
# The Systematic Development and Implementation of Key Performance Indicators for Tactical Integral Capacity Management

*A Case Study at a Single Specialty Breast Cancer Hospital*

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# Colophon

This document is a Master Thesis for the completion of the Master Industrial Engineering and Management at the University of Twente, Enschede, the Netherlands

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# Preface

It is with great pleasure and a sense of accomplishment that I present this master's thesis in Industrial Engineering and Management, focusing on the topic of integral capacity management on the tactical level of control in single specialty healthcare. This thesis represents the culmination of my academic journey of the past 6 years, and it would not have been possible without the support, guidance, and inspiration provided by numerous individuals.

Throughout this thesis, I have investigated and explored various aspects of integral capacity management. I have delved into the theoretical foundations, examined real-world practices, and applied analytical methods to gain insights into the care process challenges, opportunities, and best practices associated with managing capacity in the single specialty hospital, Alexander Monro Hospital. By analyzing the interplay between demand and resources, this thesis seeks to offer practical recommendations for optimizing capacity utilization and enhancing operational performance.

I would like to express my deepest gratitude to my thesis supervisor, dr. Gréanne Leeftink, for her invaluable guidance, expertise, and unwavering support throughout the research process. Her availability, insightful feedback, and continuous encouragement have been instrumental in shaping the direction and quality of this thesis. I would also like to thank dr. Sebastian Rachuba for his time and effort to provide me with valuable feedback towards the end of my thesis.

Furthermore, I am grateful to the healthcare professionals at Alexander Monro Hospital who generously shared their experiences and data, enabling me to conduct meaningful research. Their contributions have been essential in bridging the gap between theory and practice and have added a practical perspective to this study. I would like to specially thank my external supervisors, Esther van Beek and Mieke van Schuppen, for their guidance during this thesis.

Finally, I would like to express my heartfelt thanks to my family, friends, and husband for their unwavering support, patience, and understanding throughout this journey. Their encouragement, belief in my abilities, and unwavering presence have been the pillars of strength that propelled me forward.

Ilse Super
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# Management Summary

The healthcare sector wants to become more efficient and effective in their healthcare delivery because of rising expenditures and increasing demand for quality healthcare. This research focusses on integral capacity management for single specialty hospitals. We conducted our research at a case study hospital, Alexander Monro Hospital (AMH) which is specialized in the diagnosis and treatment of breast cancer. The objective of this study is to:

*Formulate and implement a set of key performance indicators that provide integral insight into the tactical capacity management performance of the care pathway.*

*Methodology*

In this research, we discover the care process of AMH through process mining, for which we follow the stages of the L*-methodology. After that we assess the current status of capacity management at our case hospital by using the framework for planning and control by Hans et al. (2012) to determine whether demand and capacity are aligned. Next, we conducted a systematic literature review to find key performance indicators (KPIs) for integral capacity management in healthcare organizations. Leveraging a Delphi study with iterative rounds, we select appropriate KPIs on the tactical level for our single specialty hospital. Finally, we design a dashboard in PowerBI visualizing all KPIs in an effective and efficient manner. All data in this research that is used for analysis is derived from the electronic patient record system of AMH. For process mining we use data from the last three years, and for the dashboard we use data of the last ten years.

*Key findings*

There are three main findings from our *process mining analysis*. In total there are 4559 variants of the care process to be distinguished in an event log of patient data covering three years. The top 10 variants cover 30% of all patient cases, identifying opportunities for standardization and predictability. Second, from the process mining analysis we discover that more than 80% of the cases start with one of six patient type appointments. After analyzing the process for each of these six patient types, we see that there are differences in the process sequence and the outflow of patients from diagnostics to surgery. From our analysis, we see that a new patient is the most occurring entering patient (35%), followed by reassessment second opinion (20%), mammography general practitioner (14%), Referral National screening program (5%), Mammography National screening program (4%), and Second opinion appointment (3%). From these patient-type processes, we also conclude that most patients go from diagnostics into further treatment in the form of surgery for the type referral National screening program (47%), followed by reassessment second opinion (39%), second opinion appointment (22%), New patient appointment (12%), Mammography general practitioner (5%), and Mammography National screening program (1%). Third, in our last analysis we look at the demand for the starting appointment types and treatment types. Overall, we see an increasing trend in demand for diagnostics and treatment.

From our *current state capacity analysis*, we find that decision-making has relied heavily on the intuition of experienced healthcare professionals, with limited reliance on data analysis through a spreadsheet-based solution. This method is becoming less reliable, more prone to errors as planning becomes more complex, and data collection expands. While the hospital has observed capacity shortages overall, there is still untapped capacity at the departmental level. Instead of expanding capacity, the hospital aims to improve efficiency by tactically managing their current capacity. By shifting to a data-driven approach, the hospital can appropriately plan capacity, enhance preparedness for demand peaks, and bridge the gap between departments for integral capacity management.

After identifying demand and capacity, we perform a systematic literature review and Delphi study, where we *select and formulate* 16 *KPIs* appropriate for integral capacity management on a tactical level in single specialty hospitals. These KPIs are stated in Table 1.

*Table 1: All the selected KPIs with their formulation and norms/target.*

| KPI | Final formulation | Norm/target |
|---|---|---|
| **Utilization** | Ratio of the actual patient use of resources to the maximum available amount | • OR: AMH target will be 65%.<br>• Chemo: AMH target: AMH target 65%<br>Diagnostics: AMH target: 65% |
| **Occupancy** | Ratio of the total use of resources to the maximum available amount | • OR: AMH target will be 90%.<br>• Chemo: AMH target: 90%<br>Diagnostics: AMH target: 90% |
| **Number of cases performed** | Number of cases performed per treatment type | • Chemo: AMH norm: 50 per week<br>Oral therapy: AMH norm: 50 per week |
| **Throughput** | Access time to first treatment | Max. AMH: 4 weeks (28 days) |
| **Cancellation** | Number of procedures or appointments that are cancelled by the patient | AMH norm: 10 per month |
| **Number of consultations given** | Number of consults per DBC per doctor | AMH target: 3 per DBC |
| **Number of first consultations** | Number of initial consultations with new patients | AMH production agreement: 157 for first 3 months of 2023, 203 for the other months of 2023. |
| **Number of diagnostic tests** | Number of diagnostic tests conducted | • Radiology: AMH norm: 150 per month per test.<br>Nuclear: AMH norm: 30 per month per test. |
| **Number of surgeries performed in the hospital** | Number of surgeries performed in the hospital | AMH target: 20 patients per week. |
| **Number of treatment starts** | Number of treatment starts | AMH production agreement: 32 per month for 2023 |
| **Admissions** | Number of patients admitted to the ward and chemotherapy department | • DAGA: 50 patients per week<br>Ward: 20 patients per week |
| **Length of stay** | Length of time patients stay in the ward and the chemotherapy department | • DAGA: AMH Max.: 180 minutes.<br>• Ward: between 0 – 5 days. AMH Max.: 2,5 days.<br>OR: AMH Max.: 120 minutes. |
| **Access time** | Access time for a patients first appointment (time between referral date and first appointment date) | • AMH norm: 24-48 hours, Max. 48 hours. |
| **Time between process steps** | Time between start diagnostics until PA outcome | AMH Max.: half of maximum, so 11,5 days. |
| **Appointment rescheduled** | How many times are appointments rescheduled | AMH norm: 10 per month |
| **Length of waiting list** | Length of waiting list of patients | AMH norm: 50 patients |

Our final result of this research is a *dashboard visualizing* all of the selected KPIs. This dashboard gives an integral view for tactical capacity management and many possibilities to dive into more depth through the several pages of the dashboard. The dashboard is customized to the needs of our case hospital including norms and targets for the KPIs and intended for use by the management team. Figure 1 depicts the first page of our user-friendly interface of the dashboard with visualizations of some of the KPIs.

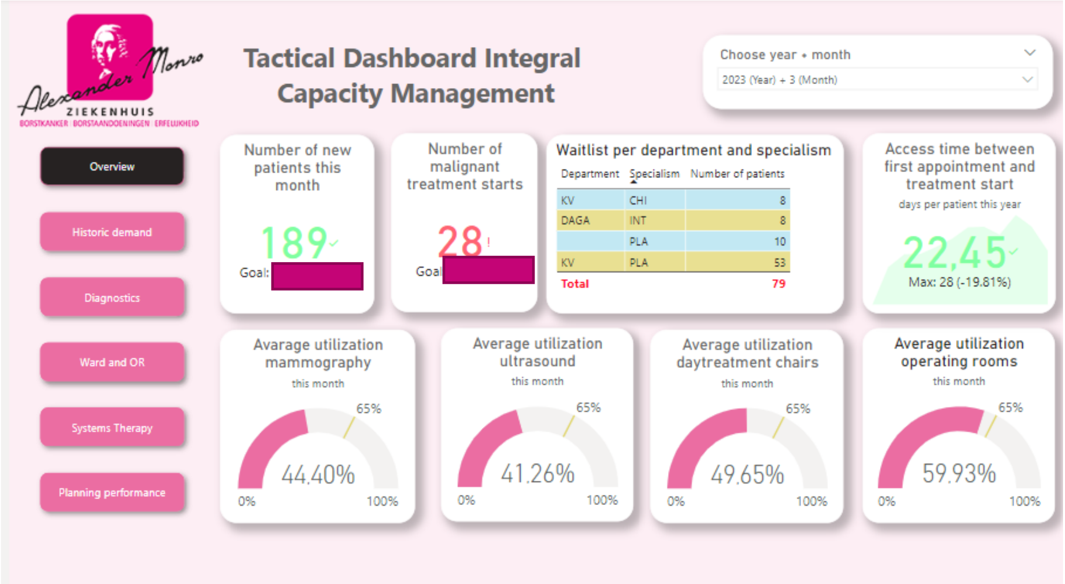


*Figure 1: Overview page of the dashboard*

*Conclusions and discussion*

In conclusion, we have reached our objective of formulating and implementing a set of key performance indicators that provide integral insight into the tactical capacity management performance of the care pathway. A first step into the direction of evidence-based integral capacity management would be to implement the selected KPIs and the dashboard proposed in this research as these give an integral solution and insight into the performance, challenges, and opportunities AMH is facing. The dashboard can be implemented guided by the implementation plan provided in this research. The process mining and capacity identification analysis provide us with useful steering information for patient flow that can be used for interpretation of the dashboard.

This thesis offers valuable practical and theoretical insights for improving integral capacity management on the tactical level of control in single specialty breast cancer hospitals. The development of KPIs and a capacity management dashboard facilitates data-driven decision-making and optimized resource allocation. On the theoretical front, this research addresses gaps by exploring process mining in a single specialty breast cancer hospital and developing KPIs for tactical capacity management.

We recommend the case hospital AMH to:

- Implement the KPIs formulated in this research as an integral set of key performance indicators measuring the performance of capacity management to manage capacity in an efficient and effective manner.
- Implement the tactical integral capacity management dashboard using the implementation plan.
- Invest in a connection to the EHR database for data reliability.

Opportunities for further research are a comparative study between general hospitals and single specialty hospitals, predictive capacity models, and appointment scheduling methods.

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# 1 Introduction

In today's healthcare sector, integral capacity management (ICM) is becoming more and more popular (Schneider, 2020). Hospitals want to become more efficient and effective in their healthcare delivery to deal with the increasing demand for quality healthcare and increasing expenditures (Hans, van Houdenhoven, & Hulshof, 2012). Due to the Covid pandemic, hospitals have experienced unprecedented financial pressures. Hospitals experience exponentially increasing cost of equipment and supplies further complicated by significant supply chain issues and labor shortages forcing hospitals to rely on temporary staffing (Healthstream, 2023). In many hospitals, capacity management is still managed per step in the care pathway leading to myopic optimization because the effects on other steps in the care pathway are not considered. ICM aims to optimize integral care pathways for all stakeholders. This is realized by improving access and flow, in terms of speed and variability, in care pathways by agile capacity (Schneider, 2020).

Over the last decades, there has been a growth in single specialty hospitals (SSH). Single specialty hospitals are defined as a hospital that is primarily and exclusively concerned with the treatment and care of patients suffering from a specific disease. Being specialized in a specific range of services could offer better care and provide services with more efficiency (Carey, Burgess, & Young, 2009). Physicians and nurses specialize in one illness and are given more control over the medical processes (Dummit, 2005).

Specializing in a certain disease comes with different capacity challenges than those for a general hospital. SSHs and general hospitals, for example, differ in the types of patients, the size of the facility, and the number of employees. These differences cause SSHs to operate differently from general hospitals. Integral capacity management is increasingly mentioned in literature for hospitals but is not yet studied for single specialty hospitals. This research focuses on integral capacity management for single specialty hospitals. For this study, research is conducted within Alexander Monro Hospital, which will be further introduced in Section 1.1. In section 1.2, an outline of what will be studied is provided with a research goal, research questions, scope, and timeline.

## 1.1 Alexander Monro Hospital

Approximately one out of seven women gets to deal with breast cancer in her life. It is the most occurring variant of cancer among females. Each year, there are more than 3000 mortality cases due to breast cancer in the Netherlands (RIVM, 2022). These statistics indicate the need for good breast cancer care. Breast cancer care, and oncology care in general, is multidisciplinary and consists of many complex care processes. It demands good organization and collaboration between departments. The goal of these care processes is to deliver good care to the patient with attention to the process, planning, and organization (Federatie Medisch Specialisten, 2012).

This research is conducted within the context of the Alexander Monro Hospital in Bilthoven, the Netherlands. This hospital is the first and only hospital specializing in the diagnostics and treatment of breast cancer. Other activities of the hospital are the treatment of benign breast conditions, genetic predisposition, familial increased risk, screening, and follow-up trajectories from the population screening. In a specialized breast cancer hospital, all medical specialists, nurses, and lab technicians work together in a multidisciplinary team that is completely focused on breast cancer only. The hospital aims to provide quicker, better, and more personal care to its patients than other cancer treatment facilities by delivering customized care, fully organized around the patient. As the hospital specializes in breast cancer, the hospital is relatively small compared to general hospitals.

The Alexander Monro hospital in Bilthoven faces the same challenges as other hospitals. The hospital's focus is to deliver quality care that evolves around the patient, but the quality of care comes at high costs. In the upcoming year, AMH expects healthcare suppliers to increase their costs by ten percent while the hospital does not receive more to cover these costs. Next to that, the hospital experiences a shortage in staff, more often turning to costly temporary staffing. To remain financially stable and eventually grow towards a more profitable organization, the hospital needs to balance the higher cost by creating more revenue. This can be achieved by making efficient and effective use of its resources and consequently serving more patients with the same resources.

## 1.2 Research outline

In an SSH patients follow a care pathway for the diagnosis and/or treatment of their specific disease. A care pathway is a logical sequence of individual steps a patient with a specific disease follows from the first admission until survival or death. These care pathways, also known as care processes, are developed to structure and standardize managing a specific medical condition or procedure. It provides specific guidance on the actions, assessments, treatments, and expected outcomes. A well-delivered care pathway is a seamless sequence of steps leading to a continuous flow for the patient (Federatie Medisch Specialisten, 2012). This contributes to the quality of care for the patient because of better waiting times and a smooth patient-friendly course of the care pathway.

To deliver this smooth course of the care pathway and reach desired outcomes, the available resources per step need to be aligned with the patient's demand in each step within the care pathway. This alignment of demand and capacity comes with multiple challenges as demand and capacity are not always certain. Not knowing current and future demand makes it difficult to intervene on the tactical level of control with flexible capacity allocations (Alp & Tan, 2006). Instead, misalignments in capacity and care demand are currently fixed by short-term solutions in operational planning which are typically time-consuming (Hans, van Houdenhoven, & Hulshof, 2012). Incorrect estimation of resource capacity could result in higher waiting times for the patients in multiple steps downstream of the care pathway when there is a high demand, or unnecessary planned capacity when there is low demand, also known as the bull-whip effect (Schneider, 2020). Solving a problem might fix the problem at hand in a certain step in the care pathway but increases the problems in another step. To monitor the impact of decisions on each step of the care pathway, key performance indicators are necessary to provide information. If key performance indicators are managed integrally, the management can focus on improvement and efficient use of resources over the whole care pathway.

The objective of this study is therefore:

*Formulate and implement a set of key performance indicators that provide integral insight into the tactical capacity management performance of the care pathway.*

To reach the research objective, we formulate multiple research questions that together also form an outline of the report. Each question below represents a chapter within this research and will eventually lead to solving the problem.

1. **What does the current process of the care pathway look like?**
    a. How many variations of the care process are there and what are the most occurring care processes?
    b. How do care processes of different patient groups differ from each other and what are the proportions of these patient groups relative to each other?
    c. What does the demand at the hospital look like? Are there any trends over time?

To answer this question, we will use historical patient data for process mining. With process mining, we visualize the care pathway in an abstract manner and deduce process information. With this information we answer all sub-questions and get an overview of what the care process is like and what can be expected from the hospitals demand.

2. **How is capacity currently managed within the hospital?**
    a. What is the current capacity available at the hospital?
    b. How does the hospital currently manage capacity on strategic, tactical and operational level?
    c. How are capacity and demand aligned?

This question is answered by observation and interviews in AMH. Next to that, we use the framework for planning and control (Hans, van Houdenhoven, & Hulshof, 2012) to identify capacity interventions on each level of control. After that we reflect on how capacity and demand are currently aligned combining the information gathered in research question 1 and 2.

3. **What do we learn from literature considering key performance indicators for integral capacity management?**
    a. What KPIs are interesting for each level of control?
    b. What KPIs are interesting for a single specialty hospital?
    c. What KPIs are formulated for tactical integral capacity management for a single specialty breast cancer hospital?

Research question 3 will be answered by conducting a systematic literature study about key performance indicators for integral capacity management. During the research special attention will be given to single specialty hospitals and the different levels of control for capacity planning. Next to that, we select the appropriate KPIs for tactical integral capacity management at a single specialty hospital through a Delphi study at our case hospital.

4. **How do we visualize the key performance indicators for tactical integral capacity management in a dashboard?**
    a. How will the data easily be transferred and translated into the dashboard?
    b. How does the dashboard help to improve integral capacity management?
    c. How reliable is the dashboard?
    d. How will the dashboard be implemented at the hospital?

Research question 4 will be answered by taking what we have learned from the literature to practice. First, we extract data that can be used in for the key performance indicator and transform and load this into the dashboard. After that, the outcomes of the key performance indicators are visualized in a dashboard. In this chapter we reflect on how this dashboard helps to improve integral capacity management, whether the dashboard is reliable, and how it can be implemented.

5. **What conclusions and discussion can be drawn from the research?**
    a. How do we interpret the results?
    b. How do we reflect on our research approach?
    c. What are the practical and theoretical contributions of this thesis?
    d. What were the limitations and opportunities for future research?

Research question 5 will provide a solution to the research objective by analyzing the output of the research. We then advise on how to use this output to improve integral capacity management. We also reflect on the chosen research approach, practical and theoretical contributions of this thesis, what were the limitations, and what could be interesting opportunities for future research.

### 1.2.1 Scope

For the scope of this research, we focus on supporting tactical integral capacity management at the Alexander Monro Hospital. The aim is to include all departments and the entire care pathway in the hospital as it is a rather small, specialized hospital. To reduce complexity, we exclude uncommon care pathways that are not significant enough to be considered. The model will be created from existing data within the hospital that is derived from the hospital information system (HIS) which is used to store all patient data and planning of resources.

### 1.2.2 Ethical Code of Conduct

During the study, research will be conducted with sensitive data. The data that is used is derived from the internal software program HIX by Chipsoft. In this program, all patient data including personal data are collected. During the data analysis, the personal data of the patients will be left out of the analysis so that the personal data of the patients cannot be derived. Data will only be used if necessary and always in correspondence with the management of the hospital.

Next to that, no names of personal that are named during an interview, or the name of the interviewee will be stated in the report. All interviewees will be made aware of the use of the information they provide in advance of the interview. If an interview is recorded, this will also be mentioned in advance of the interview. All information observed about patients or employees will remain confidential unless discussed differently with the management team.

This research is approved by the Ethics Committee of the University of Twente by request number 230064.

# 2 Process mining in healthcare

In this chapter, we present a process mining model, to identify and visualize the current care process of breast cancer diagnosis and treatment. We introduce process mining for healthcare processes and the used methodologies, and then apply this to our case study hospital. The remainder of this chapter is structured as follows. Section 2.1 introduces data-based process modeling and why we choose this approach. In Section 2.2, we provide background information about the characteristics of healthcare processes and process mining. Section 2.3 provides the methodology for this study including the software used. Section 2.4 presents the results of the process mining study and Section 2.5 describes a conclusion drawn from these results.

## 2.1 Data based process modeling

To achieve a high standard for the quality of healthcare, hospitals become increasingly aware of the need to improve their processes (Munoz-Gama, et al., 2022). To improve the performance of a process, it is necessary to get a clear view of what the process looks like. By definition, a process is a set of interrelated activities, decisions, and events with a particular goal. (Baird, 2023)In the case of healthcare processes, these include clinical processes (e.g., the execution of a care pathway that describes the treatment of a certain medical condition) and administrative processes (e.g., planning processes) (Munoz-Gama, et al., 2022). Although these processes are existing, it is not always clear what these processes exactly look like. In a hospital, patients are provided with care along procedures. While some procedures are based of protocols, some are informal and undocumented. If procedures are documented, in reality, the process of conducting these procedures could still differ from these documents (Van der Aalst, 2011).

By visualizing a process, complex processes are reduced to understandable and abstract overviews which are used for improvement of the process and communication along stakeholders. There are many existing methods to visualize a process (e.g., BPMN (Chinosi & Trombetta, 2011), Value Stream Mapping (Marin-Garcia, Vidal-Carreras, & Garcia-Sabater, 2021)). While these methods produce a good representation of the process, they often lack in providing a realistic view of the process. Mostly, these types of visualizations are made based on an idealistic view of the process and by the subjective views of management and experts. Unlike the previously mentioned methods, process mining is based on facts instead of opinions and perceptions. Process mining is a method that uses an event log based on real patient data. With this method, it is possible to obtain insights into what process steps are really executed and how the process is performing. It is an evidence-based method for process management and provides us with knowledge for process improvement. (Van der Aalst, 2011)

In this study, we focus on the discovery of the clinical care process patients follow at our case study hospital, which is one of the three types of process mining that will be further introduced in Section 2.2.2. These processes consist of the clinical steps for diagnosis and/or treatment of breast cancer. For this, we consider all the consecutive steps a patient follows from the first appointment until the last executed step. A recent literature review discovers that process mining has been used for breast cancer treatment, but the number of studies is very small (n=10) and all of these studies cover only a fraction of the entire care pathway or an overly simplified care pathway. (Grüger, Bergmann, Kazik, & Kuhn, 2020) Next to that, process mining in single specialty hospitals is still undiscovered. To our perception, there are no other papers describing process mining on the care process of breast cancer in single specialty hospitals. The limited amount of research might be due to the fact that there is a relatively smaller market share of SSHs compared to general hospitals or multi-specialty facilities. This could limit the possibilities for research because of the scale, applicability, and generalizability of the research. It is however interesting to conduct research on single specialty hospitals as these can present unique characteristics, opportunities and challenges compared to general hospitals. More insight into the care processes of such hospitals could further improve the practices of SSHs.

In the case of AMH, the management is interested in the improvement of patient flow. Next to that, they want to improve their capacity management and want to know how they best serve demand with the right capacity. To provide useful insight, we formulate questions that will guide us through our process mining research. In this study we answer the following questions:

1. How many variations of the care pathway are there and what are the most occurring care pathways?
2. How do care pathways of different patient groups differ from each other and what are the proportions of these patient groups relative to each other?
3. What does the demand at the hospital look like? Are there any trends over time?

## 2.2 Background

### 2.2.1 Healthcare process

As previously described, healthcare processes exist of administrative and clinical activities. These processes mostly revolve around serving the patient. These clinical processes revolving around the patient are known to be loosely framed and knowledge intensive. (Martin, et al., 2020) One of the reasons is that each patient is unique and responds differently to treatment in terms of co-morbidities and complications. To deal with these unforeseen situations the process involves continuous complex decision-making leading to many variations in approaches and outcomes (Munoz-Gama, et al., 2022). Next to that, there are also other healthcare specific characteristics that lead to this substantial variability, for example, personal preferences of patients and healthcare professionals, and subprocesses being executed at the same time (Munoz-Gama, et al., 2022).

Because of this variability, it becomes more difficult to oversee what happens in the process. A good thing about the healthcare sector is that all patient related activities are heavily documented. Nowadays, almost all hospitals document their patient related activities in an electronic health record (EHR) system (Rojas, Munoz-Gama, Sepúlveda, & Capurro, 2016). An EHR is an online version of a patient's paper chart. It shows real-time data about the patient which makes it possible to easily access data by people who are authorized. The data collected gives a broad view of the patient's care history, for example, medical history, diagnoses, medications, treatment plans, radiology images, and lab and test results. (HealthIT.gov, 2019) The way data is gathered within healthcare organizations is therefore extremely suitable for process analysis.

Process analysis in the healthcare context can be very valuable. Understanding care processes allow healthcare organizations to identify areas for improvement and implement evidence-based interventions. Analyzing the steps, activities and outcomes of a care process can identify variations, inefficiencies, and opportunities to enhance effectiveness, and patient-centeredness. Next to that, insight into the care process enables standardization of the process which helps to ensure consistency, quality, and reliability of care but also makes it easier to communicate among professionals involved in the care process. Apart from these general improvements of healthcare delivery, insight into the care process also helps to optimize resource utilization, including personnel, equipment, and facilities. A good understanding of the process steps and the dependencies between these steps, can help to streamline the workflows, reduce unnecessary delays, and improve the efficiency of capacity allocation.

### 2.2.2 Process mining

An evidence-based approach to process analysis is process mining. Process mining is a relatively new research discipline that lies between machine learning and data mining on one side, and process modeling and analysis on the other side. It is used to discover, monitor, and improve real processes by extracting information from event logs. (van der Aalst, Process Mining, 2016) These event logs are retrieved from information systems that store big numbers of events. Process mining is be used for a large range of systems. These systems can be information systems, but also hardware systems such as embedded systems. Examples of these systems are ERP systems (e.g., SAP), CRM systems (e.g., Microsoft Dynamics), classical workflow management systems (e.g., Staff ware), and hospital information systems (e.g., Chipsoft HIX). (Mans, Schonenberg, Song, van der Aalst, & Bakker, 2008) According to van der Aalst (2016), there are three types of process mining: *discovery, conformance checking,* and *enhancement*. Discovery is taking an event log and creating a model out of it without using any prior information. The second technique is conformance. In this case, an already existing model of the process is compared with a process derived from an event log of the process. Conformance is used to check if reality conforms to the already existing model of the process. The third technique is enhancement. For this technique, the actual process created with the event log is used to improve or extend an existing process. For example, enhancement is used to modify a process to be more realistic. The process of process mining is visually represented in Figure 2 below.

This study focusses on the *discovery* of the care process at AMH. Currently, the hospital does not have a process model in place that represents the care process. There is one document about the care process available, but this is outdated and incomplete. The hospital management can further improve their capacity management and learn about their actual process and how they can improve through process mining. In the future, process conformance and enhancement can be used on the discovered process.

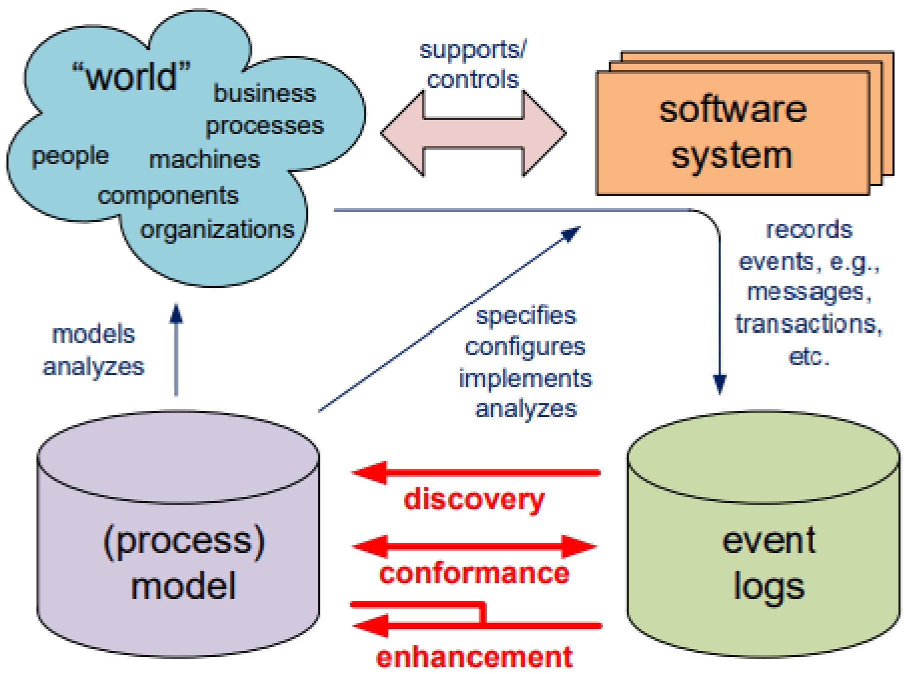


*Figure 2: Visualization of process mining. (van der Aalst, Process Mining, 2016)*

## 2.3 Methodology

In this study, we use the L*-methodology for process mining which has been suggested by van der Aalst et al. (2011) as a suitable methodology for process mining projects. This methodology provides a high-level overview of the steps that must be conducted for a process mining analysis. (Martin, et al., 2020) We choose this methodology as it provides a clear and structured guideline for the steps in conducting a process mining analysis. In total the methodology consists of 5 consecutive stages starting from stage 0 up to stage 4. the final stages of this method, stage 3 and 4, considers additional perspectives and operational support using live data. It is not possible to add these additional perspectives because there is not enough data available to provide these perspectives such as specialties for all events. Due to technical circumstances within the case hospital, it is also not possible to maintain a support tool and is therefore beyond the scope of this research. This leaves us with stages 0, 1, and 2. By following the steps in these stages we hope to reach an exhaustive view of the care processes executed at the case study and deduct useful insights from our data.

In *Stage 0: Plan and justify*, we make ourselves acquainted with the available data and the domain and develop an understanding of these two and how they interact. We then formulate the most important questions we want to answer with the data in this domain. These questions guide us throughout our analysis in stage 2. The formulated research questions of stage 0 are presented in Section 2.1 along with the motivation for the research.

In *Stage 1: Extract*, we extract the historical data to create the event log by applying selection criteria specific to our data to gather records of treatment cases for patients with breast cancer at our case hospital. This stage is extended by interactive data-cleaning methods derived from Martin (2020) to guide the data cleaning process. In this stage we manipulate our data to provide us with as much information as possible, but not go too much into details concerning certain procedures on an operational level. We want to show the steps of the entire process, which should be at a management level. For the management level it is important to see what facilities, types of diagnostics, and treatments are visited by patients and how these are dependent on each other considering patient flow.

In *Stage 2: Create the control-flow model and connect the event log*, the extracted data subsets are analyzed using process mining approaches related to the discovery of the process. The initial results might already provide answers to some of our research questions. If necessary, the event log should be filtered to answer certain questions.

There is software that is identified by literature as commonly used process mining tools. The most popular tools for process mining in healthcare are ProM, Disco Fluxicon, and RapidProM (Rojas, Munoz-Gama, Sepúlveda, & Capurro, 2016). For this study, we choose to use Disco because it has a user friendly visual interface and built-in functionalities to apply multiple and variable filtering options to our event logs. The data is extracted using the software Chipsoft HIX 6.2 HF96 combined with Excel Version 2301, as this is the current EHR system of the case study hospital which has a built in function to extract data sets to a spreadsheet. To prepare our event logs for use in Disco, we clean and merge our data using RStudios 4.2.2. There are multiple popular programming languages that are suitable for data cleaning like R and Python. We choose to use R in RStudios as this language is particularly suited for data manipulation because of its wide variety of packages for data cleaning. One of the advantages of RStudios compared to other languages is the possibility to see the outputs in the same screen as your code, by running individual lines of code to check whether the data manipulations are providing the desired output.

## 2.4 Results

### 2.4.1 Stage 1: Extract

As input for the event log, we use three years of data between 08-02-2020 and 08-02-2023 from the EHR database. Data before 2020 would not be appropriate for analysis as the EHR system is reorganized at the end of 2019 and was used differently with other appointment codes. To cover all activities involved with patients we select data from four different tables: Admissions, Appointments, Surgeries, and Deaths. The table "Admissions" covers all admissions at two departments, the ward (KV) and day treatment admissions (DAGA). The ward department (KV) is for patients that are admitted just before and after surgery for recovery. This could be for one or multiple days. Day admissions (DAGA) patients receive treatment on the same day as admitted and are always discharged on that day as well, for example, chemotherapy treatment. The table "Appointments" covers all data related to appointments between patients and doctors and administrative tasks related to the patient. These appointments are within multiple departments and cover diagnostics as well as treatment consults. The table "Surgeries" provides dates of surgeries, and the table "Deaths" provides the data on deceased patients within the provided timespan. The collected data is exported to Excel for data cleaning purposes.

From the data, we exclude certain patients who are treated at Alexander Monro but are officially registered at another organization. We exclude these patients as they are treated by other organizations which make use of the facilities at AMH. These patients are not treated by staff of the case hospital and all other records of these patients that are registered along their care process are not in the EHR of AMH as these are not AMH patients. Next to that, we exclude test patients from the data sets as these are not real patients. After observing the data, the event granularity (many distinct activities) in the table "Appointments" is high (more than 200 different event types). To reduce the number of distinct activities a good technique is to cluster certain similar activities by one name. (Bose, Mans, & Van der Aalst, 2013) To reduce the number of care pathway variations we also make some changes to the table "Surgeries" by a technique called trace clustering (Bose, Mans, & Van der Aalst, 2013). Instead of naming each surgery by what surgery is exactly performed, we mention all surgeries by the event name "surgery". The clustering of appointments and surgeries reduces the level of detail, but for the purpose of process discovery on a managerial level this is not an issue. For the table "Admissions" we also only provide whether the admission is "DAGA" or "KV" and do not disclose the exact treatment that was given to a certain patient. After these adaptions, the data is combined to one table, the event log "Eventlog". To reduce the number of events and patients we delete the administrative tasks from the appointment, as the patient is not aware of these activities and are therefore not directly patient interaction related.

For one of our analyses, we focus on the different patient types coming in at the hospital. To analyze what new patients are coming in, we only want to include new patients from the start of their care pathway. To only include these patients in our data, a start date must be available for the patient, for example, a referral date or first appointment indication. The EHR of Alexander Monro Hospital does not have an indicated starting moment for a patient. Therefore, the data set includes starting patients but also includes patients that have started their diagnosis and/or treatment at an earlier moment in time which is not known. Since patients enter Alexander Monro Hospitals in many possible ways (e.g., second opinion, referral by GP, referral by BOB) it is difficult to distinguish new patients from existing patients as their appointment codes could be the same. To approximate a list of starting patients, we develop an alternative method that filters out a significant number of existing patients. For this method, we extract two years of patient data before 08-02-2020 in the same way as we did for the other three years. For all these appointments, we collect the patient numbers and delete all duplicates from this list. We assume that all patients that are not new patients within the last three years, were under treatment at AMH in some way during the two years before. With that assumption, we filter out all patients in the three-year data set with a patient number that occurs in the two years before. In the following stage, we name the data set with existing and new patients “Eventlog” and the data set with only new patients “Eventlog2”. “Eventlog” is used for data analysis in research questions one and three. “Eventlog2” is used for data analysis in research question three.

The process of data cleaning is visualized in the Figure 3. Within the figure, number of data entries and cases are depicted before and after data cleaning.

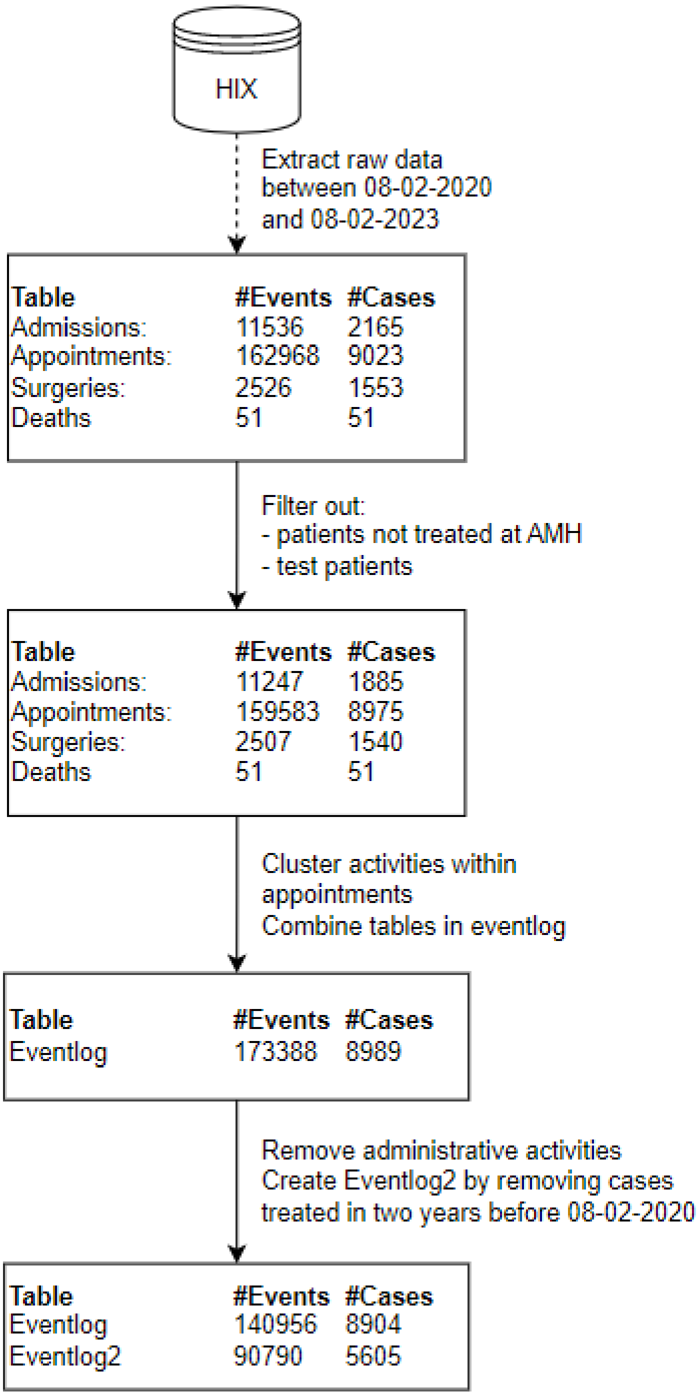


*Figure 3: Visualization of the data cleaning process*

After we have completed our event log, there still are some remaining data quality issues. The first one is missing data. Within the surgery data, there are in total 21 missing timestamps. There are 12 missing start times, and 9 missing end times. The cases with missing timestamps are automatically removed from the event log by the process mining application. Next to that, there are some incorrect time stamps within the event log. The first issue is that all times of death are recorded at midnight. In reality this would likely not be true. The date of death, however, is correct and therefore this incorrect timestamp does not cause a problem for the analysis. Another incorrect data issue occurs with the start and end time of many appointments from the appointment table. Most of these appointments start and end at the same time. This is most likely caused by the way doctors register the start and end of the appointment. This incorrect data does not cause any problems for the sequence of the event log, but when looking at the duration of tasks, this does not provide a realistic view.

### 2.4.2 Stage 2: Create the control-flow model and connect the event log.

After data cleaning the tables are combined in an event log named "Eventlog". This event log is then uploaded to the data mining tool. In total, the event log has 8,904 distinct patient numbers, which is also referred to as the number of cases. The event log consists of 141,943 events made of 97 distinct activities.

In process mining, the real processes recorded in the event logs are complex processes with many activities and paths. If we were to visualize this process, we end up with a "spaghetti model" visualizing all paths and activities which is too difficult to understand. With the process mining tool, we reduce complexity by simplifying the process. This is done by reducing the number of activities to only the most frequently occurring activities and/or reducing the number of paths to only the most frequently occurring connections between activities.

If we minimize the number of paths but show all activities, it is still hard to have an overview of the process as there are 97 distinct activities. Looking at the activities, the top 5 activities are visited with a relative frequency of 50%, while the bottom 20 activities are only visited with a relative frequency of 1%. To reduce the complexity of the process maps, we reduce the number of paths and activities to a point where the map is readable and understandable but does include as much as possible. The level of abstraction is always mentioned in the caption of the depicted process maps throughout the chapter by stating the percentages of activities included, and the percentage paths included in the visualization. Process maps are visualizations created with the application Disco, visualizing the processes within the event logs.

- *How many variations of the care pathway are there and what are the most followed paths?*

To answer the first research question, we analyze the event log "Eventlog" containing all patient data over 3 years. In total there are 4559 variants of the care process at our case hospital within this event log. A variant is a set of activities in a certain sequence that occurs for a set of cases. As most patients follow their unique care pathway variant, some variants are shared by a fair share of cases. The top 10 variants cover 30% of all cases. For interpretation of these variants, it is good to understand that other cases could still include these processes but are not limited to these processes. Cases only share a variant when they follow the same set and sequence of activities.

In Table 2, the top 10 most occurring process variants are given. These care pathways are shared by most cases and are therefore the most predictable processes. What is interesting about the variants in the table, is that all processes are diagnostics or follow-up diagnostics. Since we use data over three years, we see that variants 5, 6, and 9 cover the follow-up patients for which these start at year 1, 2, and 3 of the event log and are not followed up by any other diagnostics or treatment. Next to that, we see diagnostics of different patient types in the other variants. For these variants also only diagnostics take place after which there is no additional diagnostics or treatment.

If we look at the mean duration of these variations, we see that some of the durations of the process variants are zero seconds. This is caused by the low data quality of the time stamps. For many appointment times, start and end of the event is recorded at the same time, while this is not possible in reality. For the two-year follow-up appointment repetition (variant 6), we see that on average there is one year and 103 days between the first and the second year. The median of this variant is around 60 days lower which indicates that the mean is influenced by higher duration outliers. For the variant with three repetitions of the follow-up diagnostics (variant 5), we see a mean duration of two years and 40 days. Again, if we look at the median for this variant, we see an 8 days lower median which indicates there might be some high outliers. For both variants, the mean duration is a bit higher than expected as the follow-up appointments are expected to have intervals of 1 year. This also goes for the median as this is still higher than a year and two years. For the other variants (Variants 1,2,7,9,10) we see that these appointment sets are on average always within a few hours, and therefore take place within the same day. The medians of these variants are again lower than the average, indicating a skewed distribution, however, the median at most deviates 45 minutes, which still makes us believe the appointments are mostly conducted within the same day.

*Table 2: Top 10 most occurring variants in the event log "Eventlog"*

| Variant | Cases | Process | Mean duration (y/d/h/m/s) | Median duration (y/d/h/m/s) |
|---|---|---|---|---|
| **Variant 1** | 873 (9.8%) | New patient appointment > mammography > Ultrasound > Outcome | 00:00:3:15:00 | 00:00:2:30:00 |
| **Variant 2** | 442 (5%) | Mammography GP > Ultrasound | 00:00:00:21:55 | 00:00:00:20:00 |
| **Variant 3** | 357 (4%) | Mammography BOB | 0 | 0 |
| **Variant 4** | 301 (3.4%) | Mammography GP | 0 | 0 |
| **Variant 5** | 205 (2.3%) | Mammography follow-up > Follow-up appointment > Mammography follow-up > Follow-up appointment > Mammography follow-up > Follow-up appointment | 2:40:00:00:00 | 2:32:00:00:00 |
| **Variant 6** | 151 (1.7%) | Mammography follow-up > Follow-up appointment > Mammography follow-up > Follow-up appointment | 1:103:00:00:00 | 1:42:00:00:00 |
| **Variant 7** | 119 (1.3%) | New patient appointment > Ultrasound > Outcome | 00:00:2:22:00 | 00:00:2:15:00 |
| **Variant 8** | 109 (1.2%) | Ultrasound | 0 | 0 |
| **Variant 9** | 90 (1%) | Mammography follow-up > Follow-up appointment | 00:00:1:05:00 | 00:00:1:05:00 |
| **Variant 10** | 82 (0.9%) | New patient appointment > Mammography > Outcome | 00:00:2:23:00 | 00:00:2:15:00 |

- *How do care pathways of different patient groups differ from each other and what are the proportions of these patient groups relative to each other?*

To answer this research question, we use the data set containing only new patients in the last three years "Eventlog2". This event log only contains newly starting patients at AMH as described in stage 2. The event log contains 5,605 different patient cases. To analyze the different patient groups, we analyze the starting activities and consider the processes that cover more than 2% of the cases. In Table 3, we name all different patient types and the percentage of patients that are considered as this patient type within the data set. In total these patient types make up 87% of the patients in the data set. The missing 19% of the patients are exceptional cases that only occur for less than 2%.

*Table 3: Patient types and their case coverage*

| Patient Type (starting activity) | Case coverage |
|---|---|
| **New patient appointment** | 35% |
| **Reassessment second opinion** | 20% |
| **Second opinion appointment** | 3% |
| **Mammography GP** | 14% |
| **Referral BOB** | 5% |
| **Mammography BOB** | 4% |
| **Total** | 81% |

Within AMH there are 6 different entering patient types that are be distinguished: new patients, Second opinion (Reassessment second opinion and second opinion appointment), Mammography General Practitioner (GP), Referral BOB, and Mammography BOB. BOB stands for "Bevolkingsonderzoek Borstkanker" is a Dutch abbreviation for national breast cancer screening. These patient types enter the hospital for diagnostics after which some of these patients leave and the other patients follow up with treatment. For each of these patient types, we visualize their process with a process map and analyze what happens in each process.

**New patient appointment**

The first patient group is the new patient which starts with a new patient appointment. These are patients that are referred for diagnostics by their general practitioner (GP) because they suspect breast cancer. This is the most common way to enter the hospital. From the process map, in Figure 4, we analyze by the color intensity which activities are the most visited and by the thickness of the arrows what are the most followed paths. The numbers along the paths and activities are the cases that follow the paths or visit the activities. Because the process is simplified by reducing the number of activities and paths, we must consider that the numbers do not always add up.

The main path for a new patient starts with a new patient appointment followed by a mammography and ultrasound. Some of the patients get an ultrasound biopsy instead of an ultrasound. After that, the diagnostics part is (in most cases) concluded with an outcome appointment. After that appointment, part of the patients leaves the hospital, and a part remains for further treatment or diagnostics. 1,096 cases leave the hospital after the outcome appointment which is 55% of the new patient entries. Of the remaining patients (903 patients), there are 142 (7% of the total) patients that visit the day admissions for treatment, and 231 (12% of the total) patients undergoing surgery.

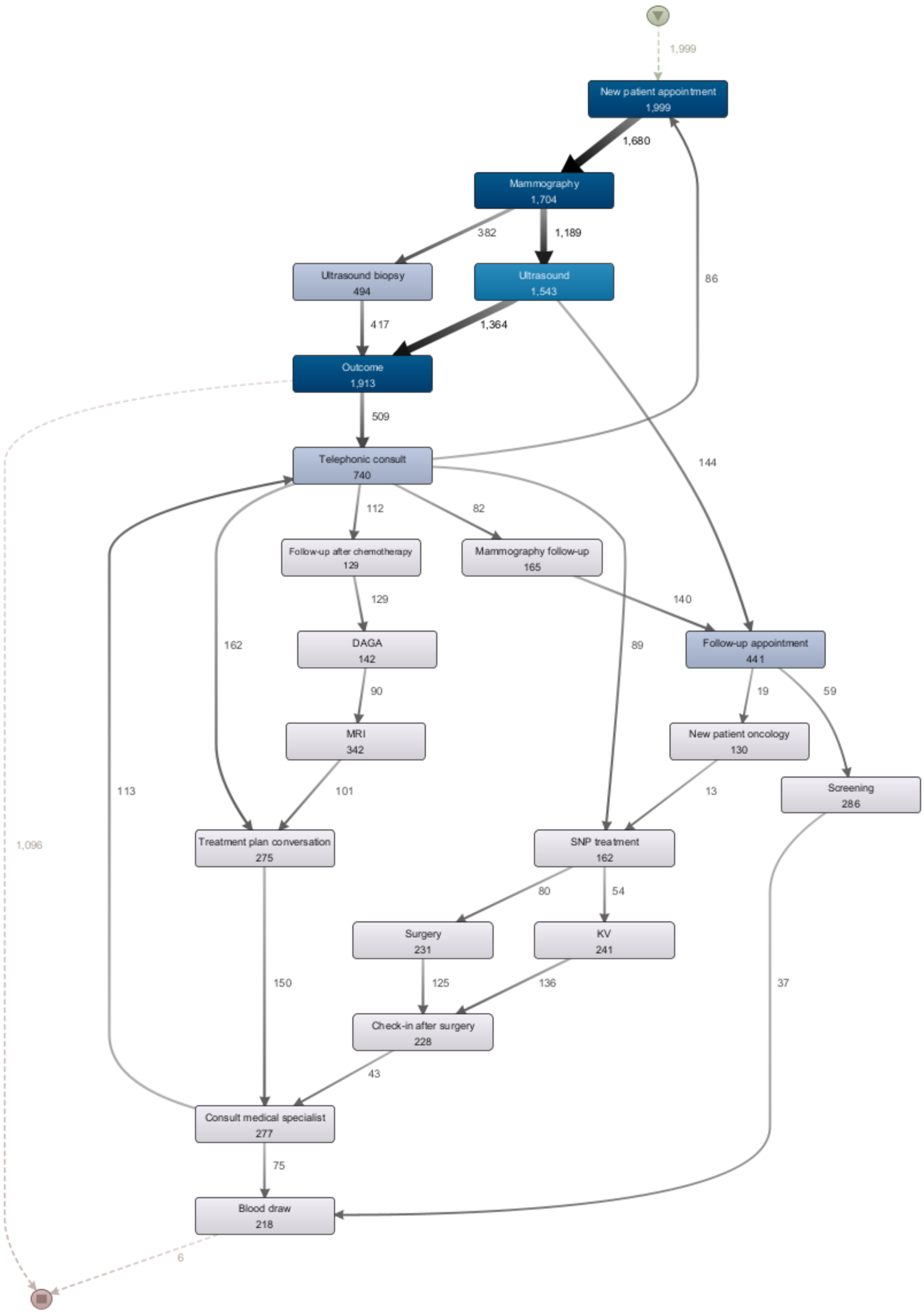


*Figure 4: Process map starting with a new patient appointment, 20.3% activities, 0% paths.*

**Reassessment second opinion**

The next patient type is a second-opinion patient for which the process is visualized in Figure 5. For this type of patient, the process starts with a reassessment of the second opinion. Then for most of the patients, this is followed by a second opinion appointment and diagnostics including mammography and ultrasound or only ultrasound. The diagnostics are then concluded with an outcome appointment after which some of the patients get extra diagnostics in the form of an MRI. For the second opinion entries, 39% of the cases receive surgery.

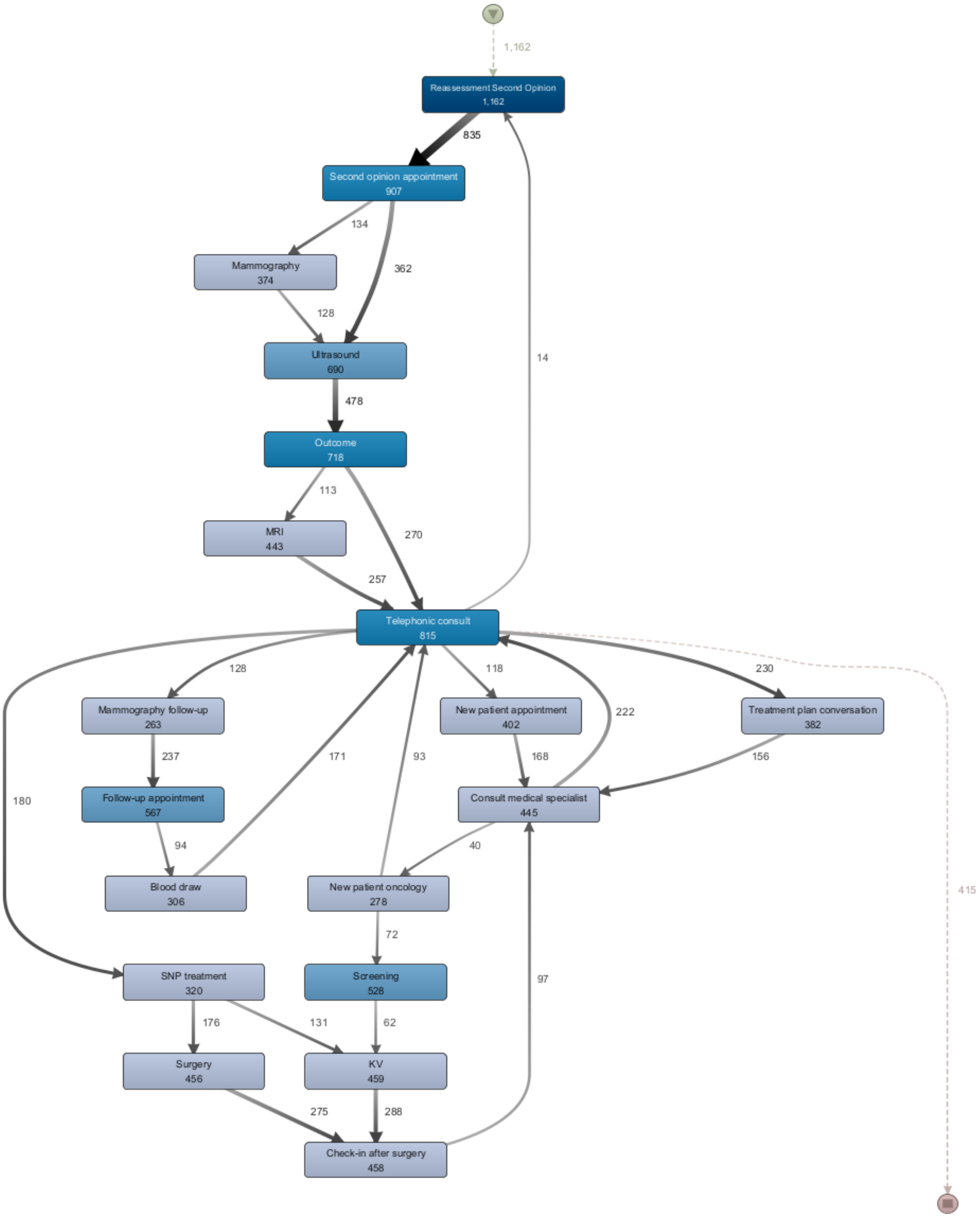


*Figure 5: Process map starting with reassessment second opinion, activities 20.3%, paths 0%.*

### Second opinion appointment

Although most second opinions start with a reassessment second opinion, they can also directly start with a second opinion appointment. The process in Figure 6 is similar to the process in Figure 5, but the sequence of activities and the number of cases per activity is different. From the total entries of this patient type, 22% undergo surgery.

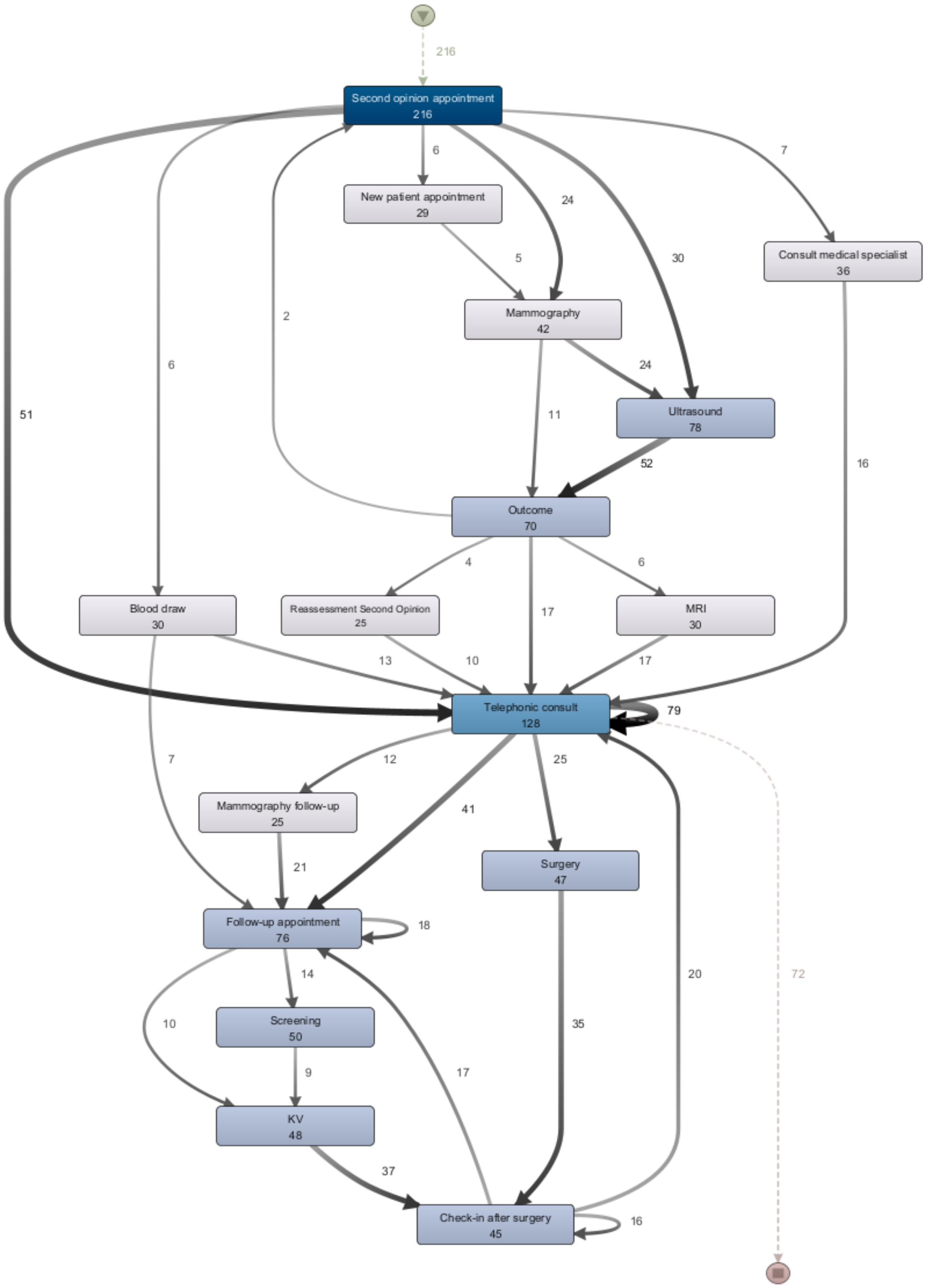


*Figure 6: Process map starting with second opinion appointment, activities 31.8%, paths 2%.*

**Mammography GP**

14% of the patients start their process with a mammography GP. What makes this mammography different from other mammography's, is that this type is requested by the general practitioner (GP), but there is no request for a new patient appointment before an outcome appointment after. From the process map in Figure 7, we see by the color intensity and arrow thickness very clearly that most patients only come for mammography. Of the total patients entering for mammography, 64% of the patients also get an ultrasound, 10% get an ultrasound biopsy, and 9% an MRI. Although these patients are sent for imagery, if the hospital finds a malignant tumor, they plan an appointment with the patient to start treatment. 17% of the entering patient gets a new patient appointment. Of all patients 5% eventually undergo surgery.

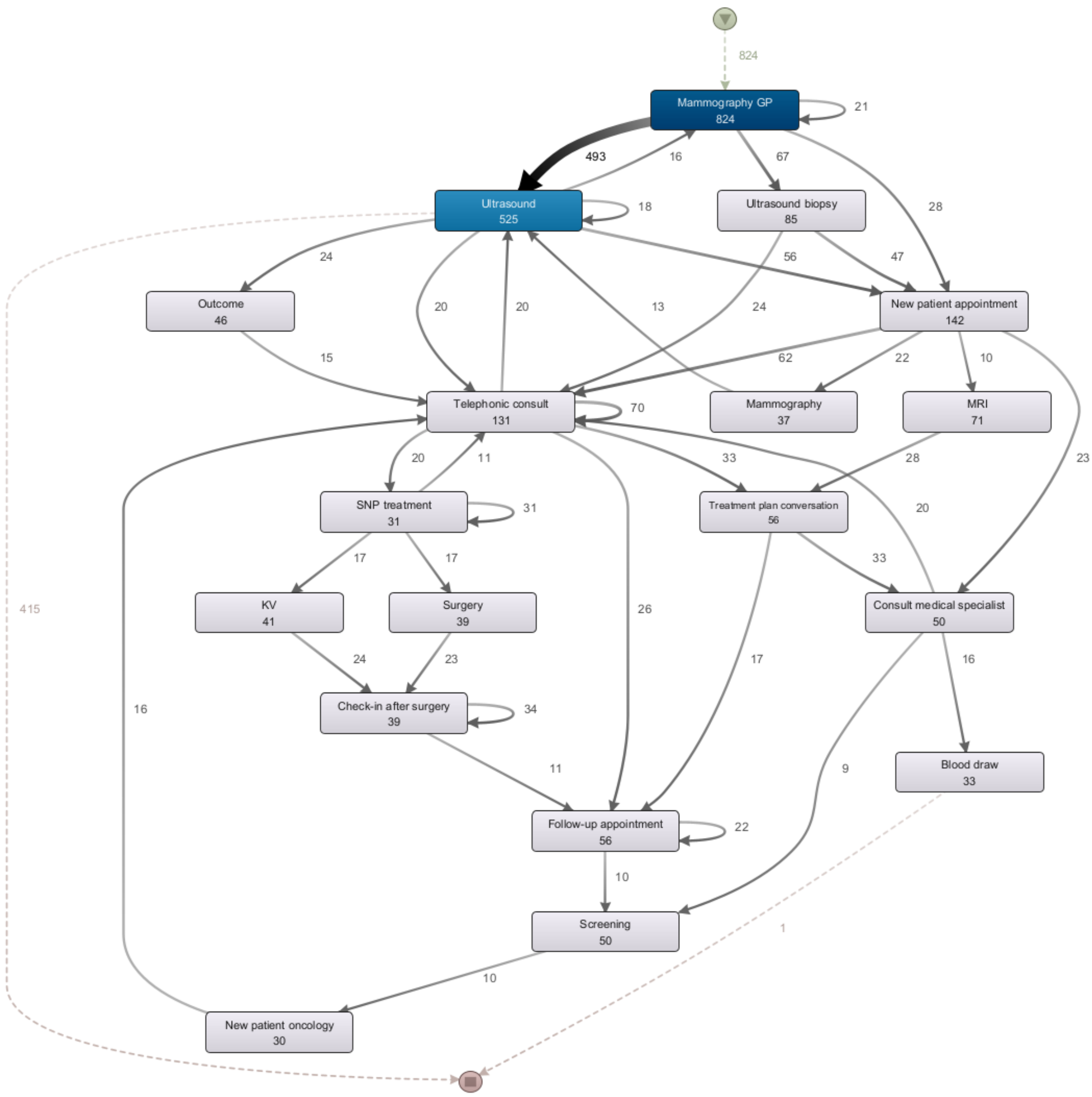


*Figure 7: Process map starting with mammography GP, activities 24.5%, paths 5.2%.*

**Referral BOB**

The next patient type starts with a referral BOB appointment. Patients that enter the hospital with a referral BOB appointment are referred to the hospital after something suspicious has been detected during the national breast cancer screening. In the process map in Figure 8, we see that compared to the other process maps, this map has a relatively high color intensity. This means that after diagnostics relatively many patients stay for treatment. After a referral BOB, the patient still undergoes diagnostics at the hospital. Almost all patients (94%) get a mammography followed by an ultrasound biopsy (47%) or stereotactic biopsy (53%). Of all entering patients of this type, 47% undergo surgery.

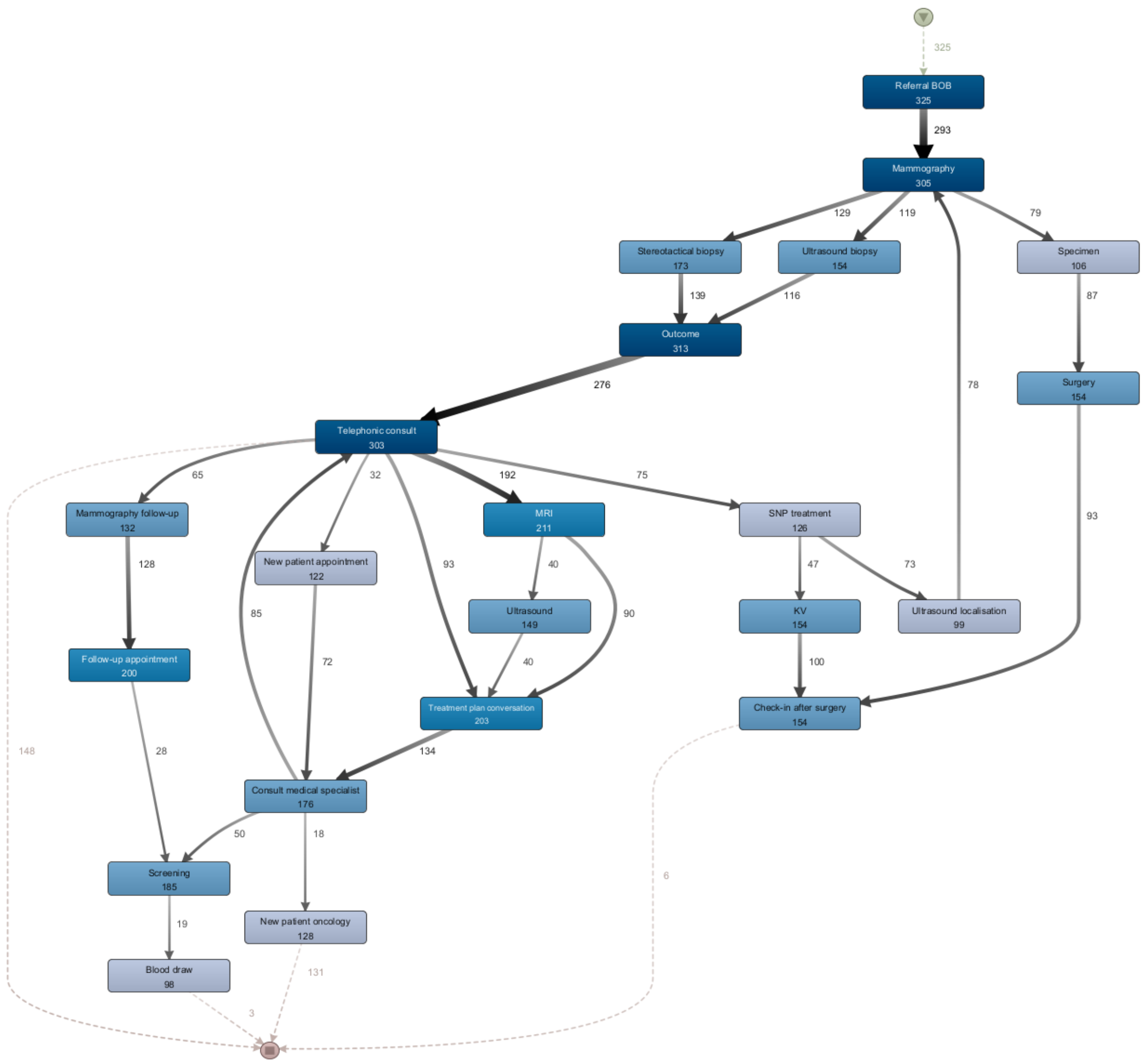


*Figure 8: Process map starting with referral BOB, 23.5% activities, 0% paths.*

### Mammography BOB

Another patient type starts with mammography BOB, of which the process is visualized in Figure 9. This type of mammography is for patients that do not want to participate in the national breast cancer screening but choose to be screened at AMH. All these patients get mammography, after which 82% of the patients leave without further diagnostics or treatment. The number of patients that stay for treatment at the hospital is relatively low. Only 1% of the patients undergo surgery.

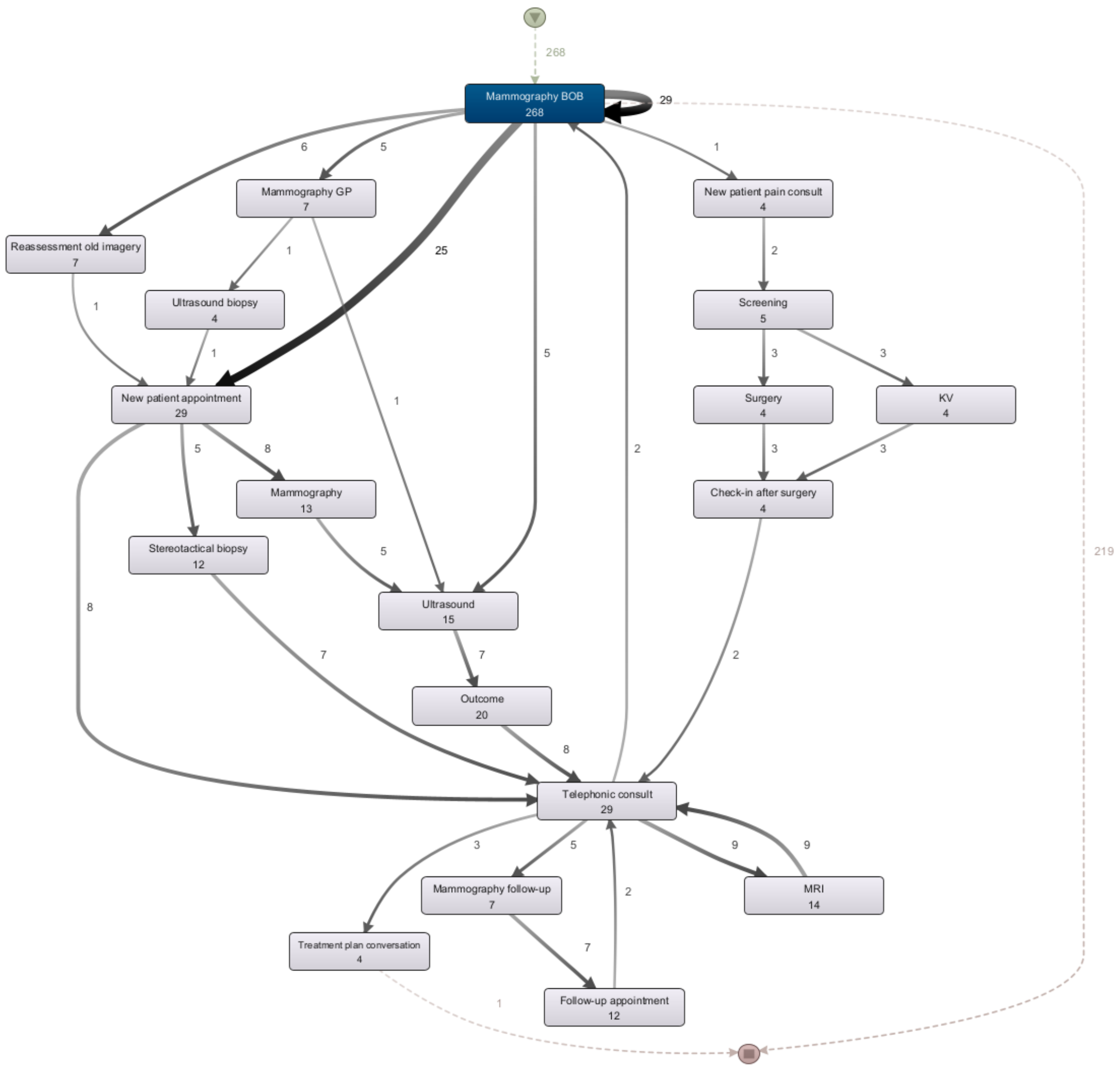


*Figure 9: Process map starting with mammography BOB, 23.5% activities, 0% paths.*

- *What does the demand at the hospital look like? Are there any trends over time?*

To answer this research question, we look at the data with all events, “Eventlog”. We use this data set as it includes data on all patients’ activities and not just entering patients’ activities. To get an idea about the entering demand of the hospital, the ideal measurement would be the number of referrals. However, the number of referrals is currently not registered. To approximate the demand, we look at the number of first appointments for the patient types and follow-up appointments per month for the three years of the data set. Although this explains the historical demand, it does not completely represent actual demand as no more appointments can be planned than capacity available, which means, the number of planned appointments is constrained by the available capacity.

In Figure 10, we see all the first appointments of patient types discussed in the previous question together with the follow-up appointments. The line of the new patient appointments shows more fluctuation in the first two years than in the last year and has a decrease in number of new patient appointments following the trend line. A reason for this could be due to the Covid pandemic which took place from March 2020 until approximately mid-2023. As Alexander Monro is a specialized hospital for breast cancer, they were unable to help patients suffering from Covid. In other hospitals in the Netherlands, breast cancer treatment was delayed as Covid patients were taking up a lot of the capacity of the hospitals. Because of this, patients of other hospitals sought for help at the Alexander Monro Hospital, causing a big demand for breast cancer diagnostics and treatment. Now that the pandemic is over, patients tend to seek help at other hospitals as well, which might cause the decline in demand. Next to that, in early 2022, the hospital started to work with a blueprint schedule for planning new patient and follow-up appointments at the outpatient clinic. This blueprint provides planners with suggested spots on how to plan certain appointment in the EHR system. This could be a reason for the decrease of fluctuation in patient appointments since the number of slots per week was determined in advance. Another noticeable observation from the graph, is that the number of follow-up appointments is a lot higher than the number of other entering patients. Over three-year time, we see an increase in the trendline of follow-up appointments. The reason behind this difference is in the characteristics of the patient and their appointment type. As a newly entering patient, you only enter once, whereas follow-up appointments are planned for a patient each year for 5 years after being cured from breast cancer. The more new patients enter the patient group, the bigger the follow-up patient group will grow in the years thereafter. For the other patient types, we see a relatively lower demand as can be seen on the y-axis of the graph. We see that for some of the patient types the trendline inclines (Mammography GP, Reassessment Second Opinion, Mammography BOB) and for some of the patient types the trendline declines (Second opinion appointment, Referral BOB). These inclines and declines are however neglectable compared to the incline for new patient and follow up patient. Although this gives some information about demand trend, we also see that compared to the new patient appointment and follow-up appointments the change in demand is relatively small. For a more in depth analysis of the trend behavior of each patient, we refer to the figures in Appendix A.

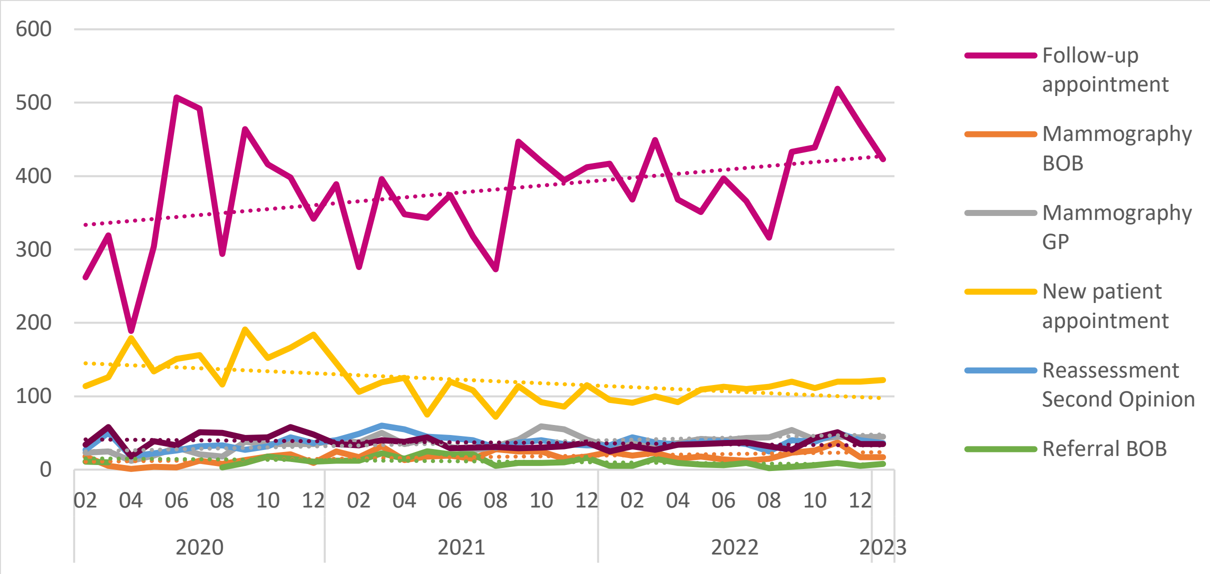


*Figure 10: Visualization of demand for all patient types*

In Figure 11, we analyze the planned number of surgeries and day treatment appointments. For both the number of surgeries and day treatment, we see an increase in the trendline over the years. Again, this increase most likely is caused by the increased demand during the Covid pandemic. What is also very clear is that the number of day treatments is a lot higher than the number of surgeries. This can also be logically explained by the fact that treatment in the form of day treatment almost always comes with multiple appointments, whereas one surgery most of the time is sufficient for surgical treatment.

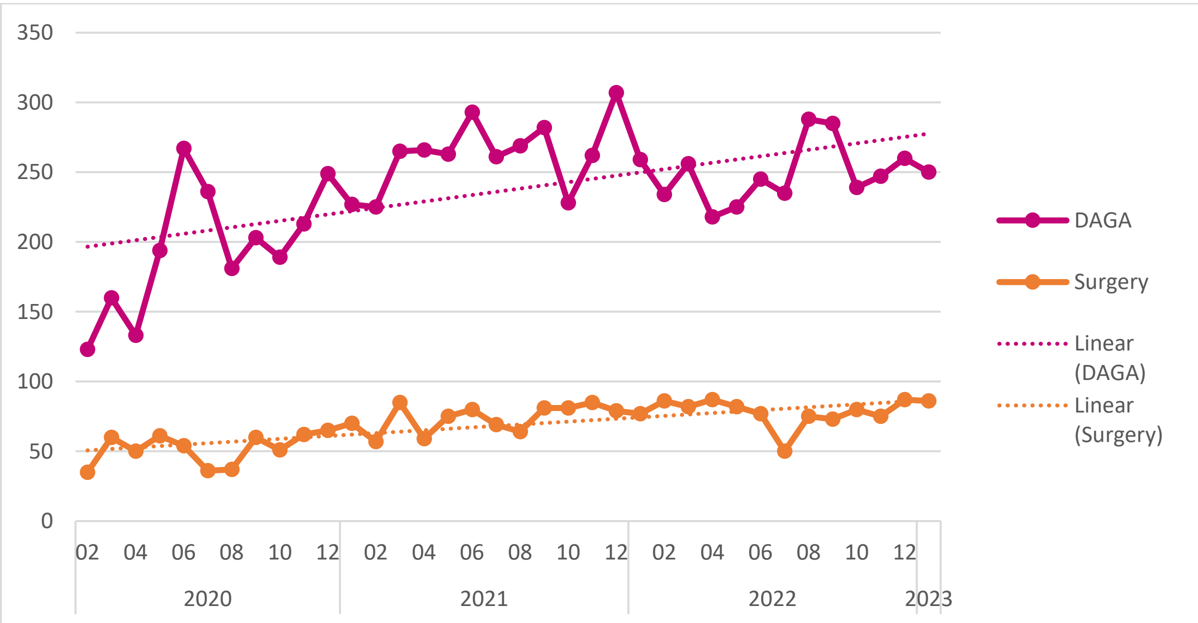


*Figure 11: Demand for surgery and day treatment with trendlines*

Because of its size, the capacity at Alexander Monro is limited by its resources, and because the hospital is relatively young, the hospital sees its demand rising because new patients are not yet fully compensated by patients leaving the system and is reaching its current capacity limit. From observation in the hospital, we know that currently there is a waiting list for follow-up appointments that need to be planned. The goal of the hospital is to have new patients enter within one day from referral, and therefore prioritizes planning of new patient over follow-up patients. In previous years, this goal was maintainable but at this point, the hospital feels like it cannot guarantee this access time. When it comes to treatment like surgery or day treatments, the hospital does not have a waiting list.

## 2.5 Conclusion

From our process mining analysis and answering of the research questions we come to multiple of conclusions.

First, a care pathway is a complex process with many activities and paths. From our analysis, we see that there are many ways the care process can unfold by the variants that occurred in our event log. Within the data set patients are included at different stages of treatment with varying treatment sequences. However, we have also seen that some variants occurred more frequently than others. Diagnostics without further treatment and follow-up appointments without further treatments are more predictable than patient specific treatments and the processes are more standardized.

Second, we observe that more than 80% of the entering patients belong to one of 6 different patient types. From our analysis, we see that the new patient is the most occurring entering patient (35%), followed by reassessment second opinion (20%), mammography GP (14%), Referral BOB (5%), Mammography BOB (4%), and Second opinion appointment (3%). From these patient-type processes, we also conclude that most patients go from diagnostics into further treatment in the form of surgery for the type referral BOB (47%), followed by reassessment second opinion (39%), second opinion appointment (22%), New patient appointment (12%), Mammography GP (5%), and Mammography BOB (1%).

Last, by analyzing the planned appointments for the follow-up appointments and the starting appointments of the entering patient types, we see that there are significantly more follow-up appointments compared to entering patient appointments. We also see an increasing trend in new patients and follow-up patients over the years. While the entering patients are planned steadily over the months, the graph of the follow-up patients is more fluctuant. When we look at the demand for treatment categorized by surgeries and day treatments, we see that there is a slight increase in both treatments over time by looking at the trendline. From our observations at the hospital, we conclude that there are no waiting lists for treatment, but there is a waiting list for follow-up appointments. With the rise in demand for diagnostics and treatment, it becomes more relevant for the hospital to optimally use their resources.

With this knowledge of the care process and the current demand, we want to further investigate how this demand is served by the resources available at the hospital and how this capacity is managed currently.

# 3 Identification and management of capacity

To get an overview of the current capacity and how this capacity is managed, in this chapter, we identify all types of capacity considering people, equipment, and facilities. Next to that, we make use of a framework for planning and control to identify what methods are used to manage capacity at this moment. In Section 3.1, we provide a brief introduction about capacity management and the framework for planning and control. Section 3.2 provides an overview of the identified capacity at our case hospital. In Section 3.3, we describe what capacity management strategies are used at our case hospital. In Section 3.4, we reflect on the alignment of capacity and demand. Last, in Section 3.5, we give a conclusion.

## 3.1 A framework for planning and control

Healthcare planning and control stretches throughout the entire healthcare organization. To provide some structure and break down all the functions of healthcare planning and control, Hans et al. (2012), developed a hierarchical framework. Within this framework, four managerial areas of planning and control are distinguished: *medical planning, resource capacity planning, materials planning*, and *financial planning*. Our focus for this research is on resource capacity planning. Within the framework, these managerial areas are combined with four hierarchical levels, by which decision making in planning and control can be categorized. These hierarchical levels are *strategic, tactical, offline operational*, and *online operational*. An example of the framework used for a healthcare organization is presented in Figure 12, the red border indicates the managerial area of our focus.

As time goes by, more information becomes available for decision making. Next to that, as time progresses, the options for decision making become more limited. The highest hierarchical level is the *strategic* level. Strategic planning has a long planning horizon where information is limited. The lowest levels, offline and online operational, have a short planning horizon and there is low flexibility in decision making as decisions at this point are mostly set. This level focusses on planning and executions of (daily) operations. Offline means that the decision making is done before execution of operations, online means reactive decision-making during execution of operations. The level in between, tactical, has a planning horizon that lies somewhere between long-term and short-term. It is similar to operational planning, but the planning horizon is longer which results in more flexibility, but less available information.

*Resource capacity planning* considers dimensioning, planning, scheduling, monitoring, and control of renewable resources. Renewable resources include employees, equipment, and facilities which the healthcare organization features. For the strategic level, decision making about resource capacity planning focusses on resource capacity expansions (e.g., acquisition of new machines, new employees, new facilities) and prioritizations about how to best use capacity (e.g., case mix planning, length of consultations). For the tactical level, resource capacity planning considers temporary capacity expansions (e.g., flexible staff) and further in advance planning (e.g., block planning, admission planning). Offline operation planning considers all short-term planning decisions which are planned just before execution (e.g., Scheduling of appointments, scheduling of staff) and Online operation planning considers short-term reactive decision making which is mostly controlling unexpected events (e.g., emergency coordination).

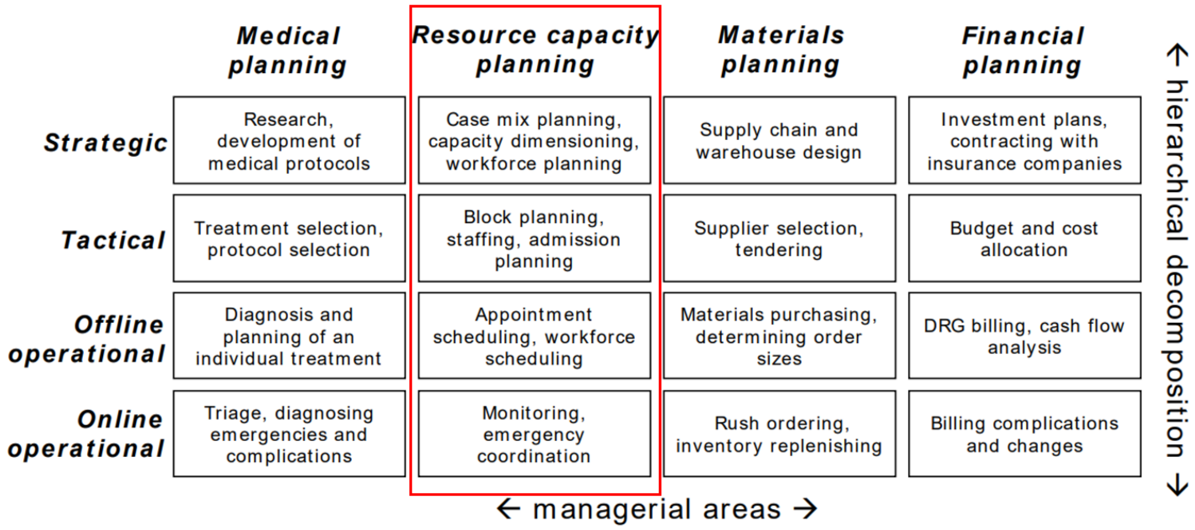


*Figure 12: Example of an application of the framework to a general hospital planning and control (Hans, van Houdenhoven, & Hulshof, 2012).*

## 3.2 Current capacity identification

For the capacity of the case hospital AMH, we consider all the renewable resources that are available at the hospital. There are three types of resources to consider for resource capacity planning: employees, facilities, and equipment (Hans, van Houdenhoven, & Hulshof, 2012). In Table 4, all employees that are involved in the care pathway are identified and counted. In Table 5 all facilities and equipment at the hospital are identified and counted. These two resources are placed in one table, as these type of resources both can accommodate and serve patients in a similar way. Facilities and equipment may be accompanied with other equipment (e.g. transfusion pump) but these are not mentioned in the table if they do not impact capacity management at this point. At AMH all employees work less than 5 days a week. This is something that also should be considered for the capacity planning. Next to that, certain human resources can work at multiple facilities. If that person works in one of the facilities, that means they cannot work at the other facility at that time. An example of such an occasion is when a surgeon is operating, they cannot see patients in the outpatient clinic rooms. Another important factor for the capacity of the hospital is that the hospital is closed during the weekend. When planning the capacity, the dependencies should be considered. For example, a surgery cannot be planned at the end of the week, as the patient cannot stay at the ward over the weekend.

*Table 4: Human resources Alexander Monro Hospital*

| Human resource type | Number of people |
|---|---|
| **Surgeons** | 4 |
| **Plastic surgeons** | 7 |
| **OR assistants** | 20 |
| **Oncologists** | 5 |
| **Anesthesiologists** | 3 |
| **Radiotherapist** | 1 |
| **Mamma care nurses** | 6 |
| **Specialized nurses** | 2 |
| **Radiologists** | 2 |
| **Nuclear medicine doctor** | 1 |
| **Lab technicians** | 12 |

*Table 5: Facilities Alexander Monro Hospital*

| Facility or equipment type | Number of facilities |
|---|---|
| **Outpatient clinic beds** | 16 |
| **Operating rooms** | 2 |
| **Ward beds** | 10 |
| **Day treatment chairs** | 8 |
| **CT scan** | 1 |
| **Bucky scan** | 1 |
| **Ultrasound** | 2 |
| **Mammography** | 2 |
| **MRI scan** | 1 |
| **Dexa scan** | 1 |
| **Gamma-camera** | 1 |
| **Administer space** | 1 |

## 3.3 Current interventions

Over the last ten years, the hospital has developed itself from a small start-up to a growing hospital. Over the years, the hospital has grown in patient demand, staff, and facilities. Early on, the planning at the hospital was rather simple because of its small demand, but now that demand is rising, planning can become very complex and quickly become inefficient. To manage capacity, the hospital has developed their own methods and ways to deal with it. From observations at the hospital, we make an index of all capacity management interventions that take place at this current moment and describe these along the framework mentioned earlier. After identification, the observations are confirmed by the manager healthcare and business operations.

### 3.3.1 Strategic

Since the start, AMH has a very strong and clear vision. Their vision is that specialized breast cancer care leads to excellent quality of care, the best client experience, an improved quality of life, and reduced healthcare cost for the patient. These values have impact on the way capacity in the hospital is used. For example, the hospital aims for an access time of one day for new patient diagnostics, have a one-stop-shop for all diagnostics as much as possible with as low as possible waiting time in between appointments, and have a personal approach that can take up more time per patient to make the patient feel comfortable. To steer upon these strategic goals, there is one recurring follow-up meeting. That is the management board and supervisory board meeting, a meeting to make decisions about the course of the hospital and big financial decisions.

### 3.3.2 Tactical

Since two years, AMH has implemented some tactical capacity management interventions. These interventions were introduced after the operational planning methods became too inefficient and complex. The first tactical intervention is the appointment block schedule. This block schedule is a framework for all nuclear, radiology and outpatient clinic appointment spots that are available to be planned three months in advance. In that way, inefficient planning is reduced because planners can only plan certain appointments for which the slot is reserved. With this intervention it becomes easier to ensure the one-stop-shop goal and a short access time.

On a tactical level, there are two regular meetings. The first one is a recurring meeting with radiology team leader, medical manager and manager healthcare and business operations. In this meeting is discussed what can be expected from the patient flow from diagnostics towards the outpatient clinic and other departments later in the care pathway. The second meeting is the management team meeting. In this meeting three managers of the hospital discuss the inflow of new patients and the number of procedures conducted each week. These insights are obtained by the financial administrator and are reported in a spreadsheet. This document contains data of operations within the entire hospital covering ten years. The weekly report takes approximately two hours to update each week and is very error prone. Most of the calculations are formulated with standard spreadsheet formulas and pivot tables, and considering the big amount of data, the spreadsheet software often breaks down and shuts off as this software is not suitable to handle calculations on big data. Although this is a useful tactical intervention, there is not made use of any key performance indicators to indicate whether capacity is reaching its limits or if planning is done efficiently, and the current solution is past its optimal performance. The management team meeting is currently mostly financially oriented, but in the future this meeting is most interesting for tactical capacity steering.

### 3.3.3 Offline and Online Operational

For operational interventions we distinguish offline operational and online operational.

*Offline operational*

The offline operational interventions at AMH are very straightforward. For staff, workforce planning is done per department. Exact shift planning is done a few days before but planning of vacations and days off need to be scheduled three months in advance. For system therapy, appointments are always scheduled with recurring appointments in a series. A few times a week, new system therapy patients are scheduled for their whole series and if there are any adjustments to be made for existing series these are also taken into consideration at that moment. OR scheduling is also done every day for a week in advance. When scheduling a surgery on an OR, the planners take into account the expected stay of the patient in the ward as the hospital is closed during the weekend. This results in most invasive surgeries at the start of the week and plastic surgeries at the end of the week. On Tuesday and Wednesday there are weekly meetings with OR planners and medical staff to check whether the planning for the upcoming week is correct and all materials are ordered or available. All appointments for nuclear, radiology and the outpatient clinic are planned daily at the secretary office.

*Online operational*

For online operational intervening, there are some daily meetings to deal with these kind of scheduling issues. Every morning, all planners gather at the secretary office for a daily start up. In this meeting all issues that might occur are discussed. Next to that, every morning the OR has a meeting with all OR staff of that day to go over all the surgeries of the day and discuss any issues. Another online operational issue that could occur are emergency appointments. For this a protocol is in place that can be followed.

## 3.4 Alignment of capacity and demand

In Chapter 2, we analyze the current demand and incoming patient flows at AMH. From our analysis we conclude that the demand for care at the hospital is growing by an increasing new patient inflow and by the fact that patients do not leave the system because of growing demand in control patient appointments. After looking into how the current capacity is managed, we notice that a lot of capacity planning is done based of intuition. Now that the demand is rising, it becomes more difficult to plan all new patient appointments within one day, and the list of to be planned control patients becomes longer. Although this waiting list is growing, it does not mean that there is not enough capacity. From observations at the departments, we notice most health professional think most of the time rooms, staff and facilities are unoccupied for some times of the week or day. Capacity and demand seem to be misaligned because of inefficient planning and limited communication between departments, but this feeling is not yet backed up by numerical evidence. To improve the alignment of capacity and demand, management wants to know how they can optimize their capacity use and steer upon data on a tactical level. By doing this they want to be ahead of upcoming capacity problems and work more efficiently together between departments.

## 3.5 Conclusion

Alexander Monro Hospital has seen a lot of growth during the past 10 years. The hospital has expanded in facilities, equipment, staff because of a growing demand. For 10 years, the hospital has made decisions based on the intuition of experienced healthcare professionals. The hospital is using data to analyze their production, but the current solution as a spreadsheet is becoming less reliable and error prone. For a long time, these methods were sufficient, but it is now reaching its limit as planning becomes more complex and data collection becomes bigger. From observation it becomes clear that the hospitals experiences shortage in capacity, but at the individual departments there still is unused capacity left. Instead of expanding capacity, the hospital wants to use their current capacity more efficiently by managing capacity on the tactical level. In this way, the hospital can plan their capacity appropriately and be more prepared for peaks in demand. Instead of using intuition, which is subjective, the hospital needs to shift to a data-based approach for their tactical management. By using data, an objective view on the capacity use is created which can be used to bridge the gap between departments and integrally manage capacity. An objective view on capacity management can be achieved by using key performance indicators that tell us more about how capacity and demand are aligned in the form of numerical measures.

# 4 Performance indicators for integral capacity management on the tactical level in a single specialty hospital

Now that we have a view on what the care process at the hospital looks like, and know what are the current demand and capacity, we want to systematically develop a set of performance indicators for integral capacity management in a single specialty hospital. In this chapter, we conduct a systematic literature and an additional Delphi Study. Section 4.1, introduces the goal and motivation for this research. In Section 4.2, we describe the methodology used. Section 4.3 presents the results of the study and Section 4.4 provides a conclusion.

## 4.1 Why should we use performance indicators?

To introduce integral capacity management in a hospital, the strategy of a hospital needs to be addressed with measurable and achievable goals in the form of key performance indicators (KPIs). KPIs are well formulated performance measures that are used to observe, analyze, optimize, and transform healthcare processes (InsightSoftware, 2021). Without these KPIs, goals and objectives can become ambiguous. These measurable goals can be operationalized which contributes to the improvement of the process and eventually improve the quality of care (Schneider, 2020).

When considering integral capacity management for a single specialty hospital, there are some differences with general hospitals that should be considered. In the introduction of the research, some key differences between SSH and general hospitals are mentioned. One of these is the demand for care, which influences the capacity of the hospital (fewer patients, means fewer facilities and less personnel needed). Because a single specialty hospital only treats patients with the same disease, there is less variability in the treatment possibilities than with patients with all different types of diseases. Next to that, within a general hospital, a lot of the resources are shared between specialties. For example, a master surgery schedule determines which specialty can use the operating room at which time of the week (Marques, Captivo, & Barros, 2019). This is not the case in SSHs where only one specialty makes use of all the resources.

Until now, most performance indicators for integral capacity management have been focused on general hospitals. Although we could not find these developed systematically in literature, performance indicators are used to access performance in projects aiming to improve integral capacity management. For example, Kortbeek et al. (2017) present a generic analytical approach to predict bed census on nursing wards as a function of the Master Surgical Schedule and arrival patterns of emergency patients, for which performance measures are the bed occupancy and time of admission and discharge. To our knowledge, no clear performance indicators have been systematically developed for SSHs, or hospitals in general, and there is no research available about integral capacity management at SSHs. As there is only limited literature for SSHs, we search for performance indicators for integral capacity management in general hospitals which could also apply to SSH. Our goal is to develop a list of performance indicators that can be used to assess the performance of integral capacity management at an SSH.

The development of key performance indicators in healthcare has been largely driven by the arrival of healthcare information systems. These performance indicators can be developed using systematic or non-systematic methods. Non-systematic approaches are based on data availability and real-time monitoring of critical incidents. Although this might play an important role, it fails to include much of the available scientific evidence. A systematic approach to indicator selection relies directly on available evidence, complemented if necessary with expert opinion. (Boulkedid, Abdoul, Loustau, Sibony, & Albertini, 2011) A systematic method to facilitate the development of performance indicators is the Delphi Method. A Delphi study is a research method used to gather insights and opinions of a group of experts on a specific topic. It is a structured and iterative process that aims to reach a consensus of opinions through a series of rounds of feedback (Boelkedid, Abdoul, Loustau, Sibony, & Alberti, 2011). We use this method because it is useful to build consensus when developing a standard approach, as it captures the perspectives and recommendations of experts in a particular field (Nasa, Jain, & Juneja, 2021). To develop a comprehensive list of performance indicators for integral capacity management that can be used as input for the Delphi study, we conduct a systematic literature review. To make this list as complete as possible for our situation, we also include KPIs related to capacity management found within guidelines for oncology and breast cancer care available at the case hospital. For the systematic literature review we will include all KPIs found for all levels of control, but for the Delphi study questions we only focus on the selection of KPIs for the tactical level of control as this is the focus for our case hospital and this research overall.

## 4.2 Methodology

To select a number of KPIs for a tactical capacity management tool, two methods are used. These two methods are a systematic literature review and a Delphi study. The output of the systematic literature review is used as input for questions in the Delphi study.

### 4.2.1 Systematic literature review for KPI identification

For our literature search, we developed a search strategy which is documented in Appendix A. From our databases of choice, PubMed and Scopus, we find 122 articles using our search string. We then exclude articles that were published before 2018 to only include the latest five years of findings on the topic as there is a lot of research conducted on the topic and the outcomes are continuously evolving. Next to that, we exclude non-English documents. This results in a set of 43 articles. The remaining number of articles for title-abstract-keyword screening is 41 after duplicates are removed. During title-abstract-keyword screening we exclude articles of which we know from the given information the article does relate to our research topics, general hospitals, or capacity. The number of articles included for full text screening is 33. Here we also include one extra document with existing hospital guideless used by AMH, resulting in a total of 34 full text screenings. During full text screening we exclude all articles that were not accessible through the library of University of Twente or by Google Scholar. Next to that, we have excluded articles that were not related to capacity. After full-text screening 18 articles are included in the research and are used for data extraction. The process of the systematic literature review is visualized in Figure 13.

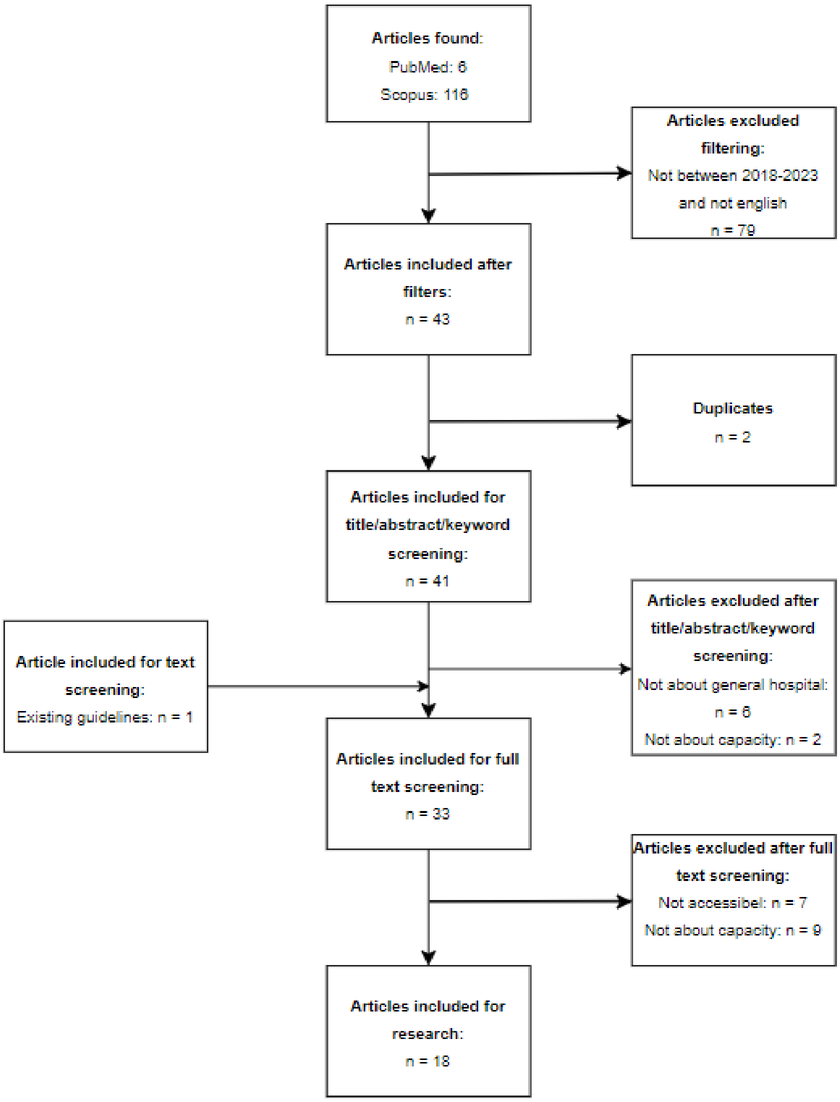


*Figure 13: Visualization of the search strategy for systematic literature review.*

### 4.2.2 Delphi setup for KPI selection

The Delphi method is a systematic process for the selection of performance indicators using the collective opinion of an expert panel. The most important elements of the Delphi study are anonymity, iteration, controlled feedback, and consensus requirements. In literature, there are no existing standards for the parameters of a Delphi study, which are the expert panel, Delphi rounds, and closing criteria (Nasa, Jain, & Juneja, 2021). In the following sections we state for each parameter of the Delphi method how we (pre-)define them and why we choose these settings. The value that is created with this method are the ideas that are brought up throughout the feedback loops of the questionnaires, that either evoke consensus or those that do not. Extreme opinions and moderate opinions are combined and can be expressed in a constructive method that moves towards consensus. And if consensus is not reached, it becomes clear what are the reasons behind it (Gordon, 1994).

*Selection of expert panel*

In a Delphi study, experts from the required disciplines are first identified and then asked to participate in the study. There is no standard size of the expert panel, but usually the number of participants vary from 10 to 100 in published studies. The appropriate size depends on the complexity of the problem, homogeneity of the panel, and available resources (Nasa, Jain, & Juneja, 2021). The experts should together cover knowledge of all aspects of the subject. After deciding on the participants, all experts are individually invited to participate in the study through an e-mail. This letter contains a description of the study, the goal, the number of rounds in the study, and the promise of anonymity. (Gordon, 1994) The participants are assured of anonymity in the sense that none of their input will be attributed to them as a person. In this research, the participants are asked to provide their point of view based of their experience in capacity management in the hospital or in previous projects.

*First questionnaire round*

The first questionnaire consists of all KPIs that are relevant to this research, which are found in the systematic literature review. Since some of the found KPIs are from papers considering only an emergency department, we only include KPIs that could be applicable to a breast cancer single specialty hospital. Next to that, we only include KPIs that can be used on the tactical level of control. For each KPI we provide a description for more clarification.

We conduct the first questionnaire round at the start of April 2023. The questionnaire is created in Google forms and is sent by email to all participants. The questionnaire asks all participants to provide their viewpoint of how well a KPI would fit within a certain context of the hospital and whether it is useful for capacity management by assessing the relevance using a 9-point Likert scale (1 is "very irrelevant" and 9 is "very relevant"). The expert panel can provide comments for each KPI as well as the possibility to rephrase the KPI. At the end of the questionnaire, participants can provide their own input for additional relevant KPIs. We choose to use a 9-point Likert scale because we can group the scale into three tertiles, the first one being irrelevant (1,2,3), the second one being neutral (4,5,6), and the last one being relevant (7,8,9). Grouping the Likert scale makes it easier to define a consensus rule for rejection, discussion, and acceptance. A advantage of using a 9-point scale instead of a 3-, 5-, or 7-point scale, is that it becomes easier to distinguish between the relevance of KPIs by providing additional granularity to the outcomes (Bertram, 2007).

The results from the first questionnaire are analyzed using a pre-defined standardized consensus methodology developed for this research in particular. KPIs are accepted if the average score is above an 8 and 100% of the scores were in the top tertile, 7 or above. The KPI is rejected if the average score of the KPI is a 6 or below and the number of people with a score of 7 and above is at most one. All other KPIs are denoted as up for discussion.

*Expert panel meeting*

After completing the first questionnaire round, all participants are asked to join in an expert panel meeting. Before the meeting, all experts were sent a report of their personal scores per KPI as well as the average scores of the expert group and the percentage of participants in the top tertile (7,8,9). During this meeting only the accepted and up for discussion KPIs are discussed. The rejected KPIs are only briefly mentioned. For all the accepted KPIs, the suggestions for rephrasing are discussed. If the group agrees on rephrasing the old KPI is replaced by the new KPI formulation. After that the KPIs that are up for discussion are discussed combined with the suggestions for rephrasing. The group can either reach consensus to accept, rephrase or reject the KPI. At the end of the expert panel meeting also suggestions for additional KPIs are discussed until consensus is reached to accept, rephrase, or reject the new KPI.

*Second questionnaire round*

In the second questionnaire round the participants receive a questionnaire with all the rephrased KPIs. All the experts are asked for a final time to express their agreement with the rephrased and added KPI formulations by assessing the relevance using a 9-point Likert scale (1 is "very irrelevant" and 9 is "very relevant"). This round, there is no option to leave comments as this is the final round. Just like the first questionnaire round, the results are analyzed using a pre-defined standardized consensus methodology developed for this research in particular. Because in this round there is no room for discussion anymore, we relax the constraints for acceptance a little bit. To accept the added and rephased KPIs, at least two of the three participants should be in the top tertile (7,8,9) and the average score should be above 7. If the KPI does not satisfy these constraints the KPI is rejected.

## 4.3 Results

### 4.3.1 Systematic literature review results

From our systematic literature review 18 articles are used for extraction of KPIs. A list of these articles and their reference number for referencing in this chapter are presented in Table 11 in Appendix B. In Figure 14 we visualize the distribution of the publications over the years. We see that the papers are divided over all the included years with most of the publications in 2019 (5). In Table 6, the context of each selected article is provided. Most of the selected articles describe research in the context of an emergency department (7), followed by entire general hospital (3) and ward (3), operating room (2) and oncology (2), and long-term care (1). The context of this research is a single specialty hospital for breast cancer diagnostics and treatment. Because this context is very different from some of the contexts of the selected articles, we only use KPIs that could be of application within our research context.

From the 18 articles we deduct in total 44 KPIs which are presented in Appendix C. In this table we provide per KPI in which article(s) the KPI occurs and whether the KPI is useful on strategic, tactical and/or operational level of capacity management. To decide on which level the KPIs are useful, we use the analysis in the previous chapter, and decide for each KPI whether the KPI would be useful for capacity management at each level of control. If the KPI could in any way be useful for a certain level of control, we indicate this in the table. In the last column on the right of the table we also indicate whether the KPI is used for the Delphi study. We include KPIs for the Delphi study if the KPI is applicable in the context of a single specialty breast cancer hospital and if the KPI can be used on the tactical level of control.

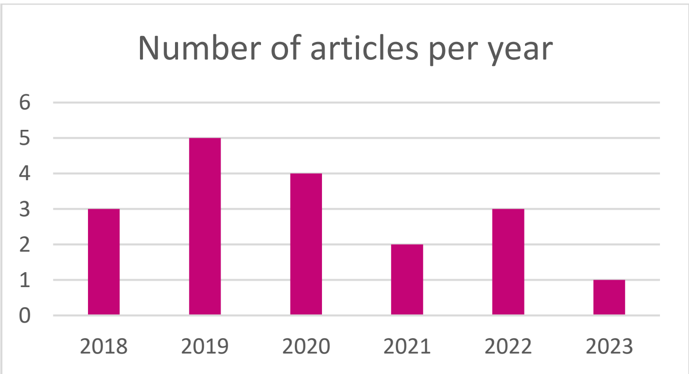


*Figure 14: Number of selected articles per year*

*Table 6: Research context of the selected articles*

| Context | Reference article |
|---|---|
| **Entire general hospital** | 1, 8, 15 |
| **Emergency department** | 2, 5, 7, 9, 10, 11, 14 |
| **Operating room** | 3, 6 |
| **Ward** | 4, 12, 18 |
| **Long-term care (Elders)** | 13 |
| **Oncology** | 16, 18 |

### 4.3.2 Delphi study results

*Expert panel*

For the expert panel, we invite three breast-cancer and healthcare specialists to participate in our research. These experts are listed in Table 13 of Appendix C. The experts were selected based on their role within the hospital and their affiliation with capacity management on a tactical level. Each of the experts has another role within the hospital and all together they cover knowledge and input of all departments. Next to their departmental roles, each of the participants has a stake in the improvement of capacity planning and has worked on capacity management improvement projects before this research. The list of participants is chosen in collusion with the problem owner, manager healthcare and business operations. The three participants are all part of the Management Team which meets every week to discuss capacity management performance.

*First questionnaire round*

All three of the invited participants have filled out the first questionnaire. Based on the standardized consensus method described above, 9 KPIs are accepted, 14 KPIs are up for discussion, and 6 KPIs are rejected. In total there are 10 suggestions for rephrasing and 1 newly proposed KPI. The results from the first questionnaire round are presented in Appendix C Table 14.

*Expert panel meeting*

All three experts were physically present during the expert panel meeting. The group discussed the 9 accepted KPIs with comments, 14 KPIs that are up for discussion and their comments, and 1 newly proposed KPI. One of the accepted KPIs is split into two new KPIs, the other 8 accepted KPIs with comments are rephrased. From the 13 KPIs that are up for discussion 9 KPIs are rejected, 1 is accepted, and 3 are accepted after rephrasing. Next to that the single proposed KPI is also accepted. During the meeting one more KPI is proposed which is also accepted by the entire expert panel. The results from the first questionnaire round and the expert panel meeting can be found in Table 15 in Appendix C.

*Second questionnaire round*

In the second questionnaire the participants are provided with a list of 13 rephased or added KPIs. By assessing the scores of the participants, we conclude that all KPIs in this questionnaire are accepted. The results of the second questionnaire are presented in Table 16 in Appendix C. From the expert meeting, we add the three KPIs that were already accepted, resulting in a list of total 16 KPIs for tactical integral capacity management. These KPIs are presented in Table 7.

*Table 7: Final list of KPIs from the Delphi study*

| KPI | Final formulation |
|---|---|
| **Utilization** | Ratio of the actual patient use of resources to the maximum available amount |
| **Occupancy** | Ratio of the total use of resources to the maximum available amount |
| **Number of cases performed** | Number of cases performed per treatment type |
| **Throughput** | Access time to first treatment |
| **Cancellation** | Number of procedures or appointments that are cancelled by the patient |
| **Number of consultations given** | Number of consults per DBC per doctor |
| **Number of first consultations** | Number of initial consultations with new patients |
| **Number of diagnostic tests** | Number of diagnostic tests conducted |
| **Number of surgeries performed in the hospital** | Number of surgeries performed in the hospital |
| **Number of treatment starts** | Number of treatment starts |
| **Admissions** | Number of patients admitted to the ward and chemotherapy department |
| **Length of stay** | Length of time patients stay in the ward and the chemotherapy department |
| **Access time** | Access time for a patients first appointment (time between referral date and first appointment date) |
| **Time between process steps** | Time between start diagnostics until PA outcome |
| **Appointment rescheduled** | How many times are appointments rescheduled |
| **Length of waiting list** | Length of waiting list of patients |

## 4.4 Conclusion

To our knowledge, there is no research that systematically developed KPIs for the use of tactical integral capacity management in healthcare. In this chapter, we bridge this gap in literature by completing a Delphi study resulting in a set of 16 KPIs. These KPIs are general of nature and almost all KPIs can be used for single specialty hospitals in general.

For our case hospital, these KPIs can be used for the measuring and monitoring of capacity management performance. The KPIs can be applied throughout the different activities in the care process resulting in an integral overview of demand and resource alignment. The KPIs comply with the wishes of the management team who will be using the KPI output which can be used for evidence based support in their decision making considering capacity and patient flow. The results from this study can be used for the input of a tactical integral capacity management dashboard that visualizes the performance in a user-friendly interface. When KPIs are measured it is possible to set goals to improve the performance.

# 5 The design of a tactical integral capacity management dashboard

In the previous chapter, we conclude with a list of KPIs appropriate for integral capacity management on the tactical level in a single specialty hospital. This chapter brings these KPIs to practice by designing a tactical integral capacity management dashboard. In Section 5.1 we give an introduction into dashboard design for data visualization and why it is suitable for integral capacity management on a tactical level. In Section 5.2 we describe our approach for designing the dashboard. In Section 5.3, we present and elaborate the dashboard. Section 5.4 reflect upon the dashboard in terms of usability and reliability. In Section 5.5, we provide an implementation plan that helps AMH to implement the dashboard. Finally, we end our chapter with a conclusion in Section 5.6.

## 5.1 Communication of KPI measurements

Healthcare organizations sometimes experience the feeling of reaching the limit of its capacity. This feeling is experienced because they observe longer waiting times, patients on a waitlist for planning, and professionals who have to work overtime. While on the surface this might look like the hospital is working beyond their full capacity, this might be caused by poor capacity management. If capacity is not managed properly, this could result in underutilized resources (Kumar & Shastri, 2018). Imbalances like these can be brought to light by data analysis of demand and capacity along the care process. Such data analysis can be done by calculating KPIs, which tell us something about the performance of the hospital considering their care process and integral capacity management. Numerical outcomes can be placed in perspective to each other in an objective sense and can be steered upon for improvement. On a tactical level, these KPI outcomes are useful for decision making and care process improvement.

As healthcare costs are rising, hospitals can no longer support inefficient care practices like poor communication among departments and siloed functional areas. Next to that, hospitals cannot afford to waste resources by delay, cancellation, and underutilization (De Pourcq, Gemmel, & Trybou, 2016). Throughout this research, we focus on the care process of our case hospital. With the knowledge of the care processes at a hospital and the selected KPIs to assess the performance, a hospital can focus on managing the patient flow by using capacity efficiently.

At AMH, the KPI outcomes are interesting for the management team which oversees all operations within the hospital and make decisions around capacity for the mid-to-long term. This team consists of three managers with each a different background within the hospital. For this team, it is important that all their different perspectives are interpreting the data in the same clear manner. To communicate data quick and effectively, it is good to visualize the outcomes by designing a dashboard. A dashboard is an interactive performance management tool that presents the most important information about pre-defined objectives. A dashboard enables managers to measure, monitor, and manage KPIs effectively. With the right IT infrastructure and well thought performance measurement placement, managers can identify bottlenecks, trends, and overall performance time efficiently (Ghazisaeidi, et al., 2015).

## 5.2 Dashboard design approach

In the pervious chapter we have defined a set of KPIs that should be measured and monitored on the dashboard. To do so, we need the corresponding data from the EHR system at our case hospital. In this section we first provide our approach to the data integration with our dashboard tool and set norms and targets for the KPIs in Section 5.2.1. After that we describe our approach for the visual design of the dashboard in Section 5.2.2.

### 5.2.1 Data integration

*Data source*

The data that we need for our dashboard is based on the KPIs that will be visualized. In Table 8 is given what tables from the EHR system at our case hospital provide information necessary for the visualization of the KPIs and for what resources they can be operationalized in the dashboard. These tables, “Agenda”, “Admissions”, “Operations”, “Surgeries”, and “Waitlist”, cover all patient related information available for the dashboard and are called fact tables. In order to derive useful information in our KPIs, we make use of several reference tables. These tables, “Openingtimes”, “CriticalOperations”, and “CriticalDiagnosis”, determine for certain codes and values in the fact tables whether they belong to a certain type or subcategory. These tables were already existing and managed by the financial administrator at our case hospital or generated in consultation with internal planners. For some of the KPIs, no data was available at AMH. For these KPIs we generate “fake” data that reflects what the data would look like if it existed. The KPIs for which this is created and the operationalizations for the dashboard are presented in Table 9.

*Table 8: All KPIs and their responding tables from the EHR system and possibilities for operationalization on the dashboard*

| KPI | Tables used | Operationalization |
|---|---|---|
| **Utilization** | • Agenda<br>• Admissions<br>• Surgeries | • Radiology equipment<br>• Nuclear equipment<br>• Daytreatment chairs<br>• ORs |
| **Occupancy** | • Agenda<br>• Admissions<br>• Surgeries | • Radiology equipment<br>• Nuclear equipment<br>• Daytreatment chairs<br>• Ward beds<br>• ORs |
| **Number of cases performed** | • Agenda<br>• Admissions | • Chemotherapy treatments<br>• Surgeries |
| **Throughput** | • Agenda<br>• Operations | |
| **Number of consultations given** | • Operations | • Per DBC number |
| **Number of first consultations** | • Agenda | |
| **Number of diagnostic tests** | • Agenda | |
| **Number of surgeries performed in the hospital** | • Surgeries | |
| **Number of treatment starts** | • Operations | |
| **Admissions** | • Admissions | • Ward<br>• Daytreatment |
| **Length of stay** | • Admissions | • Ward<br>• Day treatment |
| **Length of waiting list** | • Waiting list | • Ward<br>• Day treatment |

*Table 9: Table with generated "fake" data for KPIs that cannot be created by existing data*

| KPI | Data generated | Operationalization |
|---|---|---|
| **Occupancy** | • Agenda, column added with +5 minutes per appointment representing changeover time.<br>• Admissions, for each day treatment +5 minutes and an additional number of minutes defined by a random number between 0 and 25 is added representing changeover time at the day treatment facility. | • Radiology equipment<br>• Nuclear equipment<br>• Day treatment chairs<br>• ORs |
| **Cancellation** | • Cancellations: new table filled with randomly generated data about cancellations. | • Ward<br>• Radiology<br>• Outpatient clinic |
| **Access time** | • Agenda: Column added with date randomly picked between 0 and 5 days before first appointment representing the date of referral. Time between these dates represents the access time. | |
| **Time between process steps** | • Agenda: Random date between 3 and 10 days added after diagnostics representing the pathology outcome date. Time between start date and outcome date represent time between process steps. | • Time between start diagnostics and outcome pathology |
| **Appointment rescheduled** | • Mutations: new table filled with randomly generated data about mutations of appointments. | • Ward<br>• Radiology<br>• Outpatient clinic |

*Data extract, load, transform*

To extract data from the EHR, we copy data tables from the software HIX 6.2 HF96 to Excel Version 2301. These spreadsheet files we place in one folder in our local directory. From this folder, we directly load our files into PowerBI Version 2.117.984.0. We choose PowerBI as our dashboarding tool because it is a user-friendly dashboarding tool and according to Schlegel (Schlegel, et al., 2023), the leader on the market for analytics and business intelligence platforms. Next to that, the software is a licensed extension to Microsoft 365, which is already used at AMH. Another reason to choose PowerBI is that it is future proof, as Chipsoft, the company providing the EHR system for AMH, also works with PowerBI for data visualization within the EHR system. After loading the data, we start with transforming our data.

The first thing we do, is creating a calendar table in PowerBI. In this way, all visualizations later on can be created using the same time hierarchy. Next to that, we create three new tables, which are derived from the fact tables. These tables are “NewPatients”, “TreatmentStarts”, and “DBCConsults”. To do calculations, we create relationships between tables. These relationships are visualized in Figure 15. Using the relationships between tables, we extend the tables with calculations if necessary. For a more in depth analysis of the calculations, transformations, and generation of data per KPI, we refer to Appendix D.

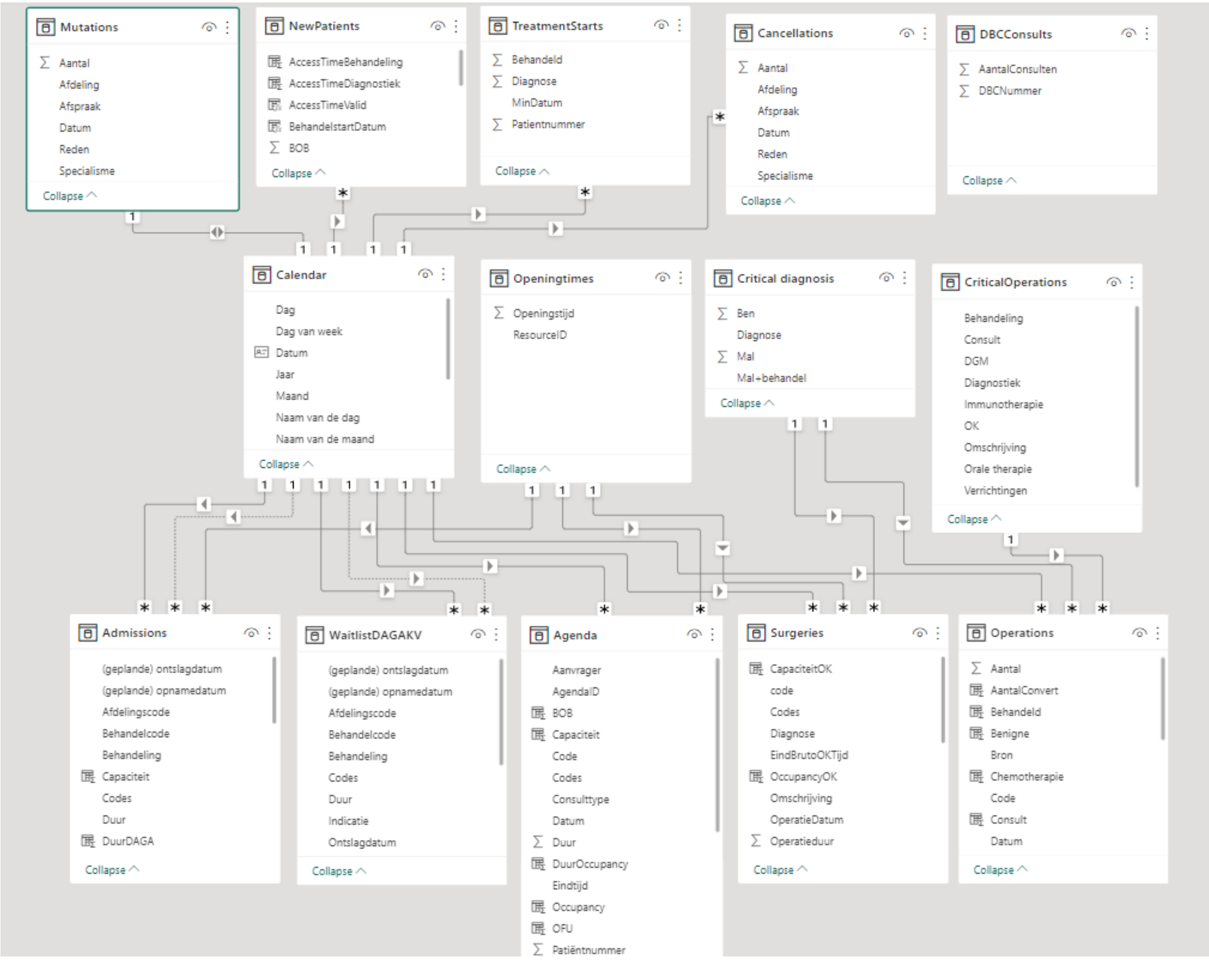


*Figure 15: Visualization of relationships between tables in PowerBI*

*Norm and targets*

In order to derive useful information from the visualizations, the outcomes need to be put in perspective to a desired norm or a target. To determine these targets we have conducted literature research and looked into requirements for breast cancer care in the Netherlands. In combination with this, all norms for the dashboard are discussed with the manager care and business operations at AMH. For some of the KPIs, targets are already known because of agreed upon production by the management of the hospital. In Table 10 , we determine per KPI what will be the norm that is used in the dashboard. If there are references to literature or norm agreements these are mentioned in the reference column on the right. Some of the KPIs have no norm or target defined by management or literature yet, as they are very hospital specific. For these KPIs we set an initial target that seems to be appropriate at this moment. Note that the norms and targets set by the hospital are very hospital dependent and should be evaluated over time based on results and desired outcomes.

*Table 10: KPIs and their respective norms and targets*

| KPI | Norm/target | Reference |
|---|---|---|
| **Utilization** | • OR: AMH target will be 65%.<br>• Chemo: AMH target: AMH target 65%<br>• Diagnostics: AMH target: 65% | • (Tabish, Ahmad Jan, & Qazi, 2003), norm found in literature 66% for OR. |
| **Occupancy** | • OR: AMH target will be 90%.<br>• Chemo: AMH target: 90%<br>• Diagnostics: AMH target: 90% | • (van Houdenhoven, Hans, Klein, Wullink, & Kazemier, 2007), norm found in literature 90% for OR. |
| **Number of cases performed** | • Chemo: AMH norm: 50 per week<br>• Oral therapy: AMH norm: 50 per week | |
| **Throughput (time between first appointment and treatment)** | • Max. AMH: 4 weeks (28 days) | • (Stichting Oncologische samenwerking, 2022), Max. 6 weeks |
| **Cancellations** | • AMH norm: 10 per month | |
| **Number of consultations given per DBC** | • AMH target: 3 per DBC | |
| **Number of first consultations** | • AMH production agreement: 157 for first 3 months of 2023, 203 for the other months of 2023. | • AMH internal production agreement |
| **Number of diagnostic tests** | • Radiology: AMH norm: 150 per month per test.<br>• Nuclear: AMH norm: 30 per month per test. | |
| **Number of surgeries performed in the hospital** | • AMH target: 20 patients per week. | • (Stichting Oncologische samenwerking, |

| | | |
|---|---|---|
| | | 2022), At least 50 per year |
| **Number of treatment starts** | • AMH production agreement: 32 per month for 2023 | • AMH internal production agreement |
| **Admissions** | • DAGA: 50 patients per week<br>• Ward: 20 patients per week | |
| **Length of stay** | • DAGA: AMH Max.: 180 minutes.<br>• Ward: between 0 – 5 days. AMH Max.: 2,5 days.<br>• OR: AMH Max.: 120 minutes. | |
| **Access time** | • AMH norm: 24-48 hours, Max. 48 hours. | • (Stichting Oncologische samenwerking, 2022), Max. 1 week. |
| **Time between process steps (time between test and pathology outcome)** | • AMH Max.: half of maximum, so 11,5 days. | • (Stichting Oncologische samenwerking, 2022), Max. 3 weeks. |
| **Appointment rescheduled** | • AMH norm: 10 per month | |
| **Length of waiting list** | • AMH norm: 50 patients | |

### 5.2.2 Dashboard visualization

Before designing our user interface, we want to ensure that our design is effective and efficient. For this we determine our target audience approach, design principles, and functionalities of the dashboard based on literature, best practices on the internet, and observations at AMH. These finding are used in the design of the user interface of the dashboard.

*Target audience*

The target audience of the dashboard is the management team of AMH. The dashboard is supposed to be used once a month during the management team meeting and should provide the team with information on their KPIs in an effective manner on management level. To ensure that the management can quickly draw conclusions, it is necessary to quickly determine whether pre-determined targets are met. If problems can simply be identified, action can be taken to improve organizational performance (Bugwandeen & Ungerer, 2019). Next to that, it is important that this dashboard provides an overview of the entire care process and the relationships between care process activities so capacity can be managed integrally.

*Design principles*

For the content and display of the dashboard it is important to customize the dashboard to the desires of the organization. (Bugwandeen & Ungerer, 2019). Visualizations should be interpretable at a glance and should be easy to read. For some data, a simple graphic visualization is enough, if the data is more complex the visualization might also be. People tend to read the dashboard from top to bottom, from left to right. In order to tell a story through your visualizations, you should place the visualizations in this order on the page. (PowerBI, 2022) The design of the dashboard should be simple and uncluttered. Avoid excessive visual elements, complex layouts, and unnecessary information that can distract or confuse users. Another important aspect is to be consistent throughout the entire dashboard when it comes to design. This can be accomplished by using the same colors, fonts, and layouts throughout the dashboard. To make the dashboard intuitive for the user, effective use of colors can highlight important information. The dashboard should have a calm balanced use of colors, but bright intuitive colors like red and green can be used to indicate positive or negative performance outcomes (Few, 2006).

*Functionalities of the dashboard*

The main dashboard should provide an overview of the entire care process, but the user should be able to dive into the details along the different stages of the care process. Next to that, there should be a possibility to filter on certain input parameters, for example what month or a certain activity. By providing these options, the user can manage the output and will not be overloaded by data (Bugwandeen & Ungerer, 2019). Interactive elements, such as filters, drill-down options, and navigation panels help to gain deeper insight into the data (Few, 2006).

## 5.3 Dashboard user interface results

The result of our dashboard design approach is a tactical dashboard for integral capacity management, existing of 6 different user interface views. The story that is told with this dashboard is on one side what is the demand for care by patients and on the other side how well is capacity used considering this demand. In an ideal situation this would mean that production targets are met, a short waiting list, and the capacity is optimally used. In this section, we evaluate each user interface of the dashboard and reflect on the results. An elaborate explanation of the calculations and meaning of each visualization is given in Appendix D.

### 5.3.1 Overview

For the starting page of our dashboard, depicted in Figure 16, we try to capture the entire care process in eight visualizations to provide an overview of the most important measures for the management team. These visualizations indicate how the hospital has been performing over the last month, whether production targets are being met, and how the current flow from diagnostics to treatment is performing. Next to that, it indicates for the most used diagnostic and treatment resources how the capacity is utilized. On the top right of the dashboard, we let the user choose the month that is analyzed in the graphs. On the left of the dashboard, we provide a navigation tool that helps the user switch between dashboard pages. All dashboard pages are customized to the corporate identity of AMH.

The KPI outcomes that are visualized on the dashboard are for month 3 of 2023. As can be seen on the dashboard, this month the production target for number of new patients is met. If the target is met, the KPI colors green with a check mark, if not, it colors red with an exclamation mark. The target for number of malignant treatment starts this month is not met, indicating that more patients need to be served in order to reach production agreements. In the next graph, we see the patients that are on the waiting list at the end of this month. This indicates for the different treatment departments whether there is demand at that moment. The waitlist here indicates that there are patients waiting to be planned for treatment. The overview also provides information on the access time between the first appointment and treatment starts. As can be seen, the KPI is below its maximum and therefore considered as an acceptable flow from diagnostics to treatment. On the bottom of the overview, four similar KPIs provide insight into the utilization of resources. The first two give us insight into the two most used diagnostic tools, mammography and ultrasound. The last two give us insight into the two most used treatment resources, day treatment chairs and operating rooms. On the dashboard we notice that none of these KPIs meet their utilization target. This outcome, combined with the fact that a production target is not met and a filled waitlist, indicates that the appointments are not planned efficiently and capacity is not used optimally. To dive more into depth about production and capacity utilization, the user can dive more into depth with the other views of the dashboard, to discover underlying possible causes and more information about diagnostics and treatment.

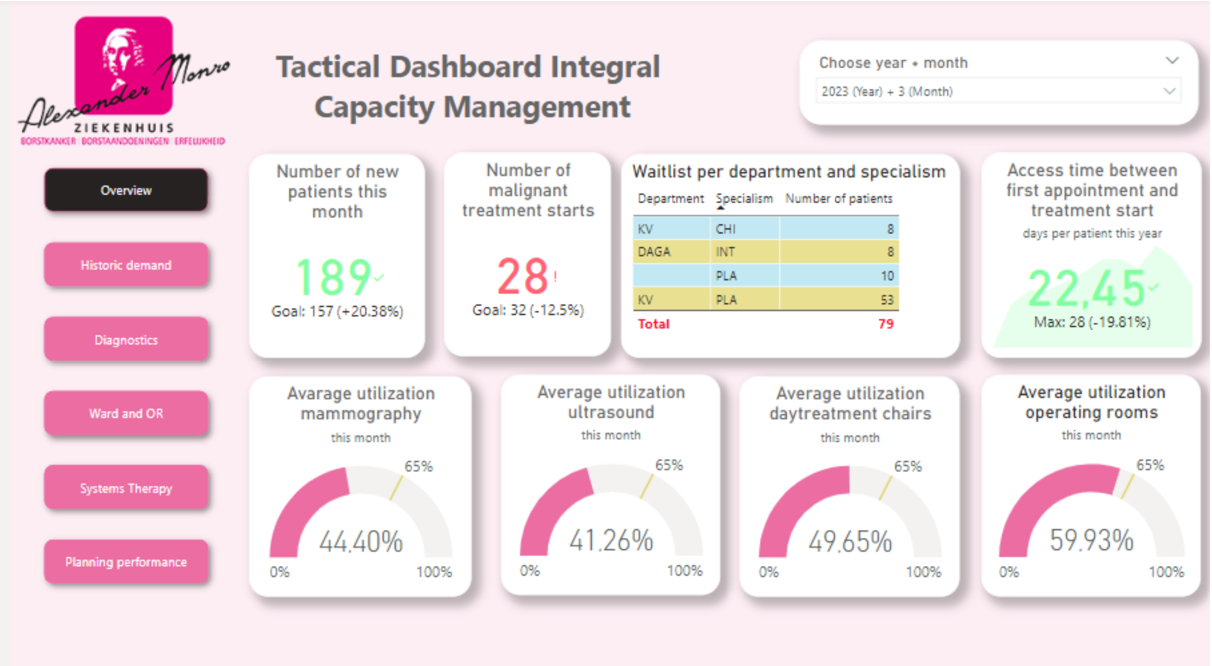


*Figure 16: Tactical dashboard integral capacity management overview*

### 5.3.2 Historic demand

The second page of the dashboard, depicted in Figure 17, gives an in depth analysis of the historical demand. It provides insight into what are the different new patient types that come in each month, what is the trend over the last 10 years considering new patients and treatment starts, and whether production targets of new patients and treatment starts are met each month of 2023. When we analyze these results we see that over the last 10 years the number of new patients and treatment starts increases, and although we are not even at the half of 2023, the number of treatment starts and new patients approaches the numbers of the previous year. In 2023, the number of new patients is always above the desired target, whereas the number of treatment starts falls a bit below target in month 2 and 3 of 2023. This results indicate that patients come to AMH more than expected, but not enough patients start treatment after diagnostics, or there are not enough treatments scheduled and performed. This might indicate that capacity at the treatment facility is underused.

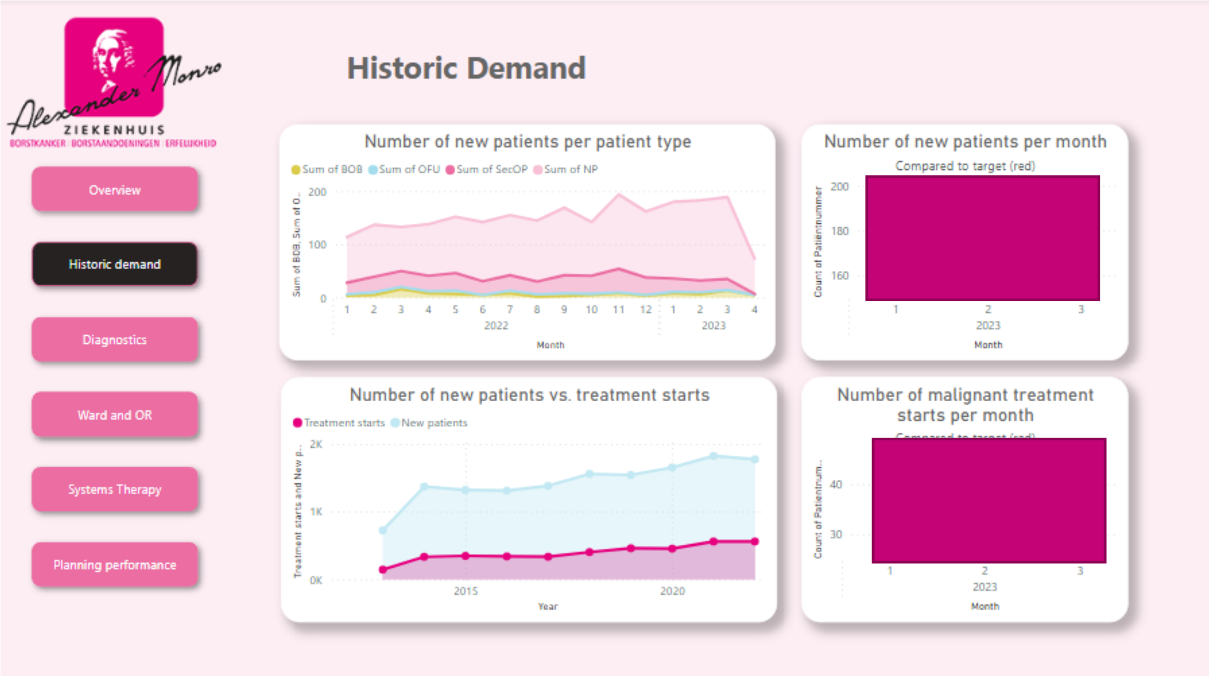


*Figure 17: Tactical Dashboard Integral Capacity Management Historic demand*

### 5.3.3 Diagnostics

The third page, depicted in Figure 18, provides us with more information about the diagnostics at AMH. For the inflow of patients into the diagnostic process, the average access time between referral and the first appointment is visualized in a KPI. This KPI indicates that the access time in this month is higher than the maximum acceptable access time. This might indicate planning issues for diagnostic tests. Next to that, we see the average time between biopsy and pathology outcome. This KPI indicates that it is below its max and is performing well. In the graph below these two, we see the utilization and occupancy of the diagnostic equipment. We see that there are big differences between equipment types when it comes to these KPIs. If we take into account the frequency with which these equipment types are used in the graphs on the right, we notice that although the mammography and ultrasound are used relatively the most, their utilization and occupancy is not very high. This might indicate that the opening times of these equipment types are to broad or that planning is not done efficiently. We also notice that the utilization and occupancy of the MRI is very high, and even over a 100%. We can explain this because the MRI is only opened one morning each week and planned very efficiently. If there is an exceeding demand for the MRI, sometimes the MRI is opened a little longer on that day. This however is not taken into account for the standardized opening times of this dashboard, causing over utilization/occupation in our dashboard. The other diagnostic equipment types, Gamma-camera, PET scan, and DEXA scan, show a relatively low utilization and occupancy rate. These equipment types also have a relatively low frequency of use. This might indicate that the opening times of these equipment types can be decreased. For the KPIs on this page, it should be noted that the data used for access time between referral to fist appointment, time between biopsy and pathology outcome, and occupancy are created with generated “fake” data.

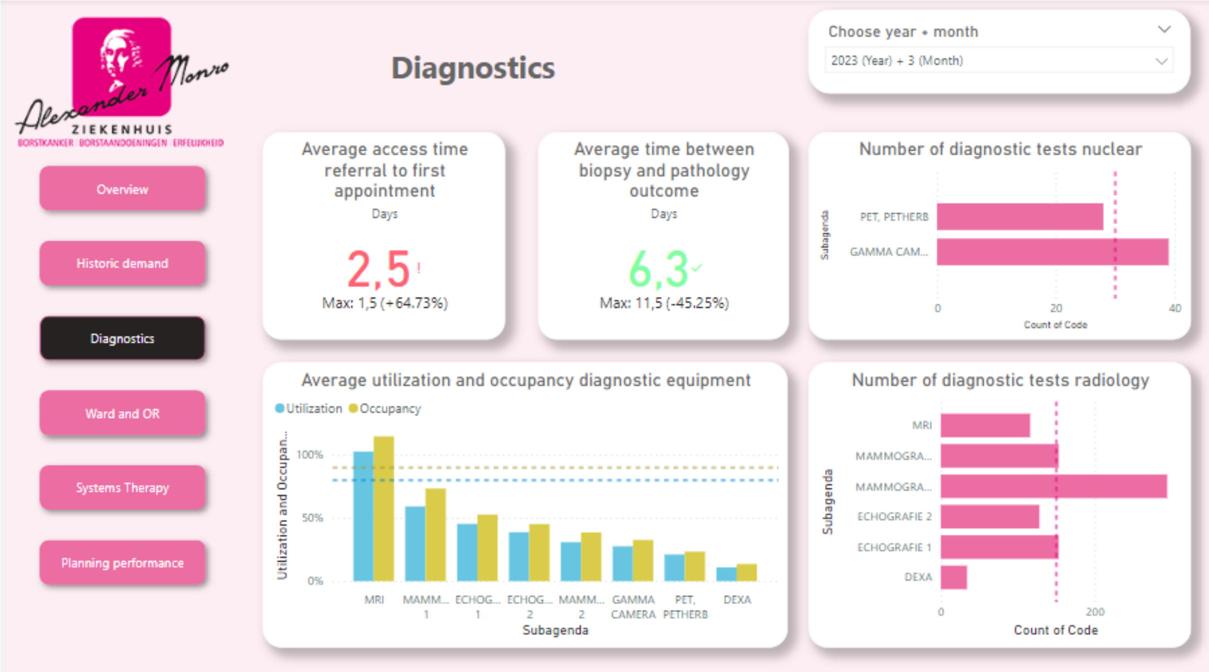


*Figure 18: Tactical Dashboard Integral Capacity Management Diagnostics*

### 5.3.4 Ward and OR

The fourth page, depicted in Figure 19, provides us with more information about the ward and the operating room performance. The more insight into how the capacity is used there. The two graphs on the left, tell us the number of admissions and surgeries in the selected month(s). The number of admissions should be around the same as the number of surgeries, but could deviate a little bit by patients having complications at the day treatment or from earlier surgery. The number of surgeries and admissions are close to or above target almost all weeks. Only the first week, week 10, seems to be under performing, but this is because only a really small part of week 10 falls in month 3. To reduce this type of behavior in the graphs, the user can select a wider time frame for analysis at the top right slicer. On the top right side, we see two graphs indicating the average length of stay at the ward and average length of stay at the OR. As can be seen, the KPIs are both performing well, staying below the set maximum for this KPI. In the four KPIs below these, we reflect on the utilization and occupancy of the individual OR rooms. We see that for the utilization of the rooms, we meet the target. This indicates that surgeries are scheduled efficiently enough. Our occupancy however indicates that the OR is not occupied enough of the available time. This indicates that the time for other activities than surgery at the OR is lower than expected. A way to higher the occupancy would be to decrease the opening time window, or to plan more surgeries, consequently also having a higher utilization. For this page, it should be noted that the occupancy KPIs are created using generated “fake” data. The actual occupancy of the ORs might be different in reality. To create more insights into surgeon performance, diagnose treatment, and performance per surgery type, the user can make selection on the data with the three slicers at the top of the page.

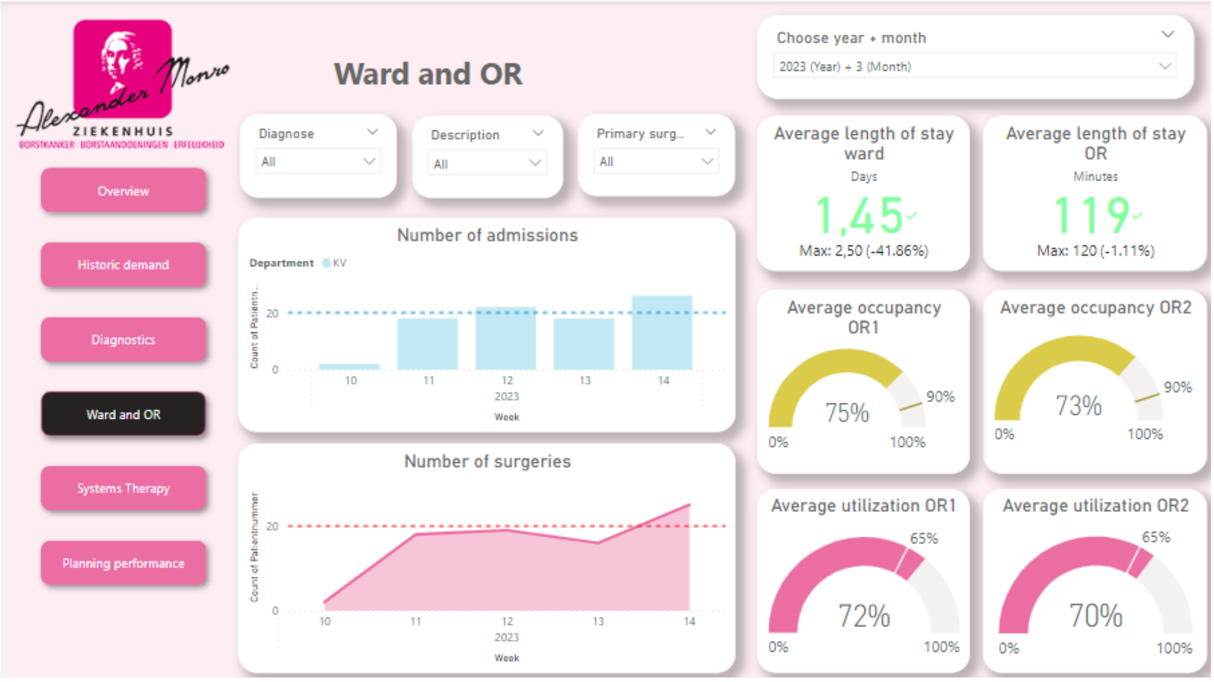


*Figure 19: Tactical Dashboard Integral Capacity Management Ward and OR*

### 5.3.5 Systems therapy

The fifth page, depicted in Figure 20, provides more insight into the systems therapy treatment at AMH. The first KPI on the top left, shows the average length of stay at the day treatment. This KPI is colored green indicating that the KPI is performing well below its set maximum. Below this KPI, we see the utilization and occupancy of the individual day treatment chairs. In this graph we see that there are slight differences between the chairs, but nothing unexpected. The utilization and occupancy of are below target for almost all chairs. Only chair one reaches the utilization target. Utilization can be improved by efficient planning or reducing the opening times. On the right of the dashboard we see the number of oral treatments per week. This KPI is for al weeks near the target line. Below this graph we see the number of admission to the day treatment facility. This number is for almost all weeks above the set target. Only week 10 is below target for both graphs, but this is cause because week 10 only is partially in month 3. Increasing the selected time span can reduce this effect in the graphs. For this page, it should be noted that the occupancy KPIs are created using generated “fake” data.

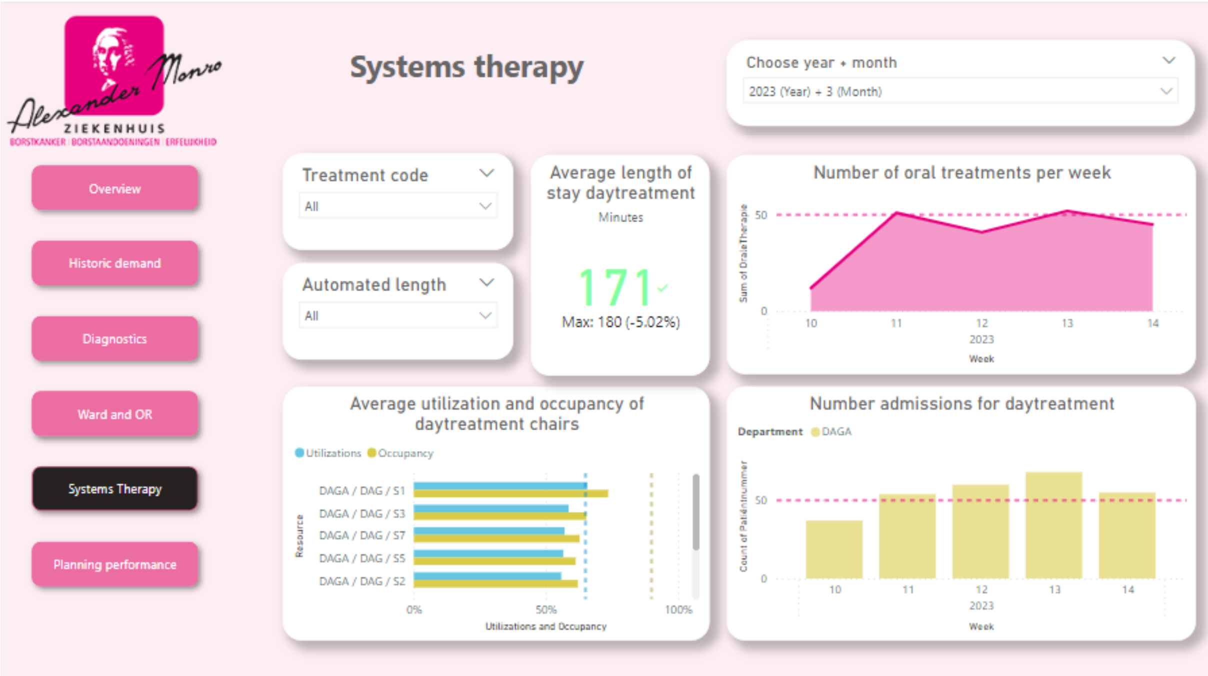


*Figure 20: Tactical Dashboard Integral Capacity Management Systems therapy*

### 5.3.6 Planning performance

The sixth and last page, depicted in Figure 21, provides insight into the planning performance. The first graph on the top left corner, visualizes the average number of consults per DBC. As can be seen, the KPI is below the maximum and therefore performing well. The other graphs on this page are included as these KPIs were selected in the Delphi study. Although in the future these KPIs might bring interesting insights, at the moment there is no existing data for the mutations in the planning and the cancellations of the patients. The graphs on this page illustrate what a planning performance page could look like.

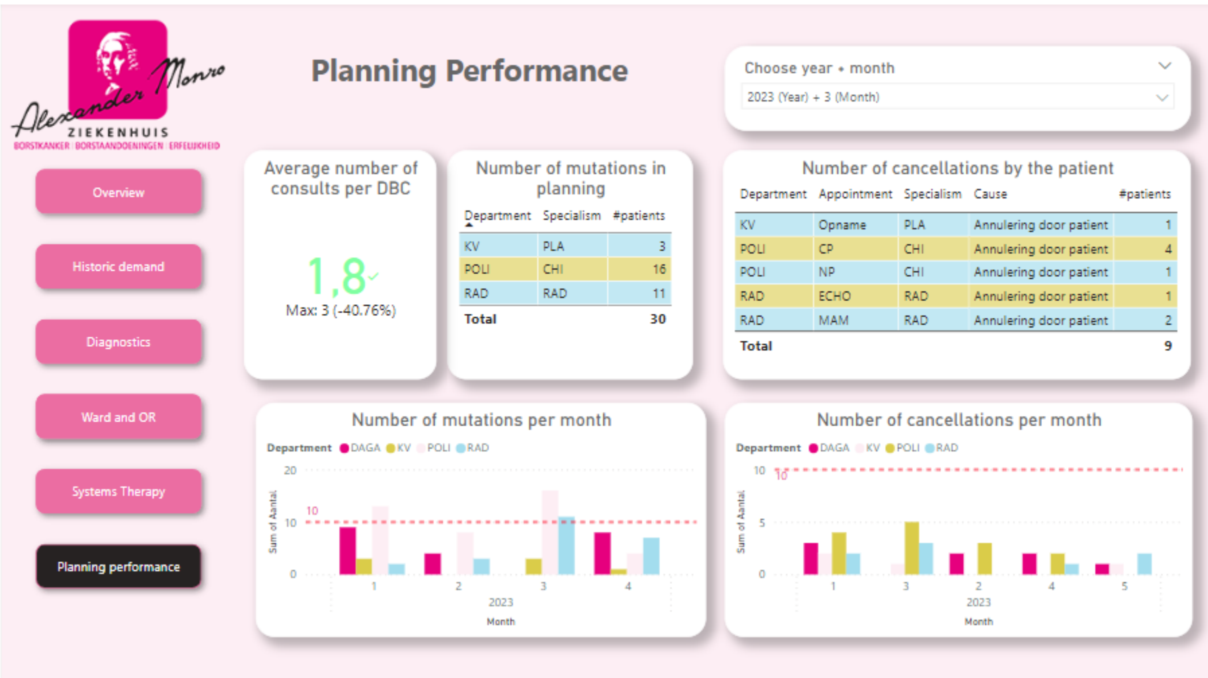


*Figure 21: Tactical Dashboard Integral Capacity Management Planning performance*

## 5.4 Usability and reliability

At this moment, the hospital does not have any steering information about how their capacity is currently used. This dashboard is a big step forward toward integral capacity management for the hospital. Currently, production information like the number of new patients and treatments starts is kept track of. However, this analysis is currently performed in a spreadsheet, which is troubling for such big amounts of data. Each week the financial administrator delivers a report with the production numbers, but the creation of a report takes up two hours of manual spreadsheet work that often crashes during the calculations as the software cannot handle such big calculations. Compared to this current method, the dashboard would be more reliable to handle this type of big data and can also be updated in less time as only the spreadsheets need to be refreshed in PowerBI. Next to the tool being more reliable, the interface of the dashboard is a lot more user-friendly than the previous spreadsheets, making it easier and more effective for management to interpret the results and compare the output to target values. Next to that, having all visualizations in one place makes it easier to connect dependencies between certain values, resulting in insightful actions.

Although all KPIs are visualized in the dashboard, not all KPIs are generated using reliable or existing data. For the KPIs that are generated using existing data, we sometimes have to make assumptions in order to generate output. The first assumption is that the opening times of equipment and facilities are static. In our model the utilization and occupancy are calculated based on a standard number of minutes available per day. Although these opening times are derived from the EHR system, the opening times can change from day to day, and week to week. A way to solve this problem would be to have a real-time connection to the data base of the EHR system, but this database cannot be accessed at this point in time by the hospital. Another data quality problem is that not all operation codes in the operations table are documented in the Critical Operations table. If a code is not found, we assume the operation should not be considered, although we do not know whether this code should be taken into account. Another assumption for the KPIs number of new patients and number of malignant treatment starts, is that these moments can only take place once. In reality, a patient might re-enter the care process after a few years for another complaint. At this moment in time, it is not possible to know when this is the case as the data is not labelled properly.

The dashboard shows that it is possible to visualize all KPIs that are selected, but at this point in time it is not possible to visualize all KPIs with existing data. For several KPIs, the data is randomly generated. These consider the KPIs Average access time referral to first appointment, average time between biopsy and pathology outcome, occupancy, number of mutations in planning, and the number of cancellations by the patient. For these KPIs we randomly generate data that reflects what this data should look like if it were available. To realize this data, changes to the data registering system should be made.

The dashboard also has a few limitations, for which future research is interesting. Currently, there is no data available about the staff scheduling and outpatient clinic rooms. The data about when staff is available cannot be extracted from the data generator in the EHR system. The outpatient clinic rooms are at this moment also not registered in the EHR system. This means that all the outpatient clinic appointments are scheduled on a person. Information about the working hours is also not available in the EHR system, making it impossible to say anything about the outpatient clinic capacity use. To calculate KPIs for the outpatient clinic, we need to know what the capacity is. Because the rooms at the outpatient clinic are also rented to other organizations, the number of resources is not static and cannot be determined. For this reason, we have decided to not include any KPIs about the outpatient clinic.

## 5.5 Implementation plan

When it comes to implementing new ways of working, a healthcare organization needs to have clear arrangements in order for the work process to change effectively. The implementation of a tactical integral capacity management dashboard is not just a technical solution that can directly be implemented, but it is a fundamental change in management that requires a change in process, roles and responsibilities. For a smooth transition and successful implementation it is good to develop an implementation plan (Performation, 2021).

For the creation of an implementation plan, we make use of a real-time clinical dashboard implementation conceptual framework (Lim, et al., 2022). This framework combines evidence from recent literature on health care dashboard implementation. The framework makes use of the three-horizon model to provide an iterative approach towards dashboard implementation. Each horizon identifies challenges for the healthcare organization on the levels of people, process, information, and technology. Although the model provides a comprehensive list of all possible challenges during the implementation of a dashboard, we only address the challenges that are applicable to the implementation of our dashboard at our case hospital and suggest methods to overcome these challenges.


*Figure 22: Implementation framework sequence (Lim, et al., 2022).*

*Horizon 1: EHR in place*

The first horizon is a prerequisite to implementation of a dashboard. This is an EHR system which AMH already has in place. Changes to this system might be necessary as result of the dashboard engineering.

*Horizon 2: Dashboard engineering*

The second horizon focusses on the building of a digital foundation. In this research we made a start with the development of KPIs for tactical integral capacity management and a tactical dashboard, but with this development come certain challenges that still need to be addressed during the implementation. For the dashboard there are challenges that can be addressed on 4 levels: people, process, information, and technology.

Considering the people involved there are two challenges. These are training and resourcing arrangements. In order to make use of a dashboard for tactical capacity management, there needs to be enough knowledge to understand how the dashboard works and what the outcomes on the dashboard mean. To overcome the these challenges there needs to be at least one person that is responsible for the dashboard who understands how it works and can make changes to it. Next to that, someone is needed who understands integral capacity management. For this it is important to train your staff on integral capacity management and/or dashboarding.

On the process level there are also several challenges. The organization needs to address financial and resource costs that come with the design and implementation of a dashboard. A dashboard needs maintenance and software licenses to remain functional. In this research we make use of PowerBI, which is a licensed tool that comes with additional costs. To make calculations for an integral capacity management dashboard, knowledge and technical skill are needed for which there might be additional resources needed in the form of temporary consultants, additional staff, or training programs. To be certain of the feasibility for the project, we suggest to make a budget plan before implementation of the dashboard. Next to financial constraints there might be time constraints. To make a timely implementation it is wise to make a planning for the implementation of the dashboard considering the challenges addressed in these three horizons. Another process challenge is the change in organizational culture.

The third level is the information level. In this research we developed a set of KPIs that provided us with a set up information requirements, but during the development and implementation of a dashboard challenges might arise as development is an iterative process. In this case the most important challenges are the quality of data and missing required data. As described in the previous section about usability and reliability, there are certain points for improvement for the dashboard. In order to eliminate these challenges, it is important to have an interdisciplinary design team to work on the improvement of the dashboard. Data for the dashboard comes from all departments of the organization and are connected to each other. An interdisciplinary team also creates a support base and understanding for the dashboard throughout the organization. Other methods that can be used in this design phase are (interactive) prototyping and human centered design. These methods help to continuously improve the dashboard by changing the dashboard until it is providing the desired output and is tailored to the wishes of the end-user.

The last level is technology. Challenges here are linking of the dashboard to the EHR data, the dashboard reliability/connectivity, information on the dashboard, and support diverse users. At the moment the connection of the EHR data and the dashboard is a manual process which needs to be managed by someone with knowledge of the data. In the future it would be preferrable to have a reliable connectivity with the database that refreshes automatically. This however again comes with a cost and resource challenge of its own. Next to that, the information that is visualized should be evaluated after each improvement or change to the dashboard. For this it is good to keep track of feedback during the dashboard engineering horizon, to continuously improve.

*Horizon 3: Care model engineering*

If the dashboard is ready for implementation into the clinical environment, we move to the third horizon which is care model engineering. In this level we focus on the implementation of the dashboard into the current way of working and the healthcare organization as a whole. This horizon has impact on the levels people and process.

For people level, the dashboard outcomes have impact on the staff, clinicians and the patient. Because of that, implementation of the dashboard might bring along staff/clinician resistance. To overcome this challenge, a workflow design should be created for the use of the dashboard. A workflow design addresses who are involved with the dashboard, when do these people interact, when will it be used, what will it be used for, and what is the goal of the dashboard. It makes sure to provide sufficient time for the users to access and interact with the dashboard, but also effectively create and implement actions out of the insights. To mitigate the risk of workflow and cultural issues early on in the implementation, it is important to pay attention to the responsibilities of the staff who have a role in the use of the dashboard. There needs to be someone who collects the data and connects it to the dashboard. Then there are the decision makers who use the dashboard and steer upon the information that comes from the dashboard, and there are executors who are responsible to implement decisions on the operational level. Between these actors, there needs to be a governance system in place. A suggestion for this would be an interdisciplinary implementation approach and stakeholder engagement meetings.

At the process level, challenges might arise about how staff using the dashboard act upon the indicators. These challenges could be ethical concerns or disagreement problems. To overcome these challenges, it is good to address these issues upfront by documenting agreements and to later on use feedback reports. Problems like these can also be addressed in an interdisciplinary implementation approach and stakeholder engagement meetings.

## 5.6 Conclusion

With the selected KPIs it is possible to create a tactical integral capacity management dashboard. The dashboard features all KPIs, created using actual and generated data. Compared to the current method used to report production in the management team meeting, the dashboard shows that there is a lot of opportunity in visualizing relevant data for integral capacity management on the tactical level. From our results, we find that capacity is mostly underutilized, while production targets are not always met. The analysis also shows a rise in demand and a waitlist for treatment, indicating that underutilization is not caused by a shortage in demand. Although the dashboard leaves room for improvement in terms of data quality and data availability, the realization of all KPIs is a step in the right direction for AMH. In general, a tactical integral capacity management dashboard is an effective way to communicate information efficiently and is a very user-friendly approach to data analysis. By coordinated placement of visualizations, a dashboard can display dependencies within the care process and alignment of demand and capacity in one overview. To integrate this dashboard into the current workflow at the hospital, the dashboard can be implemented using the implementation plan.

# 6 Conclusion and discussion

Now that we have realized the dashboard design and implementation plan, we conclude on our research and provide a solution to our research objective in Section 6.1. In section 6.2, we discuss our research by providing an interpretation of the results, a reflection on the research approach, implications of the research, and a research outlook.

## 6.1 Conclusion

At the start of this research we have formulated the following objective:

*Formulate and implement a set of key performance indicators that provide integral insight into the tactical capacity management performance of the care pathway.*

In this research we provide a clear formulation of systematically developed KPIs for integral capacity management on the tactical level. For the implementation of these KPIs, we look at the hospitals process from an integral perspective and developed a dashboard which visually represents the KPIs with corresponding norms and targets along the care process in an effective and efficient way. In combination with the dashboard, we provide an implementation plan for further development of the dashboard and implementation in the clinical workflow.

## 6.2 Discussion

### 6.2.1 Interpretation of results

In this section, we provide an interpretation of the results from our analysis. We contextualize our findings, and evaluate and explain unexpected results.

*Process mining*

Our process mining analysis has provided valuable insights into the care pathway of breast cancer patients in the single specialty hospital. We have observed that the care pathway is a complex process with multiple activities and paths, but some variants occur more frequently than others, indicating more predictability and standardization in certain aspects of the process. We have identified six patient types that account for more than 80% of the entering patients, with different treatment sequences for each type. The majority of patients proceed from diagnostics to further treatment, primarily surgeries. The differences in flow from diagnostics to surgery could mean a lot for the production numbers at Alexander Monro. A higher flow from diagnostics to surgery could increase the number of treatment starts which could higher the revenue of the hospital. Additionally, we have noted a significant number of follow-up appointments compared to entering patient appointments, with a rising trend over the years. Although the outpatient clinic is not analyzed in the dashboard, this increasing number of follow-up patients over the years could eventually accumulate and cause high demand for outpatient clinic appointments. There is an increasing demand for both surgeries and day treatments, emphasizing the need for optimal resource utilization. These findings highlight the importance of capacity management to meet the growing demand and efficiently allocate resources in the hospital. Our process mining results show all activities concerning patients in the breast cancer care process and show that it is possible to mine complex cancer processes.

*Delphi study*

Analyzing the results of our Delphi study, we see that there are several KPIs that could be used in general hospitals, but are not applicable or desired at a single specialty hospital like AMH. One interesting result is that one of the KPIs in the final list of selected KPIs is admissions, but that discharge is rejected in the study. In capacity management of general hospitals, one of the most important KPIs is how crowded the ward is, making it important to know when patients are admitted and when they are discharged. An example of this, is the John Hopkins Hospital, which has an emergency department outflow, hospital inflow, and hospital outflow which are complex interconnected root causes of hospital capacity inefficiencies (Martinez, et al., 2018). The ward in general hospitals is a shared resource that needs to be planned efficiently, or otherwise it could delay treatment starts. In our case hospital, the ward is not an important factor in the capacity management yet, as there are always enough beds available for all people scheduled to be operated and there is no emergency department. Next to that, it is interesting that AMH does not select the KPI process duration, as process duration could say a lot about the patient flow. This could be because the process of cancer does not have a clearly defined set of process steps with one start and end procedure, as was found during process mining. This is different from situations where key performance indicators are focused on one department, like the operating theater, where the start, end, and process steps are clearly defined and measurable. In this case, process duration can be a very insightful KPI (Sonmez & Pintelon, 2020).

*Dashboard*

Our first assessment of the KPI results show that although there is enough patient demand at the moment, the capacity available to serve patients is underutilized. As the number of new patients keeps rising over the years, AMH can expect to have more demand in the future. The dashboard shows that this rising demand can be served by the current capacity, but that might only be possible if scheduling of appointments improves. If the utilization remains the same, it might be beneficial to close certain facilities reducing costs. The results of the dashboard indicate that production can be increased if capacity is utilized more efficiently. Next to that, it shows that the previous understanding that there is no waitlist for treatment and that capacity is reaching its limits as experienced by hospital staff, might be the wrong understanding of what is actually happening. In a research focused on underutilization of operating rooms, researchers also found that the cause of underutilization is caused by inefficient planning, which is correlated with higher costs (Fügener, Schiffels, & Kolisch, Overutilization and underutilization of operating rooms - insights from behavioral health care operations management, 2017).

### 6.2.2 Reflection on research approach

In this research various methods were used to analyze data. In this section we reflect on these methods and describe their limitations. We also comment on our decisions and assumptions made in our research approach and how these impact our results.

*Process mining*

For the discovery of our care process we used the process mining technique with the software of Disco. In our analysis we make use of the built-in functionality to reduce the abstraction level of the process. By reducing the abstraction level, details are lost. The healthcare sector is characterized by variability and leaving out details could oversimplify the process. As we had a lot of different activities, some relevant activities of the care process were not visualized due to the abstraction level. For future research it would be interesting to investigate ways to reduce the number of activities without losing relevant information (Munoz-Gama, et al., 2022). In the future it would be interesting to look into other software for process mining like, ProM which is often used in process mining studies (Kurniati, Johnson, & Hogg, 2026). This software leaves more freedom for the researcher to develop their own process mining algorithms instead of using built-in functions. Due to the time constraint of this research, creating our own algorithms was too time consuming, but if there is more time available, this could be a solution providing more transparency. Another limitation of process mining in general, is that it assumes there always is a starting point and end point to all processes. In our case, there was missing information about the start and end of a care process. The start of a care process is not registered in the system of our case hospital, we were unable to only select processes from its start. Considering the end of the process, this is also unknown. A patient could be in the loop for several year or could just have started when the process data was extracted from the EHR system. As some patients just started their care process, they did not start their treatment yet, but are included in the process mining analysis. This means that the flow from a new patient to surgery could be even higher as these patients are not there yet in their process. For the process mining methodology, we used the L*-methodology. This methodology provides a good framework for process improvement, covering data quality issues and setting a clear objective. The method does however give a lot of freedom for interpretation, which could be difficult when challenges are experienced. The methodology could be improved by providing more guidelines in execution, like for example the PM2 methodology (van Ech, Lu, Leemans, & van der Aalst, 2015).

*Delphi study*

For the development of the KPIs we conducted a systematic literature review and a Delphi study. For our systematic literature review we make use of two databases. These databases are widely used, but we could broaden our scope by including more databases and using data from more years. This would however require a longer time scope than this research. Another limitation of our study is that the number of participants in this Delphi study is low rather, as most Delphi studies have around 15 to 35 participants (Gordon, 1994). Although there are no requirements for the number of participants, the results might be more valuable if more experts participate. We chose not to include more participants because within our case hospital there were no other participants of interest for the study. Participants from other hospitals with similar integral capacity management needs or experts in the field of integral capacity management might have been interesting to add to the study. However, due to the scope of this research it was not possible to gather a more diverse and bigger expert group. Because the number of experts in a Delphi study is usually small, the method does not, and is not intended to, produce statistically significant results. This means that the results obtained during the study, do not represent the results of a larger population, or another similar Delphi panel. The results represent the consensus of opinion of one particular group. (Gordon, 1994) To make the Delphi results more generalizable, the results requires an appropriate panel size, diverse representation of members from different specialties, and geographical distribution (Nasa, Jain, & Juneja, 2021). For this study, generalizability for other hospitals was not the goal, but if this was more important, we would advise to use a bigger expert group from multiple locations. Furthermore, there are no universally accepted requirements for performing and reporting on a Delphi study (Nasa, Jain, & Juneja, 2021). The Delphi study has multiple parameters like, definition of group consensus, expert selection, number of rounds, and reporting of the method and results (Boulkedid, Abdoul, Loustau, Sibony, & Albertini, 2011). An advantage of this is that there is a lot of freedom, but a disadvantage is that the results of the study are highly dependent on the researchers interpretation. An interesting topic for further research would be to address common practices in literature for the Delphi study and develop a standardized method with guidelines and requirements.

*Dashboard*

The dashboard developed in this research gives a good illustration of how KPIs for tactical integral capacity management can be visualized. The choses software is widely used and is very user-friendly. There are some limitations to the design and implementation of the tactical integral capacity dashboard. The dashboard is only focused on the tactical level of control as this was the only level possible to be realized within our time scope. For further research it would be interesting to create a dashboard for the strategic and operational level of control as well. These levels are highly connected to the tactical level and would provide a more comprehensive oversight of capacity management in the entire hospital. Next to that, a dashboard on strategic and operational level could provide outcomes on actions taken on the tactical level. During the creation of the dashboard we also make assumptions considering the norm and target values of some of the KPIs. Although these KPIs provide a good initial target, it would be good to further investigate what would be the best norm/target value.

### 6.2.3 Implications of the research

*Practical contribution*

The practical contributions of this master's thesis are significant and offer valuable insights and tools for improving capacity management practices in single specialty breast cancer hospitals. Firstly, the application of process mining techniques provides actionable insights into identifying and targeting new patients. By analyzing real data, this research uncovers patterns, bottlenecks, and variations in the patient journey, shedding light on the specific areas where resources and interventions can be directed to improve patient outcomes and operational efficiency.

Additionally, this study provides valuable insight into the current practices, weaknesses, and opportunities within the hospital. By conducting a detailed analysis of the capacity management processes, this research highlights areas of improvement and identifies specific challenges that the hospital may be facing. The identification of weaknesses and opportunities allows healthcare managers to make informed decisions and implement targeted interventions to enhance capacity utilization and overall performance.

Moreover, this research contributes to the practical aspect of capacity management by developing key performance indicators (KPIs) for integral capacity management on a tactical level. The developed KPIs offer a set of measurable metrics that align with the specific objectives and requirements of single specialty breast cancer hospitals. Combined with the implementation of a capacity management dashboard, these KPIs provide healthcare managers with a comprehensive tool to monitor, evaluate, and steer capacity utilization in a focused and data-driven manner. The dashboard serves as a visual representation of the KPIs, enabling real-time monitoring and facilitating informed decision-making to optimize resource allocation and improve patient flow within the hospital.

*Theoretical contribution*

The present research makes significant theoretical contributions to the field of capacity management in single specialty hospitals, particularly in the context of breast cancer diagnosis and treatment. Firstly, this study addresses a notable gap in the existing literature by being the first conduct research on the process of a single specialty breast cancer hospital. This research offers valuable insights into the potential benefits and challenges of applying process mining in such specialized healthcare environments. In literature there are researches using process mining techniques for breast cancer surgery process (Poelmans, et al., 2010), or using process mining for the process of chemotherapy (Johnson, Hall, & Hulme, 2016), but our paper is the first to cover the entire care process for breast cancer within a single specialty hospital.

Furthermore, this study contributes to the development of key performance indicators (KPIs) for tactical integral capacity management in single specialty hospitals. While previous research has investigated KPIs for capacity management in healthcare, there is a lack of systematic development and evaluation of KPIs specifically tailored to the tactical level of capacity management in single specialty hospitals. In general, this research is the first to investigate integral capacity management for single specialty hospitals. This research fills this gap by proposing a set of KPIs that are relevant, measurable, and aligned with the specific requirements and objectives of single specialty breast cancer hospitals. The developed KPIs provide healthcare managers with valuable tools to monitor and evaluate the capacity utilization in a focused and specialized healthcare setting.

### 6.2.4 Research outlook

*Recommendations*

From our research we derive multiple recommendations for our case hospital, and single specialty hospitals in general. First, we would recommend the hospital to replace its current measurement of performance, which is only considering production measures, with the formulated KPIs of this research. This set of KPIs create a more comprehensive overview of the capacity management performance. Next to that, we would recommend the hospital to implement the tactical integral capacity management dashboard, as this is more suitable for the handling of big amounts of data, and it requires fewer manual actions and time to update the measurements with new data. The dashboard also makes it easier to understand the measurement outcomes and put these into perspective with each other. The use of the implementation plan can guide the hospital for a smooth implementation. As mentioned in the implementation plan, the development of a dashboard is an iterative process that needs to be revisited every now and then. We would also recommend investing in a connection to the EHR database, as this results in a more reliable data inflow to the dashboard as it is less error-prone. The last recommendation is to focus on the improvement of data quality and the way data is registered in the EHR system. Currently, there are inconsistencies in the data registering causing the data to be incorrect, incomplete, or not existing. Investigation of the data quality and registration process should be conducted in order to get the desired input data for the dashboard.

*Opportunities for further research*

During this research we have discovered a lot about single specialty hospitals. We have come to many insights and findings that can improve integral capacity management. Although we have moved forward in integral capacity management, this research also provides us with opportunities for further research. During this research it became clear that apart from financial analysis, there is little studied about single specialty hospitals. In the future it would be interesting to conduct a comparative study between a single specialty hospital and a general hospital. The findings of our study suggest that although both hospitals are multi-disciplinary care processes, the challenges a smaller hospital treating one illness seems to be very different because of the scale and variability. Another opportunity for further research would be to look into predictive models. The hospital now only looks at historical averages and data points, but it would be interesting to study whether the demand for care at the different departments can be predicted using a mathematical model. The convolution model as proposed in the paper of Füngener et al. (Fügener, Hans, Kolisch, Kortbeek, & Vanberkel, 2014) calculates the number of patients at downstream departments using a master surgery schedule, and could be interesting for single specialty hospitals as well. Furthermore, it would be very interesting to look into methods for efficient appointment scheduling at the outpatient clinic, chemotherapy, and operating rooms.

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# 8 Appendix A

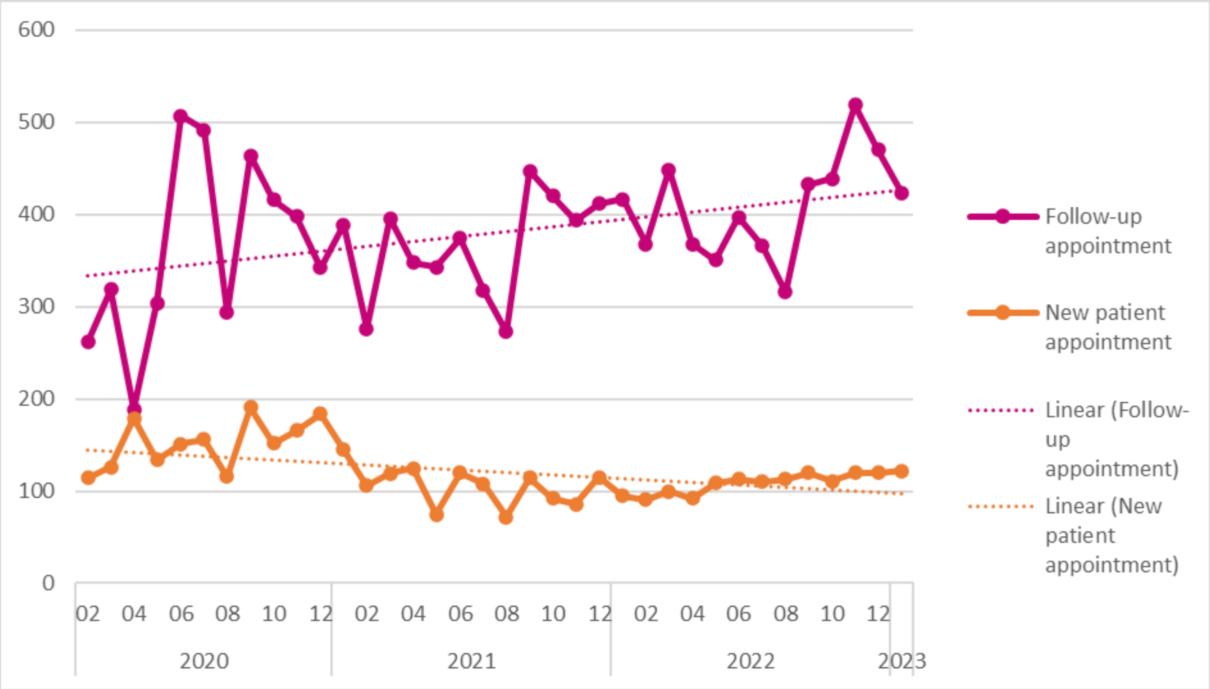


*Figure 23: Demand for patient type appointments new patient appointment and follow-up appointment*

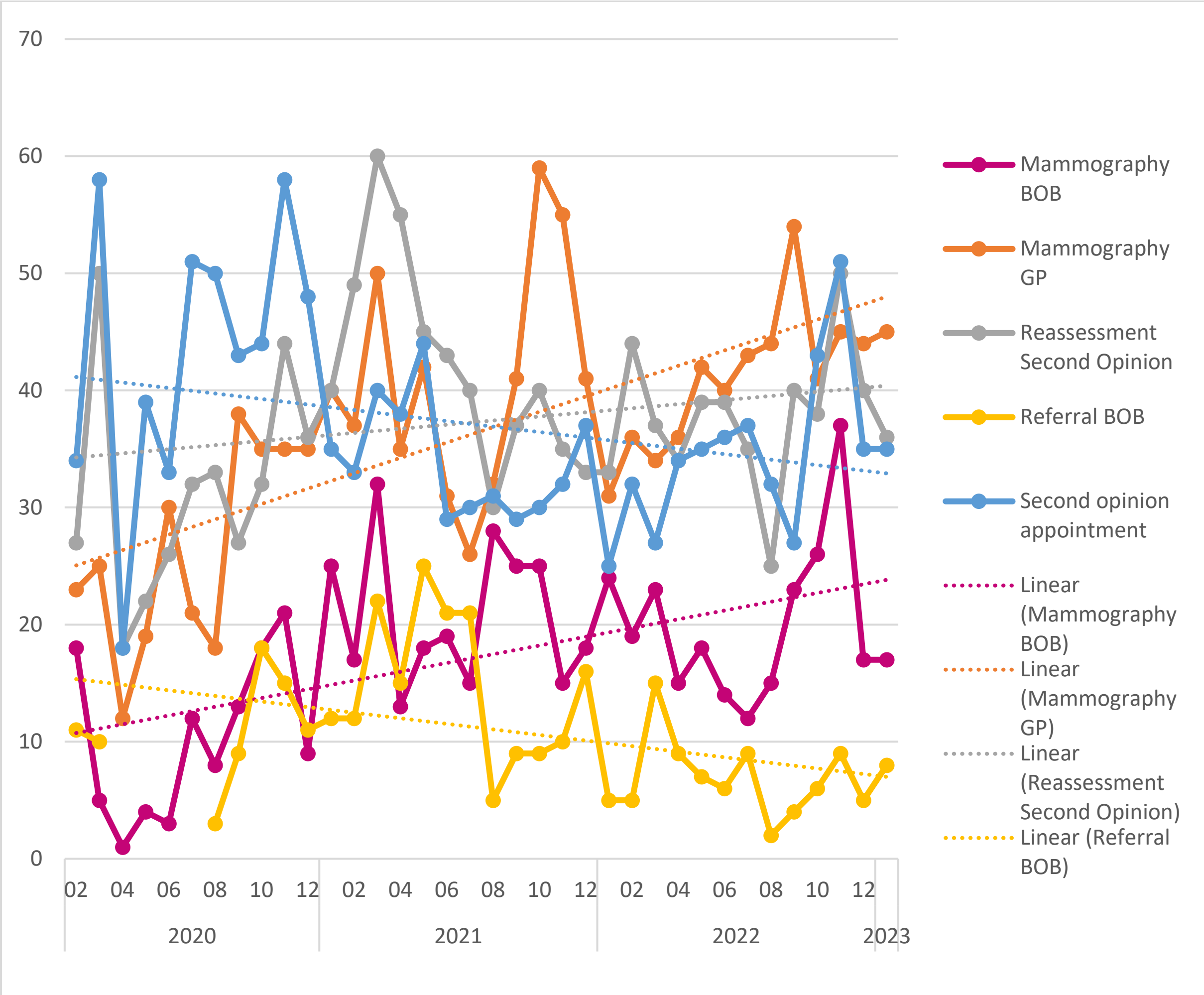


*Figure 24: Demand for patient type appointments Mammography BOB, Mammography GP, Reassessment Second Opinion, referral BOB, Second opinion appointment*

# 9 Appendix B

**Research question:**

What are good key performance indicators for integral capacity management within a hospital?

**Keywords**

1. Key performance indicator
2. Integral Capacity management
3. Hospital

**Synonyms**

| 1 | 2 | 3 |
|---|---|---|
| Quality indicator | Capacity management | Healthcare facility |
| Performance measure | Patient flow | Healthcare organization |

**Query restrictions**

1. From 2018
2. Language: English

**Data bases**

1. Pubmed
2. Scopus

**PubMed**

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|---|---|---|---|---|---|
| #19 | ••• | ! > | Search: **#14 AND #15 AND #16** Filters: **in the last 5 years, English** | 2 | 05:57:20 |
| #18 | ••• | ! > | Search: **#14 AND #15 AND #16** Filters: **in the last 5 years** | 2 | 05:57:00 |
| #17 | ••• | ! > | Search: **#14 AND #15 AND #16** | 6 | 05:56:42 |
| #16 | ••• | > | Search: **("Hospital"[Title/Abstract]) OR ("Healthcare organization"[Title/Abstract])** | 1,230,431 | 05:56:08 |
| #15 | ••• | ! > | Search: **(("Integral capacity management"[Title/Abstract]) OR ("Patient flow"[Title/Abstract])) OR ("Capacity management"[Title/Abstract])** | 2,528 | 05:55:41 |
| #14 | ••• | > | Search: **((("Key performance indicator"[Title/Abstract]) OR ("Quality indicator"[Title/Abstract])) OR ("Performance indicator"[Title/Abstract])) OR ("Performance measure"[Title/Abstract])** | 5,929 | 05:54:54 |

**Scopus**

| **Search query** | Database | #results | Filters | Next step? |
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| TITLE-ABS-KEY ( ( ( "Key performance indicator" ) OR ( "Quality indicator" ) OR ( "Performance measure" ) ) AND ( "Integral capacity management" OR "Patient flow" OR "Capacity management" ) AND ( "Hospital" OR "Healthcare organization" ) ) | Scopus | 116 | - | Reduce number f papers by including filters |

| | | | | |
|---|---|---|---|---|
| TITLE-ABS-KEY ( ( ( "Key performance indicator" ) OR ( "Quality indicator" ) OR ( "Performance measure" ) ) AND ( "Integral capacity management" OR "Patient flow" OR "Capacity management" ) AND ( "Hospital" OR "Healthcare organization" ) ) AND ( LIMIT-TO ( PUBYEAR , 2022 ) OR LIMIT-TO ( PUBYEAR , 2021 ) OR LIMIT-TO ( PUBYEAR , 2020 ) OR LIMIT-TO ( PUBYEAR , 2019 ) OR LIMIT-TO ( PUBYEAR , 2018 ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) ) | Scopus | 41 | 5 years, English | |

*Table 11: Article reference table systematic literature review*

| Reference number | Authors and Year | Title |
|---|---|---|
| 1 | (Thornton, Bonzo, Khan, & Souza, 2022) | Internal Operational Metrics and Center for Medicare and Medicaid Services Hospital Compare Quality Ratings |
| 2 | (Terning, Brun, & El-Thalji, 2022) | Modeling Patient Flow in an Emergency Department under COVID-19 Pandemic Conditions: A Hybrid Modeling Approach |
| 3 | (Amati, et al., 2022) | Reducing Changeover Time Between Surgeries Through Lean Thinking: An Action Research Project |
| 4 | (Hu, et al., 2021) | Use of a Novel Patient-Flow Model to Optimize Hospital Bed Capacity for Medical Patients |
| 5 | (Almasi, Rabiei, Moghaddasi, & Vahidi-Asl, 2021) | Emergency Department Quality Dashboard; a Systematic Review of Performance Indicators, Functionalities, and Challenges |
| 6 | (Sonmez & Pintelon, 2020) | A survey on performance management of operating rooms and a new KPI proposal |
| 7 | (Breen, Trepp, & Gavin, 2020) | Lean Process Improvement in the Emergency Department |
| 8 | (Prado-Prado, Fernández-González, Mosteiro-Anón, & García-Arca, 2020) | Increasing competitiveness through the implementation of lean management in healthcare |
| 9 | (Clay-Williams, et al., 2020) | The relationships between quality management systems, safety culture and leadership and patient outcomes in Australian Emergency Departments |
| 10 | (Cassarino, et al., 2019) | A randomised controlled trial exploring the impact of a dedicated health and social care professionals team in the emergency department on the quality, safety, clinical and cost-effectiveness of care for older adults: A study protocol |
| 11 | (Vanbrabant, Braekers, Ramaekers, & Van Niewenhuyse, 2019`) | Simulation of emergency department operations: A comprehensive review of KPIs and operational improvements |
| 12 | (Cudney, et al., 2019) | A decision support simulation model for bed management in healthcare |
| 13 | (Bae, Jones, Evans, & Antimisiaris, 2019) | Simulation modelling of patient flow and capacity planning for regional long-term care needs: a case study |
| 14 | (Patey, et al., 2019) | SurgeCon: Priming a community emergency department for patient flow management |
| 15 | (Martinez, et al., 2018) | An Electronic Dashboard to Monitor Patient Flow at the Johns Hopkins Hospital: Communication of Key Performance Indicators Using the Donabedian Model |
| 16 | (Pham, Duenas, & Di Martinelly, 2018) | Discrete Event Simulation for Chemotherapy patient flows |
| 17 | (van der Vrugt, Schneider, | Operations research for occupancy modeling at hospital wards and its integration into practice |

| | | |
|---|---|---|
| | Zonderland, Stanford, & Boucherie, 2018) | |
| **18** | (Stichting Oncologische samenwerking, 2022) | Multidisciplinaire normering oncologische zorg in Nederland |

*Table 12: KPIs found in articles with reference number, hierarchical level and whether it is used in Delphi study*

| KPI | reference | Strategic | Tactical | Operational | Included in Delphi study |
|---|---|---|---|---|---|
| **Length of stay** | 1,2,4,5,7,9,10,11,12,13,14,15 | | X | X | X |
| **Occupancy** | 1,2,3,5,6,11,15,17 | | X | X | X |
| **Discharges** | 1,5,6,15,17 | | X | X | X |
| **Readmissions** | 1,5,15 | X | X | | X |
| **Throughput** | 5,11,14,15,18 | | X | | X |
| **Mortality** | 1,5 | X | | | X |
| **Waiting time** | 2,4,7,9,12,13,16,18 | | X | X | X |
| **Process duration** | 6 | | X | | X |
| **Walk-outs** | 7,14 | X | X | X | |
| **Service time** | 7,16,18 | | X | | X |
| **Admissions** | 10,17 | X | X | | X |
| **Duration/time** | 2,5,6,10,11,12,14,15,18 | | X | X | X |
| **Changeover time** | 3,7,12 | | X | X | X |
| **Overtime** | 3,6 | X | X | X | X |
| **Bias in case duration** | 3 | | X | X | X |
| **Start time tardiness** | 3,6 | | X | X | X |
| **Cancellation** | 3,6,11 | | X | | X |
| **Delay** | 3,4,15 | | X | X | X |
| **Cost indicator** | 3,5,6 | X | | | |
| **Recovery time** | 4 | | X | | X |
| **Utilization** | 6,11,13 | | X | X | X |
| **Blocking probability** | 17 | X | X | X | |
| **Capacity related diversions** | 15 | X | X | | X |
| **Overall operating room effectiveness** | 6 | | | X | X |
| **Boarding time** | 11,15 | X | X | X | |
| **Crowding** | 2 | X | X | X | |
| **Star rating** | 1 | X | | | |
| **Safety of care rating** | 1 | X | | | |
| **Patient experience** | 1 | X | | | |
| **Transportation type** | 5 | X | | | |
| **Number of patients in the ED** | 5 | X | X | X | |
| **Number of patients admitted per triage level** | 5 | | X | X | |

| | | | | | |
|---|---|---|---|---|---|
| **Number of patients for whom a decision was mad in six hours** | 5 | | X | X | |
| **Number of consultations given** | 5 | | X | X | X |
| **Number of beds available** | 5 | | X | X | X |
| **Number of personnel in the ED** | 5 | | | | |
| **Number of cases performed** | 6 | X | X | X | X |
| **Number of complications** | 6 | | X | X | X |
| **Number of patients in the hospital** | 7 | | X | | X |
| **Number of first consultations** | 7 | X | X | | X |
| **Number of diagnostic tests** | 7 | | X | | X |
| **Number of treatment starts** | 7 | | X | | X |
| **Number of staff** | 18 | | X | | X |
| **Number of surgeries** | 18 | X | X | X | X |

# 10 Appendix C

*Table 13: Expert panel participant names and roles*

| Name | Role |
|---|---|
| **Esther van Beek** | Manager Healthcare and Business Operations |
| **Miranda Ernst** | Oncologic surgeon & Medical manager |
| **Mieke van Schuppen** | Board member |

*Table 14: Results from the first Delphi questionnaire round*

| KPI | Proposed in Delphi study in first round | Average | Percentage participants in top tertile (7,8,9) | Result questionnaire round 1 |
|---|---|---|---|---|
| **Waiting time** | Length of time patients wait for a certain service or procedure | 8,7 | 100% | Accept |
| **Utilization** | Ratio of the actual use of resources, such as hospital beds or staff, to the maximum available amount | 8,7 | 100% | Accept |
| **Occupancy** | Number of hospital resources that are occupied by patients | 8,3 | 100% | Accept |
| **Number of cases performed** | Number of cases performed | 8,3 | 100% | Accept |
| **Throughput** | Rate at which patients move through the hospital system | 8 | 100% | Accept |
| **Cancellation** | Number of procedures or appointments that are cancelled | 8 | 100% | Accept |
| **Number of consultations given** | Number of times a healthcare provider consults with a patient | 8 | 100% | Accept |
| **Number of first consultations** | Number of initial consultations with new patients | 8 | 100% | Accept |
| **Number of diagnostic tests** | Number of diagnostic tests conducted | 8 | 100% | Accept |
| **Number of complications** | Number of complications that arise during or after a procedure or surgery | 7,7 | 100% | Discuss |
| **Number of surgeries performed in the hospital** | Number of surgeries performed in the hospital | 7,7 | 100% | Discuss |
| **Number of staff** | Number of staff members employed by the hospital | 7,3 | 67% | Discuss |
| **Capacity related diversions** | Number of patients that are redirected to other healthcare facilities due to capacity limitations | 7 | 67% | Discuss |
| **Changeover time** | Length of time it takes to prepare a room or equipment for the next patient | 6,7 | 67% | Discuss |

| | | | | |
|---|---|---|---|---|
| **Bias in case duration** | Deviation from the scheduled time it takes to complete a specific type of procedure or activity | 6,7 | 67% | Discuss |
| **Number of patients in the hospital** | Number of patients in the hospital | 6,7 | 67% | Discuss |
| **Number of treatment starts** | Number of reports generated by healthcare providers | 6,7 | 67% | Discuss |
| **Admissions** | Number of patients admitted to the hospital or to a specific unit | 6,3 | 67% | Discuss |
| **Length of stay** | Length of time patients stay in the hospital or a specific unit | 6 | 67% | Discuss |
| **Discharges** | Number of patients discharged from the hospital or a specific unit | 5,7 | 67% | Reject |
| **Recovery time** | Length of time it takes for a patient to recover from a specific procedure or activity | 5,7 | 67% | Reject |
| **Duration/time** | Length of time a specific service or activity takes to complete | 6,3 | 33% | Reject |
| **Overtime** | Amount of time hospital staff work beyond their scheduled shift | 6,3 | 33% | Reject |
| **Start time tardiness** | Length of time a procedure or activity starts later than scheduled | 6 | 33% | Reject |
| **Delay** | Amount of time a procedure or activity is delayed beyond the scheduled end time | 6 | 33% | Reject |
| **Number of beds available** | Number of hospital beds that are available for patient use | 6 | 33% | Reject |
| **Throughput** | Rate at which patients move through the hospital system | 5,7 | 33% | Reject |
| **Service time** | Length of time it takes to provide a specific service or procedure to a patient | 5,7 | 33% | Reject |
| **Readmissions** | Number of patients readmitted to the hospital within a certain time frame after being discharged | 5,3 | 33% | Reject |

*Table 15: Results from the Delphi study expert meeting*

| KPI | Proposed in Delphi study in first round | Result expert meeting |
|---|---|---|
| **Waiting time** | Length of time patients wait for a certain service or procedure | Rephrased into two new more specific KPIs which are added |
| **Utilization** | Ratio of the actual use of resources, such as hospital beds or staff, to the maximum available amount | Ratio of the actual patient use of resources to the maximum available amount |
| **Occupancy** | Number of hospital resources that are occupied by patients | Ratio of the total use of resources to the maximum available amount |
| **Number of cases performed** | Number of cases performed | Number of cases performed per treatment type |

| | | |
|---|---|---|
| **Throughput** | Rate at which patients move through the hospital system | Access time to first treatment |
| **Cancellation** | Number of procedures or appointments that are cancelled | Number of procedures or appointments that are cancelled by the patient |
| **Number of consultations given** | Number of times a healthcare provider consults with a patient | Number of consults per DBC per doctor |
| **Number of first consultations** | Number of initial consultations with new patients | Accepted |
| **Number of diagnostic tests** | Number of diagnostic tests conducted | Accepted |
| **Number of complications** | Number of complications that arise during or after a procedure or surgery | Accepted |
| **Number of surgeries performed in the hospital** | Number of surgeries performed in the hospital | Accepted |
| **Number of staff** | Number of staff members employed by the hospital | Rejected |
| **Capacity related diversions** | Number of patients that are redirected to other healthcare facilities due to capacity limitations | Rejected |
| **Changeover time** | Length of time it takes to prepare a room or equipment for the next patient | Rejected |
| **Bias in case duration** | Deviation from the scheduled time it takes to complete a specific type of procedure or activity | Rejected |
| **Number of patients in the hospital** | Number of patients in the hospital | Rejected |
| **Number of treatment starts** | Number of reports generated by healthcare providers | Number of treatment starts |
| **Admissions** | Number of patients admitted to the hospital or to a specific unit | Number of patients admitted to the ward and chemotherapy department |
| **Length of stay** | Length of time patients stay in the hospital or a specific unit | Length of time patients stay in the ward and the chemotherapy department |
| **Discharges** | Number of patients discharged from the hospital or a specific unit | Rejected |
| **Recovery time** | Length of time it takes for a patient to recover from a specific procedure or activity | Rejected |
| **Duration/time** | Length of time a specific service or activity takes to complete | Rejected |
| **Overtime** | Amount of time hospital staff work beyond their scheduled shift | Rejected |
| **Start time tardiness** | Length of time a procedure or activity starts later than scheduled | Rejected |

| | | |
|---|---|---|
| **Delay** | Amount of time a procedure or activity is delayed beyond the scheduled end time | Rejected |
| **Number of beds available** | Number of hospital beds that are available for patient use | Rejected |
| **Throughput** | Rate at which patients move through the hospital system | Rejected |
| **Service time** | Length of time it takes to provide a specific service or procedure to a patient | Rejected |
| **Readmissions** | Number of patients readmitted to the hospital within a certain time frame after being discharged | Rejected |

*Table 16: Results from the Delphi second questionnaire round*

| KPI | Rephrased and added KPIs | Average | Percentage | Outcome questionnaire round two |
|---|---|---|---|---|
| Accesstime | Access time for a patients first appointment | 8,0 | 100% | Accepted |
| Time between process steps | Time between start diagnostics until PA outcome | 8,0 | 100% | Accepted |
| Utilization | Ratio of the actual patient use of resources to the maximum available amount | 8,3 | 100% | Accepted |
| Occupancy | Ratio of the total use of resources to the maximum available amount | 8,0 | 100% | Accepted |
| Number of cases performed | Number of cases performed per treatment type | 7,0 | 67% | Accepted |
| Throughput | Access time to first treatment | 8,3 | 100% | Accepted |
| Cancellation | Number of procedures or appointments that are cancelled by the patient | 8,0 | 100% | Accepted |
| Number of consultations given | Number of consults per DBC per doctor | 7,7 | 100% | Accepted |
| Number of treatment starts | Number of treatment starts | 7,0 | 67% | Accepted |
| Admissions | Number of patients admitted to the ward and chemotherapy department | 8,0 | 100% | Accepted |
| Length of stay | Length of time patients stay in the ward and the chemotherapy department | 7,0 | 67% | Accepted |
| Appointment rescheduled | How many times are appointments rescheduled | 7,3 | 100% | Accepted |
| Length of waitinglsit | Length of waitinglist of patients | 7,0 | 67% | Accepted |

# 11 Appendix D

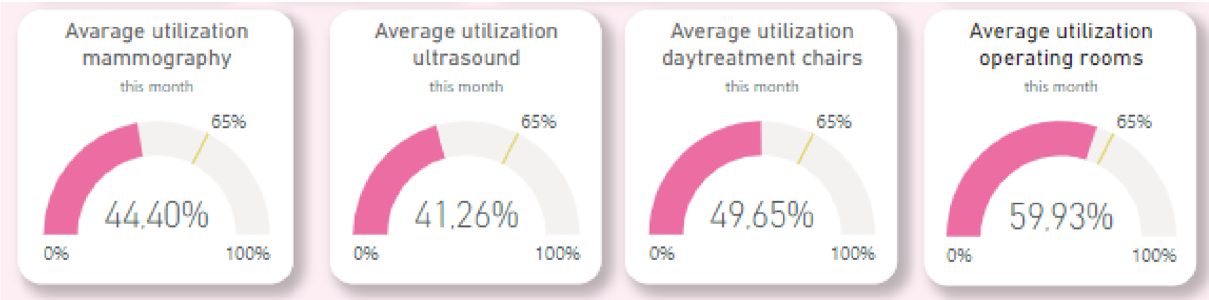
This appendix provides in depth information about the calculation and visualization per KPI.

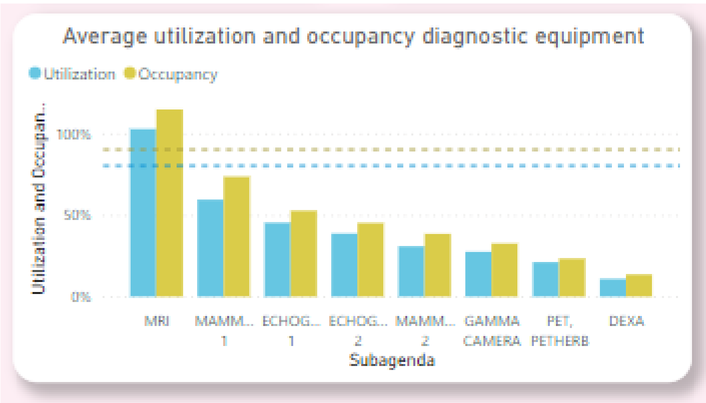
*Utilization*

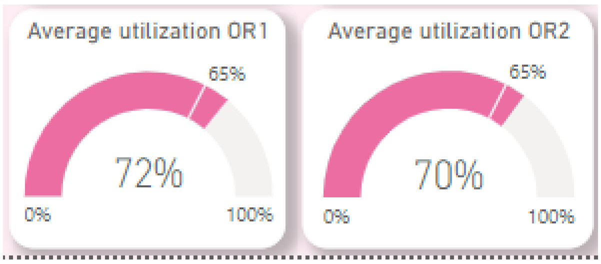
Utilization is a KPI that looks at the ratio of actual patient use of a resource by the patient to the maximum available amount the resource is available. To calculate this ratio, we use the following formula:

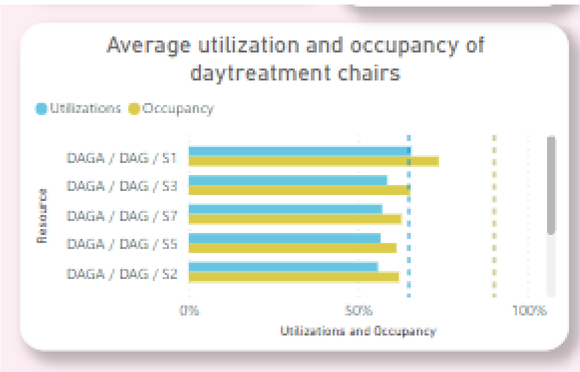
$$Utilization\ rate\ (\%) = \frac{Total\ time\ resource\ is\ used\ by\ a\ patient}{Total\ time\ resource\ is\ available}$$

This rate can be calculated for multiple resources that are of interest. In our case hospital the utilization rate can be calculated for the chemotherapy chairs, operating rooms, and rooms with diagnostic equipment. The total time a resource is available is retrieved from the reference table with opening times. The data for the utilization is retrieved from the table Agenda for diagnostic equipment, Admissions for the day treatment chairs, and Surgeries for the ORs.



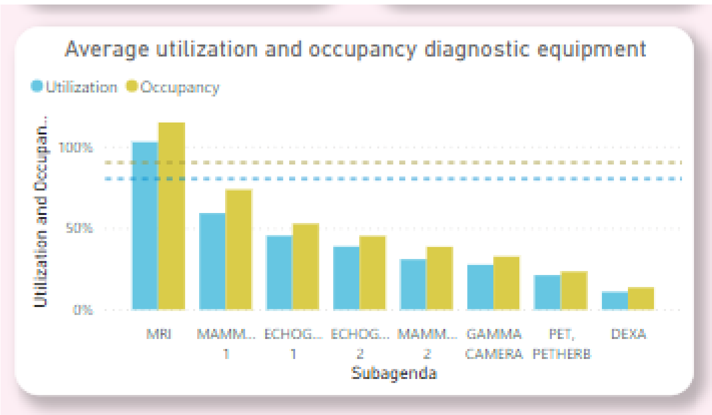



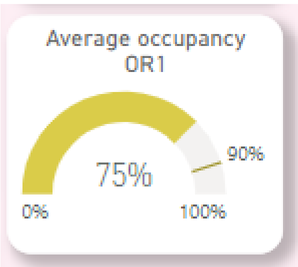


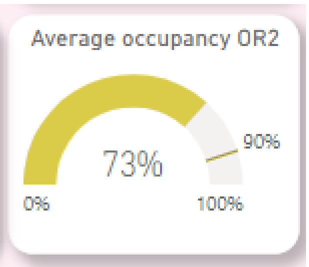

*Occupancy*

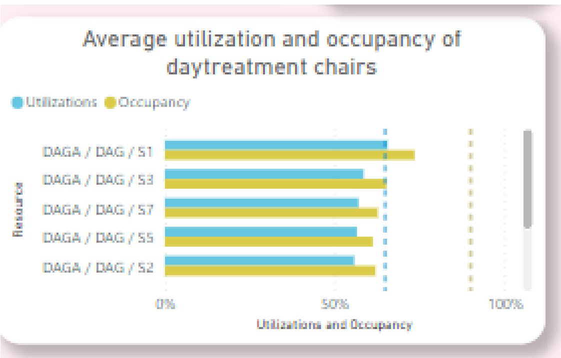
Occupancy rate is similar to Utilization rate, but differs by what we define as utilized and occupied. We define utilized as the time a resource is used for a patient and we define occupied as time the resource is used at all times. Occupancy also includes work like administrative tasks and cleaning.

$$Occupancy\ rate\ (\%) = \frac{Total\ time\ resource\ is\ occupied}{Total\ time\ resource\ is\ available}$$



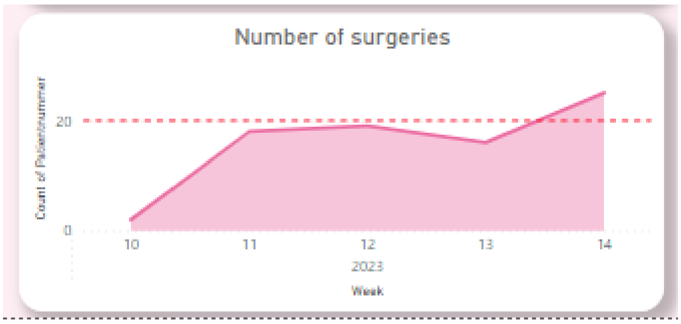



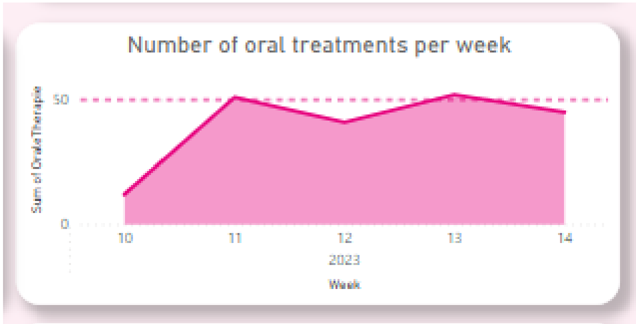



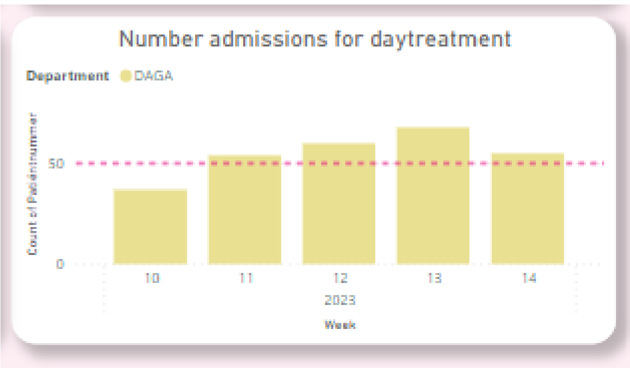
*Number of cases performed per treatment type*

The number of cases performed per treatment type counts all the patients treated per treatment type. In our case hospital there are 2 types of treatment, systems therapy and surgery. Within these treatment types it is possible to define even further what type of treatment is given. For systems therapy these can be a varying in chemotherapy treatments and hormonal treatments. For surgery the surgery can be a plastic surgery or a chirurgical surgery.

$$Nr.\,of\ cases\ performed = \sum All\ cases\ per\ treatment\ type$$




*Throughput*

Throughput can be defined in many possible ways. In broad terms this means the total amount of time that it takes to run a particular process in its entirety from start to finish. In our case we do not look at the process entirely, but we look at a particular process within our care pathway, the diagnostic process before treatment. This process can also be more clearly defined as the access time to the first treatment which is calculated by the following formula.

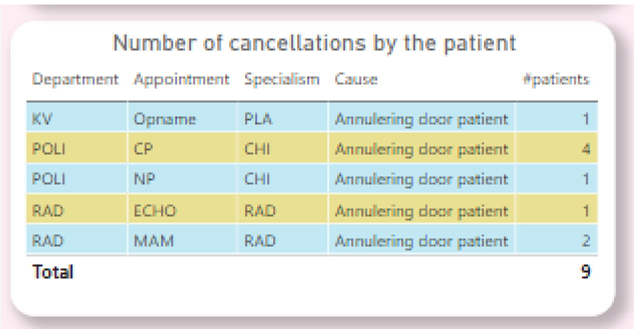
$$Average\ access\ time\ to\ first\ treatment = \frac{\sum_{1}^{n} Date\ of\ first\ treatment_n - Date\ of\ first\ appointment_n}{n}$$

The formula looks at the difference between the date of the first appointment and the date of the first treatment. We sum this difference of all patients that start with treatment and then divide this amount by the total number of patients that start treatment to get the average time.


*Cancellation*

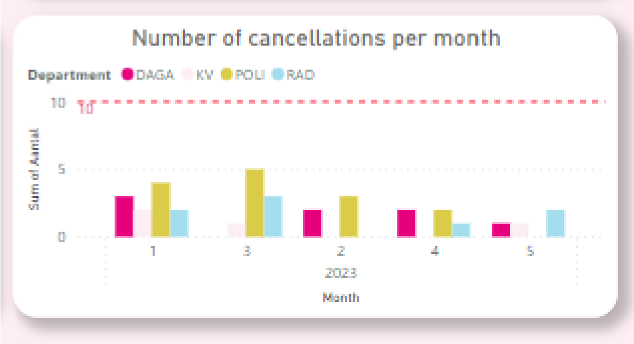
The KPI cancellations counts all cancellations of appointments by patients.

$$Number\ of\ cancellations = \sum all\ cancellations$$



Number of cancellations by the patient

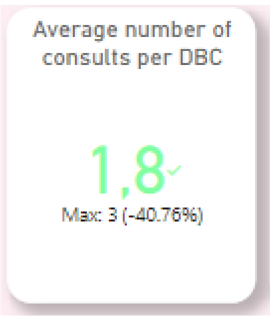
| Department | Appointment | Specialism | Cause | #patients |
|---|---|---|---|---|
| KV | Opname | PLA | Annulering door patient | 1 |
| POLI | CP | CHI | Annulering door patient | 4 |
| POLI | NP | CHI | Annulering door patient | 1 |
| RAD | ECHO | RAD | Annulering door patient | 1 |
| RAD | MAM | RAD | Annulering door patient | 2 |
| Total | | | | 9 |




*Number of consultations given*

The KPI number of consultations counts all consultations within a DBC.

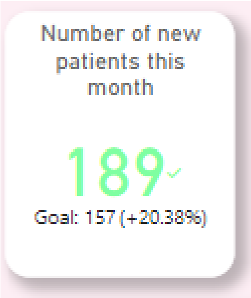
$$Number\ of\ consults\ per\ DBC = \sum All\ consults$$

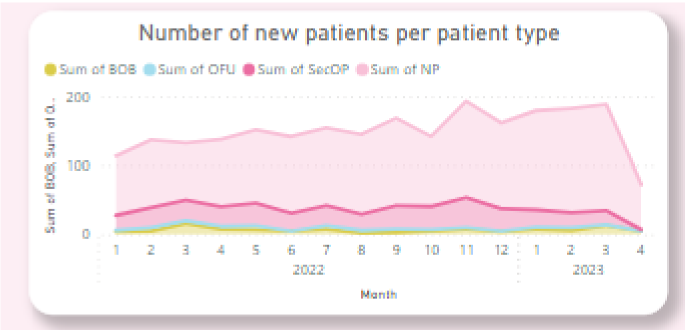


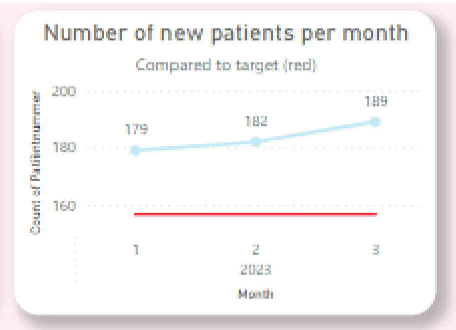
*Number of first consultations*

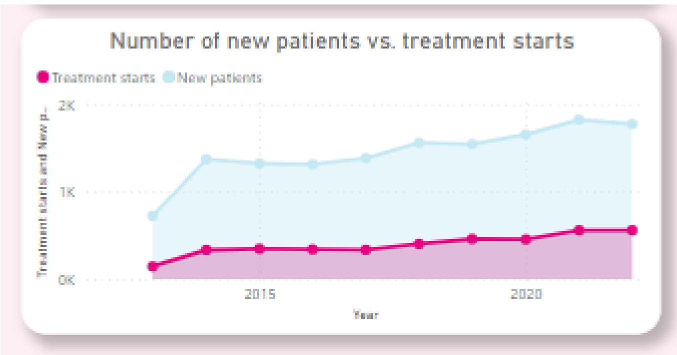
The number of first consultations, which can also be seen as the number of new patients.

$$Number\ of\ first\ consults = \sum all\ first\ consults$$



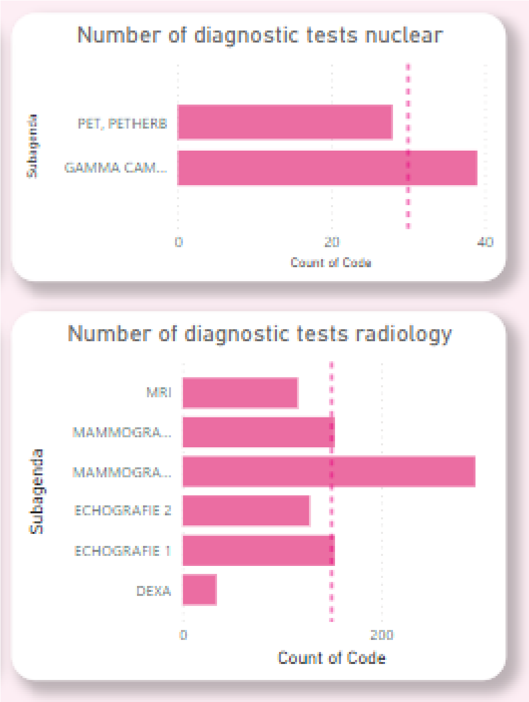




*Number of diagnostic tests*

The number of diagnostic tests counts the number of diagnostic tests per diagnostic treatment method.

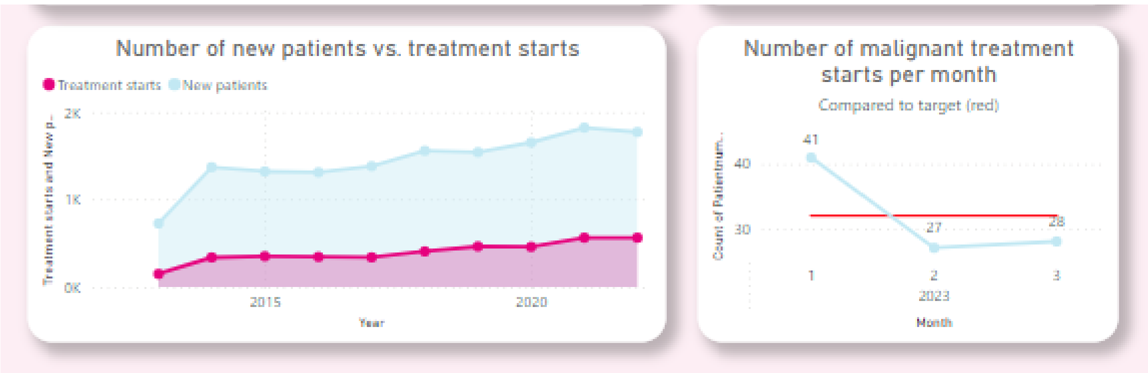
$$Number\ of\ diagnostic\ tests = \sum all\ diagnostic\ tests$$




*Number of treatment starts*

The number of treatment starts counts how many patients start with treatment in a certain time frame.

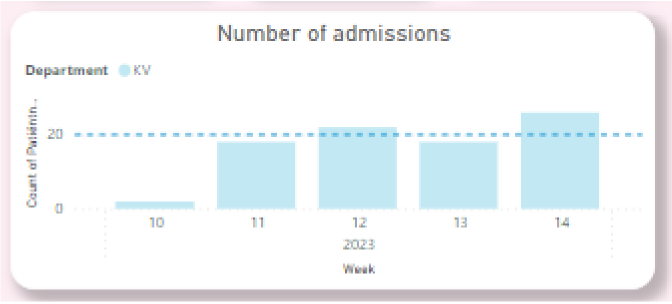
$$Number\ of\ treatment\ starts = \sum All\ treatment\ starts$$

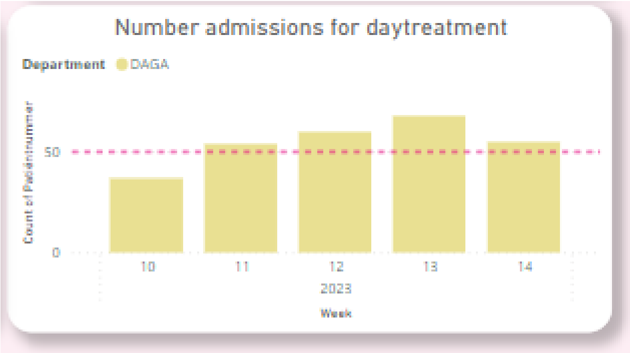




*Admissions*

This KPI counts the number of admissions. In our case hospital, a patient can either be admitted to the chemotherapy ward or the general ward. The number of admissions is calculated using the following formula:

$$Number\ of\ admissions = \sum All\ admissions$$

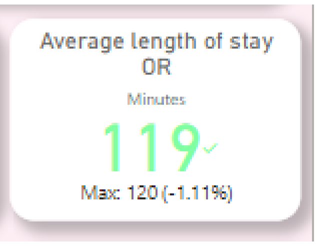


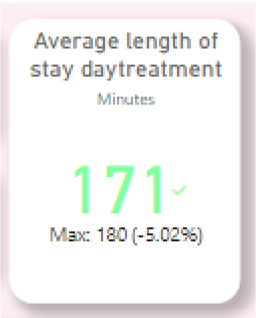




*Length of stay*

Length of stay measures the time between admission and discharge of a patient to the hospital. As for the admissions, the length of stay can be calculated at our case hospital for the chemotherapy ward and the general ward.

$$Average\ Length\ of\ Stay\ (ALOS) = \frac{\sum_1^n Date\ of\ discharge_n - Date\ of\ admission_n}{n}$$

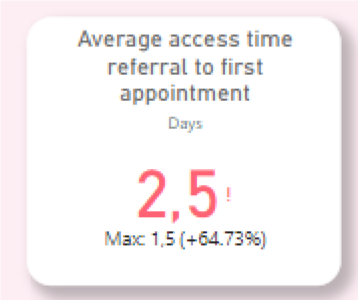




*Access time*

Access time is defined as the time between the referral to a hospital and the first time the patient can be seen.

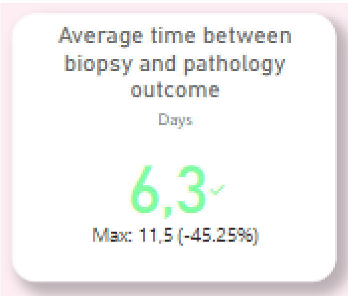
$$\text{Average access time to first appointment} = \frac{\sum_1^n \text{Date of first appointment}_n - \text{Date of GP referral}_n}{n}$$




*Time between process steps*

Time between process steps is a very broad KPI. Our case hospital is interested in the time between the first appointment and the moment a patient gets its results back from pathology.

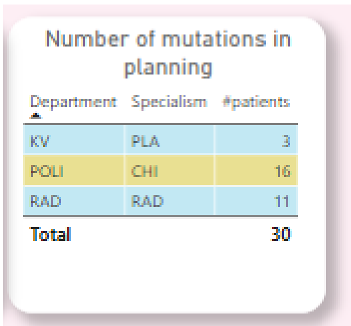
$$\text{Average time between first appointment and outcome PA} = \frac{\sum_1^n \text{Date of PA outcome}_n - \text{Date of first appointment}_n}{n}$$



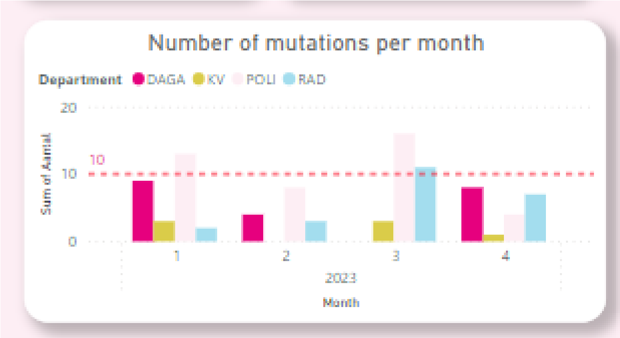

*Rescheduled appointments*

Rescheduled appointment counts the number of times an appointment has been rescheduled.

$$\text{Rescheduled appointments} = \sum \text{All rescheduled appointments}$$


Number of mutations in planning

| Department | Specialism | #patients |
|---|---|---|
| KV | PLA | 3 |
| POLI | CHI | 16 |
| RAD | RAD | 11 |
| Total | | 30 |




*Length of waitlist*

The length of waitlist counts the number of patients that has the status waitlisted.

$$Number\ of\ patients\ on\ waitlist = \sum All\ waitlisted\ patients$$

Waitlist per department and specialism

| Department | Specialism | Number of patients |
|---|---|---|
| KV | CHI | 8 |
| DAGA | INT | 8 |
| | PLA | 10 |
| KV | PLA | 53 |
| **Total** | | **79** |