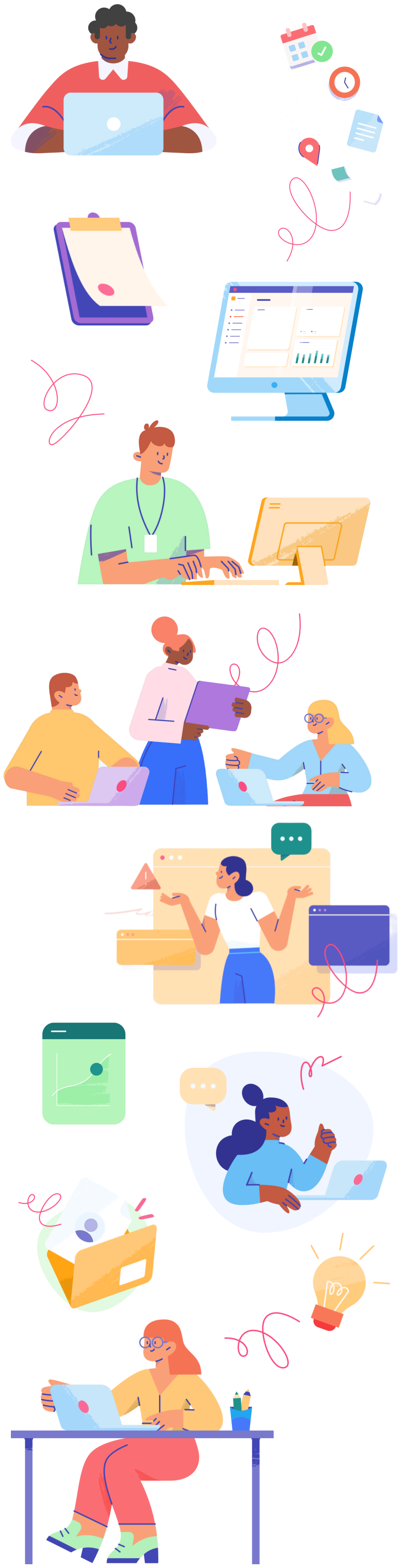

MSc Business Information Technology
Final Project

Improving the adoption of Business Intelligence and Advanced Analytics within Dutch long-term care organizations

Anne Kusters

UT supervisors: dr.ir. J.M. Moonen & dr.ir. M.J. van Sinderen
Company supervisor: Linda Meijer MSc

Enschede/Groenlo, January 2025

Department of Business Information Technology,
Faculty of Electrical Engineering,
Mathematics and Computer Science,
University of Twente

UNIVERSITY OF TWENTE.

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Preface

The document you are reading now represents my final work to fulfill the requirements of the Master Business Information Technology at University of Twente.

First and foremost, I would like to express my deepest gratitude to my university supervisors, Hans and Marten, for their guidance, advice, and support throughout this journey. Hans has been there from the very beginning, helping me find a company for my research and guiding me in shaping the scope of this thesis. His detailed feedback and advice throughout the process were highly valuable. Marten joined as a supervisor for the final four months of my project, bringing a fresh perspective and providing in-depth feedback that enriched the quality of this work. Together, their guidance helped me achieve meaningful results, navigate the challenges of this research, and grow both academically and professionally.

I would also like to extend my appreciation to my company supervisor, Linda, for her mentorship during this project. Her encouragement and practical expertise were instrumental in shaping this thesis and ensuring its relevance to industry applications.

A heartfelt thank you goes to my colleagues at Nedap Healthcare, whose teamwork and support created a positive and encouraging environment throughout my work. Their willingness to share knowledge and provide feedback was extremely helpful during this process.

Lastly, I am deeply grateful to my family and friends for their unwavering encouragement and belief in me. Their constant presence and support, even during moments of doubt, motivated me to persevere and achieve my goals. Their faith in my abilities meant more to me than words can express.

To conclude, I am profoundly thankful to everyone who contributed to my academic and personal journey, helping me complete this work.

Anne Kusters
Enschede, January 2025

Management summary

This research, on behalf of Nedap Healthcare, explores the application of Business Intelligence (BI) and Advanced Analytics to enhance decision-making and process management within Dutch long-term care organizations. The study provides an analysis of the sector's current state regarding the adoption of analytics, proposes a maturity model, and develops a roadmap to support organizations in advancing their analytics capabilities.

Decision-making in care organizations operates across three management levels. Strategic-level decisions focus on aligning with national and municipal policies, with an emphasis on patient-centered care and preventive strategies. Tactical-level decisions aim to translate strategic objectives into operational plans, ensuring efficient resource allocation and care coordination. Operational-level decisions center on individual patient needs, requiring agile and responsive processes. The study finds that research on the adoption of analytics remains limited across these levels, though such tools have the potential to address critical challenges, including resource management and operational efficiency.

The statistical quantitative analysis reveals significant differences in BI adoption between large and small organizations. Larger organizations exhibit more advanced adoption, characterized by robust infrastructure, sophisticated tools, and dedicated BI teams. Conversely, smaller organizations face resource limitations, relying on simpler tools and external support. Despite these disparities, there is a shared aspiration to expand their use of data-driven approaches to improve care delivery and operational effectiveness.

To address these gaps, the study introduces a five-level maturity model that focuses on technology, data, and organizational readiness. This framework enables organizations to assess their current analytics capabilities and identify areas for improvement. Additionally, a four-step roadmap is proposed to guide organizations through a structured approach to enhancing their analytics maturity. The roadmap emphasizes assessment, defining of strategy, phased implementation, and continuous evaluation, fostering sustainable progress in data-driven decision-making.

To validate the developed maturity model and roadmap, several semi-structured interviews were conducted with BI practitioners. The validation process affirmed the value and effectiveness of the proposed frameworks in advancing maturity.

While the proposed solutions provide a structured approach, this research acknowledges several limitations. The sample predominantly includes larger organizations, potentially limiting the applicability of findings to smaller organizations. The roadmap, though theoretically sound, has not been piloted in real-world settings, leaving questions about its practical feasibility.

Therefore, future research should include a more representative sample of organizations to ensure a broad applicability. Pilot studies are recommended to validate the roadmap's impact. Additionally, as analytics continues to evolve, future studies should consider incorporating emerging tools and methodologies to maintain relevance.

For Nedap Healthcare, the findings have resulted in several recommendations. The roadmap can be promoted to customers and partners through workshops and educational initiatives to support effective adoption. Product development efforts should align with the maturity model, enhancing the Ons® Suite to support varying levels of analytics maturity. Furthermore, the maturity model can serve as a diagnostic tool to evaluate customers' analytics practices, allowing for tailored recommendations that meet their specific needs.

Overall, these developed frameworks can help Dutch long-term care organizations overcome existing barriers, adopt analytics effectively, and, ultimately, improve both their strategic decision-making processes and the quality of care.

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Acronyms

ACT	Assertive Community Treatment.
AI	Artificial Intelligence.
ART	Active Recovery Triad.
BI	Business Intelligence.
CDS	Clinical Decision Support.
CRM	Customer Relationship Management.
DSRP	Design Science Research Process.
EHRs	Electronic Health Records.
ETL	Extract, Transform, Load.
GGZ	Geestelijke Gezondheidszorg (EN: Mental health care).
GHZ	Gehandicaptenzorg (EN: Disability care).
HRM	Human Resource Management.
IT	Information Technology.
KPIs	Key Performance Indicators.
MGMT	Management.
ML	Machine Learning.
VVT	Verpleeg-, Verzorgingshuizen en Thuiszorg (EN: Nursing care).

Chapter 1

Introduction

1.1 | Problem statement

The healthcare sector is currently one of the fastest-growing and most dynamic sectors [23]. This growth is also evident in the Netherlands, which ranks at the top in long-term care provision among developed countries [23, 33]. As the population ages, there is an increasing pressure on the long-term care sector to accommodate the rising number of clients [54]. This demographic shift demands improvements in how care is managed and delivered. Without improvements, there is a risk that the long-term care system may struggle to meet the increasing demand, affecting its ability to deliver quality care.

Therefore, management is looking for new effective strategies to enhance business processes and decision-making. The growing availability of data provides an opportunity to address these challenges. Business Intelligence (BI) and Advanced Analytics systems can equip management as well as caregivers with the tools needed to streamline operations, make informed decisions, and improve communication across all levels of care [43]. By leveraging BI and Advanced Analytics, the long-term care sector can enhance its efficiency and quality, and better meet the needs of its growing and aging population.

Despite these advantages, there is limited research addressing the adoption of analytics in the Dutch long-term care sector. Although other sectors have seen substantial progress in maturity, the long-term care sector might face unique challenges and constraints that hinder the adoption and integration of BI and Advanced Analytics. For instance, the sector's traditionally human-centered focus often makes it challenging to shift toward a more data-driven approach [28]. Most industrial sectors have clear, quantifiable metrics for analytics, which are straightforward to track and analyze. In contrast, the long-term care sector operates within a more complex and nuanced environment. Here, individuals' well-being, emotional state, and personal care needs are integral to care quality, yet they are inherently difficult to measure and quantify. This human-centered culture complicates the integration of analytics, as it relies on measurable, objective data.

To bridge these gaps, this research aims first to explore the current state of BI and Advanced Analytics in Dutch long-term care organizations, assessing both existing implementations and the obstacles to further development. Next, by identifying the essential steps and key challenges involved in achieving high maturity, this study intends to support long-term care organizations in effectively using data to enhance decision-making, improve care delivery, and ultimately, better meet the demands of an aging population.

1.2 | Context

This section provides background information to establish the starting point of this research and introduces Nedap Healthcare, the company where this master's thesis was conducted.

Nedap Healthcare is a Dutch company specializing in developing innovative software and hardware solutions for the healthcare sector. With a strong focus on improving care delivery and streamlining administrative tasks, Nedap Healthcare provides products that enhance efficiency and reduce the burden on healthcare professionals. Their solutions are designed to support a wide range of healthcare providers, including long-term care organizations and general practitioners, by offering user-friendly, intuitive systems that facilitate better care coordination and data management.

The Ons® Suite, Nedap Healthcare's flagship, is tailored specifically for long-term care organizations. This comprehensive software suite is designed to simplify and optimize the administration of care services, from client registration and care planning to time tracking and invoicing. The Ons® Suite integrates with other systems and provides healthcare providers with a centralized platform that enhances communication, improves workflow efficiency, and ensures compliance with industry regulations. With this software, Nedap Healthcare aims to reduce administrative overhead, allowing caregivers to focus more on providing quality care.

Currently, the Ons® Suite does not include built-in analytics features. However, its open architecture enables users to extract data and analyze it externally, allowing them the flexibility to utilize their preferred BI tools and frameworks. This creates an intriguing area for exploration, as little is known about how users are leveraging data extracted from the Ons® Suite or their approaches to external analytics for deriving insights.

1.3 | Research goal

The goal of this research is to determine the required steps and challenges for long-term care organizations to improve their analytics capabilities. In addition, it aims to provide an overview of the current implementation of BI and Advanced Analytics in Dutch long-term care organizations, specifically in nursing, disability and mental health care.

By the end of this research, it is expected to have contributed to a better understanding of the importance of BI and Advanced Analytics and to have developed a roadmap with the most important steps and challenges to a high maturity. The originality of this work is that it focuses on the Dutch long-term care sector and gives a comprehensive blueprint and this has not been broadly researched yet.

1.4 | Research questions

The main research question that results from the research goal is formulated as follows:

How can Business Intelligence and Advanced Analytics be applied to enhance decision-making and process management of long-term care organizations in the Netherlands?

To make the research more tangible, this main research question has been broken down into the next four research questions that will be used to guide this research:

RQ1: What is the current state of decision-making strategies in the Dutch long-term care sector, and how is analytics being utilized in healthcare in general?

To answer this question, four sub-questions have been formulated and have to be answered first.

1.1 What characterizes the different segments of the long-term care sector in the Netherlands?

1.2 What distinguishes decision-making and process management at different management levels in Dutch long-term care organizations?

1.3 What is the state-of-the-art in Business Intelligence and Advanced Analytics of the healthcare sector?

1.4 Which maturity models exist in terms of Business Intelligence and Advanced Analytics in the healthcare sector?

RQ2: What is the current state regarding analytics adoption of the Dutch long-term care sector?

RQ3: What roadmap can be developed to enhance the analytics maturity of Dutch long-term care organizations?

To answer this question, two sub-questions have been formulated and have to be answered first.

3.1 What maturity model can be designed to assess the analytics adoption of Dutch long-term care organizations?

3.2 What steps are necessary to guide Dutch long-term care organizations in improving their analytics capabilities?

RQ4: What potential impact could the proposed frameworks have on analytics adoption in Dutch long-term care organizations?

To answer this question, two sub-questions have been formulated and have to be answered first.

4.1 How do the proposed frameworks perform in terms of extending existing theories to the sector?

4.2 How do the proposed frameworks perform in terms of their practical value in organizational contexts?

1.5 | Research outline

The remainder of this paper is divided into six parts. Chapter 2 will start by describing the different approaches that have been taken to answer the identified research questions. Chapter 3 provides an overview of the existing literature on the Dutch long-term care sector and of BI and Advanced Analytics, answering Research Question 1. Thereafter, the state and trends regarding analytics adoption in the Dutch long-term care sector, analyzed with data collected in a survey about BI and Advanced Analytics, will be presented in Chapter 4, addressing Research Question 2. Next, Chapter 5 discusses the development of the maturity model and roadmap, answering Research Question 3. In Chapter 6, validation of the designed maturity model and roadmap will be described, addressing Research Question 4. To finish, the research will be summarized in Chapter 7.

Chapter 2

Methodology

This chapter outlines the multifaceted approach to improving the adoption of BI and Advanced Analytics in the Dutch long-term care sector. Figure 2.1 provides an organized overview of the research methods employed in this study, linking them to a research step to its corresponding research question.

2.1 | Design Science Research Process

The design cycle of this research followed the Design Science Research Process (DSRP) model by Peffers et al. [35], ensuring a structured methodology that encompasses problem identification, artifact creation, and evaluation. The implementation of each stage within the cycle was detailed as follows:

Step 1: Problem identification & motivation

The research began by identifying the need for effective BI and Advanced Analytics in Dutch long-term care organizations. The initial exploratory and systematic literature reviews, combined with the statistical quantitative analysis, were utilized to reveal gaps in current BI practices in this sector. This phase justified the necessity of developing a solution that helps achieve a higher maturity.

Step 2: Objectives of a solution

The primary objective is to create a roadmap that guides long-term care organizations in the Netherlands toward higher maturity by detailing key steps and addressing sector-specific challenges. The goal is to provide a clear pathway for organizations to enhance their use of BI and Advanced Analytics for improved decision-making and process management. This roadmap incorporates a maturity model as a foundational component to identify the state of analytics adoption of an organization.

Step 3: Design & development

The design and development phase utilized insights from systematic literature reviews and statistical quantitative analysis to construct the roadmap. The maturity model is developed as a tool to assess the current state of analytics maturity of a long-term care organization. The roadmap incorporates this model in its actionable steps to improve the organization's analytics capabilities. This phase includes iterative refinements to ensure that the roadmap and maturity model are both practical and theoretically sound.

Step 4 & 5: Demonstration and evaluation

Evaluation of the roadmap involved feedback collection through semi-structured interviews with BI practitioners in the Dutch long-term care sector. This feedback helps to confirm if the roadmap effectively provides clear, practical steps for achieving higher maturity and addresses real-world challenges. Adjustments were made based on this input to refine the frameworks' applicability and effectiveness.

Step 6: Communication

The research findings, including the developed roadmap and supporting maturity model, are documented and communicated via this study. This stage ensured that the research contributes to both academic and practical discourse, offering potential valuable insights into the pathway to higher analytics maturity and providing organizations with the necessary guidance to navigate this complex journey.

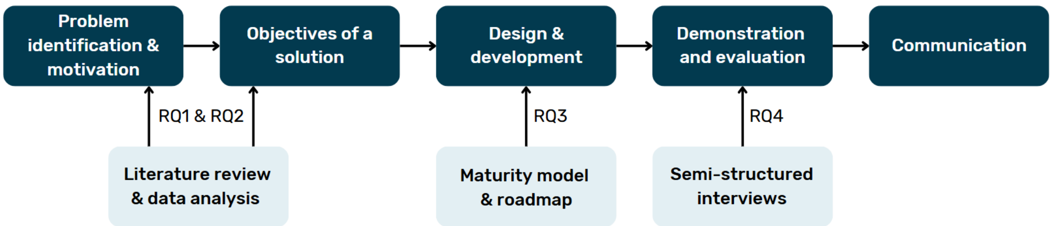

Figure 2.1: Design Science Research Process

2.2 | Literature review

2.2.1 Exploratory literature review

In the research, multiple methods of doing research have been used. First, an exploratory literature study was performed at the start of this research. This exploratory study aimed to identify important concepts, terminology, and studies related to the use of BI and Advanced Analytics in the Dutch long-term care sector. In this way, search terms could be formulated, and interesting studies were identified which could be used for a more structured literature study. The exploratory study was performed using a combination of Google and Google Scholar. This review resulted in a total of seven relevant research papers, used in Chapter 1.

2.2.2 Systematic literature review

Secondly, a descriptive and systematic literature review was performed on Dutch long-term care organizations (Section 3.1), their decision-making processes and management strategies (Section 3.2), the current state-of-the-art in BI and Advanced Analytics (Section 3.3) and various analytics-related maturity models (Section 3.4). In the exploratory review, it was found that there are not a lot of articles published about BI and Advanced Analytics in the Dutch long-term care sector. Therefore, the decision was made to broaden the search for the last two sections to the healthcare sector. This systematic literature review was based on the five-stage grounded-theory approach of Wolfswinkel [52]. The online literature database Scopus was used to find research papers related to the research questions. The search has been broken down into three search queries, shown in Table 2.1.

Literature review	Search term
Dutch long-term care sector	TITLE-ABS-KEY(long-term OR nursing OR "mental health" OR disability) AND TITLE-ABS-KEY(healthcare OR "health care" OR care) AND TITLE-ABS-KEY(netherlands OR dutch)
Decision-making and process management	TITLE-ABS-KEY(long-term OR nursing OR "mental health" OR disability) AND TITLE-ABS-KEY(healthcare OR "health care" OR care) AND TITLE-ABS-KEY(decision-making OR process* OR management) AND TITLE-ABS-KEY(strategic OR operational OR tactical)
BI and advanced analytics	TITLE-ABS-KEY("business intelligence" OR "advanced analytics") AND TITLE-ABS-KEY(healthcare OR "health care")

Table 2.1: Systematic literature review: Queries used in the literature review

Several exclusion criteria for the main search query were established. These ensure that the literature reviewed is understandable to the researchers, maintaining the accuracy and reliability of data interpretation, is available and therefore can be scrutinized for validity and reflects recent developments and current trends in the field, providing up-to-date and relevant findings. Using a 10-year window is a common practice in literature reviews, as it strikes a balance between including enough studies to provide a comprehensive overview while ensuring that the research is still current and relevant to the present day.
The exclusion criteria applied are as follows:

1. The papers not written in Dutch or English are excluded;
2. Papers that are not available are excluded;
3. Studies before the year 2014 are excluded.

The search process procedure that was used is as follows:

1. Enter search query;
2. Apply filters for the section criteria;
3. Read title, abstract and keywords;
4. Read introduction and conclusion;
5. Select relevant studies;
6. Add papers via backward citations

The initial searches have a combined result of 17,776 papers, as shown below in Figure 2.2. After applying the selection criteria and excluding duplicates, 5,870 papers remain. Following the rest of the procedure led to the 29 results. Lastly, 12 extra papers were found through backward citations and were added as relevant. This resulted in a total of 41 relevant research papers.

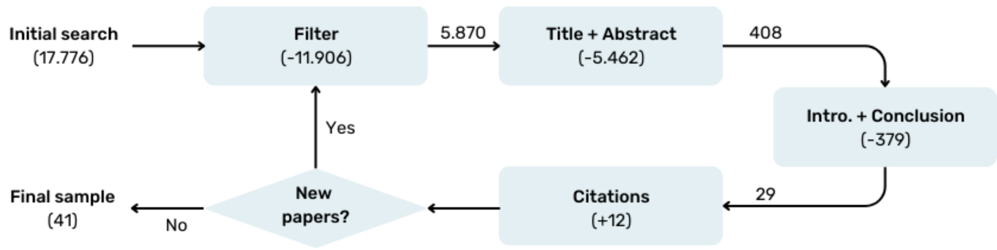

Figure 2.2: Systematic literature review: Selection process

2.3 | Statistical quantitative analysis

Next to the literature review, a statistical quantitative analysis was performed. The data set was gathered by a survey on the use of BI and Advanced Analytics among organizations in the Dutch long-term care sector. This data has been used to identify the current state and trends regarding analytics adoption of the Dutch long-term care sector (Chapter 4). Additionally, it helped to create a classification of levels of analytics maturity (Section 5.1).

The survey was distributed via Samenwerken, the collaboration portal for customers of Nedap Healthcare. Additionally, direct invitations were sent to 42 customers who had previously expressed interest in participating in research studies or pilot projects.

The survey was available for a period of four weeks, from September 9 to October 7, 2024. This timeframe provided respondents with sufficient opportunity to complete the survey at their convenience while maintaining a focused window for data collection.

The questions of the survey are depicted in Appendix B. Some questions made use of exclusion criteria which changed the number of answers. The data is not generalized but only used to describe the state of BI and Advanced Analytics of the Dutch long-term care sector as this research was performed only on companies in this country and sector.

2.4 | Design and development

2.4.1 Maturity model

For the development of the Care Analytics Maturity Model, the literature on the existing maturity models and the findings of the data analysis were combined to determine the dimensions and levels of the new model. Additionally, the guidelines of Becker et al. (2009) will be used to determine the scope and design of the model [2]. These guidelines emphasize a structured approach, ensuring that each phase of the maturity model is documented and developed.

The new maturity model follows Becker's procedure model for designing maturity models, which includes the phases problem definition (Section 1.1), comparison of existing models (Section 3.4), iterative development (Chapter 5), and evaluation and refinement (Chapter 6), as shown below in Figure 2.3.

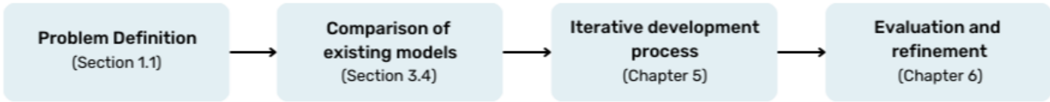

Figure 2.3: Design process: Maturity model

2.4.2 Roadmap

To develop the roadmap, the findings of the data analysis as well as the newly designed maturity model are combined to determine the steps of the new roadmap (Section 5.2). This roadmap will outline the required steps for Dutch long-term care companies to reach a higher maturity.

2.5 | Semi-structured interviews

Lastly, to validate the developed maturity model and roadmap, several interviews were conducted with BI practitioners in the Dutch long-term care sector to gather feedback. The chosen method for these interviews was semi-structured, with the reasoning that it gives a lot of flexibility to get input about the validity of the developed maturity model and roadmap. Semi-structured interviewing provides a strong understanding of the thoughts and experiences of individuals [9]. Additionally, this interview format enables to ask follow-up questions based on the interviewees' answers.

The questions, shown in Appendix C, sought to explore several key aspects of the maturity model and roadmap, including their relevance, completeness, usability, clarity and applicability. The interviews aimed to assess how well the model and roadmap align with the real-world challenges faced by long-term care organizations in the Dutch sector. By gathering feedback on the model's components, such as its levels of maturity and dimensions, the interviews can provide valuable insights into areas where adjustments or additional details might be needed. The feedback collected also focused on the overall impact of the model and roadmap on analytics adoption.

This validation process ensures that the frameworks offer actionable, realistic, and effective guidance for long-term care organizations looking to enhance their analytics capabilities. The interviews were conducted in Dutch to ensure clarity and comfort for the participants. The results of these interviews can be found in Chapter 6, where the analysis of the feedback will be presented and discussed.

Chapter 3

Structure of the Dutch long-term care sector

This chapter presents the findings of a systematic literature review (described in Section 2.2) and provides a comprehensive overview of the organizational structure and decision-making processes in the Dutch long-term care sector and an overview of BI and Advanced Analytics. It is structured into four sections. First, the chapter introduces the Dutch long-term care sector, covering the three different segments and their key components, objectives, and approaches to service delivery (Section 3.1). The second section delves into the decision-making and process management in long-term care, detailing the strategic, tactical, and operational practices in general and in specific to the Dutch context (Section 3.2). Finally, the chapter examines the different types of BI and Advanced Analytics, its current state in the healthcare sector (Section 3.3) and various analytics-related maturity models applicable to this sector (Section 3.4).

3.1 | Long-term care sector

Long-term care organizations play a central role in providing sustained healthcare services and support to individuals who require ongoing assistance due to age, disability, or chronic and mental illness. This section delves into the different segments within long-term care in the Netherlands, emphasizing their different structures, objectives, services and approaches to care.

3.1.1 Nursing care

Nursing care, known as Verpleeg-, Verzorgingshuizen en Thuiszorg (VVT) in Dutch, represents the segment of the long-term care sector dedicated to supporting individuals who are no longer able to live independently [31]. This segment encompasses a wide range of services designed to address the diverse and complex needs of this population. Through a combination of physical, emotional, and social support, the VVT aims to mitigate the challenges associated with long-term care, promoting a holistic approach to well-being.

The main objectives of the VVT are to maintain or improve the quality of life, ensure safety, and provide both medical and personal care tailored to the individual needs of patients [31]. Central to this approach is the development of personalized care plans that reflect the unique preferences and requirements of each individual. This person-centered approach is fundamental to the care philosophy in the Netherlands, emphasizing the importance of recognizing and respecting the individuality of each patient. The care plan of a patient with a chronic illness will, for instance, be involve regular reviews and adjustments based on their progress and preferences, while the care plan of a patient with asthma was customized to include education for their family on managing triggers and medication.

The VVT is organized into two main categories: intramural and extramural care [24]. Intramural care involves providing a residential solution for individuals requiring more intensive care and supervision than can be provided in their own homes [41]. This type of care is offered in facilities such as nursing homes and long-term care institutions, which provide a safe and supportive environment where individuals receive assistance with daily activities like personal hygiene, meal preparation, medication management, and social engagement. Extramural care, on the other hand, refers to care provided outside of residential facilities, typically in the individual's own home [41]. This type of care is designed for individuals who can live independently but still require some level of medical or personal assistance. Services under extramural care include home nursing, physical therapy, home help, and social support, all tailored to the individual's needs.

Another aspect of nursing care is the concept of integrated care, which involves the collaboration of multidisciplinary teams [10]. These teams typically include nurses, physicians, physiotherapists, and social workers, among others. By working together, these professionals can provide comprehensive care that addresses not only the physical health needs of individuals but also their emotional and social well-being. This integrated approach ensures that all aspects of an individual's health are considered and treated, leading to more effective and holistic care outcomes.

Dutch culture emphasizes self-reliance and independence, fostering a preference for home care and small-scale living solutions [42]. This cultural inclination supports a care model that prioritizes autonomy and community-based services. In contrast, Southern European countries like Italy and Greece, rely more on family members to provide care. This cultural expectation often results in fewer formal care services and a greater reliance on familial support.

Laws and regulations

The VVT is predominantly paid through public funding, notably the Long-Term Care Act (Wet langdurige zorg), which provides coverage for individuals requiring constant supervision or 24-hour care [48]. This publicly financed model ensures that those in need of extensive care receive necessary support without undue financial strain. In addition, the Health Insurance Act (Zorgverzekeringswet) assigns the responsibility of home nursing, which includes personal care, to insurance companies. This legislation ensures that individuals who prefer or need to stay at home can still access professional medical and personal care services. Home nursing covers a range of services, from basic personal care to more intensive nursing care, depending on the individual's needs. Third, the Social Support Act (Wet maatschappelijke ondersteuning) delegates the management of most non-residential care services to municipalities. This law encompasses various forms of social care, such as assistance with daily activities, provision of aids and adaptations, and support for social participation. The Social Support Act aims to enable individuals to live independently for as long as possible and to participate fully in society.

The Electronic Data Processing Act (Wet elektronische verwerking van gegevens) regulates electronic data exchange in Dutch healthcare, ensuring security and privacy [49]. This legislation addresses the need for specific regulations on electronic medical data exchange, focusing on patient privacy. Healthcare providers must inform and obtain consent from patients for data sharing. Additionally, patients can specify which data can be accessed by which provider and have the right to free electronic access to and copies of their health records.

3.1.2 Disability care

Disability care, or Gehandicaptenzorg (GHZ) in Dutch, caters to individuals with physical, intellectual, or developmental disabilities. The primary objectives are to enhance independence, promote participation in society, and improve the quality of life through tailored support services [39]. Personalized care plans are developed to address the specific needs and goals of each individual, ranging from daily living assistance to specialized therapies. These plans are designed to maximize the individual's abilities and support their goals for independence and participation in society.

The GHZ contains a wide range of services and support options, including medical care, therapies, education, day programs, employment, housing, and social integration [16]. The care can range from light support in daily life to intensive care, depending on the needs and capabilities of the person with a disability. The care provided spans a range of living arrangements, from residential care facilities to supported living in community settings, accommodating different levels of independence. In addition, this segment emphasizes social inclusion and participation, and facilitates access to education, employment, and recreational activities [38]. Various programs and initiatives are in place to support individuals with disabilities in finding and maintaining employment, enhancing their financial independence and sense of purpose.

Family involvement is highly encouraged in disability care [32]. Families play a crucial role in care planning and decision-making processes, ensuring that the care provided aligns with the preferences and values of the patient. This collaborative approach helps create a supportive environment that promotes the well-being and development of individuals with disabilities. The caregivers can, for instance, invite family to participate in regular care planning meetings. During these meetings, the family shares insights about their routines, preferences, and communication methods. Based on this information, the care team customizes the support plan to include activities the patient enjoys, like art therapy and music sessions, and establishes communication strategies that they respond to well. The family's ongoing involvement ensures that the care provided is consistent with the individual's values and needs, creating a nurturing and effective support system that enhances their overall well-being and personal development.

Similar to the VVT, disability care is provided by a multidisciplinary team of professionals, such as doctors, nurses, therapists, counselors, and social workers [16]. The aim is to provide personalized care, taking into account the individual needs, desires, and capabilities of the person with a disability.

The GHZ is funded through the Health Insurance Act for general disability care, through the Social Support Act for non-residential care services, and through the Long-Term Care Act for long-term, intensive care [48]. This means that health insurers are responsible for financing most care, although there may be deductibles and co-payments.

3.1.3 Mental health care

Mental health care, Geestelijke Gezondheidszorg (GGZ) in Dutch, focuses on the diagnosis, treatment, and prevention of mental disorders and emotional problems [47]. It encompasses a range of disciplines and approaches, including psychotherapy, medication, counseling, rehabilitation, and social support [24]. The goal of this segment is to improve the well-being of individuals, to reduce or manage mental disorders, and to help them lead a healthy and appropriate lifestyle. Mental health care addresses a wide range of mental disorders, including depression, anxiety disorders, bipolar disorders, schizophrenia, and addiction problems [47].

The GGZ is strongly influenced by a culture of egalitarianism and individual rights, which is reflected in the approach to mental health care and the emphasis on self-reliance and freedom of choice [42]. There is a strong focus on empowering patients to take an active role in their own care. This includes involving them in decision-making processes and respecting their preferences and values.

Recovery-oriented care is central to this segment, with models such as the Active Recovery Triad (ART) emphasizing recovery as a personal process [53]. The ART model integrates the roles of professionals, service users, and significant others to foster cooperation and empowerment, ensuring that all parties are actively involved in the care process.

Flexible Assertive Community Treatment (ACT) is another approach used in the GGZ [3]. Flexible ACT is designed to provide continuous and flexible care to individuals with severe mental illness, aiming to reduce hospital admissions and support community living. This model allows individuals to remain in their own homes while receiving the necessary care, promoting independence and enhancing their quality of life.

High-intensity care is provided during crisis periods to ensure safety and stabilization before transitioning back to community-based support [47]. This approach ensures that individuals receive the intensive care they need during critical times while maintaining a focus on long-term recovery and community integration.

Peer support utilizes individuals with lived experiences of mental illness to offer support and share insights fosters hope and recovery among service users [3]. Peer workers, who have firsthand experience with mental health challenges, can provide practical advice and different perspectives that traditional professionals may not be able to offer. Their personal journeys through recovery can give encouragement, helping others navigate their recovery journeys and regain confidence in their abilities.

Just like the VVT, the GGZ is covered under the Health Insurance Act, the Long-Term Care Act and the Social Support Act [48]. In addition, the Youth Act (Jeugdwet) focuses on preventive and mental health care for children. This legislation is designed to address the specific needs of children and adolescents, providing support that ranges from early intervention and prevention to more intensive mental health services. The Youth Act ensures that young people receive the appropriate care and support tailored to their developmental stages and specific challenges.

Overall, these segments, summarized in Table 3.1, collectively aim to provide comprehensive and person-centered care to different populations with long-term needs in the Netherlands. By focusing on personalized care, community involvement, and integrated support services, the Dutch long-term care system has the goal to offer each individual the necessary support to lead a fulfilling and dignified life.

Care Type	Target Group	Facilities	Focus	Personnel
VVT	Elderly and chronically ill people	Nursing and care homes, home care	Physical care, medical care, support with daily activities, palliative care	Nurses, physicians, physiotherapists, social workers
GHZ	People with physical, intellectual, or sensory disabilities	Residential facilities, day care, ambulatory care, respite care	Support for independent living, learning and working, behavioral issues, socio-emotional development	Caregivers, psychologists, physiotherapists, therapists
GGZ	People with psychological, psychiatric, or addiction problems	Outpatient clinics, inpatient care, ambulatory care, crisis intervention	Diagnosis and treatment of mental disorders and addiction, prevention and recovery-focused care	Psychiatrists, psychologists, social workers, nurses, therapists

Table 3.1: Long-term care segments

3.2 | Decision-making and process management

The long-term care sector necessitates a well-defined decision-making and process management framework to ensure the provision of high-quality care and services to patients. In this section, the decision-making and process management approaches at different management levels: strategic, tactical, and operational will be explored. Furthermore, the specific management practices typical for the Netherlands will be examined.

3.2.1 Management levels

Strategic

Strategic management encompasses setting the overall direction and goals for an organization, including long-term planning, resource allocation, and policy development to achieve its mission and vision [21, 25]. This approach is central for navigating complex financial challenges and maintaining a competitive edge within the sector. Healthcare leaders must develop robust strategies that ensure organizational resilience, performance improvement, and the ability to adapt to changing market dynamics and future trends.

A critical aspect of strategic management is the effective allocation of resources and the development of policies that align with the organization's mission and vision [25]. This involves a deep understanding of the healthcare market, including competitive forces, regulatory changes, and technological advancements. By leveraging pragmatic and real-world evidence, organizations can create strategies that not only enhance performance but also build strong stakeholder alignment and support.

Moreover, the strategic implementation of information technology plays an important role in enhancing decision-making processes within organizations [21]. This includes long-term planning for the integration of Electronic Health Records (EHRs) and other information systems that support the overall goals of healthcare providers. The integration of these technologies helps improve patient care, streamline operations, and ensure data interoperability across various healthcare settings. By focusing on these strategic initiatives, organizations can achieve higher efficiency, quality of care, and patient outcomes.

Tactical

Tactical management bridges the gap between strategic planning and daily operations, ensuring that high-level goals are effectively translated into practical, actionable plans [21, 25]. This involves the development and implementation of programs and services that align with the organization's overarching strategic objectives. This could involve launching new care programs, specialized rehabilitation services, or initiatives aimed at improving patient quality of life. Tactical managers oversee the creation of these programs, develop implementation protocols, and coordinate across departments to ensure that new services are seamlessly integrated. They also focus on continuous quality improvement by monitoring care performance metrics, addressing patient and family feedback, and making necessary adjustments to enhance care outcomes and satisfaction.

Another aspect of tactical management is the allocation of resources, such as medical staff, equipment, and finances, to various departments or patient care areas based on immediate needs and strategic priorities [21]. For instance, a nursing home may need to adjust staffing levels in response to increased patient needs during flu season or invest in new assistive technologies to enhance patient mobility. Tactical managers are responsible for designing and implementing these resource allocation strategies, which help in optimizing care delivery and ensuring that the facility remains responsive to both routine and emergent needs.

Operational efficiency and regulatory compliance are also central [25]. Managers work to streamline daily operations, such as optimizing care routines and administrative processes, to improve overall efficiency and patient satisfaction. Ensuring compliance with state and federal regulations, as well as industry standards, involves implementing rigorous oversight and regular audits to maintain high standards of care. By managing these operational and compliance aspects effectively, tactical managers help create a well-organized, compliant, and patient-centered environment that supports the long-term care facility's strategic goals and enhances the quality of life for its patients.

Operational

Operational management in the long-term care sector is essential for the effective execution of day-to-day activities, ensuring that strategic objectives are translated into actionable plans and that resources are utilized efficiently to deliver high-quality care. It encompasses several key aspects, including workforce management, process optimization, and maintaining high standards of patient care [25]. These elements ensure the smooth functioning of organizations and the provision of consistent, high-quality services to patients.

Best practices often involve the implementation of continuous quality improvement processes [25]. This proactive approach ensures that operations are constantly assessed and refined to meet evolving standards and patient needs. This iterative process involves regular evaluation of practices, outcomes, and feedback to identify areas for improvement and implement changes that better meet the evolving needs of patients and adhere to current standards. Additionally, it fosters a culture of collaboration and engagement among staff members, patients, and their families. By encouraging open communication and feedback, long-term care facilities can gain valuable insights into the effectiveness of their care practices and the satisfaction of those they serve. Engaging staff in the improvement process not only empowers them to contribute to solutions but also fosters a sense of ownership and commitment to high standards of care.

Kiel et al. provide compelling case studies that illustrate leveraging technology plays an important role in enhancing efficiency [21]. For instance, the adoption of EHRs and other health information systems can significantly improve the accuracy, accessibility, and management of patient data, leading to better clinical outcomes and streamlined operations. Another example is the use of data analytics to monitor and improve clinical workflows. By systematically analyzing patient data, organizations can identify bottlenecks in processes, predict patient needs, and allocate resources more effectively. This data-driven approach not only improves the efficiency of healthcare delivery but also enhances the overall quality of care provided to patients. Through these advancements, organizations can achieve a higher level of operational excellence, ultimately benefiting both patients and healthcare providers.

In conclusion, effective management at all levels, summed up in Table 3.2, is crucial for the success of long-term care organizations. Together, these management levels create a cohesive framework that drives continuous improvement, enhances patient outcomes, and supports the organization's mission and vision.

Management Level	Main Elements	Key Positions
Strategic	Long-term planning, resource allocation, development of policies	CEO, CFO, Board of Directors
Tactical	Making short-term decisions and adjustments to ensure that day-to-day operations are aligned with the organization's strategic goals	Department heads, operations manager
Operational	Focus on day-to-day activities, translate strategic objectives into actionable plans, ensure efficient resources use	Nursing, administrative and support staff

Table 3.2: Management levels in the long-term care sector

3.2.2 Decision-making in the Netherlands

Within the Dutch long-term care sector, management practices underscore collaboration, innovation, and patient-centered care [15, 51]. Operating within a regulated framework that prioritizes equity and accessibility, organizations integrate diverse healthcare settings to ensure seamless care for patients with complex needs. This integrated approach supports continuity of care and multidisciplinary collaboration, essential for managing chronic conditions effectively.

Furthermore, management places a strong emphasis on preventive care and health promotion [42]. By focusing on early intervention and lifestyle modifications, organizations aim to reduce disease burden and prevent hospitalizations or long-term institutionalization. Patient empowerment is also central, with active engagement in care planning and decision-making processes, promoting autonomy and improving health outcomes.

The decentralization of healthcare, which has shifted responsibilities to municipalities, requires care organizations to dynamically adjust their strategies, plans, and processes to operate effectively within a diverse and changing municipal landscape [50]. Management must develop flexible long-term plans that balance local and national goals. Diversification of services and risk management are crucial due to varying municipal requirements and funding. Collaboration with local partners and investments in adaptable IT systems are essential. Additionally, care packages are adjusted daily to meet municipal requirements.

Flexible planning, adaptation of IT systems, and employee training are necessary to ensure high-quality care. Local quality standards and accurate reporting ensure compliance and transparency.

Strategic management revolves around collaborative planning with government agencies, insurance companies, and healthcare providers [25]. This collective effort aims to formulate inclusive policies that meet diverse population needs while ensuring sustainable and high-quality care. This approach fosters alignment across sectors and enhances the resilience of the healthcare system in responding to evolving challenges. Operational management practices prioritize patient-centered care and efficient resource allocation. Organizations often adopt integrated care models to coordinate services among providers, ensuring seamless transitions and comprehensive patient care. Such models not only enhance patient satisfaction but also optimize healthcare resource utilization, promoting cost-effectiveness and operational efficiency. Tactical management emphasizes cohesive decision-making through collaboration across management levels. Transparent communication and shared decision-making processes enable organizations to effectively navigate internal complexities and external pressures. This collaborative approach ensures that operational strategies align with overarching goals, maintaining organizational agility in a dynamic healthcare landscape.

Effective decision-making and process management are crucial in the long-term care sector, ensuring high-quality care and efficient operations. Management at the strategic, tactical, and operational levels forms a cohesive framework that drives improvement, supports patient-centered practices, and aligns with organizational goals. In the Netherlands, collaboration, innovation, and flexibility within a regulated framework enhance care delivery and ensure equity, accessibility, and continuity for patients with complex needs. By leveraging technology, integrating care models, and fostering preventive care, organizations can optimize resource use and improve outcomes while navigating local and national challenges.

3.3 | BI and Advanced Analytics in healthcare

This section first explores the different types of Business Intelligence (BI) and Advanced Analytics. Next, it delves into the current state of BI and Advanced Analytics within the healthcare sector.

3.3.1 Types of analytics

BI and Advanced Analytics are crucial components for organizations looking to harness data to drive decision-making and strategic planning. BI encompasses a range of processes, technologies, and tools that transform raw data into meaningful insights. Advanced Analytics refers to the use of sophisticated techniques and methods to analyze complex data sets, providing deeper insights into market forces and trends. Unlike BI, Advanced Analytics employs a range of complex techniques to uncover patterns, predict future trends, and guide strategic decision-making. This section delves into the four primary types of analytics as described in Gartner's analytics ascendancy model and shown in Figure 3.1 [27].

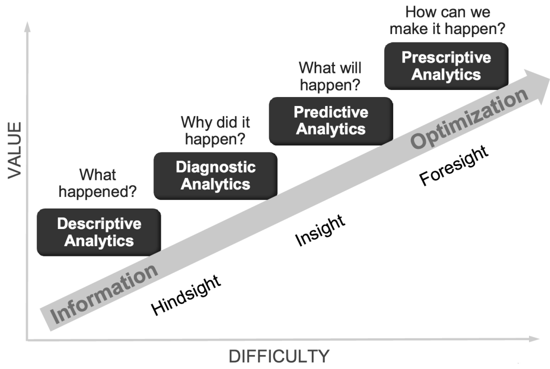

Figure 3.1: Gartner's analytics ascendancy model [27]

Descriptive analytics

Descriptive analytics is the foundation of data analysis, focusing on summarizing historical data to understand what has happened in the past [27, 30]. This type of BI involves the collection, processing, and visualization of data to provide a clear picture of past performance. Descriptive analytics is characterized by data aggregation, where data from various sources is compiled to create comprehensive reports. Data visualization tools, such as dashboards and charts, present this data in an easily understandable format. Regular reporting on Key Performance Indicators (KPIs) and other metrics tracks performance over time.

Applications of descriptive analytics include tracking patient demographics, treatment outcomes and utilization rates of various services as well as the analysis of the quality of data [12]. For instance, a long-term care facility might use descriptive BI to monitor the average length of stay for patients, the frequency of specific treatments or interventions, and overall patient satisfaction scores. Common tools and technologies used in descriptive analytics are BI platforms like Microsoft PowerBI, data warehouses that store aggregated data, and ETL (Extract, Transform, Load) tools that prepare data for analysis.

Diagnostic analytics

Diagnostic analytics goes a step further than descriptive analytics by not only showing what happened but also explaining why it happened [6, 27]. This type of BI focuses on identifying the root causes of past performance and uncovering underlying patterns and relationships in the data. Diagnostic analytics features drill-down analysis, allowing users to delve deeper into data to uncover more detailed insights. Correlation analysis identifies relationships between different data variables, while anomaly detection spots outliers and unusual patterns that may indicate underlying issues.

In practice, diagnostic analytics can be used to understand why certain patient outcomes are better or worse than others [12]. For example, a healthcare provider might investigate why the rate of hospital readmissions is higher for a specific group of patients. By examining factors such as age, underlying health conditions, and types of treatment received, the provider can identify potential causes and take corrective action.

Predictive analytics

Predictive analytics leverages statistical models and machine learning algorithms to forecast future trends based on historical data [27, 30]. This type of Advanced Analytics helps organizations anticipate potential outcomes and make proactive decisions. Predictive analytics involves predictive modeling, where historical data is used to build models that forecast future events. Trend analysis identifies patterns that are likely to continue in the future, and risk assessment evaluates potential risks and opportunities.

Applications of predictive analytics include the forecasting of patient needs and optimizing resource allocation [12]. For instance, a facility might use predictive models to anticipate the future demand for certain types of care based on demographic trends and patient data. This can help in planning for future capacity and ensuring that the necessary resources and staff are available. Tools and technologies used in predictive analytics include Machine Learning (ML) platforms, predictive analytics software and big data technologies.

Prescriptive analytics

Prescriptive analytics is the most advanced type of analytics, providing actionable recommendations based on predictive insights [27, 30]. This type of Advanced Analytics not only predicts future outcomes but also suggests the best course of action to achieve desired results. Prescriptive analytics uses optimization models to identify optimal solutions, decision support systems to provide recommendations, and scenario analysis to evaluate different scenarios and determine the best course of action.

Applications of prescriptive analytics include resource allocation, where organizations optimize the allocation of resources such as staff, budget, and equipment, supply chain management to improve patient outcomes and reduce costs, and strategic planning to guide long-term strategy with data-driven insights [12]. For example, by integrating data from various sources, a healthcare provider can develop personalized care plans that recommend specific treatments and interventions based on a patient's unique health profile. This can lead to more effective and efficient care, ultimately improving patient outcomes and satisfaction. Tools and technologies used in prescriptive analytics include optimization software, prescriptive analytics platforms, and Artificial Intelligence (AI) and machine learning algorithms for generating recommendations.

3.3.2 Current state

The adoption of BI and Advanced Analytics in healthcare is growing globally. Organizations are leveraging data analytics to enhance clinical decision-making, operational efficiency, and patient care.

To optimize analytics, there are a lot of new developments. A notable example is openEHR, an open standard for health data [8]. OpenEHR provides a standardized framework for capturing, storing, and sharing health information across diverse systems and platforms. The adoption of openEHR enhances data interoperability, as it facilitates the seamless exchange of information between different healthcare systems. The adoption of openEHR is gaining momentum across the healthcare sector, with an increasing number of healthcare systems, from individual healthcare organizations to entire regions and even countries, opting to integrate this standard into their operations [1]. When integrated with BI tools, it allows more accurate and comprehensive reporting, trend analysis, and predictive analytics, leading to better-informed decisions.

Another example is visual analytics, where BI tools are used to aggregate and analyze patient data for the visualization of complex data sets, making it easier for healthcare professionals to interpret and utilize the information effectively [19]. One application is in anesthesia, where visual analytics tools help monitoring patient vitals and outcomes in real-time, providing anesthesiologists with critical insights that enhance patient safety and care quality.

Lastly, upcoming BI tools like SAP Lumira and SAP Predictive Analytics allow healthcare providers to predict outcomes such as birth rates based on various factors like fertility rates, public health expenditure, and sanitation facilities [18]. In addition, they enable the visualization of complex data through interactive maps and charts, making it easier for healthcare professionals to understand and act on data insights.

3.3.3 Benefits

Improved patient care is one of the most significant advantages, with predictive analytics enabling early intervention by identifying high-risk patients [7, 20, 22]. By analyzing historical data and patterns, organizations can proactively address potential health risks, improving patient outcomes and overall care quality. Additionally, by facilitating the integration and comprehensive analysis of patient data from multiple sources, analytics empowers healthcare providers to craft individualized treatment plans that are more effective and precisely aligned with the needs of each patient [26, 29].

Operational efficiency is enhanced through streamlined operations, optimized scheduling and better resource allocation [20, 36, 37]. Data-driven insights help reduce wait times, prevent bottlenecks, and ensure that resources are used effectively, leading to smoother facility operations and improved patient flow.

Cost reduction is another key benefit, as analytics help identify areas of waste and inefficiency, allowing organizations to cut unnecessary expenses without compromising care quality [20, 36, 46]. By examining spending patterns and resource use, facilities can achieve significant cost savings and manage budgets more effectively.

Additionally, automated reporting simplifies the process of meeting regulatory requirements [36, 46]. These systems reduce the risk of errors, ensure timely and accurate reporting, and minimize the administrative burden on staff, allowing more focus on patient care.

3.3.4 Challenges

Despite the clear benefits, several challenges impede the widespread adoption of BI and Advanced Analytics. The effectiveness of analytics depends heavily on the quality and completeness of the data [8, 37]. Integrating data from disparate sources, such as EHRs, lab results, and imaging systems, can be challenging and time-consuming due to differences in data formats, standards, and structures. [36, 45]. Inconsistent, incomplete, or inaccurate data can lead to misleading insights and poor decision-making.

Implementing BI and Advanced Analytics systems can be expensive [37]. Costs include not only the purchase of technology and software but also the expenses associated with integrating these systems into existing infrastructure, training staff, and maintaining the systems. Smaller organizations, in particular, may struggle with these financial burdens. While there are potential profits from using these technologies, the initial costs can be prohibitively high, making it a significant barrier to adoption.

The volume of data generated and analyzed can be overwhelming. Without proper tools and strategies for data management, healthcare providers may face difficulties in sifting through vast amounts of information to extract actionable insights [14, 22]. This can lead to information overload and decision paralysis.

Data privacy and security considerations

The sensitive nature of health data leads to significant concerns about data privacy and security [8, 37, 45]. Healthcare organizations must navigate a complex landscape of regulations designed to protect patient data. The General Data Protection Regulation (GDPR) in the European Union mandates stringent data protection requirements for any organization processing personal data of EU citizens. These regulations require that systems, including BI tools and analytics platforms, incorporate robust security measures to safeguard protected health information and other sensitive information. Compliance involves not only implementing technical safeguards, such as encryption and access controls but also ensuring that organizational policies and procedures align with regulatory requirements.

To mitigate privacy risks, particularly when using data for research, analytics, audits, or reporting purposes, healthcare organizations often employ data anonymization techniques [37, 45]. This involves removing or obfuscating identifiable information, making it impossible to trace data back to an individual. Anonymization is vital in maintaining patient confidentiality while still allowing for the meaningful use of data in BI applications. However, it is essential to balance data utility with privacy, as overly aggressive anonymization may reduce the data's analytical value.

AI and ML algorithms, increasingly used in analytics, bring additional privacy and security considerations [29]. AI systems often require vast amounts of data to train models effectively, which raises concerns about data aggregation and the potential re-identification of anonymized data. Moreover, AI models themselves can inadvertently introduce privacy risks. For example, if a model is trained on biased or incomplete data, it may produce discriminatory or inaccurate outcomes, which could harm patients or violate ethical standards. Additionally, AI models can sometimes be vulnerable to adversarial attacks, where malicious actors manipulate input data to deceive the model, potentially leading to incorrect or harmful decisions. To address these challenges, organizations must implement privacy-preserving AI techniques such as federated learning, where models are trained across decentralized data sources without sharing raw data, and differential privacy, which adds noise to data to protect individual identities while allowing for accurate analysis.

BI and Advanced Analytics have transformative potential in healthcare, enhancing patient care, efficiency, and cost management. Tools like openEHR and visual analytics improve decision-making and interoperability, but challenges such as data quality, cost, and privacy must be addressed through robust governance, privacy-preserving methods, and proper infrastructure to fully realize their benefits.

3.4 | Existing maturity models

The integration of BI and Advanced Analytics in healthcare is enhancing both quality of patient care and operational efficiency of care processes. This section explores the various maturity models that help healthcare organizations assess and improve their capabilities, progressing from basic reporting to advanced predictive insights.

To continuously improve, organizations must accurately assess their positioning regarding analytics. However, achieving an objective evaluation of a company's current state presents significant challenges. Key questions include what specific metrics need to be measured, how they should be measured, and what benchmarks they should be compared against. Maturity models are structured frameworks used to assess the development and optimization of processes, technologies, and organizational capabilities over time [4, 5]. These models provide organizations with a systematic approach to evaluate their current state, identify areas for improvement, and develop a path toward higher levels of maturity [11, 34]. This section explores various maturity models with a focus on healthcare and BI and Advanced Analytics, the levels or stages they encompass, and the dimensions they assess.

3.4.1 Maturity models in healthcare

Several models offer a detailed, multidimensional approach to analytics maturity. For example, Brooks et al. (2015) offers a 5-level model for BI in healthcare, with 12 dimensions distributed across four key areas: organizational processes, people and team processes, technology processes, and specific healthcare complexities [4]. It emphasizes the integration of BI with both administrative and clinical data, ensuring a holistic approach to data management and decision-making in healthcare. Additionally, Gastaldi et al. (2018) presents a detailed 4-level model for BI in healthcare, encompassing 23 dimensions across four broad areas: functional, technological, diffusional, and organizational [13]. This model is particularly useful for organizations seeking to thoroughly assess and improve their BI initiatives, addressing every aspect from goal definition to technological integration. Silva et al. (2022), on the other hand, also addresses BI in healthcare but through six stages distributed across three levels, focusing on technology, processes, and people [40]. This approach is designed to guide healthcare organizations in developing robust BI systems that are well-integrated across technological, procedural, and human resources aspects.

Two other models target more specific aspects of healthcare and BI. Espinoza et al. (2023) specifically focuses on social and environmental determinants of health informatics, organizing progress into seven levels across five domains, such as data collection policies, technologies, and analytics capacity [11]. This model is particularly relevant for organizations seeking to understand and integrate complex social determinants into their health informatics strategies. Orenstein et al. (2019) addresses Clinical Decision Support (CDS), outlining five levels that are structured around 3 key pillars: content creation, analytics and reporting, and governance and management [34]. It helps healthcare providers develop and manage CDS systems that enhance clinical decision-making. Stoldt et al. (2019) introduces a 4-level model for analytics adoption in primary care, organized into six dimensions including data, analytics, governance, IT infrastructure, skills, and privacy/security [44]. This model provides a comprehensive view of the maturity of primary care practices, focusing on critical areas that affect data-driven decision-making.

There are also models that take a more linear or stage-based approach. Carvalho et al. (2019) offers a 6-stage model for health analytics in hospitals, structured into a single column of levels, focusing on the characteristics of each stage [5]. While this model provides a streamlined view, its simplicity may limit the depth of analysis compared to more dimension-rich models. Similarly, HIMSS (2021) presents an 8-stage maturity model for analytics adoption in healthcare, providing a clear, stage-by-stage guide without explicitly detailing dimensions, making it a straightforward tool for healthcare organizations to measure their progress in analytics adoption [17].

3.4.2 Similarities

It is interesting to see that although the dimensions of these models are divergent, there is some overlap. Dimensions, also called domains, levels or pillars, often include data, technology, organization and people. Effective data management ensures accuracy, consistency, and accessibility of data, while the technology dimension includes the systems and tools that support BI, such as data warehouses, analytics platforms, and reporting tools. Organizational processes, including leadership and culture, are essential for aligning BI initiatives with strategic objectives and securing the necessary resources for their success. Lastly, the people dimension highlights the importance of skills and competencies, emphasizing the need for trained personnel who can effectively utilize BI tools.

There are several other similarities in the described maturity models. All of the proposed models describe the first stage or level either as non-existent or as the initial phase with fragmented, inconsistent practices where data management is manual and lacks standardization. As organizations move through these stages, they adopt standardized processes, implement automation, and integrate BI tools more effectively. In the highest stage, analytics is fully embedded in decision-making processes, with continuous optimization and strategic use of data.

Models	Scope	X-axis	Y-axis
Espinoza et al. (2023)	Social and environmental determinants of health informatics	7 levels	5 domains
Silva et al. (2022)	BI in healthcare	6 stages	3 levels
HIMSS (2021)	Analytics adoption in healthcare	8 stages	-
Carvalho et al. (2019)	Health analytics for hospitals	6 stages	-
Orenstein et al. (2019)	Clinical decision support	5 levels	3 pillars
Stoldt et al. (2019)	Analytics adoption in primary care	4 levels	6 dimensions
Gastaldi et al. (2018)	BI in healthcare	4 levels	4 areas, 23 dimensions
Brooks et al. (2015)	BI in healthcare	5 levels	4 areas, 12 dimensions

Table 3.3: Maturity models in healthcare and BI

The maturity models, summarized above in Table 3.3, are structured frameworks that help organizations with assessing and ultimately improving capabilities in specific domains. By focusing on key areas within healthcare and BI, these models help organizations identify their current level of maturity and understand gaps that need to be addressed for achieving higher levels of performance. The levels or stages within these models offer a clear path for growth, guiding organizations from basic, ad-hoc practices to optimized, fully integrated processes. The dimensions within these models provide a granular view of maturity, enabling organizations to evaluate their strengths and weaknesses in specific areas and to prioritize their improvement efforts effectively. By offering a systematic approach to assessment, maturity models ensure that organizations can focus their efforts on areas that will yield the most significant impact.

Chapter 4

Current state of BI in Dutch long-term care

The previous chapter highlighted the potential of BI and Advanced Analytics to improve patient care, efficiency, and cost management, while addressing challenges like data quality, cost, and privacy. However, there is still limited knowledge about the current application of BI and Advanced Analytics in the Dutch long-term care sector. Therefore, in this chapter, data collected from a survey (described in Section 2.3) is analyzed to identify the current state and trends regarding analytics adoption of Dutch long-term care sector.

The data analysis is divided into four sections. The first section covers the demographic profile of the respondents (Section 4.1), while the remaining three sections focus on key aspects of the BI and Advanced Analytics implementation in Dutch long-term care organizations. The second section shows the adoption of BI (Section 4.2), highlighting how organizations are currently utilizing BI. It covers tool preferences, BI applications, usage frequency in decision-making, and outsourcing approaches. It also identifies the role of Advanced Analytics. The next section addresses the quality, accessibility, and structure of data within the organizations, as well as the data infrastructure that is necessary for BI and analytics initiatives (Section 4.3). The last section examines the organizational culture and competencies within long-term care organizations (Section 4.4), focusing on data-driven leadership, organizational coverage, and BI training frequency. It also reviews BI expansion plans.

4.1 | Demographics

The survey was filled in by a total of 87 respondents. However, no respondent answered every question due to exclusion criteria or personal choice. Exclusion criteria were applied to filter out respondents who did not meet the necessary conditions for certain questions. For example, participants who did not have experience with BI were excluded from certain questions. As a result, the number of responses varied between questions, with some having fewer responses than others. Despite this, the completion rate, defined as the percentage of participants who made it to the end of the survey, was 73,6%, indicating a strong level of engagement among the participants. Fifteen respondents did not progress beyond the demographic section of the survey. As these participants did not provide relevant data regarding their BI adoption, their responses have been excluded from the analysis.

The demographic profile of the survey respondents is, as depicted in Table A.1 in Appendix A, distributed across four size segments; S, M, L and XL. Seventeen organizations fall within the S segment, which are organizations providing care to less than 400 clients. Next, the M size segment, with 400 to 1000 clients, includes four organizations. Thirteen organizations are classified as size segment L, meaning organizations providing care to between 1000 and 2000 clients. Lastly, the XL size segment, with over 2000 clients per organization, comprises 38 organizations.

Organizations are also divided into six different sectors; VVT, GGZ, GHZ, Youth care, Multi-sector, and others. First, the VVT sector is, with 43 organizations, the best represented within the survey. This sector is seen across all size segments, with a high concentration in the XL segment. Next, the GGZ sector includes eleven organizations and is also represented across all size segments but with the majority in the XL segment. Comprising seven organizations, the GHZ sector shows a balanced distribution between the L and XL segments. The Youth care sector, Multi-sector and Other sector include four, four and three organizations, respectively, spread across the different size segments.

To streamline the analysis and facilitate clearer comparisons, the S and M size segments, as well as the L and XL segments, are grouped together in subsequent analyses. This grouping enables a more coherent examination of trends across organizations with comparable resource capacities and operational scales. Additionally, as the distribution of organizations within each sector varies substantially, there is an absence of substantial differences in BI usage or practices across sectors and, therefore, the analysis does not break down results by sector.

4.2 | Adoption of Business Intelligence

The survey revealed a high adoption rate of more than 80% of BI across Dutch long-term care organizations, with nearly all large organizations implementing BI, compared to less than half of smaller organizations, as shown in Table 4.1. This discrepancy underscores the resource and capacity differences across organization sizes. In larger organizations, around 60% reported having dedicated BI teams, often composed of multiple employees focused solely on BI. Conversely, in smaller organizations, none reported having a dedicated BI-team and these tasks are mainly handled by a limited number of staff, with one to six employees generating BI insights (Table A.2).

Organization	BI adoption	Dedicated BI-team
Large (L + XL = 1000+ clients) (N=51)	98% (50)	61% (31)
Small (S + M = 50-1000 clients) (N=21)	48% (10)	0%
Total (N=72)	83% (60)	43% (31)

Table 4.1: Organizations with BI adoption

BI tools

The presence of a dedicated BI-team influences BI tool selection, as depicted in Table 4.2. Organizations with dedicated BI-teams mostly utilize self-service BI tools like Power BI and QlikView to analyze data and generate insights, enabling more organization-specific visualizations and data management capabilities that contribute to better-informed decision-making processes. While half of the organizations without dedicated BI teams also use self-service tools, the remainder is more likely to acquire off-the-shelf tools like the Accordis Zorgmonitor, which provide more straightforward analytics solutions tailored to the general needs of the long-term care sector or a specific segment. A fifth of organizations in both groups uses a combination of both. This blended approach suggests that some organizations see value in leveraging the strengths of both types: using self-service tools for custom, high-level analytics, while relying on off-the-shelf solutions for more standardized or routine reporting.

Differences are also noticeable between large and small organizations. Among larger organizations, the majority prefers self-service BI tools, while less than a fifth rely exclusively on off-the-shelf solutions, and a fourth use a combination of both approaches. This suggests that larger organizations benefit from the flexibility of self-service tools, which allow for greater alignment with their unique operational and analytics needs. Smaller organizations exhibit a more balanced distribution: half uses self-service tools and 40% rely on off-the-shelf options, only a tenth employ a mix of both. This pattern reflects the resource constraints smaller organizations may face, where off-the-shelf tools provide an efficient and affordable means of gaining BI insights without the need for dedicated BI infrastructure or teams.

Organization	Self-service tools	Off the Shelf Tools	Both
Large (N=48)	60% (29)	15% (7)	25% (12)
Small (N=10)	50% (5)	40% (4)	10% (1)
Dedicated BI-team (N=30)	67% (20)	10% (3)	23% (7)
No dedicated BI-team (N=28)	50% (14)	29% (8)	21% (6)
Total (N=58)	59% (34)	19% (11)	22% (13)

Table 4.2: BI tool preferences

Applications of BI insights

As shown in Table 4.3, the application of BI insights shows little variation across organizations, in terms of organization size and the presence of dedicated BI teams. In large organizations, BI is largely applied in client-care analysis. Financial reporting, quality control and operational efficiency are also notable areas of application, suggesting a broad approach to BI across multiple functions. Smaller organizations, while also engaging BI for various functions, show slightly different patterns. Financial reporting is prioritized, which may reflect the focus on resource management in smaller institutions. Client-care analysis, operational efficiency and quality control are also present by in lower quantities, indicating that smaller organizations may have more targeted applications for BI, depending on available resources and organizational priorities.

Organizations with BI teams tend to have marginally higher usage across functions, with client-care analysis and quality control leading. This pattern suggests that BI teams may enhance the organization's ability to apply BI more comprehensively, especially in quality-related functions. Organizations without dedicated BI teams prioritize BI usage in client-care analysis and financial reporting, with significantly lower application in quality control, indicating a strong alignment of BI usage with core operational and financial oversight needs.

Organization	Client-care analysis	Financial reporting	Operational efficiency	Quality control
Large (N=50)	90% (45)	76% (38)	66% (33)	72% (36)
Small (N=10)	80% (8)	90% (9)	70% (7)	60% (6)
Dedicated BI-team (N=31)	94% (29)	77% (24)	65% (20)	84% (26)
No dedicated BI-team (N=29)	83% (24)	79% (23)	69% (20)	55% (16)
Total (N=60)	88% (53)	78% (47)	67% (40)	70% (42)

Table 4.3: Applications of BI insights

Frequency

The frequency with which organizations use BI insights varies significantly across both organization sizes, reflecting differences in the integration of data-driven decision-making processes. Larger organizations tend to use BI more consistently, with more than half incorporating it into their daily operations and another 40% using it weekly. This consistent application of BI suggests a proactive approach to leveraging analytics for enhanced decision-making and performance improvement. In contrast, smaller organizations use BI less frequently, with the vast majority relying on it weekly or monthly rather than on a daily basis. This indicates a more sporadic and potentially reactive approach to data analysis, where BI insights may not be fully embedded in the day-to-day management and operational processes.

Usage frequency differs even more in the presence of dedicated BI teams. Among organizations with dedicated BI teams, three-fourths reported daily usage of BI insights, almost a fifth weekly and only one monthly. Conversely, of organizations without dedicated BI teams, only a tenth utilize BI on a daily basis, while more than half rely on BI insights weekly and almost a fourth even monthly. This difference, shown in Table 4.4, suggests that the presence of a BI team leads to frequent, continuous access to data for decision-making and performance evaluation, while organizations with a BI team utilize BI insights on a more ad-hoc or periodic basis.

Organization	Daily	Weekly	Monthly
Large (N=50)	52% (26)	40% (20)	8% (4)
Small (N=10)	10% (1)	50% (5)	40% (4)
Dedicated BI-team (N=31)	77% (24)	19% (6)	3% (1)
No dedicated BI-team (N=29)	10% (3)	66% (19)	24% (7)
Total (N=60)	45% (27)	42% (25)	13% (8)

Table 4.4: Usage frequency of BI insights

Outsourcing

Most organizations reported some level of BI outsourcing, as displayed in Table 4.5. However, the level of BI outsourcing varies notably depending on whether an organization has a dedicated BI team. Among organizations with a dedicated BI team, the majority adopt a partially outsourced model where external providers are used to support BI operations, while core functions remain in-house. The rest of these organizations manage BI entirely internally, no organizations are fully outsourcing their BI functions. This suggests that dedicated BI teams enable organizations to maintain more control over their BI processes while utilizing external resources for support.

In contrast, organizations without a dedicated BI team demonstrate a greater reliance on external resources. While a similar percentages of organizations manage BI internally without external support, more than a fifth fully outsource their BI functions. Lastly, more than half partially outsourcing BI. This distribution highlights a varied approach to BI management when dedicated teams are not in place, potentially indicating limited in-house BI capacity or expertise in these organizations.

The level of BI outsourcing also varies by organizational size, with larger organizations demonstrating similar patterns to those with dedicated BI teams, partially outsourcing BI, leveraging external support for specific tasks while keeping core functions in-house. In contrast, smaller organizations show an almost even distribution across the three outsourcing approaches. They are most likely to fully outsource BI and equally likely to manage all BI internally or partially outsource.

Organization	**All Internal**	**Only Supportive**	**Completely Outsourced**
Large (N=50)	22% (11)	74% (37)	4% (2)
Small (N=10)	30% (3)	30% (3)	40% (4)
Dedicated BI-team (N=31)	23% (7)	77% (24)	0%
No dedicated BI-team (N=29)	24% (7)	55% (16)	21% (6)
Total (N=60)	23% (14)	67% (40)	10% (6)

Table 4.5: Level of outsourcing BI to business partners

Advanced Analytics

Advanced Analytics adoption remains relatively low across all organizations, as below shown in Table 4.6. Around 10% of both large and small organizations have adopted AA, but only 6% of large organizations have implemented Machine Learning, in contrast to none of the smaller organizations. Applications of AA are largely focused on use cases, such as risk management, prediction of healthcare outcomes and capacity/staff planning.

Similarly, in organizations with a dedicated BI team, 17% have adopted AA, and 10% have implemented ML. In contrast, organizations without a dedicated BI team show a lower adoption rate, with only one organization adopting AA and none implementing ML. This limited adoption suggests that while BI is increasingly utilized, the transition to more Advanced Analytics tools is still in its early stages.

Organization	**AA**	**ML**
Large (N=47)	11% (5)	6% (3)
Small (N=10)	10% (1)	0%
Dedicated BI-team (N=29)	17% (5)	10% (3)
No dedicated BI-team (N=28)	4% (1)	0%
Total (N=57)	11% (6)	5% (3)

Table 4.6: Advanced Analytics (AA) and Machine Learning (ML) adoption

4.3 | Data quality and infrastructure

Data quality

Data management practices differ considerably across organization sizes, as depicted in Table 4.7. In terms of data quality, large organizations report higher quality levels, with around two-fifths indicating high quality, more than half average quality, and only one organization reports low quality. In contrast, smaller organizations exhibit challenges in data quality, with ratings showing that only a little over a fifth have high-quality data, two-thirds have average quality, and a tenth report low quality.

The differences in data quality are supported by the reliance on the use of shadow systems, or non-standardized systems used for data handling outside official protocols. Larger organizations reported fewer shadow systems, with 55% indicating any reliance on such systems. In contrast, three-quarters of smaller organizations rely on shadow systems. Shadow systems were most commonly reported in financial administration, client and staff planning, and client and medical data management, highlighting the areas where data management challenges are most pronounced.

Organization	Quality rating	Use of shadow systems
Large (N=47)	High 43% (20), average 55% (26), low 2% (1)	55% (25)
Small (N=18)	High 22% (4), average 67% (12), low 11% (2)	76% (13)
Dedicated BI-team (N=29)	High 52% (15), average 48% (14), low 0%	52% (15)
No dedicated BI-team (N=26)	High 35% (9), average 65% (17), low 0%	62% (16)
No BI (N=10)	High 0%, average 70% (7), low 30% (3)	90% (9)
Total (N=65)	High 37% (24), average 58% (38), low 5% (3)	58% (38)

Table 4.7: Data quality: rating and use of shadow systems

Similarly, organizations with dedicated BI teams generally report higher data quality than those without. Over half of the organizations with dedicated BI teams rated their data quality as high, the other half reporting it as average, and none reporting a low data quality. These organizations also reported a lower reliance on shadow systems, with just over half indicating use of such systems. This is in stark contrast to organizations without a dedicated BI team, where only a third rated their data quality as high and almost two-thirds reported using shadow systems. Organization without BI adoption report an even lower data quality, with 70% rating their data quality as average and the other 30% as low. Of these organizations, only one reported not relying on shadow systems.

Data infrastructure

When examining the data infrastructure within organizations, clear differences are apparent based on organization size and the presence of dedicated BI teams, summarized in Table A.3 in Appendix A.

In terms of data infrastructure quality, larger organizations report a more robust infrastructure. An eighth of large organizations rate their infrastructure as high quality, while the majority rate it as fair, and around a third as moderate. In contrast, of small organizations almost half rates their infrastructure fair and the other half rates it moderate, with none reporting high-quality infrastructure. Looking at data accessibility, the trend is similar. Large organizations report higher accessibility. Smaller organizations, on the other hand, show a much lower percentage of high accessibility and a higher percentage reporting fair accessibility.

An explanation for these differences can be the reliance on manual copying of data between different IT systems. Among large organizations, only one reports copying data on a weekly basis, while a third do so monthly, and almost two-fifths rarely need to copy data manually. Additionally, a fourth report that they never manually copy data. For smaller organizations, a much higher proportion report more frequent manual copying: a fifth does so weekly, more than half monthly, and a tenth rarely.

When comparing organizations with and without dedicated BI teams, the differences in data infrastructure quality are even bigger. Organizations with dedicated BI teams report better infrastructure quality, with a fifth rating it as high quality compared to none of the organizations without BI teams. These organizations also report better accessibility, with 55% rating it highly, compared to only 15% among those without BI teams. Interestingly, these substantial differences are not observed in the frequency of manual data copying. While both groups report similar frequencies of manual data copying, more organizations without BI teams report that never engages in manual data copying.

Data storage

Organizations with dedicated BI teams demonstrate a more mature approach to data storage and integration as shown in Table 4.8. Among these, 65% have already established a central data storage solution, such as a data warehouse. Another 30% of these organizations reported having a central data storage system in development, while only 5% are still in the consideration phase. None reported having no plans for central data storage. This widespread use of centralized storage supports advanced data accessibility and integration, enhancing the organization's ability to generate consistent BI insights.

In contrast, organizations without dedicated BI teams are much less likely to have centralized data storage. Only 20% of these organizations have a data warehouse in place, with an additional 20% actively developing one, and 20% still considering it. Almost 40% of organizations without a BI team reported having no plans for a central data storage. This lack of centralization can hinder effective data analysis.

Similarly, of the organizations without BI adoption, only 20% has implemented a data warehouse. Additionally, 20% reported currently developing one and 30% considering it. Lastly, 30% of these organizations reported no plans for centralizing data storage.

Dedicated BI-team	**Fully operational**	**In development**	**In consideration**	**None**
Large (N=47)	51% (24)	28% (13)	11% (5)	11% (5)
Small (N=18)	11% (2)	22% (4)	22% (4)	44% (8)
Dedicated BI-team (N=29)	65% (19)	30% (9)	5% (1)	0%
No dedicated BI-team (N=26)	20% (5)	23% (6)	20% (5)	38% (10)
No BI (N=10)	20% (2)	20% (2)	30% (3)	30% (3)
Total (N=65)	40% (26)	26% (17)	13% (9)	20% (13)

Table 4.8: Data infrastructure: Central data storage adoption

When comparing organization size, similar differences can be identified. Larger organizations are more likely to have a data warehouse in place, with half reporting that they have a fully operational central data storage. In contrast, small organizations report a much lower adoption rate, with only one-tenth having a fully operational system. Moreover, nearly half of small organizations have no plans to improve their data storage, compared to just one-tenth of large organizations. This highlights the challenges smaller companies face in implementing centralized data storage due to limited resources or infrastructure.

4.4 | Organizational culture and competencies

Strategy

When looking into the BI strategy implemented within organizations, specifically focusing on management's understanding of the potential of BI, their willingness to invest in BI, and their encouragement of data-driven decision-making, there are only minor differences found between large and small organizations, as well as between those with and without dedicated BI teams, as displayed in Table A.4 in Appendix A.

Regarding management's understanding of the potential of BI and their willingness of management to invest in BI, both large and small organizations show similar distributions. In both categories, the majority of respondents rate their management's understanding of BI as fair, with only a small proportion assigning it either a moderate, high or low rating. However, respondents from larger organizations tend to be slightly less optimistic, which may be attributed to the more complex hierarchical structures and reduced autonomy in bigger organizations. A similar pattern is observed when considering the presence of a dedicated BI team.

The most significant difference appears in management's encouragement of data-driven decision-making. Organizations with dedicated BI teams rate this much higher, with 17% marking it as high, compared to none of the organizations without dedicated BI teams. This suggests that dedicated BI teams help foster a culture of data-driven decision-making. Both large and small organizations show similar trends, where smaller organizations rate management's encouragement slightly lower.

Training

Across both large and small organizations, there is a trend toward infrequent BI-related training. As shown in Table 4.9, many respondents indicate that these events occur rarely or never. However, large organizations reported slightly more regular training, with an eighth conducting BI training at least once a year and almost a third every two years. In contrast, of smaller organizations, a third indicated rarely having BI training and the other two-thirds reported never having training sessions.

The presence of a dedicated BI team also correlated with slightly higher training frequency. Half of the organizations with dedicated BI teams provide BI-related training either annually or every two years. In contrast, organizations without a dedicated BI team mostly reported rarely or never having such training, indicating that in these environments, BI knowledge may not be as systematically updated or emphasized.

Organization	Once a year	Once 2 years	Rarely	Never
Large (N=46)	13% (6)	28% (13)	35% (16)	24% (11)
Small (N=9)	0%	0%	67% (6)	33% (3)
Dedicated BI-team (N=29)	21% (6)	35% (10)	31% (9)	14% (4)
No dedicated BI-team (N=26)	0%	12% (3)	50% (13)	38% (10)
Total (N=55)	11% (6)	24% (13)	40% (22)	25% (14)

Table 4.9: Training or courses related to BI

Organizational coverage

In examining the application of BI insights, it is notable that organizations with dedicated BI teams apply BI across a wider range of departments: all report using BI in management (MGMT), administration, and finance, almost 90% in coordinating care, and almost 40% also in direct care tasks. In contrast, organizations without dedicated BI teams tend to limit BI use to management and administrative functions, with less than half extending BI to coordinating care and only a fifth applying it in direct care. This difference, depicted in Table 4.10, suggests that dedicated BI teams facilitate broader BI integration, allowing insights to reach into care-related functions beyond administrative oversight.

Large organizations similarly report broader BI usage across departments. All large organizations utilize BI within management, and almost all apply it in administration and finance. A substantial portion also extends BI to coordinating care, although BI use in direct care remains more limited, around a third. Of small organizations, while also consistently using BI in management and finance, only half reports using BI application in coordinating care, and even only one in direct care.

Organization	MGMT	Administration/ Finance	Coordinating Care	Executing Care
Large (N=50)	100%	94% (47)	76% (38)	34% (17)
Small (N=10)	100%	90% (9)	50% (5)	10% (1)
Dedicated BI-team (N=31)	100%	100%	87% (27)	39% (12)
No dedicated BI-team (N=29)	100%	86% (25)	45% (16)	21% (6)
Total (N=60)	100%	93% (56)	72% (43)	30% (18)

Table 4.10: Organizational coverage

Future plans

As shown in Table 4.11, both organization size and the presence of a dedicated BI team appear to influence the timeline but do not significantly alter the shared priority for advancing BI capabilities in the near future. The majority of organizations, both large and small, indicate plans to expand BI usage within the next two years, demonstrating a shared commitment to growth in BI capabilities. However, large organizations show a slightly stronger inclination toward a quicker expansion, with almost half planning to expand BI within the next year compared to a third of smaller organizations.

When comparing organizations with and without dedicated BI teams, those with dedicated teams show a modestly higher inclination to expand BI within the next year, reflecting their likely readiness and resources for quicker implementation. Organizations without a BI team also show significant interest, albeit with a slightly higher percentage planning for expansion within a two-year period rather than one year, possibly indicating a more gradual approach.

Organization	Within 1 year	Within 2 years	Within 5 years	No plans
Large (N=38)	45% (17)	39% (15)	8% (3)	8% (3)
Small (N=6)	33% (2)	67% (4)	0%	0%
Dedicated BI-team (N=23)	48% (11)	39% (9)	9% (2)	4% (1)
No dedicated BI-team (N=21)	38% (8)	48% (10)	10% (1)	5% (2)
Total (N=44)	43% (19)	43% (19)	7% (3)	7% (3)

Table 4.11: Future plans to expand BI adoption

Chapter 5

Framework development

The previous chapter explored the current state and trends regarding analytics adoption in the Dutch long-term care sector. It was revealed that while BI adoption is growing, there is also a clear divide between larger and smaller organizations. Larger organizations typically have dedicated BI teams, advanced tools, and better data management practices, leading to higher data quality and more frequent use of BI insights. Smaller organizations, constrained by resources, rely on simpler tools and external support. Despite these differences, both groups express a strong intention to expand BI usage, highlighting the need for guidance to achieve higher maturity in data-driven decision-making.

In this chapter, the design and development of a structured approach to analytics maturity in long-term care organizations is presented. It begins with the development of the Care Analytics Maturity Model (Section 5.1), which defines key dimensions and maturity levels tailored to the unique challenges and opportunities in long-term care. Next, the chapter introduces the Care Analytics Adoption Roadmap (Section 5.2), a step-by-step guide for organizations to progress toward a high analytics maturity.

5.1 | Maturity model

While existing maturity models (Section 3.4) address critical aspects such as data management, technology, and people, they are not entirely applicable to the long-term care sector due to its unique needs and priorities. To address this gap, a new maturity model will be developed. As described in Section 2.4.1, the development of the maturity model combines the literature of these existing models and the findings of the data analysis (Chapter 4) to determine the dimensions and levels of the new maturity model. The third section (Section 5.1.3) provides a detailed description of the proposed model. The model is reviewed by colleagues with expertise in analytics in long-term care.

5.1.1 Identifying relevant dimensions

The maturity model will consist of three key dimensions: Technology, Data, and Organization. These dimensions assess the organization's ability to implement BI across its infrastructure, data management, and organizational structure. Each dimension, also depicted in Figure 5.1, will be divided into sub-dimensions that focus on specific aspects necessary for achieving maturity in BI implementation.

Technology

The first dimension will be Technology and evaluates the technical infrastructure that supports BI implementation. As the literature review highlights, modern care organizations benefit significantly from using advanced technologies. These technologies enable faster decision-making, improved operational efficiency, and potential cost savings. Additionally, multiple maturity models, including those of Brooks et al. (2015) and Silva et al. (2022), emphasize the importance of technological infrastructure. Several key technological elements are also discussed in 'Adoption of Business Intelligence' of the data analysis.

Technology will include three sub-dimensions, EHR systems, BI functionalities and Integration. The first sub-dimension, EHR systems assesses the use and integration of EHR systems in BI processes. Organizations move from no EHR usage to full integration of all healthcare applications, where data is used coherently in real-time BI analysis. Next, the BI functionalities sub-dimension measures the adoption of BI, ranging from basic BI like ad-hoc analysis and descriptive analytics to Advanced Analytics that use AI and ML for predictive or prescriptive analytics. The final sub-dimension, Integration, focuses on the integration of various other IT systems, such as CRM or HRM, into BI processes. Organizations progress from isolated system usage to seamless, coherent integration of data of all relevant IT systems within BI platforms.

Data

The second dimension will be Data and assesses how long-term care organizations collect, manage, and secure their data. As healthcare becomes increasingly data-driven, the ability to store, process, and ensure the quality of data is critical for BI maturity. Data integrity, security, and semantics are paramount, especially in sensitive healthcare environments. Data is also observed in some existing maturity models, like the one of Stoldt et al. (2019) and relates to the 'Data quality and infrastructure' section of the data analysis.

Data will have two sub-dimensions, Data quality and Data infrastructure. The sub-dimension Data quality assesses how the organization manages the accuracy, consistency, and reliability of its data. Organizations evolve from fragmented, manually maintained data to automated, real-time quality monitoring and implementation of semantic standards to ensure data consistency and interoperability across systems. In addition, Data infrastructure, the second sub-dimension, focuses on the architecture and systems that store, process, and secure data. Organizations mature from using manual, disconnected systems to having a fully integrated, scalable, and automated data infrastructure with robust security measures.

Organization

The last dimension, Organization, relates to the cultural and structural readiness of the organization to adopt BI practices. As the literature review emphasizes, successful BI adoption requires more than just technology. It also requires alignment of people, processes, and leadership. Therefore, the mindset, strategy and data-driven encouragement of management, and the gathering of knowledge, are key elements of this dimension, which are also covered in the 'Organizational culture and competencies' section of the data analysis. Multiple maturity models, including those of Brooks et al. (2015) and Gastaldi et al. (2018), also include an organizational dimension.

The sub-dimensions within Organization will include Strategy, Skills & training, and Organizational coverage. The Strategy sub-dimension evaluates the organization's culture and financial commitment to BI. Organizations move from little to no BI awareness or budget to a fully embedded BI culture with strong leadership support. Next, Skills & training, the second sub-dimension, assesses the availability of BI-related skills and training within the organization. As organizations mature, they provide comprehensive training to ensure employees at all levels can utilize BI tools effectively. The final sub-dimension, Organizational coverage, focuses on the extent of BI usage across the organization. The maturity journey begins with BI use limited to a small group, such as management or other BI enthusiasts within the organization, and expands to all relevant employees, including frontline care providers, using BI in their daily tasks.

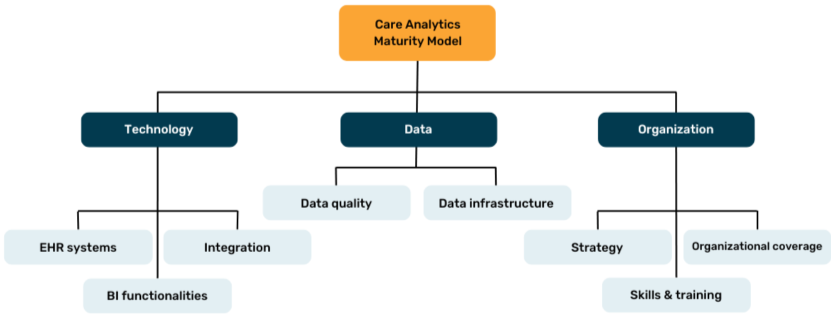

Figure 5.1: The dimensions of the Care Analytics Maturity Model

5.1.2 Identifying maturity levels

In Table A.5 to be found in Appendix A, the maturity levels from five maturity models mentioned in Section 3.4 are shown. The other three models are not mapped as their levels are not named but range from 0 to 3, 1 to 5 and from 0 to 5. It is interesting to see that although the dimensions of these models are divergent, the levels are similar. One big difference is that some maturity models start at level 0, the other starts at level 1. Level 0 implies that there are no initiatives to realize analytics yet. Additionally, the number of levels differ, some only have four levels, others have seven or even nine.

For the Care Analytics Maturity Model, a maturity scale from 0 to 4 with sequential stages will be used. Level 0 will be included, as it is important to have a starting point for organizations that have not started with analytics. Five levels provide a sufficient number of stages to capture meaningful differences in maturity, without being overly granular or difficult to assess. Table 5.1 shows a complete overview with a description of the levels.

Level	Description
0 | Non-existent	No analytics.
1 | Initiating	Basic BI use; initial awareness, limited tools.
2 | Enabling	Early analytics projects, initial integrations.
3 | Managing	Analytics integrated across departments; advanced analytics emerging.
4 | Transformative	Fully integrated, real-time, advanced analytics driving innovation.

Table 5.1: The maturity levels of the Care Analytics Maturity Model

Each dimension and sub-dimension in the maturity model follows the same five-level scale. This consistency ensures that the assessment is straightforward and comparable across all aspects of the organization's maturity. By using the same number of levels for all sub-dimensions, it becomes easier to track progress and identify areas that need improvement in each specific area, whether it's technology, data, or organizational readiness.

While the maturity model uses the same five levels for all dimensions and sub-dimensions, it is not necessary for all sub-dimensions to be at the same level during the assessment. Different aspects of the organization may mature at different rates, and this should be reflected in the model. The model allows for these asymmetries, acknowledging that organizations may not progress uniformly across all sub-dimensions. This flexibility enables a more accurate and realistic reflection of an organization's true maturity.

However, while different dimensions and sub-dimensions may progress at varying rates, the sub-dimensions within each of the three dimensions are highly interrelated. Advances in one sub-dimension can drive progress in others, making a holistic approach essential for organizations aiming to improve their analytics maturity. For instance, improvements in data infrastructure can facilitate better data quality, while advancements in organizational strategy can help ensure broader adoption and usage of BI across the organization. This interdependency highlights the need for a coordinated, multi-dimensional approach to BI maturity.

5.1.3 Care Analytics Maturity Model

The maturity of BI in long-term care can be assessed using a structured model, shown in Table 5.2, that categorizes its development across five distinct levels, incorporating the dimensions of technology, data, and organization. Each level represents a progression in the organization's capacity to utilize BI for improved decision-making, operational efficiency, and patient outcomes.

At Level 0, the organization lacks any formal BI adoption. There is no integration of data from the EHR system and other IT systems, and no data platforms. Data is manually managed, scattered across various silos, and often stored in shadow systems like spreadsheets. There is no focus on data quality, no formal policies for data management, and the organization operates with little to no awareness of the potential of BI. Decision-making is based on intuition and experience rather than data-driven insights, with no budget or organizational support for BI.

At Level 1, BI activities start to emerge in isolated pockets of the organization. Basic BI is used for personal or ad hoc analysis, often driven by immediate needs or specific departments. There is limited integration, with EHRs or other IT data analyzed separately. Data quality issues persist, with manual processes and shadow systems still playing a significant role. Organizational awareness of BI is limited to a few key individuals, and there is little to no coordination across departments. Any insights gained are inconsistent and difficult to scale across the organization. The organization recognizes the potential of BI but lacks the strategic approach and infrastructure to support broader implementation.

At Level 2, the organization begins to formalize its approach to analytics. Descriptive BI is introduced to facilitate data visualization and reporting. Initial integration efforts between EHR and other IT systems are made, but many systems still function in silos. There is a growing focus on data quality and infrastructure, with some centralized platforms emerging to reduce reliance on shadow systems. BI initiatives are piloted in specific areas, often driven by individual departments or teams, but a cohesive strategy is still lacking. Data governance processes are under development, and the organization is beginning to provide formal training on BI tools to key staff. The mindset shifts toward recognizing the strategic value of analytics, and a budget is allocated for initial projects and tools.

At Level 3, analytics is embedded in more structured and strategic ways. The organization integrates data from multiple systems, including EHR and other IT platforms, to enable real-time data analysis. Diagnostic BI is introduced to help identify trends and patterns and BI tools are used coherently across departments, supporting cross-functional decision-making. Data quality governance is established, and data is consolidated into a centralized infrastructure with automated validation and cleansing processes. Shadow systems are mostly eliminated, and the organization leverages data to drive decision-making at all levels. Leadership actively supports analytics, allocating a dedicated budget and ensuring that training and tools are provided across the organization. Analytics is used widely in clinical, operational, and financial departments, and decision-making becomes more data-driven.

At Level 4, analytics is fully integrated into all aspects of the organization's operations. Data of all company-critical IT systems are linked, enabling seamless real-time data flow and supporting Advanced Analytics such as predictive and prescriptive models. Data quality processes are automated, and the infrastructure is scalable, supporting high-level analytics and continuous improvement. The organization operates with a data-driven culture, where all relevant employees, from management to frontline caretakers, use BI tools to inform their daily decisions. Advanced training programs ensure data literacy across the workforce, and leadership fully backs BI initiatives with significant financial and operational support. Analytics not only informs decision-making but also drives innovation, with measurable improvements in patient outcomes and organizational efficiency.

This five-level model provides a clear overview for care organizations to determine their analytics capabilities, from no analytics to a fully integrated, data-driven environment. The tables A.6, A.7, and A.8 in Appendix A show a more detailed outline of the subdimensions and maturity levels defined for each of the three dimensions.

By assessing analytics maturity through this model, companies can identify areas for improvement in data management, technology, processes, people, and culture. Advancing through the maturity levels enables organizations to better leverage their data, enhance decision-making, and drive overall business performance, positioning them for sustained competitive advantage in an increasingly data-centric world.

Maturity level	Technology	Data	Organization
Level 0 | Non-existent	No analytics; manual systems for managing data. No EHR system or integrations.	Fragmented, inconsistent data; heavy use on shadow systems (e.g. spreadsheets). No centralized data infrastructure.	No awareness or support for BI. No budget, skills, or training. Decision-making is entirely intuition-based, no BI usage at any organizational level.
Level 1 | Initiating	Use of isolated and ad-hoc analysis. Partial use of EHR or other IT systems, no integration with each other.	Minimal control over data quality. Lots of data stored in shadow systems; manual copying between systems. Basic infrastructure with disconnected systems.	Limited BI awareness; minimal budget and skills. BI is confined to a small group, such as upper management or other BI enthusiasts within the organization enthusiasts. No training or organizational support.
Level 2 | Enabling	Introduction of descriptive BI used for data visualization and reporting. Some integration between EHR and IT systems.	Initial data quality and integration efforts. Shadow systems persist in some areas. Centralized data platforms emerging.	Growing recognition of BI's value. Budget allocated for tools and projects. Irregular training sessions, extending use of BI to middle management and select departments.
Level 3 | Managing	Multiple systems integrated for real-time data analysis. Diagnostic BI together with EHR and other data from IT systems like CRM/HRM used coherently in cross-functional decision-making.	Formal data governance and quality processes. Most systems integrated into a centralized infrastructure with automated data validation. Manual processes largely eliminated.	BI becomes strategic. Dedicated budget and leadership support. Training is widespread across departments. BI usage expands to clinical, operational, and financial teams.
Level 4 | Transformative	Full integration of all relevant IT systems and advanced BI tools (AI/ML). Real-time data enables predictive and prescriptive analytics.	Continuous data quality monitoring with real-time validation. Fully automated, scalable infrastructure supporting real-time analytics from all sources.	BI is embedded in the culture. All relevant employees, including caretakers, use BI in their daily tasks. Advanced training and data literacy are core competencies for everyone.

Table 5.2: Care Analytics Maturity Model

5.2 | Roadmap

With the help of the new Care Analytics Maturity Model, organizations can assess their current maturity. However, the goal is to determine the required steps and challenges for long-term care organizations to reach a higher maturity. Therefore, this section discusses the development of a roadmap that guides organizations to a higher state of analytics. As described in Section 2.4.2, the findings of the data analysis and the Care Analytics Maturity Model are combined to determine the steps of the new roadmap.

5.2.1 Identifying relevant steps

The Care Analytics Adoption Roadmap will consist of four steps, as shown Table 5.3. Additionally, the roadmap has been given an iterative approach as it is important for organizations to continuously improve their processes.

In the first step, the maturity of the organization is assessed. The organization uses the developed maturity model to get a valuable overview of the as-is situation for each of the (sub-)dimensions.

The second step will cover defining the target state and implementation strategy. The developed maturity model can also be leveraged here to define the future direction. The goal can be to improve a single process or improve the maturity of a specific department, division or whole organization. In addition, the organization should make a clear strategy to achieve this goal.

The third step is the implementation phase, which focuses on the processes needed to bridge the gap between the current and target states. The approach will vary based on the organization's unique needs but will address at least one of the three key dimensions; technology, data, and organization. This step is flexible and customizable, allowing the organization to prioritize and tailor these elements according to its specific context and target goals.

The last step is where the approach and implemented solution will be evaluated. The organization identifies all challenges and limitations experienced during any of the steps. In addition, they examine if the solution improved the maturity.

Steps	Description
1	Initial maturity assessment
2	Defining of target state and strategy
3	Implementation phase; tailored to target goals
4	Evaluation of approach and implemented solution

Table 5.3: The steps of the Care Analytics Adoption Roadmap

5.2.2 Care Analytics Adoption Roadmap

Initial maturity assessment

The first step in the Care Analytics Adoption Roadmap is to assess the maturity of the organization using the Care Analytics Maturity Model. This step provides a comprehensive baseline of the current state by evaluating the organization's practices, processes, technologies, and culture in relation to analytics.

The maturity model is a structured framework that helps organizations understand their capabilities in various (sub-)dimensions. By mapping the organization's current practices against defined maturity levels, stakeholders can gain insights into where they stand in terms of their analytics journey. It identifies areas that are performing well and those that require improvement. The maturity model also highlights the organization's readiness for adopting more Advanced Analytics techniques, helping to pinpoint gaps in skills, technology, processes, and infrastructure.

To gain a holistic perspective, the maturity assessment should involve multiple employees across different levels and departments of the organization. By incorporating diverse viewpoints, organizations can identify areas of agreement, variability, and potential blind spots. The results should be discussed collaboratively and agreed upon to provide a well-rounded representation of the current state, ensuring a balanced and comprehensive understanding of maturity.

Once the maturity assessment is complete, the organization should have a clear understanding of its existing analytics capabilities and challenges. It provides a benchmark for measuring progress and serves as a basis for setting realistic goals for the subsequent phases.

Defining target state and strategy

The second step in the roadmap is focused on defining the target state and implementation strategy. After gaining an understanding of the organization's current maturity level, the next phase involves outlining where the organization wants to be. This step is crucial for aligning leadership and team members with a shared vision, ensuring that the adoption of analytics moves forward with a common purpose.

The Care Analytics Maturity Model, which was used to assess the organization's current state, can also be leveraged in this phase to define the future direction. Organizations must set clear, measurable goals based on their assessment. For example, if the assessment revealed that the organization's data management practices were in the early stages, a goal might be to enhance data governance or implement an enterprise-wide data platform.

When defining targets, it is essential to recognize that the goal does not need to be achieving the highest maturity level in all areas. If the maturity assessment in the first step reveals imbalances across (sub-)dimensions, a good goal might be to aim for a more balanced maturity level, ensuring functionality and alignment without introducing unnecessary complexity.

For organizations beginning their BI adoption journey, the initial focus should be on identifying the desired analytics functionalities rather than specific tools. This ensures that technological decisions are guided by the organization's actual needs rather than by prevailing market trends. Next, it's crucial to determine if data quality and infrastructure must improve to effectively leverage analytics. Gaps in data accuracy, completeness, or governance must be addressed to ensure meaningful insights. Lastly, the organization must assess which parts of the organization should improve to maximize analytics' effectiveness.

Overall, this phase establishes the to-be state for the organization's analytics capabilities and provides a well-defined strategy to get there.

Implementation

Once the target state is defined, the next step involves the implementation of processes, technologies, and/or organizational changes needed to bridge the gap between the current and target states. This is where the real work of transformation takes place. The implementation phase is crucial for turning the strategy into tangible results, and it requires careful planning and coordination.

Depending on the defined target state, the implementation phase has the focus on one or more of the three key dimensions:

- **Organization**: To make real changes, people, processes, organizational structures and culture should be aligned. Therefore, it is important to first create awareness and support throughout the organization. Management and employee engagement is a critical factor to the success of change. In addition to having an open mindset regarding analytics, it is crucial that all parties are digitally and analytically educated and have the right decision-making skills.

  This focus on education and skill-building should not end after implementation. Employees should also be educated frequently to ensure their BI knowledge remains up to date. This applies both to those generating analytics (e.g., data analysts or engineers) and those using analytics for decision-making, enabling the organization to stay agile and competitive in an evolving landscape.

- **Data**: Data is the foundation of analytics, and next, the organization must address data quality, governance, and accessibility. Processes must be established to ensure that data is clean, accurate, and easily accessible to those who need it. This might involve enhancing data collection methods, improving data integration across departments, or implementing a centralized data repository that allows for an unified view of organizational data.

  This focus on data quality also continues after implementation. Ongoing monitoring is essential to maintain high standards. Quality control dashboards are an effective tool for tracking and ensuring data quality over time, enabling organizations to identify and address issues promptly.

- **Technology**: Lastly, the technology infrastructure might need to be upgraded to support more Advanced Analytics capabilities. This might involve implementing new BI platforms, integrating more IT systems, or adopting more advanced tools, such as AI and machine learning, for data visualization and predictive analytics. The technology solution should be scalable and flexible, supporting the future growth and evolving needs of the organization.

This phase is customizable, allowing organizations to prioritize the areas most critical to achieving their target state. For example, a company might choose to focus on technology upgrades initially or may prioritize organizational changes if the current workforce lacks the necessary analytics skills. Flexibility and adaptability are key in ensuring that the organization can tailor the implementation to its specific context and goals.

The implementation phase also includes detailed project management, resource allocation, and time management to ensure that the strategies are executed efficiently. Clear communication channels and regular progress reviews will help in addressing challenges and making any necessary adjustments.

Evaluation

The final step in the Care Analytics Adoption Roadmap is the evaluation phase, which focuses on assessing the outcomes of the implementation and identifying areas for further improvement. This step is essential for ensuring that the adopted strategies and solutions have been effective and that the organization is progressing toward its desired target state.

The organization should evaluate whether the implemented solutions have successfully improved its maturity. This can be done by revisiting the Care Analytics Maturity Model and assessing the progress made. Additionally, the organization must review the challenges faced during the implementation phase. Therefore, it is important to gather feedback from key stakeholders within the organization. This feedback can provide valuable insights into the effectiveness of the implementation and highlight areas that may need further attention.

The evaluation step is not the end of the process; it feeds into an ongoing cycle of continuous improvement. Based on the insights gained from the evaluation, the organization should identify areas for further optimization. Maturity is not a static achievement but a dynamic journey. Continuous efforts to reassess and refine the strategies and solutions are necessary to maintain and advance maturity levels over time. Without regularly checking, reflecting, and improving, there is a risk that the organization may regress in its maturity. Without ongoing attention, initial progress could be lost, and the organization may experience a decline in its capabilities over time.

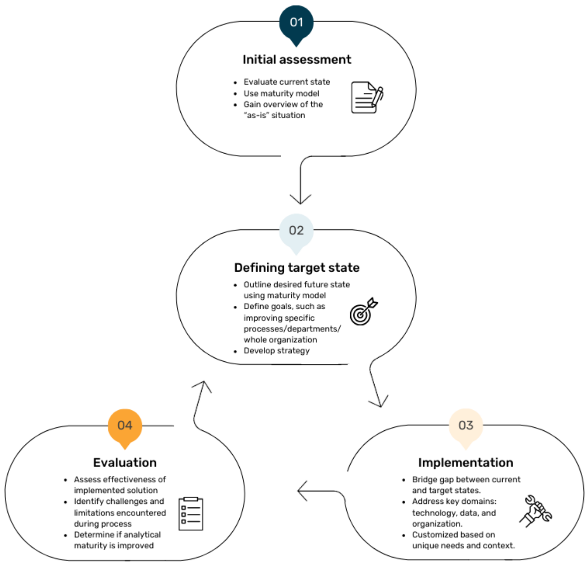

Figure 5.2: Care Analytics Adoption Roadmap

5.2.3 Guidelines for implementation

As previously mentioned, the implementation of analytics strategies varies depending on the organization's current maturity level. The following examples highlight how organizations at different maturity levels might approach their analytics implementation, considering their unique contexts and needs. These examples include four maturity levels, as well as three instances of mixed maturity. In each case, technology is assumed to be the highest maturity domain, as it is often the most developed within organizations. However, it should be noted that other variations of mixed maturity are also possible.

Early maturity (Non-existent)

- **Assessment outcome:** Organizations at this level have no formal BI systems in place. Data is largely fragmented and stored in shadow systems such as spreadsheets, and there is no central data infrastructure. The organization lacks awareness of the value of analytics, and no formal leadership support or budget is allocated for analytics.
- **Target state:** To begin the journey toward data-driven decision-making by raising awareness and developing basic BI practices.
- **Implementation strategy:**
  - Focus on educating leadership and key stakeholders about the potential benefits of analytics.
  - Begin formulating KPIs to create measurable goals.
  - Start basic data collection efforts, even if this means manually consolidating data from disparate sources.
  - Begin establishing the foundations for a centralized data infrastructure, perhaps by exploring low-cost or simple BI tools.
  - Introduce ad-hoc reporting and visualization to demonstrate the value of data-driven insights to upper management.
  - Start small pilot projects with data quality improvement efforts, like basic data cleansing and documentation of data sources.

Low maturity (Initiating)

- **Assessment outcome:** Organizations at this level may have isolated BI activities and limited EHR or IT system integration. Data quality control is minimal, and data is still largely stored in separate systems. There may be some recognition of analytics' value but no dedicated strategy and limited skills across the organization.
- **Target state:** To formalize basic data governance and begin integrating some key systems for more coherent analysis.
- **Implementation strategy:**
  - Promote analytics awareness throughout the organization with targeted training for upper management and select departments.
  - Begin with small-scale efforts to integrate some data sources, like EHR systems, and focus on manual reporting and visualization.
  - Introduce basic data governance processes, ensuring that there is more structure around data storage and quality.
  - Provide training to a select group of employees to improve their analytics skills.
  - Invest in a small but scalable BI tool to support descriptive analytics and history reporting.

Intermediate maturity (Enabling)

- **Assessment outcome:** At this stage, organizations are working on integrating more IT and EHR systems into their analytics efforts. Data quality has started to improve, and a centralized data platform may be emerging. Organizationally, there is growing recognition of analytics' value, with some budget allocated for tools and projects. Analytics is spreading beyond upper management into middle management and specific departments.
- **Target state:** To standardize and expand the integration of data and improve organizational readiness to handle analytics across multiple departments.
- **Implementation strategy:**
  - Enhance data integration by linking more IT systems (e.g., CRM, HRM) with EHR data to enable cross-functional decision-making.
  - Continue building a centralized data infrastructure and implement more structured data governance processes.
  - Introduce advanced BI tools to improve data visualization and reporting capabilities, such as descriptive analytics.
  - Expand analytics training across middle management and some departments, ensuring that more employees have basic skills.
  - Foster collaboration across departments to ensure that BI efforts align with organizational goals.

High maturity (Managing)

- **Assessment outcome:** Organizations at this level have integrated most IT systems with BI tools, and data governance and quality processes are formalized. Data is centralized and automated, and the organization is moving towards real-time analytics. BI is becoming a strategic part of the organization, with a widespread culture of BI usage across departments.
- **Target state:** To further mature data governance practices, implement real-time analytics, and build organizational support for continuous analytics usage and expansion.
- **Implementation strategy:**
  - Fully integrate all IT systems with BI tools for real-time, data-driven decision-making.
  - Implement Advanced Analytics such as diagnostic and predictive models, leveraging AI and machine learning for deeper insights.
  - Further enhance data governance with automated data validation, monitoring, and ensuring that security protocols are robust.
  - Continue to expand training efforts to cover all levels of the organization, ensuring that all employees have advanced analytics and data literacy skills.
  - Create a data-driven culture where analytics is embedded into everyday tasks across departments, from operational to financial teams.

Mixed maturity: high Technology, low Data & Organization

- **Assessment outcome:** This organization has implemented advanced BI tools and integrated many of its IT systems, creating a solid technological foundation. However, the data quality and governance processes are still underdeveloped, and the organization has not yet developed widespread analytics skills or a strong organizational support structure for analytics.
- **Target state:** To build data governance processes and expand analytics skills across the organization to fully leverage the technological investments.
- **Implementation strategy:**
  - Focus on improving data quality by introducing data governance frameworks and establishing processes for automated data validation.
  - Invest in centralizing data infrastructure and creating an unified data platform to ensure that the advanced BI tools can fully function across all systems.
  - Expand BI training efforts to ensure that both middle management and operational teams develop the skills needed to use advanced BI tools.
  - Promote organizational awareness of analytics' strategic value to foster leadership support and allocate the necessary budget for training and data quality improvement.
  - Initiate small-scale analytics projects in departments with lower maturity to demonstrate the value of analytics and gain buy-in across the organization.

Mixed maturity: high Technology & Organization, low Data

- **Assessment outcome:** This organization has implemented modern BI tools and established a high level of technological integration across various systems. The organization is highly supportive of analytics, with leadership backing and widespread skills training in place. However, the data quality is inconsistent, and fragmented data from shadow systems remain, undermining the effectiveness of the BI tools.
- **Target state:** To improve data governance and quality to align with the organization's high level of technology and organizational readiness for analytics.
- **Implementation strategy:**
  - Begin by conducting a comprehensive data quality audit to assess the current state of data across all departments and identify areas for improvement.
  - Implement strong data governance frameworks to centralize and standardize data, eliminating shadow systems.
  - Invest in data cleaning and validation tools that can be integrated with the existing BI tools to ensure high-quality data is used for analysis.
  - Provide focused training on data management and quality control for employees to ensure consistency in data practices.
  - Enhance BI tools by integrating data validation mechanisms to prevent the use of poor-quality data and ensure actionable insights.

Mixed maturity: high Technology & Data, low Organization

- **Assessment outcome:** The organization has advanced BI tools and a high level of technological integration. Data quality is consistent, and the infrastructure is robust with high security. However, BI tools are primarily used by a small group of BI enthusiasts, and there is a lack of organizational support, as management doesn't yet see the full value of BI.
- **Target state:** To drive broader organizational adoption of BI by securing leadership support, aligning BI efforts with strategic goals, and promoting analytics usage across all departments.
- **Implementation strategy:**
  - Engage leadership in understanding the strategic value of analytics by showcasing successful use cases and potential ROI through pilot projects.
  - Develop a clear organizational analytics strategy that aligns with overall business objectives, emphasizing the importance of data-driven decision-making.
  - Expand analytics usage beyond the "enthusiast" groups by providing department-specific training and support to increase analytics adoption at all levels.
  - Introduce formal data governance and support mechanisms to ensure consistency, facilitate cross-departmental collaboration, and eliminate silos.
  - Foster a culture of data literacy by offering ongoing training programs and making BI tools more accessible to non-technical staff.

Chapter 6

Framework validation

To achieve a high maturity, the previous chapter presented the Care Analytics Adoption Roadmap that aligns with organizational goals and addresses sector-specific challenges. It incorporates a comprehensive assessment of the current maturity level using a tailored Care Analytics Maturity Model, emphasizing technology, data, and organizational readiness.

This chapter presents the validation of these frameworks (Section 2.5) and is organized in three sections. The first section outlines the validation process (Section 6.1), including the protocol, criteria, participant selection, and interview design. The next section presents the findings from the validation (Section 6.2), discussing insights on both the maturity model and the roadmap. The third section summarizes the key takeaways (Section 6.3), highlighting the strengths of the frameworks and identifying opportunities for improvement to refine and enhance their applicability. The last section shows the refinement of the frameworks (Section 6.4), building upon the insights and feedback presented in the preceding sections.

6.1 | Validation process

6.1.1 Validation protocol

The validation process follows a four-step protocol, focusing on collecting detailed feedback from experienced professionals through semi-structured interviews. The protocol is structured as follows:

1. **Preparation**: The participant receives the maturity model and roadmap in advance and is asked to read through and evaluate them based on the validation criteria in the next section.

2. **Evaluating the maturity model**: During the interview, the participant is asked to provide comments, insights, and recommendations for improvement for the maturity model, based on their experience and perspectives.

3. **Evaluating the individual steps of the roadmap**: Again, the participant is asked to provide comments, insights, and recommendations for improvement but to each step of the roadmap and also to reflect on how the roadmap could be applied within their organization.

4. **Evaluating the complete roadmap**: The participant is asked to reflect on the roadmap as a whole, focusing on its theoretical foundation, practicality, and potential effectiveness.

This multi-step validation process was designed to ensure a comprehensive evaluation of both the maturity model and the roadmap. By including preparation, step-by-step analysis, and holistic review, the protocol ensures that participants could provide meaningful insights into specific elements and the frameworks as a whole. The structured yet flexible approach allowed participants to focus on predefined areas while also highlighting any unexpected issues or strengths, thereby enhancing the depth and rigor of the validation process.

6.1.2 Validation criteria

To guide the validation process, five evaluation criteria were selected to provide a balanced evaluation of the maturity model and roadmap: relevance, completeness, and clarity, which address their theoretical robustness, and usability and applicability, which focus on their practical utility.

- **Relevance**: The extent to which the model and roadmap address the key problems and needs of the target audience in the long-term care sector.
- **Completeness**: The inclusion of all necessary dimensions and aspects critical to a comprehensive maturity model and roadmap.
- **Clarity**: The degree to which the levels and dimensions of the model, as well as the steps of the roadmap, are clearly defined and easy to understand.
- **Usability**: The practicality and ease of applying the framework in real-world scenarios.
- **Applicability**: The adaptability of the model and roadmap to diverse organizational settings, including variations in size, complexity, and maturity.

Together, these criteria provide a comprehensive foundation for assessing the effectiveness and impact of the proposed frameworks.

6.1.3 Participants

Participants were selected based on their expertise and job roles in the BI domain within the long-term care sector. The participants included BI developers, managers, and consultants, representing a range of perspectives and organizational contexts.

The validation involved eight participants from four different organizations. These participants represented a mix of roles and organization types, which are detailed in Table 6.1. This diversity enabled the collection of varied insights and experiences, enriching the validation outcomes.

Ref	Job role	Organization type	Experience BI & Care	Date interview
1a	Projectmanager BI	VVT organization (XL)	5 years	27-11-2024
1b	BI Developer	VVT organization (XL)	10+ years	27-11-2024
2a	BI Developer	VVT organization (XL)	10+ years	28-11-2024
2b	Team lead BI	VVT organization (XL)	10+ years	28-11-2024
3a	Consultant BI	BI Consultancy	10+ years	29-11-2024
3b	Consultant BI	BI Consultancy	10+ years	10-12-2024
4a	Consultant BI	ECD Consultancy	10+ years	05-12-2024
4b	Consultant ECD	ECD Consultancy	3 years	05-12-2024

Table 6.1: Validation interview participants

6.1.4 Interview design

The interviews were conducted online via Microsoft Teams, enabling participants to participate remotely, making scheduling easier. Each session was planned to last one-and-a-half hours, one interview concluded earlier, lasting one hour. The interviews included a combination of open-ended questions and guided discussions. Participants were provided with a whitepaper containing the maturity model and roadmap in Dutch, shown in Appendix D, which served as a reference during the sessions. Although the whitepaper was shared at least one week in advance, only half of the participants had thoroughly reviewed the material prior to the interview; however, this did not appear to impact the quality or depth of the feedback provided.

To ensure accuracy and reliability, all interviews were recorded with the participants' consent. This facilitated accurate transcription and analysis of the discussions. The interviews were conducted in collaboration with a colleague, providing diverse perspectives and ensuring comprehensive coverage of the topics discussed.

6.2 | Findings

This section outlines the key findings of the validation interviews. It explores the validation criteria: relevance, completeness, clarity, usability, and applicability, highlighting both the strengths and areas for improvement. These findings provide insights into whether the maturity model and roadmap can effectively guide long-term care organizations in adopting and advancing their analytics capabilities. For ease of reading, all participant quotes have been translated from Dutch to English.

6.2.1 Maturity model

Relevance

The relevance of the maturity model was affirmed by the participants. Some emphasized the lack of existing maturity models specifically tailored for the long-term care sector, a gap that this model effectively addresses. Others had not previously used a maturity model but expressed satisfaction as well. The participants appreciated the sector-specific focus. One participant highlighted the significance of this specificity:

"I think it has significant added value. The model I currently use has a very generic background, while this one is specifically tailored to long-term care. If a care organization can recognize itself in such a model, the assessment often becomes much easier." [3a]

Another participant emphasized the importance of the organizational dimension, noting its relative complexity compared to the other dimensions:

"From the three dimensions -technology, data, and organization- the last one is, for us, but I suspect for many care companies as well, the most challenging. And that dimension is described in good detail." [1b]

A third participant emphasized the broad applicability of the model within the long-term care sector, stating:

"I think it's applicable to all different care organizations, not just Nedap customers." [4a]

These insights underscore the added value of a model that aligns closely with the unique challenges and operational contexts of the long-term care sector, particularly in addressing the complexity of organizational factors.

Completeness

The completeness of the maturity model was viewed positively and described as comprehensive and well-aligned with the sector's needs. However, participants suggested that the strategy sub-dimension within the organizational dimension could benefit from further elaboration, particularly in its alignment with strategic goals and innovation. One participant remarked:

"Management wants to guide their organization in a particular way, and they can have ambitious goals, such as striving for predictive values or just being able to look back. ... So, I would suggest describing this a bit more goal-oriented." [3a]

This comment highlights the importance of framing the strategy sub-dimension in terms of specific strategic objectives. Another participant suggested incorporating innovation as part of the organization's strategy:

"You could include it as part of the strategy, that you consciously aim for innovation." [2a]

These insights point to an opportunity to refine the strategy sub-dimension by explicitly linking it to strategic ambitions and the proactive pursuit of innovation, thereby enhancing the model's completeness.

Additionally, participants expressed differing views regarding the integration of governance processes within the data quality sub-dimension of the maturity model. This divergence highlights varying perspectives on the role of governance in ensuring data quality across maturity levels. One participant questioned whether governance processes and quality control should be separated, suggesting that at a managing maturity, organizations may need to prioritize quality control mechanisms over governance until foundational governance structures are in place instead of the other way around:

"I wonder if you should make a distinction between quality controls on the one hand and governance processes on the other?" This participant further explained, *"If you do not yet have good governance, you rely more on those controls to address issues as quickly as possible."* [2b]

Conversely, another participant argued that governance processes are an essential component at a managing maturity:

"At level 3, which is managing, governance processes should be in place. Data quality is also influenced by how, for example, master data is maintained. In many care organizations, anyone can make changes to master data. This leads to inconsistencies or errors in decision-making information, so at this stage, governance processes are absolutely necessary." [3a]

While governance may not always be a priority at lower maturity levels, its integration becomes critical as organizations advance, particularly to ensure consistent and reliable data quality. Therefore, the model's current structure, which allows for a progressive development of governance processes in alignment with maturity levels, appropriately addresses this dynamic need.

Clarity

Participants commended the clarity of the maturity model, describing it as well-structured and easy to understand. They highlighted its straightforward presentation, which allows users to quickly grasp its dimensions and levels without confusion. The intuitive design and logical flow were noted as features that enhance its accessibility and practical use. One participant summarized this clearly:

"Very clear" and *"Easy to use."* [2a]

Another participant expressed how easily the model allows for a quick assessment of an organization's maturity:

"At a glance, I can determine our maturity level; I think we're generally at level 4 across the board. However, you also have different dimensions, and for each dimension, it could be different." [1b]

These insights suggest the model's clarity in providing a quick and comprehensive overview of an organization's maturity, while still allowing for nuanced assessments across individual dimensions.

Usability

The simplicity and practicality of the model were identified as its core strengths. Participants appreciated its user-friendly design, which contrasts with other models that they described as overly complex and unwieldy. One participant captured this sentiment, stating:

"The simplicity with which it can be applied is the strength of this model. Many other models are broad and lengthy, both horizontally and vertically. This makes it much easier to apply." [3a]

Another participant noted how the model facilitates organizational awareness and improvement:

"It is really very helpful, also for creating awareness of where they stand now and how they can evolve as an organization." [4b]

This feedback highlights how the model's straightforward approach can facilitate its adoption and implementation in real-world settings, particularly for organizations that may lack extensive resources or technical expertise.

Applicability

The model's adaptability to varying organizational sizes and capabilities was perceived as a critical asset, enhancing its potential for real-world impact. One participant confirmed:

"Yes, I think I could use this with a wide range of our customers." [4a]

Another participant highlighted the model's practicality, especially in facilitating accurate self-assessment, even for organizations that may not have the budget for external support:

"Normally, I would never share a model like this directly with a customer because they tend to overestimate themselves based on such frameworks. However, this model clearly outlines the characteristics for each level, making it much easier to assess where they truly stand." [3b]

This aspect ensures the model's accessibility, allowing organizations with limited resources to independently evaluate their maturity and plan targeted improvements without relying heavily on external consultants. The detailed level descriptions further enhance its applicability, supporting a wide range of care organizations in varying financial and operational contexts.

6.2.2 Roadmap

Relevance

The roadmap was deemed relevant to the long-term care sector, primarily due to its alignment with the sector-specific maturity model. The use of the maturity model in the roadmap provides a tailored framework that resonates with the unique needs and challenges of long-term care organizations. By addressing sector-specific nuances, the roadmap enhances its utility for these organizations, helping them navigate the complexities of BI adoption. One participant stated:

"The use of the developed maturity model makes the roadmap highly relevant for care organizations." [3b]

However, participants also noted that the steps within the roadmap are, in essence, generalizable to BI adoption in broader contexts. Participants also noted that the roadmap's relevance extended beyond customers and could be applied internally within their own consultancy. One participant commented:

"We can also use it for our own operations. I find it interesting to apply it to our organization as well." [4b]

This feedback highlights the versatility of the roadmap, showcasing its potential to support analytics maturity not only in care organizations but also within the internal operations of their stakeholders such as business partners.

Completeness

The roadmap was largely deemed complete by participants, with its structured approach addressing the key elements necessary for advancing maturity in the long-term care sector. One participant summarized:

"When looking at the different steps, I would have the same approach." [1a]

However, several participants provided valuable suggestions to enhance its comprehensiveness. One participant emphasized the importance of explicitly incorporating the concept of adoption into the roadmap:

"I would recommend explicitly including the word 'adoption' somewhere. It is often just as important. If you want to achieve your strategy, adoption is a crucial component." [3a]

This highlights the need to focus not only on technical and procedural aspects but also on ensuring that the roadmap facilitates the effective adoption of BI practices within the organization, particularly by end-users.

Another participant highlighted the role of critical success factors in enabling progress to subsequent maturity levels:

"If you ensure that certain things are present and/or well-organized, you can move to the next levels more easily." [2b]

This feedback suggests that the roadmap could be strengthened by explicitly identifying and addressing critical enablers or preconditions that support the seamless transition between maturity levels.

These suggestions point to potential enhancements in the roadmap, such as integrating adoption and emphasizing critical success factors, to ensure a more holistic and actionable framework for guiding organizations toward a higher maturity.

Clarity

Participants appreciated the clarity of the roadmap, highlighting its structured and visually appealing presentation. They found the roadmap's clear depiction of steps and progression particularly useful for understanding and planning maturity advancements. One participant suggested the use of existing frameworks and standards in supporting implementation, stating:

"For implementation, organizations can certainly make use of the standards that are available. There are many frameworks and well-thought-out resources that can really provide a guide, allowing you to focus more on filling in the details from a BI perspective." [4b]

Another participant appreciated how the roadmap captures the importance of continuous improvement:

"Continuous improvement is really important. It's never finished; it's never done, and it can always be better, smarter, or more efficient. And you've depicted that very nicely in the figure." [2b]

One participant emphasized how the roadmap aids in explaining necessary foundational improvements to organizational leadership:

"As a first step, I would start with basic hygiene, aligning the organization. Using the model within the roadmap makes it much easier to explain this to the board." [3b]

This feedback underscores the roadmap's ability to clearly convey the iterative nature of maturity development and its utility in facilitating discussions about foundational changes with decision-makers, ensuring that users can easily grasp its ongoing and dynamic process.

Usability

The roadmap was commended for its usability, with participants particularly appreciating its structured, step-by-step design. This approach was seen as both practical and actionable, providing a clear framework for organizations to assess their current state, define objectives, and implement improvements. The roadmap's continuous approach was also noted as a strength. One participant illustrated this perspective, stating:

"I would indeed start with an assessment for every new customer to see where they stand. Then you need to clearly define your goals together. ... From there, you can start implementing and keep reviewing whether you're on track, adjusting as necessary. I can definitely embrace that approach." [1a]

Participants also highlighted the flexibility of the roadmap, which can be applied from both the customer's perspective and the business partner's perspective. One participant explained:

"Customers themselves can apply this, but we can also apply it as a business partner, so we understand where the customer wants to go. That way, we avoid burdening the customer with things they aren't open to." [4a]

This feedback underscores how the roadmap's usability lies in its logical progression, flexibility, and focus on continuous evaluation and adjustment, making it a versatile tool for guiding organizations through the maturity process.

Applicability

The roadmap was found to be highly applicable, particularly due to its inclusion of examples (Section 5.2.3) that make it easier for organizations that are unsure of where to begin. These examples provide practical guidance, helping organizations navigate the initial stages of their analytics journey. One participant stated:

"As consultants, we can help with the assessment and strategy determination, but it is ultimately up to the customer to take steps in that direction. However, I think the examples of implementations are very helpful in that process." [4b]

Another participant emphasized the roadmap's versatility across different organizational types, adding:

"Although larger organizations naturally have bigger budgets, implementing these changes is often easier in smaller organizations. Regardless, I believe the roadmap can be used effectively by any organization." [3b]

This feedback highlights how examples within the roadmap can bridge the gap between strategy and action, offering a clear pathway for organizations at varying maturity levels to progress effectively. Furthermore, the roadmap's adaptability ensures its relevance across diverse organizational sizes and complexities.

6.3 | Key takeaways

Strengths

The validation process affirmed the value and effectiveness of the proposed maturity model and roadmap in advancing maturity within the long-term care sector. Participants praised the model's relevance, mainly for its alignment with sector-specific challenges and the complexity of organizational dimensions.

The roadmap was also complimented on its structured, step-by-step approach, which offers actionable guidance for organizations at various stages of analytics. Both frameworks were recognized for their simplicity, practicality, and adaptability, therefore making them accessible to a wide range of organizations regardless of size, complexity, or existing analytics capabilities.

Opportunities

Despite their strengths, areas for improvement were also identified. For the maturity model, participants suggested refining the sub-dimension, Strategy, by linking it more explicitly to strategic goals and innovation (Maturity model: Completeness).

For the roadmap, two improvements were suggested. The first is to give adoption a more prominent role in the roadmap, ensuring employee engagement and cultural alignment (Roadmap: Completeness). Effective change includes preparing individuals and organizations to embrace and effectively use these new systems, ensuring that employees integrate BI tools into their daily workflows. This process necessitates a significant cultural shift within care organizations, as they need to move from traditional decision-making methods to a more data-driven approach. The adoption of BI tools requires overcoming resistance to change, fostering trust in data, and educating staff on the value these tools can provide. Secondly, participants stipulated the importance of identifying and monitoring the critical success factors of the roadmap (Roadmap: Completeness). Understanding these enablers and blockers of analytics adoption is essential, as they will determine its effectiveness. Recognizing that some blockers can be mitigated while others must be worked around is important for developing realistic and effective strategies. Including these considerations in the roadmap would provide organizations with insights for better navigating obstacles and maximizing their chances of success.

These findings highlight the frameworks' potential to guide long-term care organizations effectively while offering actionable recommendations for refinement to further enhance their impact. In the next section, the changes to the developed frameworks are described.

6.4 | Refinement

6.4.1 Care Analytics Maturity Model 2.0

To better support goal definition and innovation, the Strategy sub-dimension of the Care Analytics Maturity Model: Organization Dimension has been refined. Table 6.2 presents the updated Organization dimension of the model, with changes made *italic* for clarity.

Maturity level	***Strategy***	**Skills & training**	**Organizational coverage**
Level 0 | Ad Hoc	No awareness or budget for analytics. No leadership support *or alignment of analytics with strategic goals.*	No analytics skills or training programs.	No adoption of analytics at any organizational level.
Level 1 | Emerging	*Basic awareness of analytics' potential, but no integration with strategic goals. Sporadic efforts with minimal budget.*	A few employees have self-taught analytics skills. No formal training.	Analytics used only a small group, such as upper management or other BI enthusiasts within the organization.
Level 2 | Formalized	*Growing recognition of analytics' value to support specific strategic goals.* Initial budget allocation for projects.	Formal training programs for key staff. Skills base growing.	Adoption of analytics extends to middle management and some departments.
Level 3 | Managed	*Clear alignment of analytics with strategic objectives. Structured budget supports innovation in analytics and data-driven decision-making. Leadership prioritizes analytics initiatives.*	Widespread analytics training across departments. Analytics skills expected in operational and management roles.	Analytics usage common across departments, including clinical, operational, and financial teams.
Level 4 | Optimized	*Analytics is integral to the strategic vision, driving innovation and continuous improvement. Strong financial backing ensures sustainability. Analytics initiatives proactively shape organizational strategy.*	Advanced skills, AI/ML training. Continuous learning is emphasized.	Analytics is used by all relevant employees, including caretakers. Embedded in daily tasks.

Table 6.2: Care Analytics Maturity Model 2.0: Organization Dimension

6.4.2 Care Analytics Adoption Roadmap 2.0

The Care Analytics Adoption Roadmap has also been revised to align with the proposed improvement of the previous section. These changes aim to streamline adoption steps and improve alignment with organizational capacities. Additions have been only made to Step 2 and 3, with changes italicized for emphasis.

Step 1: Initial maturity assessment

<no changes made>

Step 2: Defining target state and strategy

The second step in the roadmap is focused on defining the target state and implementation strategy. Outlining where the organization wants to be is crucial for aligning leadership and team members with a shared vision, ensuring that the adoption of analytics moves forward with a common purpose.

The Care Analytics Maturity Model can be leveraged in this phase to define the future direction. Organizations must set clear, measurable goals based on their assessment. For example, if the assessment revealed that the organization's data management practices were in the early stages, a goal might be to enhance data governance or implement an enterprise-wide data platform.

When defining targets, it's essential to recognize that the goal does not need to be achieving the highest maturity level in all areas. If the maturity assessment in the first step reveals imbalances across (sub-)dimensions, a good goal might be to aim for a more balanced maturity level, ensuring functionality and alignment without introducing unnecessary complexity.

For organizations beginning their adoption journey, the initial focus should be on identifying the desired functionalities of analytics rather than specific tools. This ensures that technological decisions are guided by the organization's actual needs rather than by market trends. Next, it's crucial to determine if data quality and infrastructure must improve to effectively leverage analytics. Gaps in data accuracy, completeness, or governance must be addressed to ensure meaningful insights. Lastly, the organization must assess which parts of the organization should improve to maximize the effectiveness of analytics.

This step includes identifying critical success factors, such as enablers and blockers of analytics adoption. Enablers are elements that facilitate the successful implementation and integration of BI tools and practices. Blockers, on the other hand, are barriers that hinder the effective adoption and use of analytics. By recognizing and addressing these critical success factors early on, organizations can proactively develop strategies to overcome challenges and leverage the strengths that support the adoption of analytics. Some blockers can be mitigated through targeted interventions, while others may require alternative approaches. Identifying the potential risks and understanding the factors that contribute to success also helps the organization prioritize efforts, allocate resources more efficiently, and set realistic expectations.

Step 3: Implementation

Once the target state is defined, the next step involves the implementation of processes, technologies, and/or organizational changes needed to bridge the gap between the current and target states. This is where the real work of transformation takes place. The implementation phase is crucial for turning the strategy into tangible results, and it requires careful planning and coordination.

To successfully adopt analytics, organizations must also prepare employees to embrace and effectively use new systems. This preparation involves not just offering adequate training and support, but also providing clear communication about the value of BI tools and how they will enhance work processes. Shifting from traditional decision-making methods to a data-driven approach requires a significant cultural transformation. This shift challenges established practices and demands that leaders model data-driven decision-making. They must also encourage employees at all levels to adopt a mindset of continuous learning and improvement.

The adoption of BI tools often faces resistance due to fear of the unknown or concerns about losing autonomy. Overcoming this resistance requires building trust in the data. This can be achieved through transparency and demonstrating the tangible benefits of analytics in driving better decision-making and outcomes.

It is also essential to continue monitoring the identified earlier enablers and blockers throughout the implementation phase. By doing so, organizations can make timely adjustments to address emerging challenges while reinforcing the factors that contribute to success.

Step 4: Evaluation

<no changes made>

Chapter 7

Conclusion and discussion

This final chapter reflects on the study's findings. It begins by summarizing how the results address the research questions, providing insights into how BI and Advanced Analytics can improve decision-making and process management of long-term care organizations in the Netherlands. The discussion then delves into the study's limitations and offers recommendations for practical applications and future research, aiming to support continued exploration and advancement of analytics in long-term care.

7.1 | Answering the research questions

RQ1: What is the current state of decision-making strategies in the Dutch long-term care sector, and how is analytics being utilized in healthcare in general?

1.1 What characterizes the different segments of the long-term care sector in the Netherlands?

The Dutch long-term care sector is multifaceted, comprising three segments that cater to different needs and patient demographics: the VVT, GHZ, and GGZ. The VVT focuses on providing care for the elderly and those with chronic illnesses, offering services such as nursing care in facilities, residential care, and home care aimed at maintaining independence and improving quality of life (Section 3.1.1). GHZ caters to individuals with physical, intellectual, or developmental disabilities, offering tailored care through residential facilities, day programs, and personalized support to enhance their independence and well-being (Section 3.1.2). GGZ, the mental health care segment, provides comprehensive services for individuals with mental health needs, including inpatient care, outpatient therapy, and community-based support, with an emphasis on holistic treatment (Section 3.1.3). These segments are integral to the Dutch healthcare system, ensuring that vulnerable populations receive the specialized care they require. Each segment faces distinct challenges in terms of resource allocation, patient management, and service delivery, influencing the implementation and utilization of BI and Advanced Analytics.

1.2 What distinguishes decision-making and process management at different management levels in Dutch long-term care organizations?

Decision-making and process management in Dutch long-term care organizations differ across management levels (Section 3.2). At the strategic level, decisions focus on aligning with national policies and municipal requirements. Leaders prioritize investments in patient-centered care, preventive strategies, and adaptable IT systems to support sustainability and high-quality care. They also foster integration across care settings for tailored patient care. At the tactical level, managers translate strategic objectives into operational plans, focusing on resource allocation, care coordination, and efficiency. They ensure the integration of preventive care, such as early interventions and lifestyle programs, into everyday practices. At the operational level, decisions are often patient-specific, requiring frontline staff to address complex and nuanced care needs, such as chronic conditions and emotional well-being, within resource constraints. Transparent communication and continuous feedback loops are critical at this level to adapt care delivery based on patient outcomes and evolving circumstances. This multi-level decision-making process ensures that organizations stay responsive, agile, and capable of providing sustainable, high-quality care.

1.3 What is the state-of-the-art in Business Intelligence and Advanced Analytics of the healthcare sector?

BI and Advanced Analytics are transforming healthcare by enhancing decision-making and operational efficiency (Section 3.3). Key innovations include real-time data integration, which improves monitoring and responsiveness, and predictive analytics, which forecasts patient outcomes and optimizes resources. These technologies enable better patient care, streamline operations, and reduce costs. Organizations are increasingly adopting tools like openEHR for improved data interoperability. Predictive analytics and AI are emerging but are not yet widespread. Challenges such as data integration, high costs, and privacy concerns remain, but opportunities for better data harmonization and flexible reporting are growing. The sector is actively working towards enhancing its analytics capabilities to improve care quality and operational efficiency.

1.4 Which maturity models exist in terms of Business Intelligence and Advanced Analytics in the healthcare sector?

The maturity models discussed in the literature review (Section 3.4), provide organizations with structured frameworks for assessing their capabilities. These models typically include multiple levels or stages, each focused on different dimensions such as technology, data management, and organizational processes. They assess the integration of BI tools across various domains, from administrative and clinical data to technology infrastructure and decision-making processes. Some models focus specifically on areas such as health informatics, integrating social determinants of health, or optimizing clinical decision support systems.

By focusing on key areas within healthcare and BI, these models help organizations identify their current level of maturity and understand gaps that need to be addressed for achieving higher levels of performance. While these models cover critical aspects such as data management, technology, and people, they are not fully applicable to the long-term care sector due to their focus on long-term care settings, which have different needs and priorities.

In conclusion, the current state of decision-making strategies could benefit from the adoption of BI and Advanced Analytics, as they have the potential to improve patient care, operational efficiency, and cost management in the Dutch long-term care sector. However, the sector lacks insights into the existing state of BI and Advanced Analytics, highlighting the need for further exploration. Assessing the maturity of these technologies within long-term care organizations is beneficial to identify gaps, understand current capabilities, and develop strategies to leverage BI and Advanced Analytics for better care delivery and improved outcomes.

RQ2: What is the current state regarding analytics adoption of the Dutch long-term care sector?

The data analysis of BI adoption in Dutch long-term care organizations (Chapter 4) reveals that the sector is increasingly embracing BI and data-driven approaches, but it shows a clear divide between larger and smaller organizations. Larger organizations are more likely to have dedicated BI teams, use advanced BI tools, and adopt more comprehensive data management practices. They also report higher data quality, better data infrastructure, and more frequent use of BI insights. Smaller organizations, on the other hand, face resource limitations that hinder their BI adoption and data management capabilities, often relying on simpler tools and external support. Despite these differences, both large and small organizations show strong intentions to expand their BI usage in the near future, underscoring the growing recognition of the importance of data-driven decision-making across the sector.

RQ3: What roadmap can be developed to enhance the analytics maturity of Dutch long-term care organizations?

3.1 What maturity model can be designed to assess the analytics adoption of Dutch long-term care organizations?

A maturity model for the long-term care sector in the Netherlands (Section 5.1) was developed around three core dimensions of analytics: Technology, Data, and Organization. These dimensions address critical areas of analytics adoption, including but not limited to the integration of EHR, data quality, and organizational readiness. Each dimension is divided into specific sub-dimensions to assess analytics capabilities comprehensively. The model includes five maturity levels (0 to 4), progressing from no analytics to full integration of analytics, enabling organizations to track their development. This model ensures flexibility, recognizing that sub-dimensions may mature at different rates, while promoting a holistic approach. By incorporating Advanced Analytics and emerging technologies, such as AI and machine learning, it addresses both current and future needs of the sector. This framework supports long-term care organizations in enhancing decision-making, improving operational efficiency, and fostering a data-driven culture.

3.2 What steps are necessary to guide Dutch long-term care organizations in improving their analytics capabilities?

To guide care organizations in improving their analytics capabilities, four steps have been defined that align with organizational goals and address sector-specific challenges (Section 5.2). The first step is a comprehensive assessment of the current maturity level using a tailored maturity model, emphasizing technology, data, and organizational readiness. Organizations should identify gaps in these dimensions, focusing on areas such as data quality, IT infrastructure, and workforce capabilities. The next step involves prioritizing improvements, such as integrating IT systems, standardizing data management practices, and enhancing staff training to build analytics competencies. Thirdly, a phased implementation strategy ensures that progress in one area supports broader organizational goals, allowing sub-dimensions to mature at different rates. The final step evaluates the implemented strategy, identifying challenges and limitations faced, and assessing whether this strategy enhanced the organization's maturity. This continuous evaluation and stakeholder engagement are crucial for maintaining momentum, addressing challenges, and ensuring alignment with future needs.

To enhance the analytics maturity within the Dutch long-term care sector, a structured roadmap has been developed, building upon the previously identified maturity model and its associated steps. By adhering to this roadmap, long-term care organizations should be able to progressively enhance their analytics maturity, fostering a data-driven culture that improves operational effectiveness, clinical outcomes, and overall care quality.

RQ4: What potential impact could the proposed frameworks have on analytics adoption in Dutch long-term care organizations?

4.1 How do the proposed frameworks perform in terms of extending existing theories to the sector?

Both the maturity model and roadmap were deemed relevant due to their tailored focus on the long-term care sector, addressing the sector's unique challenges regarding analytics (Section 6.2). The maturity model's comprehensiveness was appreciated, though there were opportunities to better integrate strategic goals and innovation. Similarly, the roadmap was seen as complete but could be enhanced by emphasizing adoption and critical success factors. These opportunities have been addressed in the last refinement (Section 6.4). Both frameworks demonstrated clarity, with intuitive structures and logical progression that ensure ease of understanding. Overall, the frameworks extend the existing theoretical basis, providing a deeper understanding of how to improve the adoption of BI and Advanced Analytics in the Dutch long-term care sector.

4.2 How do the proposed frameworks perform in terms of their practical value in organizational contexts?

In terms of usability, the simplicity of the model and the step-by-step design of the roadmap were standout features, making them practical for organizations at varying levels of analytics maturity. Additionally, their applicability was affirmed by participants, with both tools showing adaptability to organizations of different sizes, maturities, and contexts, making them effective guides for advancing analytics capabilities. Overall, the frameworks serve as effective tools for organizations seeking to enhance their analytics maturity and data-driven decision-making.

In conclusion, the proposed roadmap and maturity model can enhance the adoption of analytics in Dutch long-term care organizations. By offering a structured framework for assessing and improving analytics capabilities, these tools foster a data-driven culture aligned with organizational goals. The roadmap supports continuous improvement, enhancing operational efficiency and informed decision-making. Adaptable to various organization sizes and maturities, the frameworks help improve resource management and patient outcomes. Ultimately, they provide a path to sustainable improvements in the adoption of analytics, addressing sector-specific challenges and enhancing overall care quality.

7.2 | Answer the main research question

How can Business Intelligence and Advanced Analytics be applied to enhance decision-making and process management of long-term care organizations in the Netherlands?

The growing availability of data provides an opportunity for Business Intelligence and Advanced Analytics to enhance decision-making and process management. While the Dutch long-term care sector demonstrates a strong intent to expand the usage of analytics, organizations face challenges, due to the human-centered culture, that require structured guidance.

To address this, a tailored roadmap has been developed, aligned with organizational goals and these sector-specific challenges. This roadmap begins with a comprehensive assessment of the organization's analytics maturity level, focusing on technology, data, and organizational readiness. Identifying and addressing gaps in these dimensions ensures targeted improvements. A phased implementation strategy allows sub-dimensions to mature at different rates, controlling progress within the broader organizational goals. Both continuous evaluation and refinements and stakeholder management are highlighted in this roadmap to gain sustained momentum and alignment with future needs.

Using this adaptable framework, Business Intelligence and Advanced Analytics can enhance decision-making and process management of Dutch long-term care organizations of varying sizes and maturities, improving resource management, operational efficiency, and patient outcomes.

7.3 | Limitations

While this study provides valuable insights into the adoption of analytics within Dutch long-term care organizations, several limitations must be acknowledged.

A total of 87 participants responded to the survey, offering a robust dataset for analysis (Chapter 4). However, the sample is not entirely representative of the broader population of long-term care organizations as there is an over-representation of large organizations. In the survey, the majority of respondents came from large or extra-large organizations (Table A.1), while small organizations constitute to a significant portion of the long-term care sector. This skew in the sample could result in a bias toward findings that reflect the practices and challenges of larger organizations, which typically have more resources, infrastructure, and capacity to implement BI systems. This imbalance could obscure the specific barriers and realities faced by smaller organizations in adopting analytics, limiting the generalizability of the results to the entire sector.

A similar limitation applies to the validation interviews (Chapter 6), as no small organizations were available to participate. This could affect the perceived applicability of the maturity model and roadmap across the diverse landscape of care organizations. Although the inclusion of consultancy professionals in the interviews helped broaden the perspective and enhance the frameworks' applicability, it may have also influenced the findings as consultancy professionals might have a higher-level or theoretical understanding, potentially missing the practical, day-to-day challenges. These limitations highlight the need for further research involving a more balanced representation of organization sizes and direct engagement with a wider range of stakeholders to ensure the frameworks are truly inclusive and applicable to the entire sector.

Another limitation is the generalizability of the design over time (Chapter 5). The field of analytics evolves rapidly, with technological advancements, emerging trends, and innovative methodologies reshaping the landscape frequently. Consequently, the insights obtained from experts and the literature represent only a snapshot of the current situation, potentially becoming outdated as new tools, techniques, and paradigms emerge. Following this line of reasoning, the levels or dimensions of the maturity model proposed in this research might also differ if developed at a later time, reflecting shifts in industry priorities, technological capabilities, and organizational needs.

Additionally, due to time constraints, there was no opportunity to pilot or test the roadmap in live organizational settings (Chapter 6). Consequently, while the roadmap is designed to be actionable and adaptable, its practical applicability and effectiveness in diverse long-term care environments remain untested. This lack of field testing limits the ability to assess how organizations might respond to the roadmap, adapt it to their unique contexts, and overcome implementation barriers. More details on the pilot are outlined in the recommendations (Section 7.4).

The last limitation identified is the potential bias introduced by the researcher's involvement in the interviews (Chapter 6). The researcher's direct participation made it easier to explain concepts or elements of the frameworks that might not have been entirely clear on their own, which, while beneficial during the interviews, raises concerns about the usability of the roadmap for individuals less engaged with its development. These individuals may face challenges in navigating and applying the roadmap without the benefit of the researcher's implicit knowledge or contextual explanations. To mitigate this limitation, another colleague was included in the interviews to act as a buffer, reducing the reliance on the primary researcher's explanations and ensuring a broader evaluation of the frameworks. While this approach partly addressed concerns about potential bias, it is not a fully waterproof solution, as the dynamic between the interviewer and the participants may still influence the results. This limitation highlights the need for clear, user-friendly documentation to ensure broader usability of the frameworks.

7.4 | Future research

Based on the limitations identified, the following recommendations are proposed for further research:

Further research into small organizations

Future research should aim for a more balanced sample by ensuring a proportional representation of organizations of varying sizes. This would provide a more comprehensive understanding of analytics adoption and its challenges across the entire spectrum of Dutch long-term care organizations, with a particular focus on addressing the unique needs and barriers faced by smaller organizations. Smaller organizations may have limited financial resources, fewer specialized staff, and less access to advanced IT infrastructure compared to larger organizations. Additionally, decision-making processes might be faster in smaller organizations due to less bureaucracy but could lack the strategic depth seen in larger ones. Smaller organizations might focus more on immediate, operational BI use cases rather than strategic applications. As the approach includes adaptable guidelines, it should cater to organizations of various sizes, allowing smaller organizations to adopt relevant aspects without being overwhelmed but this should be validated.

Pilot testing in real-world settings

To further validate and refine the roadmap, future research should prioritize implementing it in diverse long-term care organizations, ranging from small clinics to large institutions. Conducting pilot studies will offer valuable practical insights into its usability, adaptability, and the challenges encountered during implementation. These studies can help identify areas for improvement and ensure that the roadmap is equipped to address organization-specific requirements effectively.

7.5 | Recommendations

Building on the results of this research, these additional recommendations are proposed for Nedap Healthcare:

Promote the roadmap with customers and business partners

To maximize the impact of the developed roadmap, Nedap Healthcare should share it with customers and business partners as part of its service offerings. This initiative could strengthen Nedap Healthcare's relationships with its customers and partners by providing added value beyond its core products and services. Additionally, a workshop could be organized to ensure customers fully understand the roadmap's purpose and how to implement it effectively.

Align product development with the maturity model

The maturity model can serve as a tool to evaluate Nedap Healthcare's products and identify opportunities for enhancement. For each level of the maturity model, potential improvements can be identified for the various applications in the Ons® Suite. For instance, applications at lower maturity levels could benefit from simplified data extraction or guided analytics, while those targeting higher levels may require advanced features such as real-time data extraction or AI capabilities. By aligning product development with the maturity model, Nedap Healthcare can ensure its offerings address the evolving needs of its diverse customer base.

Enhance customer engagement through maturity assessments

The maturity model can also be leveraged to assess customers' use of the Ons® Suite and identify areas where they could optimize their analytics capabilities. Nedap Healthcare's Account Managers could use the model as a diagnostic tool to determine whether customers are fully utilizing the suite's features. Based on this analysis, targeted recommendations or workshops could be offered to customers to help them unlock the full potential of their EHR system. This proactive approach would not only enhance customer satisfaction but also position Nedap Healthcare as a strategic partner in the customers' analytics journey.

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Appendix A

Tables and figures

This appendix contains tables and figures that support the analysis and findings presented in Chapters 4 and 5.

Sector	S	M	L	XL
VVT (N=43)	14 (33%)	2 (5%)	6 (14%)	21 (49%)
GGZ (N=11)	1 (9%)	1 (9%)	1 (9%)	8 (73%)
GHZ (N=7)	0	0	4 (57%)	3 (43%)
Youth (N=4)	2 (50%)	0	1 (25%)	1 (25%)
Multi (N=4)	0	0	1 (25%)	3 (75%)
Other (N=3)	0	1 (33%)	0	2 (67%)
Total (N=72)	17 (24%)	4 (6%)	13 (18%)	38 (53%)

Table A.1: Organization size segments and sectors

Organization	1-3 employees	4-6 employees	7-9 employees	10+ employees
Large (N=49)	51% (25)	37% (18)	8% (4)	4% (2)
Small (N=10)	80% (8)	20% (2)	0%	0%
Dedicated BI-team (N=31)	58% (18)	35% (11)	6% (2)	0%
No dedicated BI-team (N=28)	54% (15)	32% (9)	7% (2)	7% (2)
Total (N=59)	56% (33)	34% (20)	7% (4)	3% (2)

Table A.2: Employees generating BI insights

Organization	Quality rating	Accessibility rating	Manual data copying
Large (N=46)	High 13% (6) Fair 52% (24) Moderate 35% (16) Low 0%	High 39% (18) Fair 43% (20) Moderate 17% (8) Low 0%	Weekly 2% (1) Monthly 33% (15) Rarely 39% (18) Never 24% (11)
Small (N=9)	High 0% Fair 56% (5) Moderate 44% (4) Low 0%	High 22% (2) Fair 78% (7) Moderate 0% Low 0%	Weekly 22% (2) Monthly 56% (5) Rarely 11% (1) Never 0%
Dedicated BI-team (N=29)	High 21% (6) Fair 52% (15) Moderate 28% (8) Low 0%	High 55% (16) Fair 38% (11) Moderate 7% (2) Low 0%	Weekly 3% (1) Monthly 34% (10) Rarely 45% (13) Never 17% (5)
No dedicated BI-team (N=26)	High 0% Fair 54% (14) Moderate 46% (12) Low 0%	High 15% (4) Fair 62% (16) Moderate 23% (6) Low 0%	Weekly 8% (2) Monthly 38% (10) Rarely 23% (6) Never 23% (6)
Total (N=55)	High 11% (6) Fair 53% (29) Moderate 36% (20) Low 0%	High 36% (20) Fair 49% (27) Moderate 15% (8) Low 0%	Weekly 5% (3) Monthly 36% (20) Rarely 35% (19) Never 20% (11)

Table A.3: Data infrastructure: Quality, accessibility and manual data copying

Organization	Understanding	Investing	Encouraging
Large (N=46)	High 15% (7) Fair 54% (25) Moderate 24% (11) Low 7% (3)	High 2% (1) Fair 59% (27) Moderate 28% (13) Low 11% (5)	High 11% (5) Fair 48% (22) Moderate 30% (14) Low 11% (5)
Small (N=9)	High 22% (2) Fair 67% (6) Moderate 11% (1) Low 0%	High 0% Fair 67% (6) Moderate 33% (3) Low 0%	High 0% Fair 67% (6) Moderate 22% (2) Low 11% (1)
Dedicated BI-team (N=29)	High 10% (3) Fair 55% (16) Moderate 31% (9) Low 3% (1)	High 0% Fair 66% (19) Moderate 28% (8) Low 7% (2)	High 17% (5) Fair 52% (15) Moderate 17% (5) Low 14% (4)
No dedicated BI-team (N=26)	High 23% (6) Fair 58% (15) Moderate 12% (3) Low 8% (2)	High 4% (1) Fair 54% (14) Moderate 31% (8) Low 12% (3)	High 0% Fair 50% (13) Moderate 42% (11) Low 8% (2)
Total (N=55)	High 16% (9) Fair 56% (31) Moderate 22% (12) Low 5% (3)	High 2% (1) Fair 60% (33) Moderate 29% (16) Low 9% (5)	High 9% (5) Fair 51% (28) Moderate 29% (16) Low 11% (6)

Table A.4: BI strategy: Management's understanding of potential, willingness to invest & encouragement of data-driven decision-making

Lvl.	Brooks et al. (2015)	Carvalho et al. (2019)	Espinoza et al. (2023)	Gastaldi et al. (2018)	HIMSS (2021)
0	-	-	-	-	Fragmented Point Solutions
1	Initial	Adhocracy	Absent	Initial	Enterprise Data Warehouse
2	Managed	Starting the Foundations	Ad Hoc	Managed	Standardized Vocabulary and Patient Registries
3	Defined	Centralized Dictatorship	Emerging	Systematic	Automated Internal Reporting
4	Quantitatively Managed	Democratic Cooperation	Coordinated	Disrupted	Automated External Reporting
5	Optimizing	Entrepreneurial Opportunity	Supported	-	Waste & Care Variability Reduction
6	-	Integrated Relationships	Integrated	-	Population Health Management and Suggestive Analytics
7	-	-	Transformative	-	Clinical Risk Intervention and Predictive Analytics
8	-	-	-	-	Personalized Medicine and Prescriptive Analytics

Table A.5: Different levels across compared Maturity Models

Maturity Level	EHR systems	BI functionalities	Integration
Level 0	No EHR system in place. Information is stored in many separate spreadsheets or other files.	No use of analytics.	No data of other IT systems used in analytics.
Level 1	Single applications of EHR system are partially used (incomplete dataset).	Use of personal, isolated and/or ad-hoc analysis.	Separate analytics of data from IT systems like CRM/HRM.
Level 2	Multiple applications of EHR system separately used in analytics.	Introduction of descriptive BI for data visualization and reporting.	Some IT systems and EHR data used coherently in analytics.
Level 3	Multiple applications of EHR system coherently used in analytics.	Use of diagnostic BI and real-time data analysis for improved decision-making.	All business-critical IT systems and EHR data used coherently in analytics.
Level 4	All relevant applications of EHR system coherently used in analytics.	Predictive and prescriptive analytics with use of advanced tools like AI & ML.	Full integration of all relevant IT systems and EHR data used in analytics.

Table A.6: Care Analytics Maturity Model: Technology Dimension

Level	Data quality	Data infrastructure
Level 0	No control over data quality. Data is fragmented, inconsistent, and stored in shadow systems.	No centralized data infrastructure. Manual, disconnected systems in use.
Level 1	Basic data collection, but inconsistent quality checks. Heavy reliance on manual processes.	Fragmented infrastructure with isolated systems and basic security measures. Manual data transfers common.
Level 2	Initial focus on improving data quality. Shadow systems still persist, but some data is centralized.	Centralized data infrastructure is emerging. Some automated processes introduced. Basic encryption and role-based access controls implemented.
Level 3	Formal data governance in place. Automated data validation and cleansing. Most shadow systems eliminated. Early semantic standardization efforts.	Mature infrastructure with automated validation and seamless integration between systems. Manual processes largely eliminated. Security protocols include advanced encryption, periodic threat assessments, and compliance with regulations.
Level 4	Continuous data quality monitoring in real-time. Highly reliable, accurate data. Semantic standards widely adopted, enabling interoperability.	Fully automated, scalable infrastructure supporting real-time and predictive analytics from all sources. Proactive security measures.

Table A.7: Care Analytics Maturity Model: Data Dimension

Level	Strategy	Skills & training	Organizational coverage
Level 0	No awareness or budget for analytics. No leadership support.	No analytics skills or training programs.	No adoption of analytics at any organizational level.
Level 1	Basic BI awareness, limited budget, sporadic efforts.	A few employees have self-taught analytics skills. No formal training.	Analytics used only a small group, such as upper management or other BI enthusiasts within the organization.
Level 2	Growing recognition of analytics' value, initial budget allocation for projects.	Formal training programs begin for key staff. Skills base growing.	Adoption of analytics extends to middle management and some departments.
Level 3	Strategic commitment to analytics with structured budget. Leadership support.	Widespread analytics training across departments. Analytics skills expected in operational and management roles.	Analytics usage common across departments, including clinical, operational, and financial teams.
Level 4	Data-driven culture with strong financial backing for analytics. Part of the organization's strategic vision.	Advanced Analytics skills, AI/ML training. Continuous learning is emphasized.	Analytics is used by all relevant employees, including caretakers. Embedded in daily tasks.

Table A.8: Care Analytics Maturity Model: Organization Dimension

Appendix B

Survey questions

This appendix contains the survey questions used in the study, originally conducted in Dutch and translated into English for clarity and ease of understanding.

1. Demographical information

Q1.1 What is the size of your organization? (in terms of employees)

Q1.2 How many clients does your organization currently serve?

Q1.3 In which sector is your organization active?

Q1.4 What is your current position within the organization?

Q1.5 How many years of work experience do you have in the healthcare sector?

Q1.6 How many years of experience do you have specifically with BI or data analysis?

Q1.7 To what extent are you involved in decisions regarding BI and analytics within the organization?

2. Current application of BI

Q2.1 Does your organization use insights from BI and data analysis?

Q2.2a Does your organization have a BI department or team?

Q2.2b Which applications of BI does your organization want to use?

Q2.2c Why not?

Q2.3a How large is the BI department? / How many employees are involved in generating BI and data analysis within your organization?

Q2.3b Does your organization plan to (partially) outsource BI or analytics projects?

Q2.4 How many employees use insights from BI and data analysis? (e.g., dashboards)

Q2.5 Which departments use BI insights?

Q2.6 Which BI tools are currently in use?

Q2.7 How frequently are BI solutions used for insights, monitoring, and/or decision-making?

Q2.8 Which applications of BI are currently in use?

Q2.9 How satisfied are you with the current BI solutions within your organization?

Q2.10 To what extent are BI tools integrated with other systems (e.g., EHR, HR)?

Q2.11 Does your organization (partially) outsource BI or analytics projects?

3. Advanced Analytics and Machine Learning

Q3.1 Does your organization currently use Advanced Analytics?

Q3.2 Which applications of Advanced Analytics are currently in use?

Q3.3 Does your organization use Machine Learning models?

Q3.4 How would you rate the management's knowledge of Advanced Analytics and ML?

Q3.5 How important is Advanced Analytics for the future strategy of your organization?

Q3.6 What obstacles does your organization face in the implementation of Advanced Analytics?

4. Data and infrastructure

Q4.1 Does your organization have a central data storage (e.g., data warehouse)?

Q4.2 What data does your organization primarily use for BI and analytics?

Q4.3 How would you rate the quality of the available data within the organization?

Q4.4 How accessible is data for the BI team/employees generating BI insights?

Q4.5 How would you rate the current infrastructure for data analysis within the organization?

Q4.6 Is data copied manually from one system to another, rather than being interconnected?

Q4.7 For which of the following aspects is a separate registration kept outside the central IT systems? (shadow registration)

Q4.8 Does the organization use multiple systems for Electronic Health Records?

5. Organizational culture and competencies

Q5.1 How well does management understand the potential of BI and analytics?

Q5.2 How willing is your organization to invest in BI and analytics?

Q5.3 To what extent is data-driven decision making encouraged within the organization?

Q5.4 How would you rate the collaboration between different departments for data analysis projects?

Q5.5 Which competencies do employees most lack for effectively using BI and analytics?

Q5.6 How often are trainings/courses on BI and analytics followed within the organization?

6. Future plans and expectations

Q6.1 Does your organization plan to expand the use of BI and analytics?

Q6.2 How do you think BI and analytics could improve care within the organization?

Q6.3 What are your biggest concerns regarding the use of BI and analytics?

Q6.4 What obstacles does your organization face in implementing BI and analytics?

Appendix C

Validation interview questions

This appendix includes the interview questions used in the study. The interviews were conducted in Dutch but the questions have been translated into English for clarity and ease of understanding.

Validation Questions for Maturity Model

General Understanding and Relevance

- Does the model clearly convey the levels of BI maturity? Are there any parts that need more detailed explanation or clarification?
- How well do you think this model aligns with the unique requirements and challenges of the long-term care sector?
- Are all critical components of BI in long-term care adequately represented in the model? Are there any key areas you believe are missing?

Structure and levels

- Are the maturity levels defined in a logical and progressive manner? Would you suggest changes in the sequence or number of levels?
- Do you find the level of detail for each level appropriate, or should certain levels be further broken down or combined?
- Are the characteristics and criteria of each level distinct and easily distinguishable from other levels?
- Do the benchmarks for moving from one stage to the next accurately reflect real-world practices and capabilities?
- Are the benchmarks used to assess each stage practical and measurable (where needed) in a long-term care BI context?

Practical Application

- How easy would it be for long-term care organizations to apply this model to assess their current BI maturity level?

– What potential challenges or barriers might organizations face when trying to use this model?

– How flexible is the model to different types of long-term care organizations (e.g., small clinics vs. large facilities)?

Comparison and Benchmarking

– How does this BI maturity model compare to other industry models you have encountered (if any)?

– Does the model facilitate benchmarking across different organizations, allowing for meaningful comparisons?

Validation Questions for Roadmap

General Understanding and Relevance

– Is the roadmap easy to understand, with clear steps and guidance? Are there any sections that seem ambiguous or difficult to follow?

– Does the roadmap address the unique challenges faced by long-term care organizations aiming to improve their analytics capabilities?

– Does the roadmap encompass all key areas needed for an organization to advance analytically? Are there any essential aspects missing?

– How does this BI adoption roadmap compare to other industry models you have encountered (if any)?

Structure and Phases

– Are the phases of the roadmap organized in a logical and progressive sequence? Would you suggest changing the order or restructuring any part?

– Do the phases provide enough detail for practical implementation? Should any phases be expanded or simplified?

– Are the milestones in each phase clearly defined and distinct from one another?

– Are there any elements or phases you think are underrepresented or missing in the roadmap?

Practical Application

– How easy would it be for long-term care organizations to implement this roadmap? Are there specific challenges they might face?

– Are the steps and recommendations practical, considering typical resource constraints in long-term care organizations?

– Can the roadmap be applied to different types of long-term care organizations (e.g., small clinics vs. large facilities)?

– Does the roadmap provide adequate guidance for organizations at different stages, from beginners to advanced analytic users?

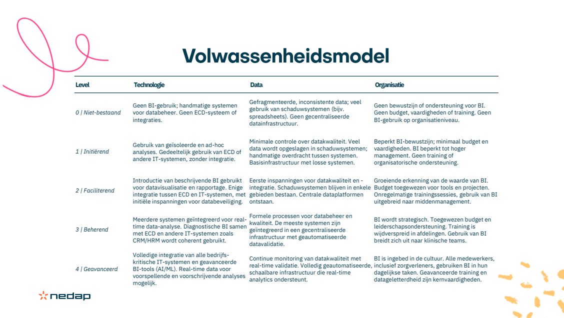
Outcome and Value

- Does the roadmap help organizations define and measure their progress toward higher analytic maturity?
- How well does the roadmap align with broader organizational goals, such as improving patient outcomes and operational efficiency?
- If followed, do you believe the roadmap will significantly improve an organization's analytics capability and decision-making processes?
- Would you recommend this roadmap to other long-term care organizations? Why or why not?

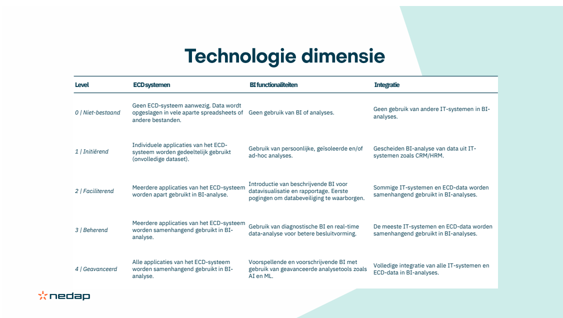
Appendix D

Validation interview whitepaper

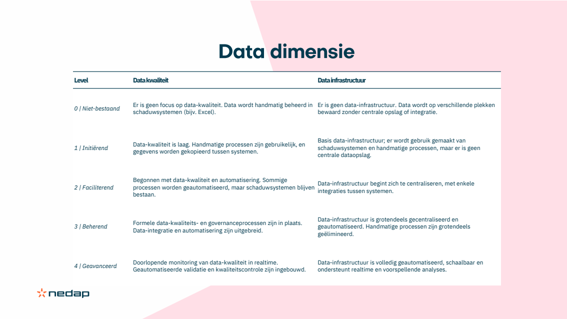
This appendix features the Dutch whitepaper used for validation interviews. It includes the maturity model and roadmap discussed with participants.



Level	Technologie	Data	Organisatie
0 | Niet-bestaand	Geen BI-gebruik; handmatige systemen voor databeheer. Geen ECD-systeem of integraties.	Gefragmenteerde, inconsistente data; veel gebruik van schaduwsystemen (bijv. spreadsheets). Geen gecentraliseerde datainfrastructuur.	Geen bewustzijn of ondersteuning voor BI. Geen budget, vaardigheden of training. Geen BI-gebruik op organisatieniveau.
1 | Initiërend	Gebruik van geïsoleerde en ad-hoc analyses. Gedeeltelijk gebruik van ECD of andere IT-systemen, zonder integratie.	Minimale controle over datakwaliteit. Veel data wordt opgeslagen in schaduwsystemen; handmatige overdracht tussen systemen. Basisinfrastructuur met losse systemen.	Beperkt BI-bewustzijn; minimaal budget en vaardigheden. BI beperkt tot hoger management. Geen training of organisatorische ondersteuning.
2 | Faciliterend	Introductie van beschrijvende BI gebruikt voor datavisualisatie en rapportage. Enige integratie tussen ECD en IT-systemen, met initiële inspanningen voor databeveiliging.	Eerste inspanningen voor datakwaliteit en -integratie. Schaduwsystemen blijven in enkele gebieden bestaan. Centrale dataplatformen ontstaan.	Groeiende erkenning van de waarde van BI. Budget toegewezen voor tools en projecten. Onregelmatige trainingssessies, gebruik van BI uitgebreid naar middenmanagement.
3 | Beherend	Meerdere systemen geïntegreerd voor real-time data-analyse. Diagnostische BI samen met ECD en andere IT-systemen zoals CRM/HRM wordt coherent gebruikt.	Formele processen voor databeheer en kwaliteit. De meeste systemen zijn geïntegreerd in een gecentraliseerde infrastructuur met geautomatiseerde datavalidatie.	BI wordt strategisch. Toegewezen budget en leiderschapsondersteuning. Training is wijdverspreid in afdelingen. Gebruik van BI breidt zich uit naar klinische teams.
4 | Geavanceerd	Volledige integratie van alle bedrijfs-kritische IT-systemen en geavanceerde BI-tools (AI/ML). Real-time data voor voorspellende en voorschrijvende analyses mogelijk.	Continue monitoring van datakwaliteit met real-time validatie. Volledig geautomatiseerde, schaalbare infrastructuur die real-time analytics ondersteunt.	BI is ingebed in de cultuur. Alle medewerkers, inclusief zorgverleners, gebruiken BI in hun dagelijkse taken. Geavanceerde training en datageletterdheid zijn kernvaardigheden.



Level	ECD systemen	BI functionaliteiten	Integratie
0 | Niet-bestaand	Geen ECD-systeem aanwezig. Data wordt opgeslagen in vele aparte spreadsheets of andere bestanden.	Geen gebruik van BI of analyses.	Geen gebruik van andere IT-systemen in BI-analyses.
1 | Initiërend	Individuele applicaties van het ECD-systeem worden gedeeltelijk gebruikt (onvolledige dataset).	Gebruik van persoonlijke, geïsoleerde en/of ad-hoc analyses.	Gescheiden BI-analyse van data uit IT-systemen zoals CRM/HRM.
2 | Faciliterend	Meerdere applicaties van het ECD-systeem worden apart gebruikt in BI-analyse.	Introductie van beschrijvende BI voor datavisualisatie en rapportage. Eerste pogingen om databeveiliging te waarborgen.	Sommige IT-systemen en ECD-data worden samenhangend gebruikt in BI-analyses.
3 | Beherend	Meerdere applicaties van het ECD-systeem worden samenhangend gebruikt in BI-analyse.	Gebruik van diagnostische BI en real-time data-analyse voor betere besluitvorming.	De meeste IT-systemen en ECD-data worden samenhangend gebruikt in BI-analyses.
4 | Geavanceerd	Alle applicaties van het ECD-systeem worden samenhangend gebruikt in BI-analyse.	Voorspellende en voorschrijvende BI met gebruik van geavanceerde analysetools zoals AI en ML.	Volledige integratie van alle IT-systemen en ECD-data in BI-analyses.



Data dimensie

Level	Data kwaliteit	Data infrastructuur
0 | Niet-bestaand	Er is geen focus op data-kwaliteit. Data wordt handmatig beheerd in schaduwsystemen (bijv. Excel).	Er is geen data-infrastructuur. Data wordt op verschillende plekken bewaard zonder centrale opslag of integratie.
1 | Initiërend	Data-kwaliteit is laag. Handmatige processen zijn gebruikelijk, en gegevens worden gekopieerd tussen systemen.	Basis data-infrastructuur; er wordt gebruik gemaakt van schaduwsystemen en handmatige processen, maar er is geen centrale dataopslag.
2 | Faciliterend	Begonnen met data-kwaliteit en automatisering. Sommige processen worden geautomatiseerd, maar schaduwsystemen blijven bestaan.	Data-infrastructuur begint zich te centraliseren, met enkele integraties tussen systemen.
3 | Beherend	Formele data-kwaliteits- en governanceprocessen zijn in plaats. Data-integratie en automatisering zijn uitgebreid.	Data-infrastructuur is grotendeels gecentraliseerd en geautomatiseerd. Handmatige processen zijn grotendeels geëlimineerd.
4 | Geavanceerd	Doorlopende monitoring van data-kwaliteit in realtime. Geautomatiseerde validatie en kwaliteitscontrole zijn ingebouwd.	Data-infrastructuur is volledig geautomatiseerd, schaalbaar en ondersteunt realtime en voorspellende analyses.

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Organisatie dimensie

Level	Strategy	Training & vaardigheden	Organisatorische dekking
0 | Niet-bestaand	Geen bewustzijn of steun voor BI. Geen budget, vaardigheden of training.	Er zijn geen BI-vaardigheden of trainingen in de organisatie.	Geen BI-toepassing door de organisatie.
1 | Initiërend	Enig bewustzijn van BI, maar geen structurele investering of budget. BI wordt alleen ondersteund door hoger management.	Beperkte BI-vaardigheden, vaak informeel of zelf-gestuurd. Er is geen formele training, en BI-vaardigheden zijn alleen aanwezig bij een selecte groep.	BI wordt alleen door het hogere management gebruikt, zonder brede adoptie in de organisatie.
2 | Faciliterend	Er is groeiend besef van de waarde van BI, met een eerste budgettoewijzing en initiële inspanningen om BI te ondersteunen.	Basis BI-training wordt aangeboden aan geselecteerde medewerkers. Het vaardigheidsniveau groeit, maar is nog steeds beperkt.	BI-bewustzijn groeit, en BI wordt in toenemende mate gebruikt door middenmanagement en enkele operationele teams.
3 | Beherend	BI is een strategische prioriteit, met een toegewijd budget en leiderschapsondersteuning.	Wijdverspreide BI-training en vaardighedenontwikkeling. BI wordt ingebed in de besluitvorming van meerdere afdelingen.	BI wordt breed toegepast in de organisatie, met BI-informatie die beschikbaar is voor management en operationele teams.
4 | Geavanceerd	BI is volledig ingebed in de cultuur van de organisatie, met een sterke financiële basis en voortdurende steun van het leiderschap.	Alle medewerkers zijn BI-vaardig. Er is een continue leercultuur en BI-vaardigheden zijn essentieel voor de organisatie.	BI wordt door alle medewerkers (inclusief zorgprofessionals) gebruikt in hun dagelijkse werk, en BI is volledig geïntegreerd in werkprocessen.

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