questions:

1. Can you describe your current role and main responsibilities at organization?
2. Does the organization focus on developing data-driven decision-making (DDDM) and knowledge management (KM)? If yes, when did these development initiatives begin, and what is the status?

3. What methods/systems does the organization use for data collection, management, and analysis? Do you encounter any specific challenges in this process?
4. What measures are in place to ensure the accuracy, reliability, and governance of data used in decision-making?
5. Are you developing a Business Intelligence (BI) environment for data analysis and visualization? If so, who is responsible for its development and use?
6. What challenges or barriers (e.g., organizational or cultural) do you face in advancing knowledge management in the organization?
7. How do leaders and departments/units collaborate to utilize data for improving healthcare services? Are there areas where collaboration could be improved?
8. How do you ensure that insights gained through knowledge management are effectively integrated into strategic and operational decision-making?
9. Based on your experience, how has the implementation of knowledge management impacted social and healthcare outcomes, operational efficiency, or resource allocation in your region?
10. How do you see the future development of knowledge management in Finland's public social and healthcare system? What are the most significant opportunities and innovations in this area?

Appendix 2 Research data management plan

1. Research data

Research data refers to all the material with which the analysis and results of the research can be verified and reproduced. It may be, for example, various measurement results, data from surveys or interviews, recordings or videos, notes, software, source codes, biological samples, text samples, or collection data. In the table below, list all the research data you use in your research. Note that the data may consist of several different types of data, so please remember to list all the different data types. List both digital and physical research data.

Research data type	Contains personal details/information*	I will gather/produce the data myself	Someone else has gathered/produced the data	Other notes
<i>Interviews</i>		x		

* Personal details/information are all information based on which a person can be identified directly or indirectly, for example by connecting a specific piece of data to another, which makes identification possible. For more information about what data is considered personal go to the [Office of the Finnish Data Protection Ombudsman's website](#)

2. Processing personal data in research

If your data contains personal details/information, you are obliged to comply with the EU's General Data Protection Regulation (GDPR) and the Finnish Data Protection Act. For data that contains personal details, you must prepare a Data Protection Notice for your research participants and determine who is the controller for the research data.

I will prepare a Data Protection Notice** and give it to the research participants before collecting data

The controller** for the personal details is the student themselves the university

My data does not contain any personal data

** More information at the university's intranet page, [Data Protection Guideline for Thesis Research](#)

3. Permissions and rights related to the use of data

Find out what permissions and rights are involved in the use of the data. Consult your thesis supervisor, if necessary. Describe the use permissions and rights for each data type. You can add more data types to the list, if necessary.

3.1 Self-collected data

You may need separate permissions to use the data you collect or produce, both in research and in publishing the results. If you are archiving your data, remember to ask the research participants for the necessary permissions for archiving and further use of the data. Also, find out if the repository/archive you have selected requires written permissions from the participants.

Necessary permissions and how they are acquired

Data type 1: Interview answers

3.2 Data collected by someone else

Do you have the necessary permissions to use the data in your research and to publish the results? Are there copyright or licencing issues involved in the use of the data? Note, for example, that you may need permission to use the images or graphs you have found in publications.

Rights and licences related to the data

This study does not contain this kind of data.

4. Storing the data during the research process

Where will you store your data during the research process?

In the university's network drive

In the university-provided Seafile Cloud Service

Other location, please specify:

The university's data storage services will take care of data security and backup files automatically. If you choose to store your data somewhere other than in the services provided by the university, please specify how you will ensure data security and file backups. Remember to make sure you know every time where you are saving the edited/modified data.

If you are using a smartphone to record anything, please check in advance where the audio or video will be saved. If you are using commercial cloud services (iCloud, Dropbox, Google Drive, etc.) and your data contains personal data, make sure the information you provide in the Data Protection Notice about data migration matches your device settings. The use of commercial cloud services means the data will be transferred to third countries outside the EU.

5. Documenting the data and metadata

How would you describe your research data so that even an outsider or a person unfamiliar with it will understand what the data is? How would you help yourself recall years later what your data consists of?

5.1 Data documentation

Can you describe what has happened to your research data during the research process? Data documentation is essential when you try to track any changes made to the data.

To document the data, I will use:

A field/research journal

A separate document where I will record the main points of the data, such as changes made, phases of analysis, and significance of variables

A readme file linked to the data that describes the main points of the data

Other, please specify:

5.2 Data arrangement and integrity

How will you keep your data in order and intact, as well as prevent any accidental changes to it?

I will keep the original data files separate from the data I am using in the research process, so that I can always revert back to the original, if need be.

Version control: I will plan before starting the research how I will name the different data versions and I will adhere to the plan consistently.

I recognise the life span of the data from the beginning of the research and am already prepared for situations, where the data can alter unnoticed, for example while recording, transcribing, downloading, or in data conversions from one file format to another, etc.

5.3 Metadata

Metadata is a description of your research data. Based on metadata someone unfamiliar with your data will understand what it consists of. Metadata should include, among others, the file name, location, file size, and information about the producer of the data. Will you require metadata?

I will save my data into an archive or a repository that will take care of the metadata for me.

I will have to create the metadata myself, because the archive/repository where I am uploading the data requires it.

I will not store my data into a public archive/repository, and therefore I will not need to create any metadata.

6. Data after completing the research

You are responsible for the data even after the research process has ended. Make sure you will handle the data according to the agreements you have made. The university recommends a general retention period of five (5) years, with an exception for medical research data, where the retention period is 15 years. Personal data can only be stored as long as it is necessary. If you have agreed to destroy the data after a set time period, you are responsible for destroying the data, even if you no longer are a student at the university. Likewise, when using the university's online storage services, destroying the data is your responsibility. What happens to your research data, when the research is completed?

I will store all data for 5 years.

If you will store the data, please identify where:

In my OneDrive and computer.