MASTER

Identifying improvement areas at radiology departments
a data science approach

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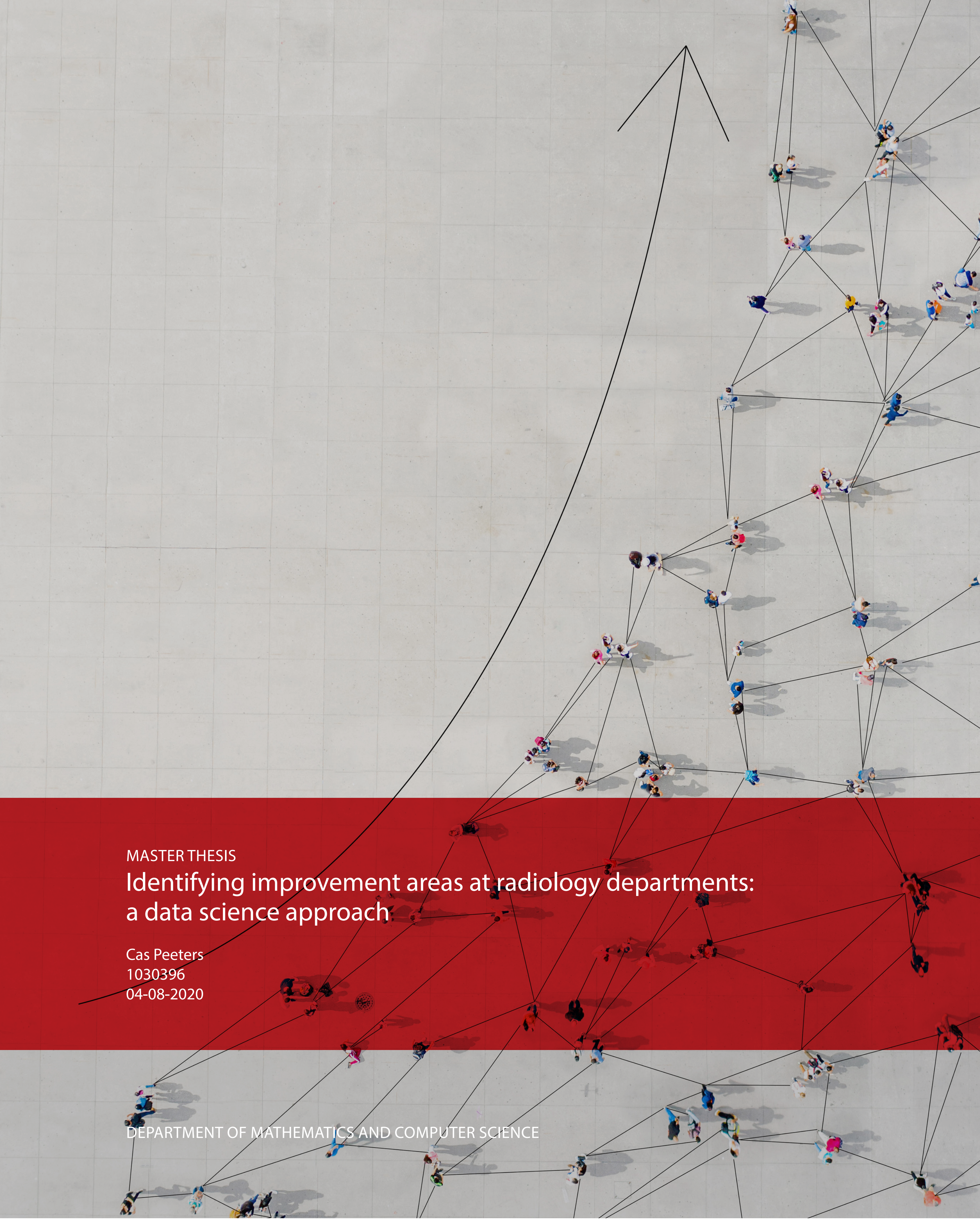

MASTER THESIS

Identifying improvement areas at radiology departments: a data science approach

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Identifying improvement areas at radiology departments: a data science approach

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Abstract

The Dutch government, healthcare providers and health insurance companies have agreed on limiting the growth of healthcare costs. Given the still increasing demand and costs of specific care, this implies that hospitals must "operate" in a more value-driven way. This thesis contributes to this by introducing data and process mining methods to identify improvement areas in radiology departments. To this end, a thorough business insight into patient planning, allocation of timeslots and throughput time have been outlined. Influential factors on patient arrival patterns and production times are then identified by regression analysis. Process mining techniques are then used to define the role and position of radiology in a healthcare path.

While practical results are found using these methods, they cannot be directly adopted in business decisions due to the quality of the underlying data. These quality issues are not only limiting the results of this thesis but also limit achieving part of the vision of the Elkerliek hospital to improve quality and transparency in data exchange between departments and other hospitals. This research compresses a multitude of different visualization techniques into an interactive dashboard which will provide support for the planning department, management, and medical technicians to identify fact-based improvement areas, and will be further optimized when the data quality is improved.

Preface

Half a year ago I walked through the doors of the Elkerliek hospital for the first time as a graduation intern. On the way to my destination, the radiology department, I was greeted kindly by the five employees who passed me. The radiology department also received me with genuine kindness and attention. This attitude is also reflected in the truly heartwarming interaction between patient and the medical staff. These observations strengthened my internal motivation to give back to the medical staff who deserve our, but especially my gratitude.

Given my specialization in information systems, my research was logically focused on information technologies (IT) and business support. During this project, I realized that the more I immersed myself in data and mathematics, the more I distanced myself from the interactions between medical staff and patients, that being the initial reason why I wanted to embark on this project. Thanks to the excellent support of my supervisors Dr. Natalia Sidorova, Lillyanne Peeters and Drs. Stan Janssen, it was possible to combine the best of both worlds by offering IT and business-driven support in which the medical staff, the patient and continuous improvement are central themes.

My parents Hans and Dorothé and my stepparents Coen and Marie-José guided me in my own personal development, and helped me overcome my inner struggle to always want to prove myself by overachieving. Without them all this would not have been possible and for that I am grateful to them. Specials thanks goes to Michelle for the loving support, inspiring dog walks and for always keeping faith in me.

I would like to thank Dr. Laura Genga for assessing my work and being part of the examination committee. In addition, I would like to thank the Eindhoven University of Technology for the humbling journey in which I met the smartest and most sincere people. Above all, my educational experience made me realize that there is an entire world full of patterns and opportunities to be discovered, and that skills required to do so can always be found by people with kind intentions and those who are willing to work for it.

Thank you.

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Chapter 1

Introduction

This master project is conducted at the Elkerliek hospital. The Elkerliek hospital, hereafter referred to as the Elkerliek, is a small peripheral hospital with three locations in Deurne, Gemert and Helmond. The three locations with various health care departments, day nursing and the nursing wards are staffed with more than 100 specialists and more than 2000 other employees, who provide healthcare for around 300.000 patients every year.

The Elkerliek has four strategic focus points for 2020, namely acute care, elective very complex care, elective low complex care, and chronic care and prevention. For acute care, the Elkerliek actively invests in the transit and internal logistics of the emergency department (ED) and its associated staff. In elective very complex care, the focus is on the elderly, skin cancer, and breast cancer. The Elkerliek wants to offer a competitive price and sufficient quality for elective low complex care, which means that waiting times and other forms of waste must be reduced. Finally, in the context of chronic care and prevention, the Elkerliek focuses on reducing double unnecessary diagnostics, transparency and data exchange between care providers. For general information: **www.elkerliek.nl**

The radiology department plays a central role in providing this healthcare. In total, the radiology department of the Elkerliek carries out nearly 120.000 examinations a year. These examinations are conducted by more than 80 employees, ranging from radiologists and medical technicians to administrative employees and managers. The demand for radiology examinations originates from various healthcare providers. At the highest level of abstraction this demand can be grouped in both internal and external requests. Internal requests may come from the departments such as cardiology and orthopedics. External requests can come from general practitioners or other hospitals.

1.1 Project context and motivation

Costs of specialist medical care, insofar as insured under the Health Insurance Act, have risen 30% since 2006 to 23 billion euro per year. This is partially due to the increased amount of care provided (volume), as with a price increase for healthcare. The growth in volume from 1998-2012 was on average 3% per year. More recently (2013-2017) this growth has somewhat stagnated with on average 1.1% per year [14]. The price increase of healthcare has also declined from 13.7% in 2001 to 2.5% in 2016.

This decline is stimulated by financial agreements between the government, healthcare providers and health insurance companies, which have agreed on limiting the growth in healthcare cost to 1% per year [31].

The cap on increasing healthcare costs, growing healthcare volume and increasingly more expensive healthcare [14], puts pressure on the efficiency and effectiveness of the specialist medical care. In summary, hospitals must "operate" in a more value-driven way. As Porter[41] describes it: "Value depends on results, not inputs, value in health care is measured by the outcomes achieved, not the volume of service delivered. Shifting focus from volume to value is a central challenge." Acknowledging this challenge to shift from volume to value, the Elkerliek has started an organizational wide LEAN optimization mind set. To this end, each health care department of the Elkerliek is tasked to find ways to deliver more value to the patient, and with addressing all types of waste (Defects, Overproduction, Waiting, Transportation, Inventory, Motion, and Extra processing[51]). The adapted LEAN mentality contributes to this added value and has guided the Elkerliek to constantly work on quality improvements.

The radiology department of the Elkerliek is tasked with implementing quality improvements. For the radiology department this mainly entails the transition from supply-driven to demand-driven healthcare, and practically reducing overproduction (overcapacity) and waiting (waiting time). The radiology department of the Elkerliek has a bottom-up organizational structure, with highly educated personnel. To maximize the potential of this personnel, responsibilities, especially these quality improvement cycles, are allocated to all employees of the radiology department.

However, many of the objectives such as optimizing schedules and capacity planning are complex problems [38]. It is therefore not surprising that the radiology department wastes a lot of time in this process. Missing connection and poor user interaction of the IT systems (HIX, RIS, ZorgDomein, VIDA and multiple Excel lists), that should provide insights into demand and capacity, only add to the complexity and unnecessary amount of work. All in all, the lack of insight into demand, capacity and resulting planning implications, raise the question whether the radiology department of the Elkerliek uses its resources effectively and whether these resources will be sufficient in the future.

The radiology department also struggles with determining the effectiveness of its services. Due to the integral position of radiology in a patients clinical path, the value of radiology in this path depends on activities of other departments and the role of radiology in the clinical path. E.g. making the correct diagnosis at an early stage, as well as stopping treatment in time, is of great importance to the patient, as for preventing waste in the clinical path. The choice and timing of radiology is therefore essential for the value of care.

All together, the healthcare and thus the radiology department is obligated to continuously implement quality improvements. However, several issues complicate this process. Providing insight and user interaction on the relevant systems and thus data on demand and capacity, would allow a more efficient and effective scheduling process and general resource effectiveness. In addition, insight into the flow efficiency and optimal position of radiology can enable the Elkerliek to come closer to desired outcomes of clinical paths and thus delivering optimal value for the patient.

1.2 Setting the stage

This chapter introduces three relevant background information topics for this research, which also serve as an outline for the general situation in the field of radiology. These topics are the trend in the demand for radiology services, the role of (diagnostic) radiology services and data mining and machine learning in radiology.

1.2.1 Trend in demand for radiology services

There are various factors that influence the demand for healthcare and therefore radiology services. The most noticeable factor is the population growth in the Netherlands, which is expected to grow until 2038, reaching a maximal population size of about 17.5 million, after which the population is expected to decrease slightly [13]. This is partly due to the increasing life expectancy in this period (plus 4.4 and 4.2 years in addition to the current life expectancy for males and females respectively) [30]. Another factor in the demand for healthcare is that the Dutch population is strongly aging. In 2003 (17 years ago), 15 percent of the population was over 65 years, twice as large as in 1953. The effect of this aging will continue to increase considerably in the coming decades (till 2050), as the baby boom generation gets older [13], [30]. It is expected that these factors will lead to a (further) increase in demand for radiology services.

The National Institute for Health and Environment (RIVM) tracks the performed radio diagnostics from general hospitals and in their reports the aspects as described above and the general increase in healthcare volume seems to be quite an understatement for the growth of radio diagnostics. Ultrasound is significantly and almost linear increasing with a total growth of 250% in the period of 2000 to 2017, and there is no indication of a hold on or reduction of this growth [43]. The same holds for CT-examinations, which have increased with 200% from 2001 to 2018 [42]. MRI-examinations have also skyrocketed with an increase of 190% from 2001 to 2015. Recently though (2015-2018), MRI growth has stagnated and is only slowly increasing [43]. Nuclear medicine examinations have rapidly grown ever since the point of data collections, 65% in 18 years (2000 -2018) to be exact [44], and are expected to grow even further [8]. Lastly, regular X-rays have grown with 30% from 2003 to 2010. After 2010, X-rays are showing a negative trend resulting in a 13% loss by 2018 [45]. Visual representation of the national trends in radiology can be found in Appendix A.

There are also arguments given for the increasing demand for radio diagnostics from an oncological point of view[54]. Namely, that the increased survival rate of patients is also increasing the amount and time-span of the monitoring and follow-up phase, in which control diagnostics are common practice. As described by [30], this is not only the case with oncology, but the survival rate will also increase for heart and vascular disease and respiratory diseases. In addition to strictly medical purposes, a patient can also attach great importance and relieve in receiving confirmation radio diagnostics [54].

1.2.2 Role of (diagnostic) radiology services

High patient service levels are becoming increasingly important in the hospital. Therefore, fast diagnosis, decision making, and treatment are crucial [46], [6]. [25] for example proved that laboratory turnaround time is directly associated to the length of stay in the emergency department. Of course, radio diagnostics play a critical role in this process for both clinical and outpatient healthcare. Imaging centers recognized this trend and positioned themselves between general practitioners and hospitals, resulting in loss of outpatient business and profit margins [7]. Increasing radiology capacity in such a demanding market therefore seems to be a feasible decision.

However, as described, hospitals are bound to a limited compensation for their services. Hence, increasing production is not financially beneficial for the hospital. Because of this disproportionate compensation for healthcare services, diagnostics are an increasingly serious cost factor on the hospital budget. Some parties therefore argue for less radio diagnostics. This results in capacity cuts and increased working pressure.

On the other side of the coin, there are parties that argue that increasing radio diagnostics will actually reduce costs in some cases[54]. Their opinion is that the costs of (unnecessarily) continuing treatment exceed those of timely use of diagnostics. For example, the effect of trastuzumab and pertuzumab for breast cancer treatment varies widely. With the use of a CT-scan (cost of 400 euro) the effect of the treatment can be measured. If not longer effective, the treatment can be stopped and potential longer treatment of 2667 euro per dose can be saved.

1.2.3 Data mining and machine learning in radiology

Decision support for the radiology department has become increasingly apparent in practice. For example, in [7] a decision support system is proposed that is based on the American College of Radiology appropriateness criteria. Based on these criteria an order from a referring physician is scored on the expected effect. By asking for conformation for low effective radiology orders, the intention of this system is to reduce overproduction.

On the other spectrum data mining and machine learning can be used for decision support on the medical assessment of scans [10]. [34] for example proved that Convolution Neural Networks (CNN) can achieve high (96%) accuracy on classifying breast tumor tissue (Based on the BreakHis dataset, containing 9,109 microscopic images of breast tumor tissue). Google analyzed mammography (mammo) scans with machine learning techniques, resulting in 5.7% less false positives and 9.4% less false negatives than a human expert team. Moreover, the machine learning model required less information than the human team [48].

Data mining and machine learning can be used for prevention of healthcare intervention, decision support for practical policies of medical technicians, authorization, interpretation of findings, or can even give rise to new diagnostic possibilities [10],[15], [18]. Furthermore, analysis on radiology demand, production times and authorization can provide insights into future demand and optimization opportunities. These aspects are visually summarized in Figure 1.1.

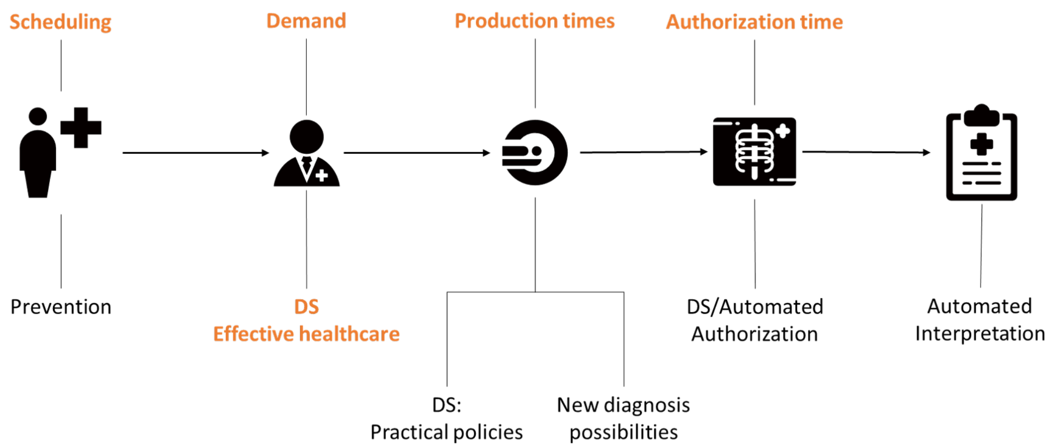


Figure 1.1: Data mining and Machine learning possibilities in Radiology

This report aims to guide hospitals in their mission to provide healthcare in an efficient and valued oriented manner. To this end, this report utilizes the vast amount of unused data that is present in the radiology department to provide information support for the continuous improvement cycles of the Elkerliek. To delineate this large-scale goal, this report focuses on decision support on effective healthcare, demand analysis, authorization time analysis, and production time analysis and optimization (as indicated in orange in Figure 1.1).

1.3 Scientific and practical relevance

Most tactical and operational decisions of the radiology department of the Elkerliek are now mainly based on education, work experience and patient interaction. Although this way of working is sufficient for well-founded decisions, it produces a lot of manual work and makes it difficult to notice the interesting demand and process patterns. This report is of practical relevance because it enables the radiology department of the Elkerliek to harness the power of data analysis for continuous improvement cycles. Ultimately, this will benefit the entire healthcare sector, as more efficient and effective healthcare will be provided. In addition, the methods described in this study are applicable to all companies that are exposed to urgent / emergency orders and have difficulty combining short- and long-term planning.

From a scientific point of view, the (performance of the) radiology department is often simplified by focusing on a particular research group, or by excluding different types of patients. These simplifications are sometimes required, but at the same time blur the overview. A broader perspective on the radiology department emphasizes the infrequently researched differences and interactions between modalities. Secondly, research into the role and position of events in a trace is relatively young. Research into the role and position of radio diagnostics in a healthcare process therefore contributes to the scientific body on this subject. Although the influence of variables on arrival patterns and production times of patients has been researched more extensively, confirmation of this influence from a small peripheral hospital certainly contributes to the scientific body on this subject.

1.4 Research Assignment

As described, the healthcare sector is under financial pressure. It is therefore a requirement to provide more efficient and value-driven care in the short term. The use of data analysis in the radiology department has been on the back burner for quite some time. Since data analysis can be a catalyst for the transition to more efficient and value-driven healthcare, it is important that data analysis becomes a high priority in hospitals. To support this, this research project therefore aims to answer the following question:

How can data analysis in radiology departments be used to identify areas for improvement in planning and operational efficiency?

This question can be divided into four parts, each of which can be considered a deliverable in itself.

1. **Is relevant data available and of sufficient quality, and how can it be improved?**
   For studies with a high data analysis content, it is common that 80% of the total project timeline goes to data cleaning. Awareness about which data is relevant for data analysis in radiology, and the necessary data cleaning steps can therefore shorten the time required for (follow-up) projects. The following deliverables will contribute to this:
   - Describing the relevant information architecture
   - Listing the required steps for data cleaning
2. **How can patient arrival and production patterns, trends and performance be identified, and how does the planning process relate to this?**
   Due to the wide variation in applications, a department such as radiology has a rather complex character. This research describes how relevant patient arrivals and production patterns can increase insight in such a complex department. In addition, knowing the main causes of variation in these patterns helps to achieve optimal use of resources. This research therefore describes potentially influential factors and methods to quantify these factors. This process is reflected in the following deliverables:
   - Mapping the current demand flow of radiology services at the Elkerliek
   - Analyzing the resource utilization
   - Assessment of the overall performance
   - Identification of potentially influential factors on production and patient arrivals
   - Quantification of potentially influential factors
3. **How can the role and position of radiology in the flow effectiveness of a healthcare process be made transparent?**
   A patient receives care from many different entities, such as general practitioners,

various hospitals and related departments. In many cases, radiology is involved in this clinical episode. Understanding the different roles and positions of radiology in such a clinical episode is also crucial for the transition from a supply-driven to a demand-driven healthcare system. Moreover, these insights can lead to clinical discussions and can even be included in clinical decision-making around new clinical protocols. To this end, this research utilizes existing process mining techniques to discover diagnosis specific process flows, resulting in the following deliverables:

- Control flow discovery with the use of process mining
- A list of research directions for assessing the role and position of radiology in the flow effectiveness of healthcare processes

4. **How can the data analysis insights be used in practice?**
In order to be useful, the insights brought to light in this research need to be updated, responsive and accessible for all layers of the Elkerliek. To this end, a responsive dashboard configuration is proposed, resulting in the following deliverables:

- An interactive radiology dashboard
- Practical use cases

1.5 Thesis outline

In this chapter the project context and motivation, as well as the practical and scientific relevance of this research is described. The rest of this report is structured as follows:

Chapter 2 describes the CRISP-DM framework which forms the basis of this research. The modelling step of this framework has three components in this research namely regression, process mining and visualization, all of which will be introduced. Chapter 3 introduces the available data, the data cleaning steps to improve the quality of this data and takes the first step in answering research question 1.

The answer on research question 2 is provided in three subsequent chapters. Chapter 4 describes the relevant aspects to understand the business at hand, from introducing resources to performance analysis. Chapter 5 describes the factors that potentially influence production performance and patient arrival patterns. Section 6.1 aims to quantify the impact of these factors by means of regression. Together these chapters provide an answer to research question 2. Also new data quality issues that occurred in this process are described, complementing the answer to research question 1.

Section 6.2 describes how process mining techniques can be used to discover the role and position of radiology in healthcare paths. It also provides a list of research directions for assessing the role and position of radiology in the flow effectiveness of healthcare processes. This section provides answer to research question 3. Section 6.3 introduces the radiology dashboard created in this study and practical use cases of this dashboard. These use cases show how, for example, the analyzes in chapter 4 and chapter 5 can be reproduced in order to obtain data analysis insights in practice.

Chapter 2

Methodology

To determine how data analysis in radiology can be used to support continuous improvement, an appropriate methodology for both the technical application of the data analysis and the methodology for its practical implementation is required. As the term continuous improvement suggests, both methodologies must be highly iterative and reproducible.

The methodology for the technical application of the data analysis is based on the CRISP-DM framework[61]. With technical application deployment as input, van Aken's Problem Solving Cycle[4] serves as the methodology of choice for the continuous improvement cycle.

Figure 2.1 depicts how this research has adapted these two methodologies as research method and which research questions will be addressed in which step of the research method. Each step of the research method is further explained in this chapter.

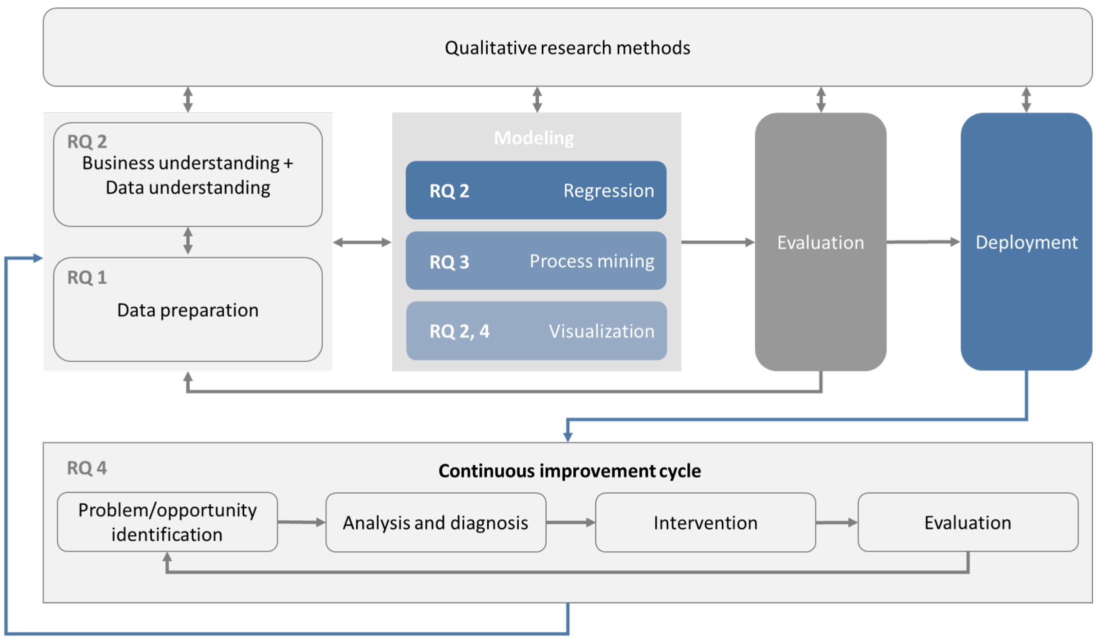


Figure 2.1: Research Methodology

Throughout this research, qualitative research methods such as interviews with managers, medical technologists and radiologists are conducted to gain a thorough understanding of internal processes and process / patient characteristics, and to evaluate methodologies and results.

Data preparation
In order to correctly interpret the results of data analysis, the underlying data set must be reliable and undisputed. Data cleaning is therefore the basis for every data analysis process. This is especially important when dealing with poor data quality databases such as RIS (Radiology Information System) [28]. The data preparation step provides answers to research question 1.

Business Understanding + Data understanding
An in-depth business understanding can be sketched based on the cleaned data set. This sketch consists of patient arrival rates, production times, capacity utilization, performance on key indicators, and tactical and operational decision points. During this process, iteration with data preparation is insurmountable as business insights will shed light on (new) data inconsistencies. Combined, the Business understanding and Data understanding (and later visualization) steps provide answers to question 2.

Modelling
Regression: The hypothesis is that the variance in production times and patient arrival, which has become apparent in the business understanding, can be explained by influential factors and expert rules [38] such as *IF it is **snowing** THEN the demand is **high***. Quantifying the influence and associated significance of these factors is assessed by regression.

Figure 2.2: Regression Approach

In the regression process, some continuous variables are clustered into logical categories, because categorical data is often easier to understand and more likely to produce meaningful results. For technical reasons, these factors are then coded and checked for multicollinearity. As expected, different examinations respond differently to different factors. Therefore, Recursive Feature Elimination (RFE) is used to automatically select the factors relevant to the different examination types. The methodology of the regression step in the overall Modelling step is displayed in Figure 2.2 and provides answers to question 2.

Process mining: Due to the extensive work of Van Aalst among others, it is possible to provide insight into business processes with relative ease.

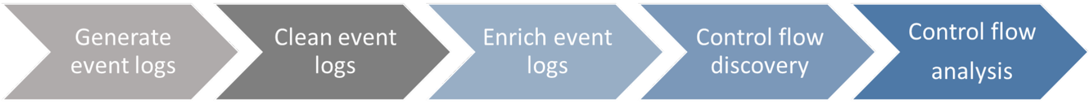


Figure 2.3: Process Mining Approach

As described in [1], a typical approach to process mining is to generate event logs (explained in section 6.2), clean up and enrich these event logs, and then discover general control flows and potential areas of interest. These control flows and event logs form the basis for more advanced analyzes such as conformity control, bottleneck analysis and comparison of process variants. The Process Mining steps (Figure 2.3) in the overall Modelling step provide answers to question 3.

Visualization: In order to make the insights derived in this research usable in practice, an analysis layer has been built on the information architecture layer. The methodology used for this is loosely based on the design study framework described by [50] and is displayed in Figure 2.4.

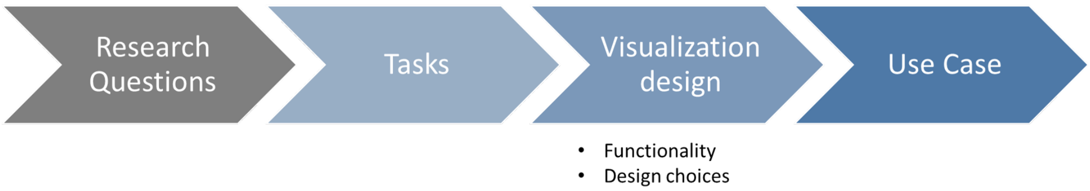


Figure 2.4: Visualization Approach

As stated by [50] it is of the utmost importance to have a clear picture of the research questions that a design aims to solve. Solving this research question then consists of several visualization tasks that must be implemented functionally and design-wise. Then the design with use cases is put to the test. The visualization step in the overall Modelling step provides answers to question 2 and 4.

Continuous improvement cycle

With the regression, process mining and visualization models deployed, the radiology department can initiate improvement cycles. The model deployments can support both the problem/opportunity identification, and analysis and diagnosis. The continuous improvement cycles will remain an ongoing process, but the setup provides a practical answer to question 5.

Software

The data cleaning steps, regression analysis, and control flow analysis are all included in a Python framework. Analyzes related to mammographic studies are the main theme of this study. However, the Python framework can be tasked with analyzing a different examination, a series of examinations or all examinations.

Chapter 3

Data exploration and preparation

This chapter introduces the relevant available data, the data cleaning steps taken to improve the quality of this data and which steps still need to be taken before the data is suitable for data analyses. This chapter answers *research question 1*: Is relevant data available and of sufficient quality, and how can it be improved?

The main information system of the Elkerliek is the Hospital Information System (HIX) from Chipsoft. This system records all patient information, diagnostic information, operations and more. Together with the laboratory, the radiology department is the last department that uses its own system for daily practices. In the case of radiology this system is called Radiology Information System (RIS) from Sectra. RIS and HIX are connected in the sense that with every order in HIX a copy of the relevant data in HIX is sent to RIS. After a data mutation in RIS (completion of an examination for example) again a copy of the data is sent back to HIX. Relevant attributes and corresponding tables of both HIX and RIS are displayed in Figure 3.2. The PACS system is used by the radiology department for storage and analysis of performed and processed scans. The Elkerliek has no query rights in PACS, hence data from this system cannot be extracted. For resource allocation multiple Excel lists are used. To support the operational workflow, the Excel schedule of the medical technicians has been digitized. However, when inspecting these files and considering their complexity, it had to be concluded that analysis of the realized capacity allocation was not feasible due to time restraints. A visual representation of the relevant systems is given in Figure 3.1

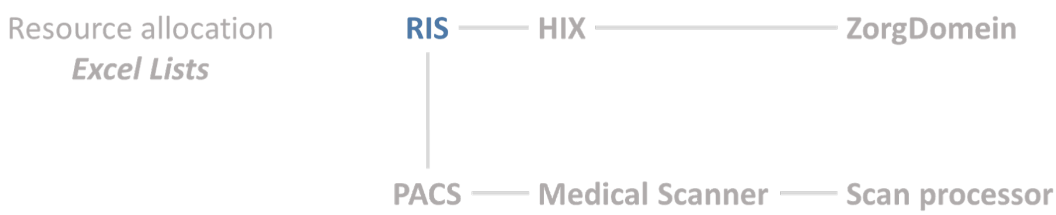


Figure 3.1: Relevant Systems for the Radiology Department

This research requires both detailed radiology data as data regarding overarching healthcare paths. Since HIX is the leading system of the Elkerliek that records the whole clinical path of patients, but only RIS captures the process steps (time stamps) of the radiology department, data from both systems have to be extracted.

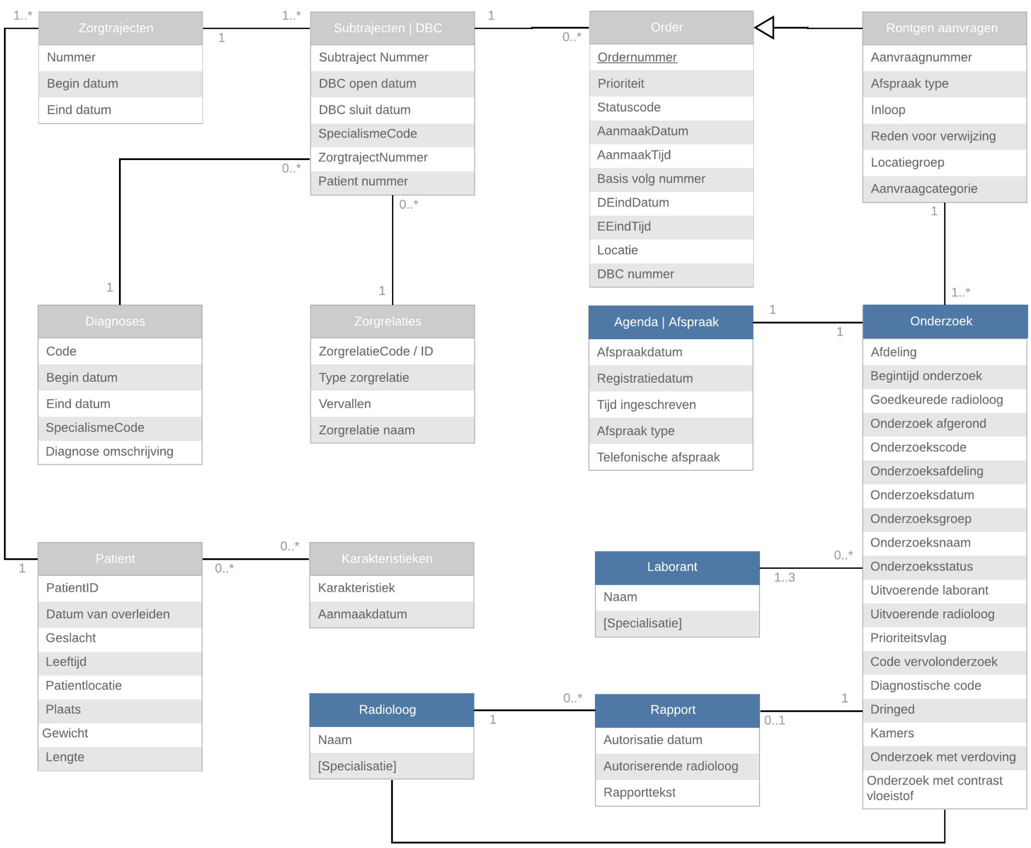


Figure 3.2: UML Diagram RIS, HIX, Zorgdomein

In total 518.953 radiology examinations are recorded in RIS for the time span 2016-2019. 20.700 records have registered values for the attribute *Admin. wijziging/afwijking* such as "cancelled by applicant" and should therefore be considered cancelled, resulting in 498.253 valid examinations. HIX kept track of 497.588 radiology orders. Despite multiple iterations with RIS system administrators, HIX system administrators and BI specialists, the search for the foreign key between the primary key in RIS (*Ordernummer*) and HIX remains inconclusive. It was however possible to join both data sets on two other attributes, namely *Aanvraagnummer* and *Onderzoeksnummer* in RIS and *ExtNummer* and *Zoekcode* in HIX. To secure all data from RIS a left join was used to connect both datasets (Figure 3.3).

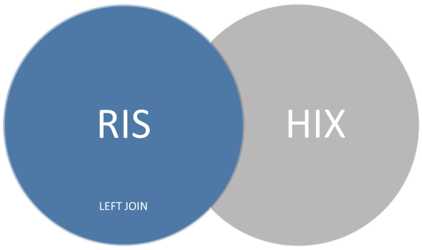


Figure 3.3: Left Join RIS and HIX

This configuration results in a dataset of 518.953 orders of which 498.253 have not been cancelled and of which 411.997 could be connected to records in HIX. Records that could not be connected are records that do not have a valid *Aanvraagnummer* in RIS, or are cancelled.

Process knowledge enrichment

After joining HIX and RIS, the data is enriched with domain and process knowledge.

1. General practitioners are recorded based on their last name. For reporting purposes, all consumers, excluding external specialist and health insurers, with *Bronnaam verwijzer* not equal to an internal hospital department are clustered as "General practitioner";
2. The *Onderzoeksnaam* attribute defines the specific radiology examination of a record, contains 591 unique examination types. This attribute is grouped into 14 unique categories. For example, "MR-Pelvis", "MR-Brain", "MR-CWK HNP" and all other categories starting with "MR" are grouped into one attribute: "MRI";
3. The process of radiology in the simplest sense does not contain loops and runs according to a standard order (order registration, check-in, wait, examination, authorization). Due to imprecise and manual logging of event timestamps, this standard order is sometimes mixed up in the data. Therefore, checks are done on whether the time between an order registration time and examination time is positive. If not, this record is marked as invalid. The same holds for the time between the check-in and start examination, and the time between stop examination and authorization;
4. Also, the exact duration of steps in the radiology process show major inconsistency. To exclude most of the outliers, the upper 10% of the time between the events in the radiology process is marked as invalid;
5. Since there is more information regarding the expected duration of an examination, the examination duration undergoes another check on validness. It is assumed that to be valid, an examination may not exceed the scheduled examination duration three times over. The same holds when an examination is completed in one third of the scheduled time;
6. Emergency orders which do not originate from the emergency department are not registered as emergency. To capture emergency behavior, a new variable "Suspected Emergency" is introduced which marks all not walk-in records having an examination start date within 3 hours of its registration date as "Emergency orders". This includes patients who were send by the outpatient clinic for which

a free spot happened to be available. According to the system administrators of RIS, however, the number of these patients is very low;

7. Orders with *code vervolgonderzoek* "9999 Geen Facturatie", such as "CD branden" or "MG Mammography geimporteerd" are marked as not applicable (N.A). The same holds for non-relevant orders such as "Multidiciplinair overleg";
8. Some orders, such as "CT Thorax & Abdomen" can be billed twice, but do not require more time than approximately one CT Thorax because it is one and the same scan. Because of billing purposes these orders are registered twice in RIS. To prevent these examinations to be counted twice in utilization calculations only the first is marked as "utilization valid";
9. The practicing medical technician, practicing radiologist and authorizing radiologist fields are transformed from an unstructured string to a structured set of medical technicians and radiologists which can be counted;
10. By grouping on registration date, the order intensity of workdays and weeks is included as a new variable. The same has been done for the examination date, yielding the production intensity.

For reasons explained in chapter 4, data regarding weather, holidays and school holidays are added. Weather data is derived from the Koninklijk Nederlands Meteorologisch Instituut (KNMI)[27] and holidays from the Rijksoverheid[57]. Since the patient population of the Elkerliek is strongly centered in the south of the Netherlands, only school holidays relevant for the south of the Netherlands are included.

Outstanding issues

Despite the greatest efforts there are still outstanding issues regarding the data.

1. The foreign key between HIX and RIS remains unknown;
2. Not all records in HIX have a *ZorgpadNummer*. The *ZorgpadNummers* that are missing are mostly general practitioner orders, and orders with a specific *Kamer* field, such as [HZ, HSEH, ZCT, ZBPH, ZDB, ZERA, ZMAM];
3. *AfspraakType* = A (i.e. a follow up appointment) is not always a reliable field according to system administrators. This becomes particularly apparent when deriving the access times of the various examination types (section 4.8.1). As a temperately solution, the appointments that have an access time higher than 3 months are considered as follow up appointments;
4. The field *aanmaakdatum* is sometimes misused for administrative workarounds, resulting in blurred control flows;
5. Human resource allocation of the radiology department is registered in such cluttered Excel files that analysis upon this allocation is hardly possible;
6. The consultation hours of departments in the hospital (e.g. surgery, neurology) are not data analysis friendly, resulting in the fact that the radiology department is not sufficiently aware of consultations hours of other departments. This holds for OR planning as well;
7. The exact dates of cancellations are not recorded, making it hard to execute optimization projects in the field of cancellation prevention/prediction;
8. Process characteristics such as "examination requires sedation", "examination requires contrast liquid", "infection hazard" are unreliable/unknown fields, while these characteristics are of crucial importance for the planning process;
9. Whether a radiologist is required to be present during an examination is not recorded. This makes analysis on human resource allocation inconclusive;

10. Choices on scan approaches are not registered in a structured field in RIS, hence analysis on this behavior cannot be conducted;
11. Due to the lack of a query right in PACS, the assessment time of a medical scan by a radiologist before authorization is unknown;
12. The patient occupancy of the Elkerliek has not been made transparent, while this is an important aspect of the expected arrival of patients at the radiology department.

Data interpretation remarks

In this paper all radiology examinations that have been conducted in 2016-2019 are included. Since the order is registered before the actual examinations this implies that also orders ordered before 2016 are included. This also means that all orders with an examinations date after 2019 are excluded, even when the registration date of the order is before 2019. Figure 3.4 gives a visual representation of this distinction.

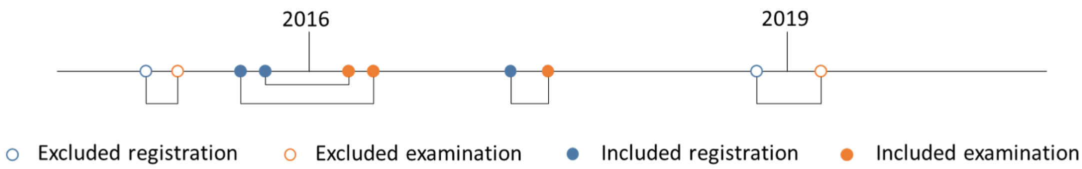


Figure 3.4: Included and excluded radiology examinations

Given the confidential nature of the data, all data identifying patients have been anonymized before leaving the secured servers of the hospital.

Sub-conclusions

Manual logging clearly has its impact on the data quality of the radiology department. Cleaning steps on this dataset improved reliability but reduced the total size of the dataset significantly (total of 518.953 orders (411.997 not cancelled), of which 309.189 with valid timestamps). In conclusion there are some structural issues that obstruct the radiology department in performing useful data analysis.

1. Using a multitude of other systems besides the main information system HIX, directly effects the interconnectivity with other departments. In addition, the systems that are available at the radiology department are not suitable for automatic and responsive reporting due to labor intensive manual querying practices and memory limits. Moreover, some information, such as the authorization time of examinations is not accessible at all due to the lack of query rights.
2. Manual logging of timestamps and process/patient characteristics is error prone and has serious consequences for the reliability of (key) performance analyses. Not logging important information such as failed scans and cancellation dates further blur the insights into processes that represent reality.
3. Currently only 270.987 orders (not all with valid timestamps) can have a HIX *ZorgtrajectNummer*. This emphasizes the structural problem with determining the role of radiology examinations in a healthcare process, which is imperative for a high over management of a hospital.

It may be possible that relevant missing data is logged somewhere in the systems, but because of the lack of interoperability between systems, this data could not be located and is therefore currently not accessible for people who rely on this data like the radiology department managers.

To escape this situation, the first step is to identify the patient/process attributes that are important to the performance of the radiology department. This report already contains many of these features. After that, system administrators need to find these attributes in the systems and create robust methods to automatically generate reports containing those attributes. If the data is not present in the systems, a decision must be made as to whether the information is actually critical and software updates are therefore required, or whether a different available patient/process characteristic will suffice. Accelerating the planned migration of the radiology department from RIS to HIX could very well spur this process. In addition, this acceleration would avoid unnecessary IT work in RIS.

Chapter 4

Business understanding

This chapter describes, in part, the patient arrival and production patterns, trends and performance. Section 4.1 to 4.2 provide an overall overview of the current demand flow in absolute numbers and growth. Section 4.3 to 4.6 introduce the radiology processes, the vast amount of patient and process characteristics and the grouping of these characteristics as currently used by the radiology department of the Elkerliek. Thereafter section 4.7 to 4.8.1 describe the key performance indicators relevant for a radiology department and the current performance of the radiology department of the Elkerliek. This chapter partially answers *research question 2*: How can patient arrival and production patterns, trends and performance be identified, and how does the planning process relate to this?

4.1 Patient population base

The distribution of the Elkerliek patient population determines the extent to which national trends in radiology demand can be adopted and is therefore an important factor to consider. Most of the patient population of the Elkerliek originates from Helmond, Deurne and surrounding villages (Appendix B, Figure B.1). The population of Deurne and Helmond follows the national aging trend. The relative percentage of elderly (60+) in Deurne has increased with 1.68% since 2015 and in Helmond with 1.22% [12].

This trend is also visible in the relative percentage of elderly that is examined at the radiology location of the Elkerliek in Deurne. However, the relative percentage of elderly that is examined in the radiology location of the Elkerliek in Helmond is getting slightly younger (Appendix B, Table B.2 and Table B.3). This slight difference does not provide sufficient ground to deviate from assuming the national aging trend, there is therefore no motive yet to deviate from the general arguments for rising demand for healthcare and diagnostics.

4.2 Demand analysis

As described in chapter 1.5, the number of radiology examinations requested and performed has increased and is expected to increase further in the coming years. Also in the data of the Elkerliek a big leap in the amount of examinations from 2016 to 2017 can be observed (Table 4.1). However, this significant increase does not continue in the following years, hinting towards a stagnation in the rise of radiology orders within the Elkerliek. Important to note is that this is the number of examinations conducted between 2016 and 2019, not the number of orders requested.

2016	2017	2018	2019
119,238	126,483	124,866	126,939

Table 4.1: Number of radiology examinations conducted within the Elkerliek

To provide more details into the specific growth of the radiology department of the Elkerliek, the absolute number of examinations conducted per modality is depicted in Figure 4.1, Figure 4.2, and Figure 4.3. X-ray examinations are following the slight negative national trend. CT is following the strong positive national trend. More recently MRI has followed a negative trend, which goes beyond the stabilizing national trend. This deviation can be attributed to the shift from some MRI examinations to CT examinations within the Elkerliek. In Figure 4.4 the Growth Rate from 2018 to 2019, the Average Annual Growth Rate (AAGR) and the Compound Annual Growth Rate (CAGR) are summarized.

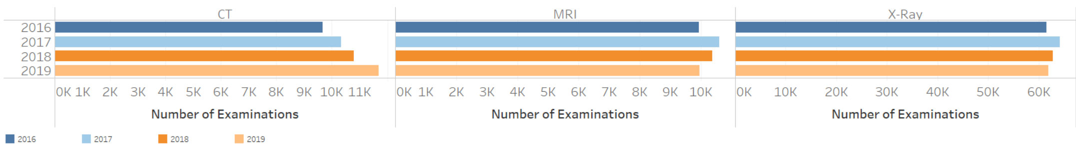


Figure 4.1: Absolute number of orders, large modalities

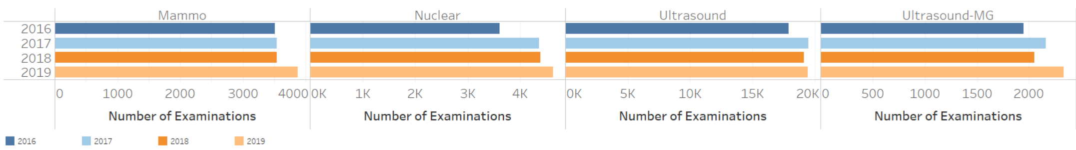


Figure 4.2: Absolute number of orders, small modalities 1

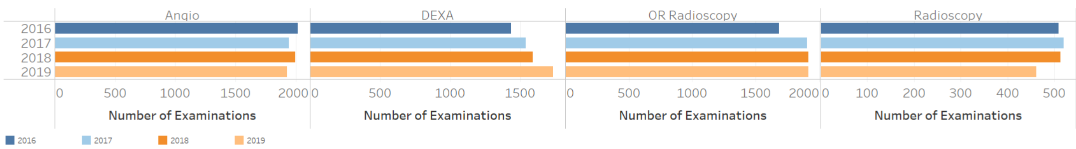


Figure 4.3: Absolute number of orders, small modalities 2

From this summary the conclusion can be drawn that the demand for CT, ultrasound-MG, DEXA, and nuclear scans has most definitely increased in the past four years. The only noteworthy decreases are angiography (angio), X-ray, MRI and radioscopy, of which the reduction in MRI examinations are due to a shift in examinations from MRI to CT. These trends should be taken into consideration when performing forecasting analysis.

	Angio	CT	DEXA	Mammo	MRI	Nuclear	OR Radioscopy	Radioscopy	Ultrasound	Ultrasound-MG	X-Ray
2019 GR	-3.46%	8.42%	9.18%	9.53%	-3.94%	5.53%	0.00%	-10.12%	1.82%	13.58%	-1.27%
AAGR	-1.48%	6.57%	6.51%	3.39%	0.16%	8.89%	4.58%	-3.04%	2.95%	6.54%	0.27%
CAGR	-1.15%	4.88%	4.82%	2.47%	0.04%	6.35%	3.28%	-2.39%	2.13%	4.63%	0.17%

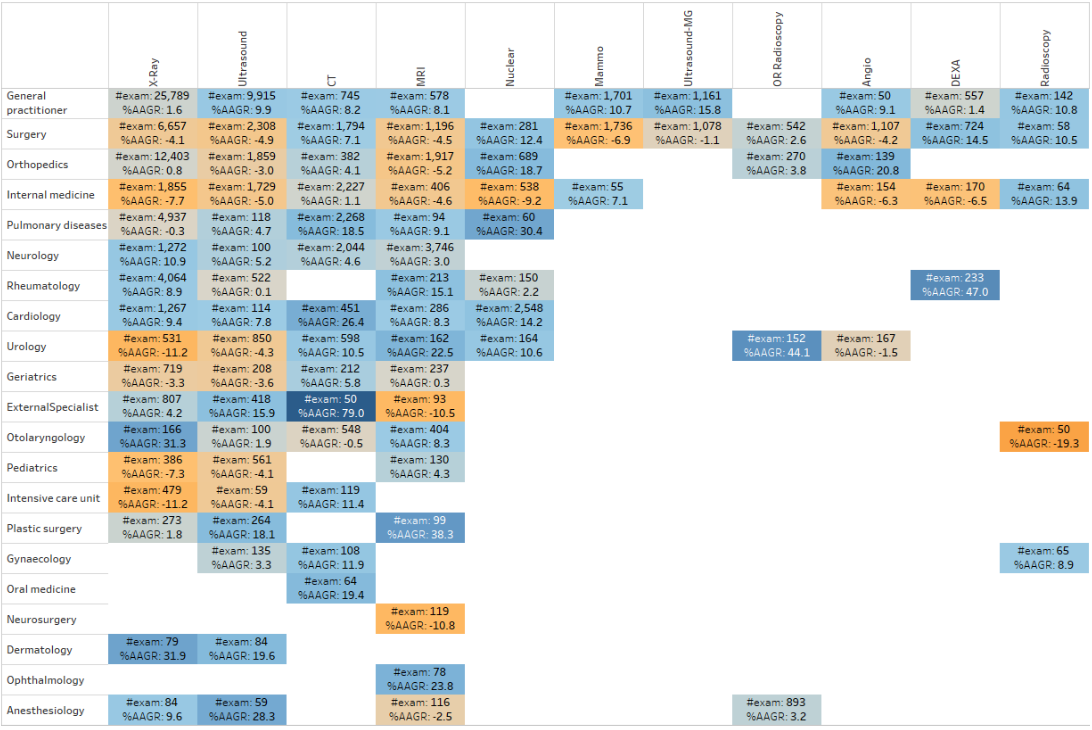
Figure 4.4: Growth rates in percentages

The vast range of examinations that the radiology department of the Elkerliek provides are requested by various, internal and external, healthcare providers. Figure 4.5 depicts the type of examinations and the requested amount per healthcare provider. General practitioners are the largest consumer, followed by "orthopedics" and "surgery". There are various examination types which are specifically important for specific departments, such as the MRI for neurology, nuclear for the cardiology, the angio for surgery and so on. These specific examination - requesting department combinations will be used in later analysis and are important for time allocation purposes.

	X-Ray	Ultrasound	CT	MRI	Nuclear	Mammo	Ultrasound-MG	OR Radioscopy	Angio	DEXA	Radioscopy
General practitioner	25,789	9,915	745	578	40	1,701	1,161	2	50	557	142
Surgery	6,657	2,308	1,794	1,196	281	1,736	1,078	542	1,107	724	58
Orthopedics	12,403	1,859	382	1,917	689			270	139	1	24
Internal medicine	1,855	1,729	2,227	406	538	55	36	1	154	170	64
Pulmonary diseases	4,937	118	2,268	94	60	1	1		12	4	4
Neurology	1,272	100	2,044	3,746	23	4	1		1	1	
Rheumatology	4,064	522	19	213	150				2	233	5
Cardiology	1,267	114	451	286	2,548				2		
Urology	531	850	598	162	164			152	167		16
Geriatrics	719	208	212	237	31	7	7			34	1
ExternalSpecialist	807	418	50	93	32	14	13		10	5	
Otolaryngology	166	100	548	404				1			50
Pediatrics	386	561	30	130	31			1		4	29
Anesthesiology	84	59	2	116				893			
Intensive care unit	479	59	119	11				1	41		3
Plastic surgery	273	264	16	99		9	35	6			2
Gynaecology	49	135	108	30		8	1	1	28	3	65
Oral medicine	39	48	64	37	16						
Neurosurgery	39		3	119				32			
Dermatology	79	84		1	16			1			
Ophthalmology	18	2	17	78					15	1	

Figure 4.5: Demand per examination type per department - 2019

In Figure 4.6 the AAGR per modality per requesting department is shown for modality-applicant combination that are conducted more than 50 times in 2019. The specific reasons behind fluctuations have to be assessed by domain experts. However, some overall conclusions can be underlined: significant increase in the amount of examinations conducted for general practitioners, a significant decrease in the amount of examinations conducted for the internal healthcare department, and for example the extreme rise in the amount of CTs for cardiology can be underlined.



	X-Ray	Ultrasound	CT	MRI	Nuclear	Mammo	Ultrasound-MG	OR Radioscopy	Angio	DEXA	Radioscopy
General practitioner	#exam: 25,789 %AAGR: 1.6	#exam: 9,915 %AAGR: 9.9	#exam: 745 %AAGR: 8.2	#exam: 578 %AAGR: 8.1		#exam: 1,701 %AAGR: 10.7	#exam: 1,161 %AAGR: 15.8		#exam: 50 %AAGR: 9.1	#exam: 557 %AAGR: 1.4	#exam: 142 %AAGR: 10.8
Surgery	#exam: 6,657 %AAGR: -4.1	#exam: 2,308 %AAGR: -4.9	#exam: 1,794 %AAGR: 7.1	#exam: 1,196 %AAGR: -4.5	#exam: 281 %AAGR: 12.4	#exam: 1,736 %AAGR: -6.9	#exam: 1,078 %AAGR: -1.1	#exam: 542 %AAGR: 2.6	#exam: 1,107 %AAGR: -4.2	#exam: 724 %AAGR: 14.5	#exam: 58 %AAGR: 10.5
Orthopedics	#exam: 12,403 %AAGR: 0.8	#exam: 1,859 %AAGR: -3.0	#exam: 382 %AAGR: 4.1	#exam: 1,917 %AAGR: -5.2	#exam: 689 %AAGR: 18.7			#exam: 270 %AAGR: 3.8	#exam: 139 %AAGR: 20.8		
Internal medicine	#exam: 1,855 %AAGR: -7.7	#exam: 1,729 %AAGR: -5.0	#exam: 2,227 %AAGR: 1.1	#exam: 406 %AAGR: -4.6	#exam: 538 %AAGR: -9.2	#exam: 55 %AAGR: 7.1			#exam: 154 %AAGR: -6.3	#exam: 170 %AAGR: -6.5	#exam: 64 %AAGR: 13.9
Pulmonary diseases	#exam: 4,937 %AAGR: -0.3	#exam: 118 %AAGR: 4.7	#exam: 2,268 %AAGR: 18.5	#exam: 94 %AAGR: 9.1	#exam: 60 %AAGR: 30.4						
Neurology	#exam: 1,272 %AAGR: 10.9	#exam: 100 %AAGR: 5.2	#exam: 2,044 %AAGR: 4.6	#exam: 3,746 %AAGR: 3.0							
Rheumatology	#exam: 4,064 %AAGR: 8.9	#exam: 522 %AAGR: 0.1		#exam: 213 %AAGR: 15.1	#exam: 150 %AAGR: 2.2					#exam: 233 %AAGR: 47.0	
Cardiology	#exam: 1,267 %AAGR: 9.4	#exam: 114 %AAGR: 7.8	#exam: 451 %AAGR: 26.4	#exam: 286 %AAGR: 8.3	#exam: 2,548 %AAGR: 14.2						
Urology	#exam: 531 %AAGR: -11.2	#exam: 850 %AAGR: -4.3	#exam: 598 %AAGR: 10.5	#exam: 162 %AAGR: 22.5	#exam: 164 %AAGR: 10.6			#exam: 152 %AAGR: 44.1	#exam: 167 %AAGR: -1.5		
Geriatrics	#exam: 719 %AAGR: -3.3	#exam: 208 %AAGR: -3.6	#exam: 212 %AAGR: 5.8	#exam: 237 %AAGR: 0.3							
ExternalSpecialist	#exam: 807 %AAGR: 4.2	#exam: 418 %AAGR: 15.9	#exam: 50 %AAGR: 79.0	#exam: 93 %AAGR: -10.5							
Otolaryngology	#exam: 166 %AAGR: 31.3	#exam: 100 %AAGR: 1.9	#exam: 548 %AAGR: -0.5	#exam: 404 %AAGR: 8.3							#exam: 50 %AAGR: -19.3
Pediatrics	#exam: 386 %AAGR: -7.3	#exam: 561 %AAGR: -4.1		#exam: 130 %AAGR: 4.3							
Intensive care unit	#exam: 479 %AAGR: -11.2	#exam: 59 %AAGR: -4.1	#exam: 119 %AAGR: 11.4								
Plastic surgery	#exam: 273 %AAGR: 1.8	#exam: 264 %AAGR: 18.1		#exam: 99 %AAGR: 38.3							
Gynaecology		#exam: 135 %AAGR: 3.3	#exam: 108 %AAGR: 11.9								#exam: 65 %AAGR: 8.9
Oral medicine			#exam: 64 %AAGR: 19.4								
Neurosurgery				#exam: 119 %AAGR: -10.8							
Dermatology	#exam: 79 %AAGR: 31.9	#exam: 84 %AAGR: 19.6									
Ophthalmology				#exam: 78 %AAGR: 23.8							
Anesthesiology	#exam: 84 %AAGR: 9.6	#exam: 59 %AAGR: 28.3		#exam: 116 %AAGR: -2.5				#exam: 893 %AAGR: 3.2			

Figure 4.6: Demand and growth per examination type per department - 2019

4.3 Process understanding

Although each health care path is unique and the various modalities of the radiology department work differently, a broad sketch of the role of radiology in a healthcare path can be made. Every healthcare path starts with the indication of symptoms. If the required healthcare cannot be provided by the first respondent (whether this is a general practitioner, or a specialist from a clinical department) the patient is referred. The capable healthcare provider then starts the process of diagnostics and treatment of which radio diagnostics may be part or not. When needed, a healthcare provider can ask co-practitioners for support, who in turn can request radio diagnostics as well.

There are various types of radio diagnostic requests. Emergency orders are assessed by radiologists and, in consultation with other specialists, are directly executed when possible. The protocol for regular orders differs per examination group and requesting party. Orders from general practitioners are for example scheduled centrally by radiology administrative employees. Outpatient clinic orders for CT examinations are scheduled by the outpatient clinic administrative employees.

Depending on the examination group and complexity of the examination itself, a radiologist is required to set up an examination plan which might for example include the amount of contrast fluid required. Meanwhile, the date of the examination is met and after check-in and waiting the patient is being called in for examination. With or without examination plan the examination is conducted and the resulting images are sent to the radiologists, with PACS as storage and analysis system.

A radiologist then examines the scans made and describes all notable deviations that can be derived. In this process the (provisory) diagnosis is kept in mind. All these insights are summarized in a report which is sent to the requesting applicant. Who in turn will continue the process of diagnostics and treatment, which might include new radio diagnostics.

This broad sketch of the radiology process in healthcare paths is illustrated in Figure 4.7 with the use of a Business Process Model and Notation (BPMN) flow chart.

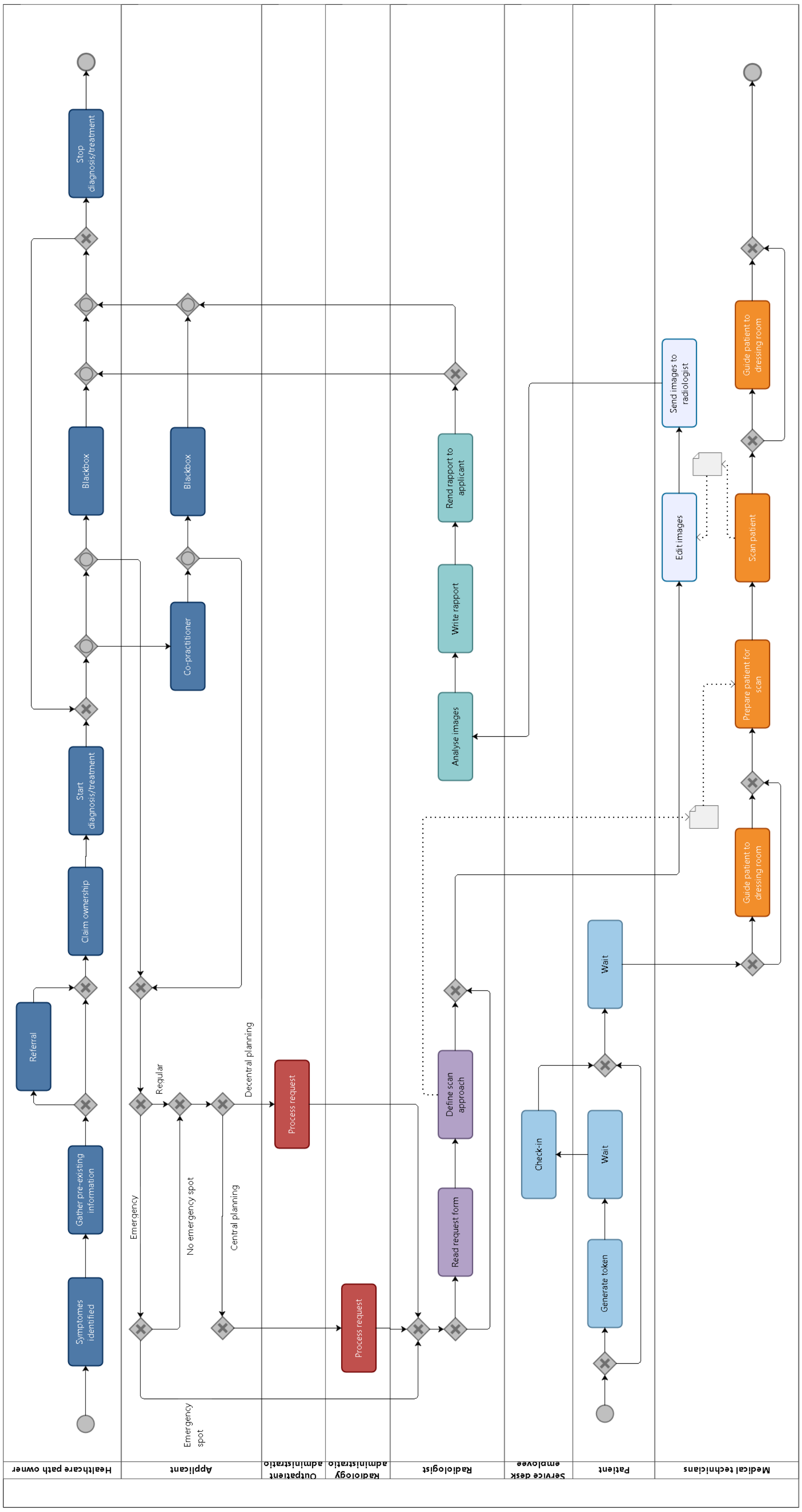


Figure 4.7: Sequence Diagram Radiology

Currently, the radiology department has no true insights into the flow and bottlenecks of this overall process. The bottlenecks that do appear, originate often from employees in an empirical fashion, which is understandable since insights into the healthcare paths of patients and especially the expected behavior of these paths are hard to clarify. This, in combination with the fact that the radiology department is appraised on inward-looking KPIs such as its access times (see section 4.7), put the emphasizes of the radiology department on its own performance rather than the overall healthcare flows of the hospital.

Important to note is that the *examination duration*, which will be referred to often in the rest of this report, is a composition of all orange activities in Figure 4.7. This therefore includes dressing and undressing of patients.

4.4 Resources

Each modality of the radiology department requires a specific medical machine (Table 4.2) and trained personnel to operate this machine. Just like in many other hospitals, the Elkerliek has allocated some of her machine capacity for emergency orders. For example, one X-ray in Helmond is reserved for emergencies, and one ultrasound in Helmond is reserved for emergencies and clinical orders. Noticeable is the single CT scan. Given the increase in CT examinations and the vision of the Elkerliek to become the go to partner for acute healthcare, the CT machine capacity could be a bottleneck in the realization of this vision (See section 4.8.2). Currently the SPECT from nuclear medicine is used as a backup for when the CT breaks down or when an emergency CT is required while a CT examination is already in progress.

Location	X-Ray	Ultrasound	MRI	CT	Nuclear	Mammo	OR Radioscopy	Angio	DEXA	Radioscopy
Helmond	3 (+1)	3 (+1)	1	1	1	1	3	1	1	1
Deurne	1	3	1	0	0	0	0	0	0	0

Table 4.2: Amount of Machines

Next to machinery, a functioning radiology department requires human resources. There are four main types of employees: radiologists, medical technologists, administrative employees (4.39 FTE) and managers (1.72 FTE). Every radiologist and medical technologist has his/her own area of expertise.

Due to the increasing technical complexity of the medical machines a medical technologist can have three areas of expertise at most. There is one set of examinations that all medical technologist are trained to perform without the necessity of additional certificates, namely [X-ray, mammo, OR radioscopy]. In total there is 36.68 FTE medical technicians capacity available of which 12.61 FTE is MRI, 6.01 FTE ultrasound, 7.54 FTE angio, 7.29 FTE CT, and 3.23 FTE nuclear specialized. Whether this capacity is sufficient will be discussed in section 4.8.2. The CT, MRI, angio, and X-ray are preferably staffed with two medical technicians. During breaks the staffing per room is sometimes reduced to one, this supposedly influences the production time.

A total of 9 FTE of radiologist capacity is available. Radiologists have a vast array of responsibilities ranging from guiding angioplasty examinations, insertion of contrast liquid, monitoring veins, and authorizing examination reports. The actual presence of a radiologist during radiological examinations is subject to many factors and can therefore not be assessed in advance. In addition, every radiologist has his own specialty, in other words, not every examination can be performed by every radiologist. The specific subdivision of specialties among the radiologists of the Elkerliek is currently unknown.

The administrative employees, medical technicians and radiologists of the Elkerliek all work in shifts. One dayshift starts at 08:00 till 12:15 and from 13:00 till 17:00. The other starts at 08:45 till 13:00 and from 13:45 till 17:45. This capacity allocation ensures that production can continue during the breaks. During the evening, night and weekend a reduced capacity is available. For example, during the night and weekends only the MRI in Helmond is available.

It is important to point out that it is possible for medical technicians and radiologists to switch between different modalities. For example, a medical technician specialized in CT can be appointed to conduct X-ray examinations when needed. Therefore, we can conclude that the radiology department of the Elkerliek has an internal competition of resources. Simulation of the system behavior should therefore include interaction between the various modalities in order to simulate real world, and thus practical, behavior.

4.5 Patient scheduling

The radiology department of the Elkerliek is open 24h a day, 7 days a week. Filling this time efficient is the task of the planning department of the Elkerliek. The optimization goal of the planning department is fourfold:

1. Comply to the demand without increasing access times;
2. Retain sufficient capacity for emergency and walk-in examinations;
3. Reduce operational waste such as changeover times;
4. Prioritize flow efficiency.

An example for the latter is aligning (poli-)clinical consults and diagnostics. [49] studied the problem of patient scheduling and divides it into three problems: capacity allocation, appointment scheduling, and short-term decisions on the day of service.

Before describing the capacity allocation, appointment scheduling and short-term decision principles of the Elkerliek, it is important to understand how the various unique patients can be grouped. After all, grouping patients will reduce complexity in scheduling processes. This is especially interesting for a healthcare department of a reasonable complexity such as radiology with 2 locations (Deurne, Helmond), 12 examination groups (e.g. X-ray, CT, MRI), 575 examination types (e.g. CR Thorax, MR Brain), 23 applicants (e.g. general practitioner, surgery, neurology), 3 patient types (walk-in, appointment, emergency), 3 appointment types (clinical, poli-clinical, outpatient), open 52 weeks a year, 7 days per week and 24 hours a day.

Patient groups can be defined based on similar behavior, required resources, profitability, and disruptive impact. In Table 4.3 the characteristics that define patient groups are described.

Attribute	Description
Examination type	What machine is required?
Urgency	Emergency or regular order
Requesting healthcare provider	Applicant of the needed appointment
Walk-in	Appointment made in advance?
Specialized medical technician	Specialist required?
Radiologist needed	Radiologist required?
Duration	Appointment/examination duration

Table 4.3: Patient scheduling attributes

Capacity allocation
Capacity allocation focuses on the problem of admitting patients and dividing capacity among these patients. At the Elkerliek this allocation is set for 8 weeks in advance (which contradicts efficient use of capacity: "a static allocation of capacity will increase variability and can reduce resource efficiency [49]"). This capacity allocation is set according to the expected demand based on domain knowledge, and availability of radiologists. In this process the planning department has to take changeover times between examinations and several other restrictions, such as limitations of examinations in Deurne, into consideration. Due to the complexity of this capacity allocation process, it takes extensive time. Moreover, (unknown) variability in the demand can cause down times of machines and medical employees. Ten days in advance the planning is again revisited and small changes based on the experiences are made to the long-term planning. During the weeks and days itself the planning department is charged with deriving ad-hoc optimizations to decrease this unwanted inefficiency, which increases the workload for the planning department. Some of these ad-hoc optimizations are described in the short-term decision beneath.

One of the main reasons for inefficiency in the static 8 weeks planning is the lack of alignment with (poli-)clinical programs and consultation hours. The root cause of this symptom is the lack of IT interoperability and accessibility, leading to lack of insights into programs of different departments and thus not optimal aligned capacity allocation. As a result, the specialists from the different departments start ordering examinations outside of the reserved timeslots for their department. Leading to unnecessary lengthy access times.

Appointment scheduling
When capacity is assigned over the different departments, patients can be scheduled. For this process it is crucial to define an estimated examination duration to allocate patients to. At this moment some of these timeslots are defined on patient characteristics such as age and mobility. For example, patients in a wheelchair who are called up for a mammography examination are scheduled twice the allotted time for regular mammography examinations. These timeslot decisions and other best practices for scheduling appointments can be found in the SmartSheet used daily by the planning department of the radiology department.

Short-term decisions on the day
After allocating capacity to a specific patient group and deciding on the methodology of scheduling appointments, unexpected cases give rise to short-term decisions on a day. These include making room for emergency orders, OR orders, dealing with a variable number of (poli-)clinical patients, cancellations and no shows. The radiology department is in control over these decisions that are mostly based on medical instances i.e. a more pressing medical situation has priority over a lesser, regardless of the patient type. The radiology department finds itself often in a difficult spot however, having to choose between two orders of different requesting departments without having a full grasp of the two clinical paths. This is again an interoperability and accessibility issue. A more systematic short-term decision is opening timeslots that were initially reserved for emergencies. If no pressing medical instances occur the reserved spots for emergencies will be set open for waitlist patients.

4.6 Separation of concerns

There are various points of interest in the patient scheduling process. First, the question is whether the information on which decisions on the 8-week static capacity scheme allocation is valid and sufficient. Second, the lack of information sharing between hospital departments gives rise to problems in appointment scheduling and short-term decisions. Third, is whether the time allocated to examinations is optimal. The latter is discussed in this section.

For a time allocation to an examination patient and process characteristics should be taken into account. As described in Table 4.3, patients can be identified by patient and process characteristics (examination type, urgency, requesting healthcare provider, walk-in, specialized medical technician, radiologist needed, and duration of examinations). Most of these characteristics can be derived from the data. The examination group (e.g. CT or MRI) is properly registered so this brings no additional challenges. Urgency of orders has been added to the data in the data processing steps. The requesting healthcare provider can be identified in three groups: general practitioner, outpatient, and clinical. Walk-in examinations are recorded, however the correctness of this field in the data is questionable. The necessity of specialized medical technicians and radiologists cannot be systematically derived from the systems (Excel lists) at this point.

Last is the duration of examinations. The way the duration of examinations is grouped and therefore to which timeslots the examination is allocated, is of paramount importance for the efficiency of the resulting schedule. A too defensive time allocation results in spare time, which is a form of waste, although an argument can be made that taking sufficient time for patients can result in a higher overall efficiency and customer satisfaction. Too strict time allocation results in increased waiting times when an examination takes longer than expected, and increases the work pressure on employees.

This section describes a method to check whether the time allocated to examinations by the planning department of the Elkerliek is not too defensive nor too strict. The 4092 valid *mammography* orders conducted in *Helmond* on *appointment* for *general* *practitioners* in the time period 2016-2019 are taken as a practical use case of this method. As displayed in Figure 4.8 these examinations range from 5 minutes to 60 minutes. Take into account that only valid (see chapter 3) examinations durations are included and thus that these minimal and maximal values are manual cut-off points as defined in chapter 3. The average time needed for these examinations is 12.5 minutes.

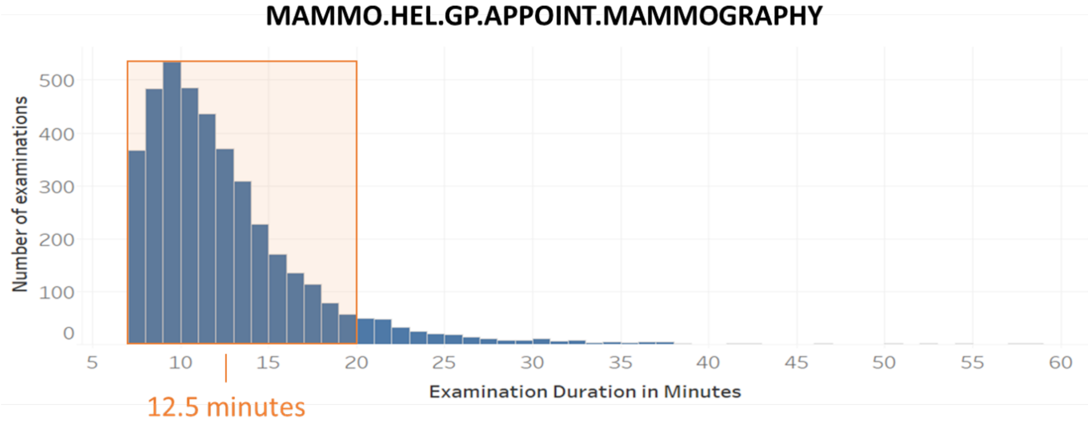


Figure 4.8: Examination duration grouping

Currently the timeslot assigned to mammography orders is 20 minutes, which covers $\sim$ 93% of the examination cases as highlighted with the orange area in Figure 4.8. Approximating the distribution of the examination duration can provide the necessary insights in order to define whether this timeslot is too defensive. Figure 4.9 and Figure 4.10 show that for both the MG Mammography and CR Thorax, a X-ray examination, a lognormal distribution can be approximated (χ^2 = *138*, χ^2 = *189*).

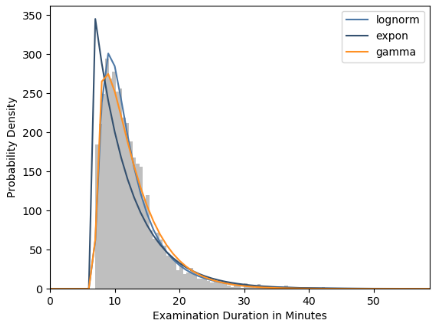


Figure 4.9: Production Time MG Mammography

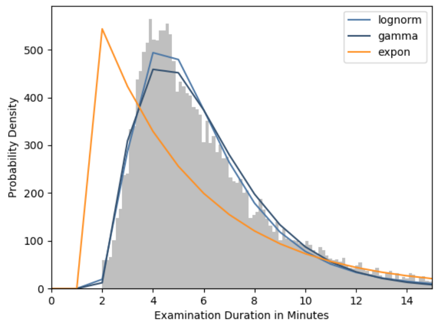


Figure 4.10: Production Time CR Thorax

The lognormal distribution fitted on the MG Mammography examination duration has the parameters $\mu = 2.47$ and $\sigma = 0.33$. The probability that the examination duration exceeds 25 minutes, and thus will go at least 5 minutes in overtime, is according to this distribution about 1%. Therefore it is safe to assume that most of the 7% of the cases that require more time, will go at most 5 minutes in overtime. The probability that an examination will take at most 15 minutes and hence catch-up 5 minutes is about 75%. Therefore the current time allocation of 20 minutes provides more than sufficient capacity to compensate for any delays.

A lower timeslot of 15 minutes will cover approximately 70% of the data. The probability to exceed this duration with at least 5 minutes and 10 minutes is 5% and 1% respectively. The probability for the examinations to take at most 10 minutes and hence catch up 5 minutes is 30%. The probability for the examinations to take at most 6 minutes and hence catch up 9 minutes is 2%. The 15-minute timeslot therefore still provides capacity to compensate for delays, but the window becomes smaller.

After deriving the 70th percentile for all examinations and comparing them to the currently allocated timeslots of these examinations, it becomes clear that MG Mammography is one of the few examinations which has a defensive timeslot allocated.

The CR Thorax is a good example to highlight the pinching timeslot allocation of some examinations. For X-RAY.Hel.GP.Walkin.CRThorax the time slot allocated is 5 minutes, which is smaller than the mean duration of CR Thoraxes (6 minutes) and covers only 44% of the cases.

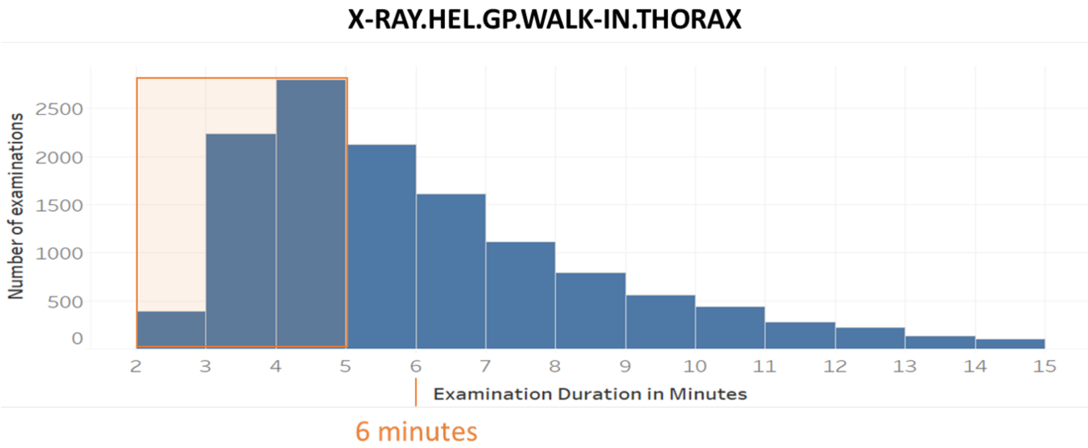


Figure 4.11: Examination duration grouping

Given that the mean of CR Thorax examination durations is longer than the allocated timeslot already indicates that the timeslot allocation for CR Thorax examinations is too strict. A 10-minute timeslot covers approximately 70% of the data. Given the lognormal distribution for CR Thorax examinations with the parameters $\mu = 1.74$ and $\sigma = 0.43$, the probability that the examination duration exceeds at least 15 minutes can be estimated on 2%. The probability that an examination will take 5 minutes and hence catch-up 5 minutes is approximately 38%. The 10-minute timeslot offers therefore sufficient capacity to compensate for any delays.

Ideally the probability that the total duration of a sequence of several (independent) examinations exceeds a given timeslot should be derived. However, since the examination durations are lognormal distributed, deriving the sum of such random variables is challenging [19]. Moreover, any conclusions from this part of the research will only be reliable and lead to changes in timeslot allocation when the data quality improves.

Therefore, the exact elaboration of the time required per examination for now is postponed to future research. However, there are still a number of sections in this study that relate to the examination duration. In section 4.8.2 the utilization of resources will be assessed which will use both the currently allocated timeslots of examinations, and a safe (70th percentile of actual examination duration) estimation of the required timeslots of examinations.

Since one size does not fit all, the influence of patient and process characteristics such as age and mobility on examination duration are assessed in section 6.1. Results from this section can be used to redefine the allocation of examination timeslots for specific patients.

4.7 Key Performance Indicators

As an organization, the Elkerliek has multiple Key Performance Indicators (KPIs). The ones relevant for (the performance of) the radiology department are: enhance provisional discharge date, develop healthcare as a system (Better-in, Better-out), reduce the amount of repeat visits, and optimize the hospitalization period. The radiology department itself has only one active KPI, namely "toegangstijd" or access time; the amount of time a patient (and applicant) has to wait between ordering and performing the requested examination. This metric is not only important for internal monitoring and improvement, but an acceptable access time is also required by the Dutch government. Every type of examination has its own acceptable access time registered in the law [37].

A lot of research is done on the efficiency and effectiveness of the radiology department of hospitals. Due to the integral role of radiology in the healthcare path defining a metric that measures the effectiveness of radio diagnostics is multidimensional and therefore complex. However, there is one golden rule mentioned by [35]: "inappropriate care and diagnostics can never be efficient". This paper will touch upon this subject later in section 6.2. General performance and efficiency performance indicators are easier to define. [3] did a great job at summarizing them as displayed in Table 4.4.

Next to these operational efficiency metrics, the exposure of radiation remains a touching subject [52], [20], [5] which could be incorporated as a KPI as well. Although measuring these inward-looking KPIs is important, it should not divert attention from the larger goal: Healthcare path efficiency and effectiveness.

To compliment the KPIs of radiology departments of hospitals there are quite a few institutions that provide benchmark information, such as the ACR [52]. The institution of choice for the Elkerliek is Performation. Performation compares production and costs of similar hospitals. The Elkerliek is compared to other small peripheral hospitals. One of the metrics that is compared is the total number of operations times the national average cost price of these operations, hence providing insight into the behavior of a hospital in comparison to another. The assimilated cost of MRI is a lot higher in the Elkerliek than at similar hospitals, indicating the Elkerliek makes more use of MRI examinations or more expensive MRI examinations. Especially in surgery a big deviation can be found in the assimilated cost of MRI. Zooming in on these costs shows the largest abnormality is in the "malignant and benign mamma neoplasms". To explain this abnormality, the benign neoplasm process is further investigated in chapter 6.2.

Key Performance Indicator	Reference in this paper
Number of patients scanned	Section 4.2
Number of referring clinical and outpatient physicians	Section 4.2
Ratio of (specialized) medical technicians and number of machines	Section 4.4
Utilization actual examination time	Section 4.6
Waiting time patients	Section 4.8.1
Throughput time single scan	Section 4.8.1
Utilization medical technicians	Section 4.8.2
Utilization medical hardware	Section 4.8.2
Percentage of open slots for the next 30 days	None
Capacity allocation utilization	None
Utilization radiologists	None
Number of no shows	None
Number of cancellations	None
Number of reports reviewed per full-time radiologists	None
Average (overtime) hours worked per employee	None
Administrative personnel peak workload	None
Total labor costs to total revenue	None
Net return on total assets	None

Table 4.4: Possible Radiology Key Performance Indicators

4.8 Performance analysis

Section 4.1 to section 4.7 sketched a broad overview of the radiology department of the Elkerliek. This section will elaborate on the performance of the radiology department of the Elkerliek. First the throughput time will be analyzed and thereafter the utilization of resources.

4.8.1 Throughput time

The radiology department of the Elkerliek does not have a clear overview of the flow and bottleneck of its internal processes. With the use of process mining, which will be elaborated upon later, these insights can fairly easy be brought to light. For throughput time analysis and access time analysis for that matter it is important to exclude follow-up appointments.

As described in chapter 3, the registration of follow-up appointments is not reliable. This can also be concluded when examining the access times for non-walk-in or emergency CR Thorax and MG Mammography examinations in Figure 4.12. Clearly follow-up appointments can be distinguished in the peaks in access times around one year (365 days) and half a year (186 days). However, these peaks contain regular MG Mammography and CR Thorax orders as well. Moreover, the three small peaks of regular

MG Mammography orders at 50, 100, and 150 days might indicate follow-up appointments which are not registered as such. Also, the high density of MG Mammography follow-up orders with a low access time is noticeable.

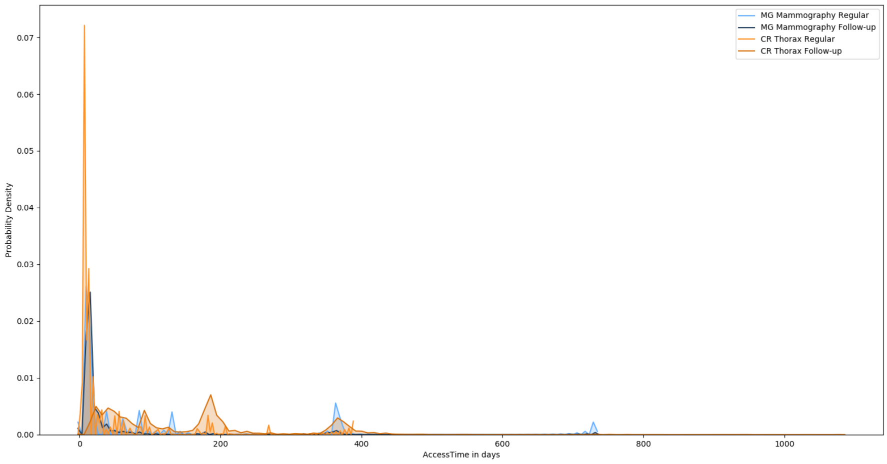


Figure 4.12: Access Time Kernel Density Estimation (KDE)

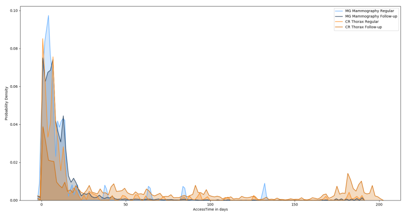


Figure 4.13: Access Time KDE max 200 days

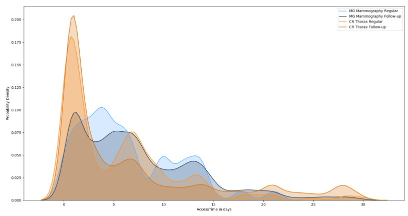


Figure 4.14: Access Time KDE max 30 days

No method for excluding the follow-up orders could be found. To still provide some insight into the performance of the radiology department, the assumption is made that every order with an access time less than 3 months is a regular (no follow-up) order.

Based on this assumption there are 4754 MG Mammography examinations ordered from 2016 to 2019 which are not cancelled, have a valid examination time, of which the trace is in the expected order (first an order then an examination etcetera), and do not involve follow-up patient ($<$ 3months access time). The minimal and maximal duration of MG Mammography of the radiology process steps can be found in Table 4.5.

Clearly also waiting times and authorization times are no reliable fields. No patient will wait 7 days in the waiting room untill a spot at the medical machine is available. Also, a radiologist will never wait 7 months until the finished scan is reviewed and authorized. The median values of all process steps appear more realistic and after consultation with domain experts seem to be plausible. Figure 4.15 shows the throughput times per stream.

Based on the same assumption and criteria there are 35.379 CR Thorax examinations ordered from 2016 to 2019. The minimal and maximal duration of CR Thorax of the radiology process steps can be found in Table 4.6.

	Access Time	Waiting time	Production Time	Authorization Time
Min	Instant	Instant	7 Minutes	Instant
Max	~12 Weeks	~7 Days	59 Minutes	~7 Months
Avg	~13 Days	14 Minutes	13 Minutes	~19 Hours
Median	~9 Days	8 Minutes	11 Minutes	~3 Hours

Table 4.5: Throughput time MG Mammography standard statistics

	Access Time	Waiting time	Production Time	Authorization Time
Min	Instant	Instant	2 Minutes	Instant
Max	~12 Weeks	~21 Hours	15 Minutes	~3.5 Months
Avg	~4.3 Days	5.5 Minutes	6 Minutes	~12 Hours
Median	11.7 Minutes	3 Minutes	5 Minutes	~2 Hours

Table 4.6: Throughput time CR Thorax standard statistics

While less excessive, the maximal waiting and authorization times for CR Thorax examinations seem to be unreliable as well. However the median values of CR Thorax examinations seem plausible as well. Figure 4.16 shows the throughput times per stream.

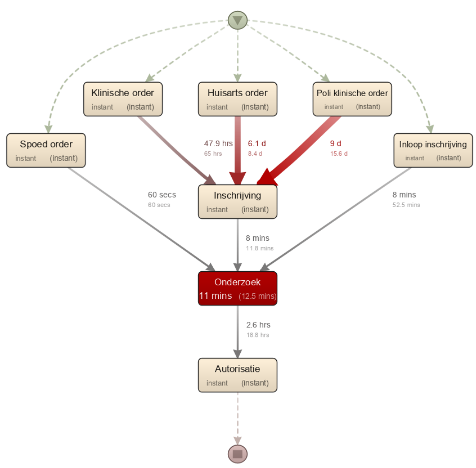


Figure 4.15: Throughput Time MG Mammography

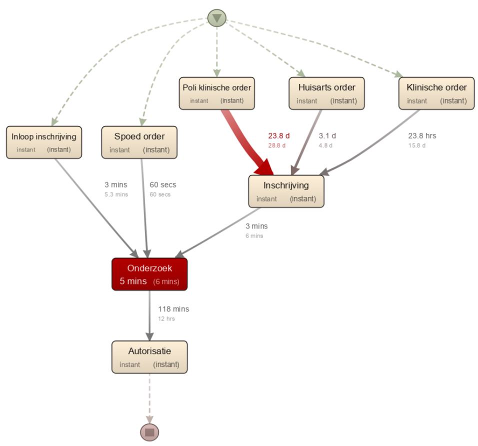


Figure 4.16: Throughput Time CR Thorax

Given the access times, clearly clinical orders gain the most priority, followed by orders from general practitioners and finally outpatient clinical orders. The waiting time for walk-in orders for CR thorax is short. For MG Mammography the waiting time is in potential (much) longer. This could indicate that the mammography process is not set up for walk-in examinations. Of course, the reliability of the data points should be considered before making such conclusions.

Access times

As described, access times is the one followed KPI of the radiology department. As Figure 4.15 and Figure 4.16 display, the access times for specific examinations and for different streams. For reporting purposes, it is useful to define these access times aggregated on modality level. As can be seen in Figure 4.17, ultrasound, mammo and X-ray perform excellently on access times. More worrying are the access times for DEXA, MRI and nuclear examinations. Again, it is important to note to that follow-up studies are manually filtered out (time between registration and examination >3 months). It is therefore possible that this view on the access times is blurred by follow-up appointments that take place within 3 months. That is why it is advised to mainly look at the median values. X-ray has a median access time of less than a day, therefore the median access time for X-ray is not visible in Figure 4.17.

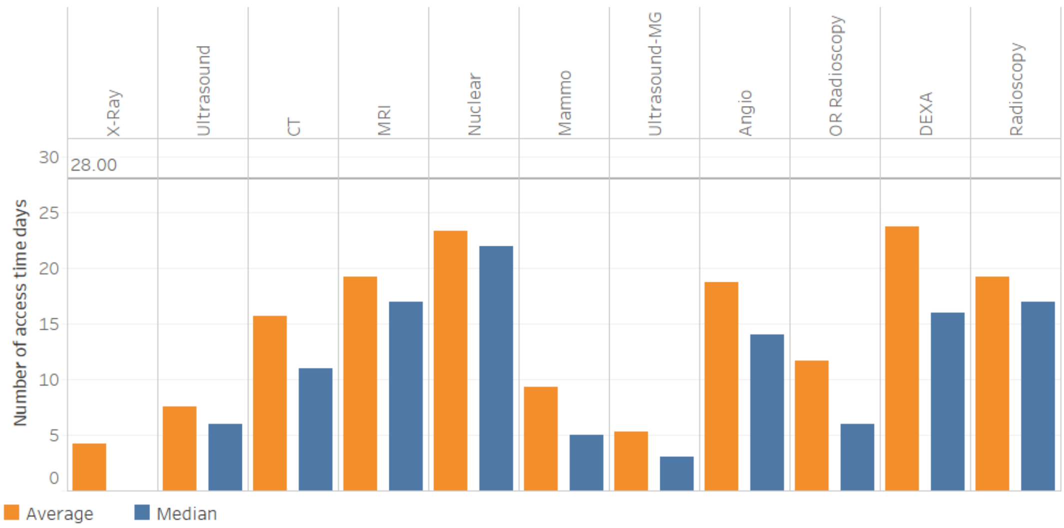


Figure 4.17: Access times per examination group

For both patient satisfaction and flow efficiency in the hospital it can be important that a patient is examined on the same day as the examination is requested. In Figure 4.18 the amount of examinations that is done on the same day as requested is displayed. The same day access metric gives insight into to what extend the idea of a "one stop shop" is utilized within the Elkerliek. For X-ray examinations 80% of the patients are helped the same day as the order was created, for CT 7% and for ultrasound 6%.

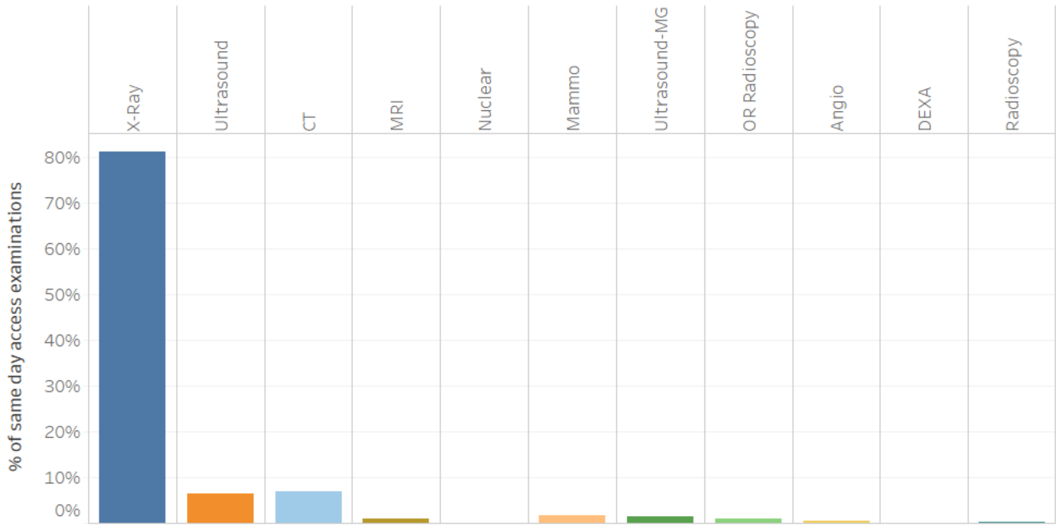


Figure 4.18: Same day access ratio per examination group

Waiting room times

It is also useful to aggregate waiting times on modality level. As can be seen in Figure 4.19, MRI, nuclear and CT have high median waiting times, indicating tight schedules, or a high change of examinations taking longer than expected.

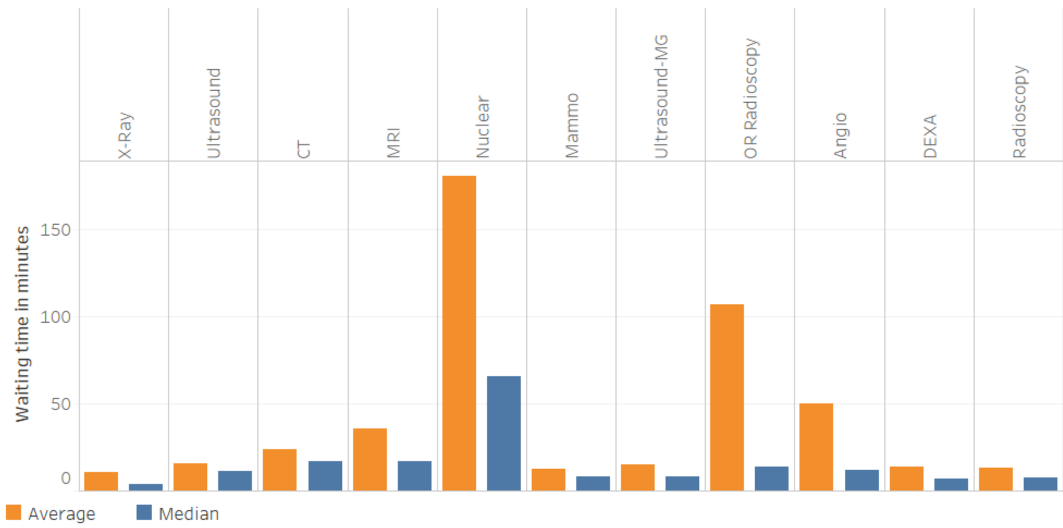


Figure 4.19: Waiting time per examination group

4.8.2 Utilization analysis

This section is intended to provide insight into the extent to which the available resources are used. The three types of resources that are important here are: machine capacity, capacity of medical technicians and capacity of radiologists. However, this section does not answer the question of whether there is sufficient capacity. This question can only be answered if the waiting times of patients, based on the stochastic (emergency) arrival and production speeds, are acceptable according to the standards of the Elkerliek.

The yearly demand for examinations per modality has been described earlier in section 4.2. The machine, medical technicians and radiologists capacity is described in 4.4. The allocated timeslots per examination have been described in section 4.6, as well as a more safe estimation of the actual production time per examination.

In appendix D the distribution of conducted examinations per modality is provided. From these patterns the modalities can be clustered into two groups. Group 1 consist of X-ray, ultrasound, mammo, nuclear, (OR) radioscopy and DEXA. This group is open for regular examinations during hospital opening hours (Mo-Fri, 08:00 AM - 17:00 PM) resulting in 45 available hours per week and approximately 2000 hours per year. Group 2 consist of MRI and CT. This group is open in the weekends as well and later in the evening. (Mo-Sun, 06:00 AM - 23:00 PM) resulting in 119 available hours per week and approximately 5000 hours per year.

The required capacity for the annual demand in hours, the capacity of a medical scan, the number of available medical scans, the number of required medical technicians per examination and the number of available specialized medical technicians allow the calculation of the utilization rate as indicated in Table 4.7.

Group	Rqd. capacity	Machine Util	Rqd. #MT	Rqd. MT CPTY	
X-ray	5.163 allocated timeslot 10.812 save estimate	5 * 2.000 = 52% 5 * 2.000 = 108%	2	10.326 21.624	n/a
MRI	4.270 allocated timeslot 6.526 save estimate	2 * 5.000 = 43% 2* 5.000 = 65%	2	8530 13052	22.000(12.61 FTE) = 39% 22.000(12.61 FTE = 59%
CT	2.424 allocated timeslot 3.950 save estimate	1 * 5.000 = 48% 1 * 5.000 = 79%	2	4848 7900	12.700(7.29 FTE) = 38% 12.700(7.29 FTE) = 62%
Ultrasound	4.437 allocated timeslot 5.830 save estimate	7 * 2.000 = 32% 7 * 2.000 = 42%	1	4437 5830	10.500(6.01 FTE) = 42% 10.500(6.01 FTE) = 56%
Nuclear	685 allocated timeslot 1.237 save estimate	1 * 2.000 = 34% 1* 2.000 = 62%	1	1370 2474	5.600(3.23 FTE) = 12% 5.600(3.23 FTE) = 22%
Angio	630 allocated timeslot 1.203 save estimate	1 * 2.000 = 32% 1 * 2.000 = 60%	2	1260 2406	13.200(7.54 FTE) = 10% 13.200(7.54 FTE) = 18%
Mammo	1.228 allocated timeslot 928 save estimate	1 * 2.000 = 61% 1 * 2.000 = 46%	1	1.228 928	n/a
OR radioscopy	324 allocated timeslot 944 save estimate	3 * 2.000 = 5% 3 * 2.000 = 16%	1	324 944	n/a
DEXA	724 allocated timeslot 723 save estimate	1 * 2.000 = 36% 1 * 2.000 = 36%	1	724 723	n/a
Radioscopy	213 allocated timeslot 281 save estimate	1 * 2.000 = 11% 1 * 2.000 = 14%	1	213 281	n/a

Table 4.7: Capacity Utilization 2019 During Office Hours

Clearly the utilization of machine capacity is quite low. Note that this does not imply sufficient capacity since demand can come all at once or that some capacity has to be reserved for emergency orders. The CT scan faces tight capacity when considering the save estimated duration of examinations. This is important to notice since the demand for CT examinations has risen in recent years and can be expected to grow further. While the machine and medical technician capacity of nuclear, DEXA and OR radioscopy offers quite a lot of room, the access times for these examinations are quite long (Figure 4.17). Whether this problem originates from planning or from inefficient utilization of personnel has to be researched by the radiology team itself.

For the utilization of medical technicians, the number of working hours per FTE is used. One FTE stands for 1748 working hours per year (based 36 hours per week, excluding weekends and 25 holidays). Although the utilization per specialization seems to be low, keep in mind that some of this capacity has to be divided amongst the modalities that do not require a specialization.

The total annual required medical technician's capacity is 33260 hours based on the allocated timeslots of examinations and 56162 hours when considering more safe estimations of the duration of examinations. The total available medical technician's capacity is 64000 hours per year, which is a utilization rate of 192% and 113% respectively. Hence the medical technician's capacity can be expected to be ranging from nearly perfect to more than sufficient. In addition, there is 4.39 FTE allocated to PACS administrative work, which is performed by trained medical technicians who can jump in when needed.

To gain insight in whether the 9 FTE of radiologist capacity is sufficient, the amount of work for the radiologists must be estimated. Since the array of responsibilities of radiologists is vast this estimation is challenging. In addition, the times spend on defining an appropriate scan approach, and reviewing and authorizing medical scans are not recorded in RIS. Therefore, the capacity utilization of the present radiologist capacity requires future investigation.

4.9 Conclusions

As shown in chapter 3, it is possible that the quality of the data relevant to radiology is insufficient to allow for interesting data analysis. In this chapter the effect of these data quality issues on access times, waiting times, production times and authorization times became even more apparent. Tracking key performance indicators (KPI) on this data, such as the access time KPI, provides an inaccurate view on reality.

There are however some conclusions regarding patient arrivals, production times and planning that can be stated.

1. Although the overall number of conducted examinations seems to be quite static, there are some noteworthy trends, for example the strong increase in examinations conducted for general practitioners and CTs in general, or the strong decrease from internal medicine department and X-rays in general. These trends should be taken into account for forecasting purposes.

2. The various radiology modalities have an internal competition for resources, which means that all modalities and their interactions should be modelled in simulations to capture practical behavior.

3. Patients can be grouped on process and patient characteristics amongst which is the expected duration of the concerned examination. Based on this expected duration, time slots are allocated to examinations. Visualizing the true production times of examinations, deriving the averages, and approximating the distributions provide insight into whether these timeslots are too defensive or too strict

in practice.

4. Bottlenecks and performance of process flows are not systematically tracked by the radiology department. Visualizing the events of a specific radiological examination in chronological order, proves to be an excellent way to provide a clear overview of the throughput times of these examinations. These overviews can be used, for example, to gain insight into the differences in performance times between applicants, and thus highlight bottlenecks.

If the assumption would be made that the data is reliable it turns out that most of the expected examination times are structurally underestimated, that outpatient clinical patients have longer access times than clinical orders and general practitioners' orders (which can indicate imbalanced capacity allocation). Moreover, MRI, CT and nuclear machine capacity is reaching its capacity limits. Ultrasound capacity on the other hand is plentiful. If the currently used expected time is assumed only half of the medical technician capacity is utilized. Also, the medical technicians seem to be over specialized.

All these conclusions should be rectified when reliable data is available. The approach on how to define patient arrival and production patterns, trends and performance and their relation to planning, as described in this chapter, can easily be reconstructed in the radiology dashboard (see section 6.3).

Chapter 5

In depth business understanding

Fundamental to optimal use of resources is knowledge about the variation in patient arrivals and production times patterns. This chapter therefore analyzes these patterns and identifies potentially influential factors on these patterns. This chapter continues the reasoning of the previous chapter in answering *research question 2*: How can patient arrival and production patterns, trends and performance be identified, and how does the planning process relate to this?

A lot of research has been done on production times of radiology processes. Therefore, the in-depth understanding of production times will be largely based on literature research and qualitative research methods. Patterns of patient arrival, however, depend on a hospital's patient population, the healthcare provided by the hospital in question, and internal planning. For this reason, the patient's arrival patterns are examined using data analysis.

5.1 Production times

As can be concluded from the previous chapter, service times are stochastic. Patients and process characteristics are very likely to influence this stochastic process. In this paper this impact is aimed to be quantified, ultimately to provide insights into more distinguished production distributions and optimization focus fields.

To this end, interviews were held with medical CT technicians and the management of the radiology department. They describe that the age of patients, mobility of the patient, complications during the examination, the urgency of the order, infection hazard of symptoms of the patient, and the amount of urgent orders on a workday are characteristics that can affect the production time. Both patients age and physical mobility are endorsed by [11]. [40] describes the difficulty for children to put up the necessary amount of patience for MRI scans, and also [39] indicates that it can be assumed that the age of a patient might affect the time needed to scan the patient.

Clinical patients tend to take more time, as the physical mobility of these patients is often reduced. In addition, these patients are often connected to an IV, which makes undressing difficult. Therefore, the patient's origin is recorded as a potentially influential factor over the study duration. In addition, the waiting time for a required radiologist is sometimes considerable. And therefore, the dependence of a radiologist is also a potentially influential factor on the duration of the examination.

Waiting for staff (e.g. technicians) and overall resource capacity is also described in [17] as a form of waste. Therefore, the ratio of realized staff level and the required staff level should be included as a factor on the variance of production times.

Literature suggests that overweight and specifically obese patients [56] effects the production time. Mixing inpatients and outpatients which have different needs increases the variability on scanning efficiency according to [33]. Limited knowledge and/or expertise influences the efficiency of production as well[17], [58]. It is suggested that that anesthetization and sedation increase duration of examinations [59]. Shortening time slots for MRI improves scheduling mistakes and can positively influence the production rates[39]. Imaging Technology News stated that improving waiting room facilities and proper staffing is just as important as faster MRI scanners to improve MRI throughput [23].

In section 4.4 the ideal number of medical technicians per type of examination is stated. For many examination types this ideal number was higher than 1. Hence the number of performing medical technicians could impact the variance in examination duration. Since the radiology department works with a reduced capacity during breaks, the night and weekends, it is assumed that the day and time of an examination influences the duration of an examination as well.

All together, Table 5.1 summarizes patient and process characteristics that are likely to influence the production time of the various examinations of the radiology department of the Elkerliek. Orange marks the factors that could not be found in the data at this time.

Patient Characteristics			
Name	Type	No. Values/Range	Description
Age	Numeric	0 - 106	In years
Gender	Nominal	2	Male or Female
Mental factors	Nominal	-	Dementia, Claustrophobia, Fear
Physical factors	mixed	mixed	Mobility, Veins, Weight, Overweight, Height
Process Characteristics			
Demand origin	Nominal	24	Name of demanding specialist group e.g. Surgeon, Orthopedics
Demand origin group	Nominal	4	GP, ED, OP, IP
Appointment Type	Nominal	2	Scheduled or Walk In
Urgency	Nominal	2	Acute - Elective
Complications	Nominal	2	Referral to IC, medical complications
Ratio realized-needed technicians	Numeric	0.0 - 300.0	Proportion of standard resources
Infection hazard	Nominal	3	Low - Existing - High
Radiologist required	Nominal	2	Yes - No
Location of patient	Nominal	unk.	One of the departments of the hospital
Environment Characteristics			
Day of the week	Nominal	7	Mon, Tues, Wed, Thurs, Fri, Sat, Sun
Time slot of the day	Nominal	6	Early AM, AM, Late AM, PM, Evening, Night
Pressure of the day	Nominal	3	Low - Normal - High
Pressure of the week	Nominal	3	Low - Normal - High
Distribution by emergencies	Nominal	3	Low - Normal - High

Table 5.1: Potentially influential factors on examination duration

5.2 Patient arrival patterns

It is certainly interesting to know the total number of orders per modality, as described in chapter 4. However, to really support the planning and management of the radiology department, it is crucial to be able to explain the variations in the patient's arrival patterns [29]. This section examines patient arrival patterns to gain better understanding of the variance in these demand patterns. In this process CR Thorax and MG Mammography examinations are again taken as an example.

The frequency of mammography orders varies per month. For example, the frequency of requested examinations is higher in March than in April, and higher in June than in July and August. This phenomenon could be explained by the number of holidays in that month (1-5 in March, 2-12 in April). The same pattern can be observed for CR Thorax examinations, where the variance between March and April is 18%. Therefore the overall hypothesis *H0 = Patients' arrivals are correlated with holidays* can be drawn. In order to capture the behavior during holidays, the variable "Holiday" was added for observations that represent typical (Dutch) holidays and the variable "School holiday" was added to indicate observations recorded in a school holiday period. In addition, weeks that consist out of more than three holidays are marked as "reduction weeks".

Holidays do not explain all behavior however. October for example has more holidays than September but the demand for mammography examinations is higher during this month as well. This behavior could be explained by the fact that orders which are necessary but not requested during holiday periods have surfaced after the summer holidays (September, October, November). This behavior is also apparent in the order distribution of CR Thorax. Therefore, the overall hypothesis *H1 = Patients' arrivals are correlated with post-holiday periods* can be drawn. In order to capture this behavior, the variable "Post-Holiday" was added for days after a holiday. The months September, October and November are marked as "Post-Holiday-Period".

What does not hold for mammography examinations, but does for CR Thorax examinations is that the amount of examinations varies per season. Indicating that demand for thorax examinations is slightly higher during winter than during spring (5%) and summer (30%). How seasons effect the demand differs per examination group, but the overall hypothesis *H2 = Patients' arrivals are correlated with seasons* can be drawn. In order to capture this behavior, the variable "season" was added.

5.2.1 Daily and hourly patterns

Because regular (schedulable) orders can be scheduled somewhere in the legally bound access time of 4 weeks, the exact date and time on which these examinations are requested seem not to be of importance. After all an examination requested on Friday night 02:00 AM can be scheduled somewhere in the next 4 weeks, any day of the week, any hour of the day. However, as described in section 4.7, the Elkerliek aims to improve healthcare path throughput time. Hence, alignment of radiology capacity to the demand of the various health-care departments is crucial.

For emergency and walk-in orders, the daily and hourly patient arrival patterns are of importance as well. After all, if an emergency patient comes in the required capacity must be (directly) available, even if this patient comes in at Friday night 02:00 AM. In order to be able to respond adequately to this emergency and walk-in demand, it is important to be aware of daily patient arrival patterns. In this subsection the daily and hourly patient distribution patterns will be explored, with the use of violin plots.

For both mammography (Figure 5.1) and CR Thorax (Figure 5.2) examinations, the number of orders clearly differs per workday. The mammography orders peak on Tuesday and Thursday with no orders in the weekend. The CR Thorax examination orders peak on Monday and steadily decrease throughout the week with a slight increase on Thursday. In order to find weekdays with similar behavior a simple χ^2 grouping can be conducted. For CR Thorax it can for example be derived that the distribution of both Saturday and Sunday ($\chi^2 = 2.26$) and Tuesday to Friday ($\chi^2 = 5.26$) can be considered similar. However, Monday to Friday ($\chi^2 = 20.93$) are not, resulting in the conclusion that a variable "type-of-weekday" should consist out of three categories weekend, post-weekend (Monday) and regular weekdays (Tuesday - Friday). However, this grouping does not hold for mammography nor all other examinations. For now, the grouping will therefore be discarded, but nevertheless the hypothesis *H3 = Walk-in patients' arrivals are correlated with weekdays* can be drawn.

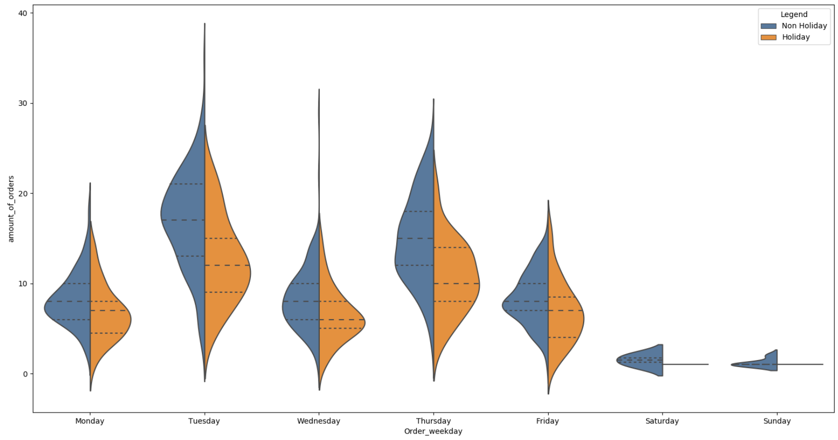


Figure 5.1: Mammography orders per weekday

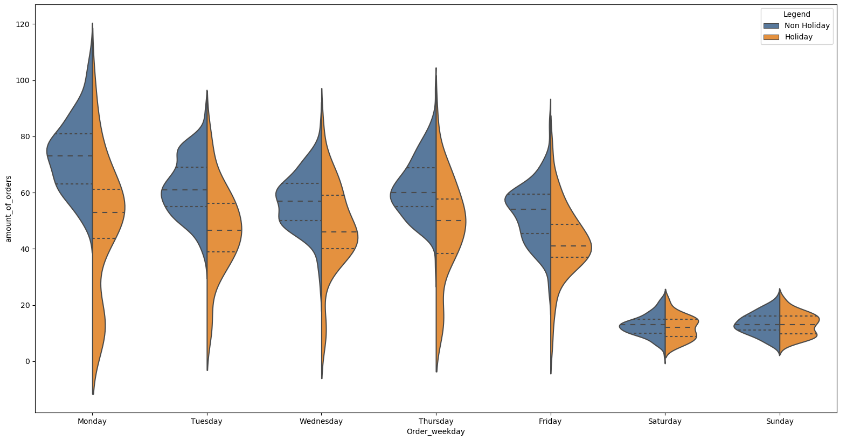


Figure 5.2: CR Thorax orders per weekday

The distributions displayed in Figure 5.1 and Figure 5.2 indicate that referring specialist might have dense consultation hours on specific weekdays. From Figure 4.5 in chapter 4 can be derived that surgery is the largest consumer of mammography examinations. As depicted in Figure 5.3 surgery has consultation hours mainly on Tuesday and Thursday, explaining the peaks for mammography examinations on these days. Surgery and orthopedics are the largest consumers of X-ray (CR) examinations. After filtering on CR Thorax examinations, it becomes apparent that the lung department and internal medicine department are the main consumers of CR Thorax. As depicted in Figure 5.3 both the Lung and Internal department have consultation hours mainly on Monday, hence explaining the peak for CR Thorax examinations on Mondays. From these finding the hypothesis $H4$ = *Walk-in patients' arrivals are correlated with consultation hours of medical departments* can be drawn.

The demand for radiology depends not only on outpatient agendas, but also on OR planning and clinical occupation. The historical OR schedules and clinical occupancy are currently unknown. Therefore, the exact effects of these characteristics cannot be determined. To be comprehensive, the hypotheses *H5 = Arrivals of walk-in patients are correlated with OR schedules* and *H6 = Arrivals of walk-in patients are correlated with clinical occupancy* are formulated.

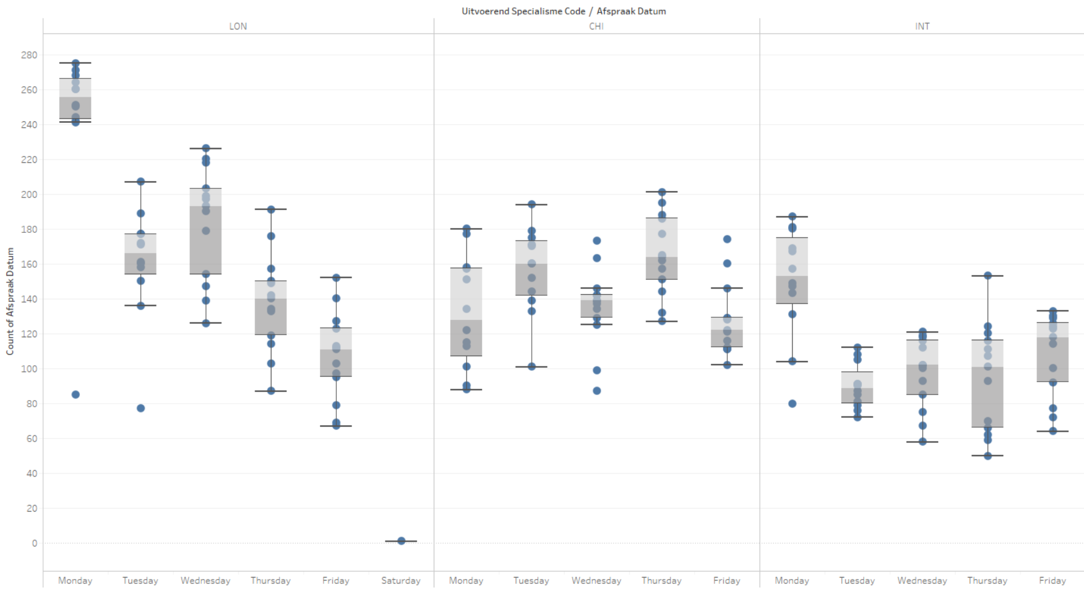


Figure 5.3: Amount of patient consultations per department

The distribution of CR Thorax emergency orders over the weekdays is quite static. In fact, none of the most common examinations do deviate from this static daily pattern. Moreover, holidays and school holidays do not seem to affect the number of emergency radiology orders. There are too few emergency mammography orders to validate these patterns for mammography examinations. In Figure 5.4 the day start, lunch, and day end is clearly visible. Also, specific examinations such as the CR Thorax and non-outpatient orders follow this distribution. Logical grouping would be Early morning (7-8, χ^2 = *60.40*), Late morning (9-11, χ^2 = *0.20*), Afternoon (12 - 16, χ^2 = *8.98*), Evening (17-23, χ^2 = *49.95*), Night (24 - 06, χ^2 = *1.32*). This grouping is used in the variable "time-of-the-day" which is used to validate the hypothesis *H7 = Patients' arrivals are correlated with time of the day.*

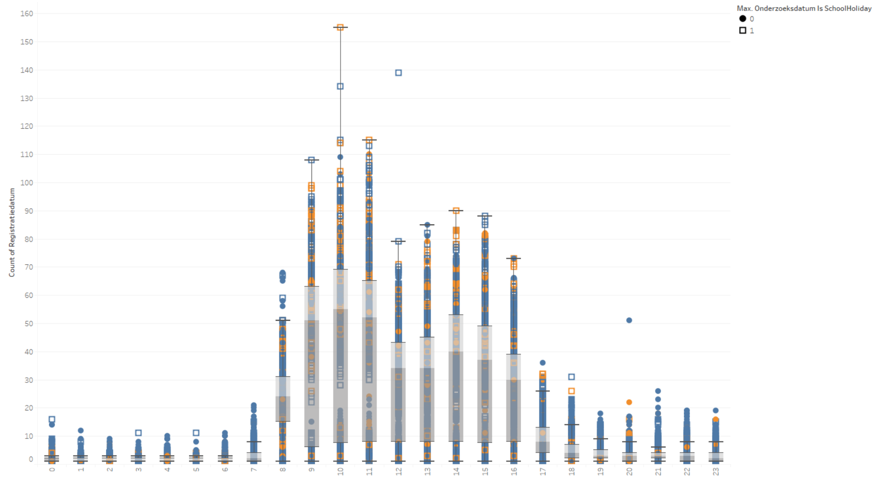


Figure 5.4: Distribution of All Types of Examinations over Work hours

All together Table 5.2 summarizes process characteristics that are likely to influence the patient arrival patterns of the various examinations of the radiology department of the Elkerliek.

Process Characteristics			
Consultation hours	Numeric	0 - 300	Amount of consultations per specialist group
Day of the week	Nominal	7	Mon, Tues, Wed, Thurs, Fri, Sat, Sun
Weather temperature	Numeric	-10.1 - 40.5	Degrees Celsius
Rainfall	Numeric	0 - 41.5	Millimeters
Wind	Numeric	10 - 180	Kilometers per Hour
Holiday	Nominal	2	Yes, No
School Holiday	Nominal	2	Yes, No
Pre and Post-Holiday	Nominal	2	Yes, No
Pre and Post-School Holiday	Nominal	2	Yes, No
Reduction week	Nominal	2	Yes, No

Table 5.2: Potentially influential factors on patient arrival

5.3 Conclusions

For production times, potentially influential factors have been derived based on literature and qualitative research methods. Potentially influential factors for patient arrival patterns have been derived from data analysis of two examinations: MG Mammography and CR Thorax. This data analysis method can be easily reconstructed for other examinations in the radiology dashboard (see section 6.3).

The number of consultation hours of both internal medicine and the lung medicine department is striking. Both peak on Monday, while both have the same demand for radiological exams (high on CR Thorax orders). Spreading the demand for radiology by smart allocation of consultation hours from departments that have a similar demand for radiology could remove the spikes in the workload of the radiology department.

Chapter 6

Modelling

Section 6.1 of this chapter begins by quantifying the impact of the different characteristics on production times and patient arrival patterns as described in chapter 5 using regression. Section 6.1 completes the work done on *Research question 2*: How can patient arrival and production patterns, trends and performance be identified, and how does the planning process relate to this?

In section 6.2 process mining techniques are then used to gain insight into the role and position of radiology in healthcare paths. This section answers *Research question 3*: How can the role and position of radiology in the flow effectiveness of a healthcare process be made transparent?

Lastly, section 6.3 describes how visualization techniques can support the use of data analysis in practice. This section answers *Research question 4*: How can the data analysis insights be used in practice?

6.1 Regression

Literature research, interviews with domain experts, and thorough examination of the data have shed light on possible influence factors on production times and patient arrival. In this chapter these hypotheses are quantified with the use of machine learning techniques. The goal of this approach is to predict production times and forecast patient arrivals with as little unexplained variation as possible.

For the latter advanced forecasting methodologies are increasingly capable of coming close to nearly optimal forecasts. However, healthcare workers are increasingly looking for forecasting methods that deliver results that are easy to understand [16]. Moreover, in some settings simple forecasting methodologies might even make better predictions than complicated ones [16]. Given its simple nature, regression analysis is used in this research for both the prediction of production times as for forecasting patient arrivals.

Since the aim is to reduce variation for all examinations, the regressions should have a high automated character. It is important to note that such a completely automatic approach is likely to be sub-optimal. However, precise estimates are for both expected patient arrivals as for production times not the goal of this research. Hence, such a automated approach is sufficient. Another important remark is that derived correlation does not imply causation. The resulting correlation findings are solely to support discussion making.

6.1.1 Pre-processing

Clustering

Continuous data is often easier understood when grouped into logical categories. Moreover, categorical variables have a higher chance of providing meaningful results towards defining target variables due to a bounded number of degrees of freedom. Therefore, numeric variables are grouped with the use of various methods. The variable "Overweight" is classified by the function $BodyMassIndex = weight(kg)/height(m)^2$. A Body Mass Index between 18.5 -25 is healthy, between 25-30 indicates overweight and above 30 obese.

Variables that do not have logical cut-off values, and are self-contained (one dimension) can be grouped with various types of discretization such as equal-width binning, equal-frequency binning and with the use of the k-means algorithm. In this paper the k-means algorithm is used for discretization. *The k-means algorithm starts with initializing k centroids with some value. Every data point in the dataset is then assigned to its nearest centroid. Thereafter the centroids are reset to the mean of the data points that are assigned to the centroid. This process continues until an acceptable score for the sum of distances between data points and centroids is found.* The pressure of the day, pressure of the week, and the intensity of consultation hours of specialists are discretized in this way.

Lastly, there are variables that can be viewed from a multi-dimensional perspective, such as a combination of rainfall, minimal temperature, and windspeed on a day. These variables are clustered, after standardization, with the k-means algorithm as well.

Encoding
Although categorical variables are often easier to understand, many classification algorithms require numerical input variables. Therefore, the categorical variables, including the variables just generated as described above, must be transformed into numeric values. There are various methods for this purpose all under the collective name "Encoding". For this research one-hot encoding is used. Label encoding was discarded because of the possible misinterpretation of assigned weights, and binary encoding seems to be a bit overkill given the small number of categories per variable.

Multicollinearity
After the encoding, the features have to be checked on multicollinearity. This is a phenomenal which arises when descriptive features are reciprocally correlated. As a general rule of thumb, variables that have a correlation coefficient, with other input variables, greater than 0.8 should to be dropped.

Feature Selection
The number of variables for both the production times and the patient arrival patterns as defined in Table 5.1 and Table 5.2 is, definitely after encoding, quite large. The

danger of overfitting a forecasting model is therefore present. This phenomenal is also known as the curse of dimensionality. To tackle this problem, a subset of the most relevant features should be extracted. To this end, various approaches can be taken. [22] for example uses a kernel density estimation to define the number of modes, assuming that a feature with a lot of modes will have more predictive power than one with less. Since different examinations react differently on the divergent variables, a method which can dynamically select the most influential factors per examination should be used. For this purpose, Recursive Feature Elimination (RFE) is used. This method fits a regression model and deletes the least influential factor recursively until a specific amount of factors is reached.

6.1.2 Implementation: Production Times

In Table 5.1 the factors that are expected to be relevant for predicting the production times are summarized. In this section these factors will be quantified by means of regression. To gain meaningful production time results from the regression, the examinations that have invalid examination times are excluded from the dataset. Moreover, since not all orders in RIS could be linked to HIX and hence some crucial information regarding patients' mobility, age, sex and pregnancy are missing, these orders are excluded from the dataset as well.

The final production times data set is now ready for regression analysis. In the specific case of MG Mammography examinations, the dataset consists of 2329 records and is distributed as displayed in Table 6.1:

Low Pressure	**Medium Pressure**	**High Pressure**	**Not pregnant**	**Emergency**	**B**	**L**
23%	59%	18%	100%	2%	0%	99%
O	**R**	**Helmond**	**M**	**V**	**No holiday**	**Holiday**
0%	1%	100%	4%	96%	99%	1%
No schoolholiday	**Schoolholiday**	**Appointment**	**Walk-in**	**GP.**	**IP.**	**OP.**
84%	16%	95%	5%	83%	1%	16%
Healthy	**Obesitas**	**Overweight**	**Child**	**Adolescent**	**Adult**	**Elder**
43%	24%	33%	0%	0%	62%	32%
Old	**Friday**	**Monday**	**Thursday**			
6%	11%	23%	22%			

Table 6.1: Production time regression input variables MG Mammography

It is important to note that the production time of examinations consists of the examination itself, guiding patients to dressing rooms and (un)dressing (Figure 4.7). This compensation of event might blur the results of the regression analysis. While running the RFE code in the Python framework for mammography examinations indeed barely any predictive power was found in any of the variables included in the analysis (Figure 6.1).

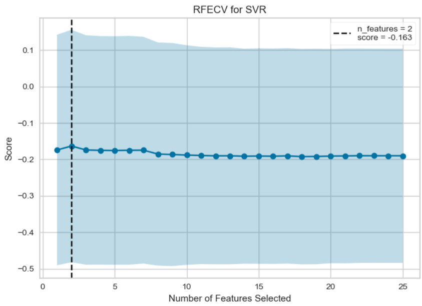


Figure 6.1: RFE Mammography

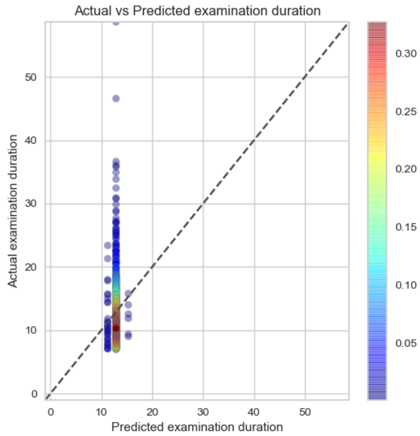


Figure 6.2: Regression output

The two variables with some predictive power are patients in a wheelchair and having appointment type "Walk-in" (Table 6.2).

Name variable	Coefficient	Standard deviation of Coefficient	P Value
Coef	13	0.1	0.000
Wheelchair	1.7	1.4	0.242
Walk-in	-1.7	0.6	0.004

Table 6.2: Regression coefficients production times MG Mammography

As depicted in Figure 6.2, clearly no regression line can be found with the these variables. The extreme outliers that can be observed have no special patient or process characteristics such as mobility, age, or emergency order. These results are curious since medical technician's state that some significant extra time is needed for patients in wheelchairs for example. One explanation for the lack of predictive power of variables could be that examination durations are logged in a too inconsistent manner.

After verification with medical technicians it became indeed apparent that the various medical technicians were inconsistently registering examination duration. During the observed CT scans no examination duration is registered. The medical technicians just start and stop the examinations after the examination is finished. During the observed angio examination, the examination time was started 28 minutes before the examination truly took place, granted that some preparation had to be done before committing to the actual examination and that the examination had to wait for the radiologist to arrive. While observing DSI examinations it became apparent that no hardware (PC) is available for registering the start and stop times in time. For the ultra sound the various medical technicians are sometimes starting the examination before preparing the patient and other times after the preparation. Start and end times of X-ray and mammography examinations seem to be registered the most consistent.

Given the inconsistency of the registered examination duration, the regression anal-

ysis of the production time has not been elaborated further. This analysis can be easily continued in the Python framework once the examination times have become reliable.

The fact that medical technicians find it unpractical and irrelevant to register these times more consistently, gives rise to the question how examination duration could be analyzed in a robust way. Next to the examination duration logged in RIS, the exact scan duration is logged by the medical scans and thereafter uploaded to PACS. This time could be used to conduct a regression analysis on the exact scan time duration. The time between examinations can be assigned to finishing up a previous patient, preparing the next patient, or to breaks and other forms of waste (Figure 6.3).

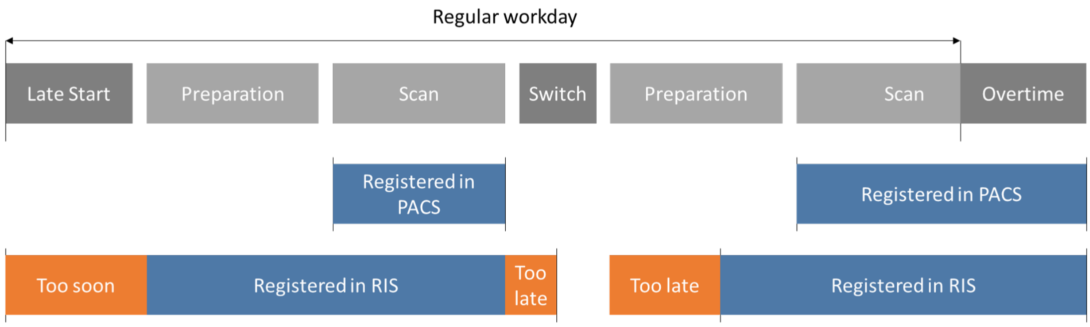


Figure 6.3: RIS and PACS registration of examination duration

The alternative would be to ask the medical technicians to register their production times more accurate and constant. This is already the case in the daily practices of the nursing staff. They do register their start and stop times for examinations very precise. Although this is the most practical scenario, it adds to the administrative burden that medical personnel experience. Another option would be to automatically request feedback when an examination took longer or shorter than expected, asking for the cause of this anomaly. In essence, this process is already used when reporting incidents (called VIMmen). However, this method uses unstructured data, which makes quantifying the problems difficult.

6.1.3 Implementation: Patient Arrival Patterns

In Table 5.2 the factors that are expected to be relevant for predicting the patient arrivals are summarized. In this section these factors will be quantified by means of regression. All factors that are expected to have impact on patient arrival patterns are registered in or can be derived from records in RIS. Hence after the data preprocessing steps no future data cleaning steps are necessary. In the specific case of MG Mammography examinations, the dataset consists of 11974 records and are distributed as displayed in Table 6.3.

Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
14%	28%	15%	24%	15%
Saturday	**Sunday**	**Holiday**	**Next Day Holiday**	**Prev Day Holiday**
2%	2%	1%	2%	3%
Reduction week	**Autumn**	**Spring**	**Summer**	**Winter**
16%	27%	25%	25%	23%
Weather 1	**Weather 2**	**Weather 3**		
47%	11%	42%		
MinTemp	**Wind**	**Rain**		
Min: -10.1 Max: 23.6 Mean: 6.3	Min: 10 Max: 180 Mean: 57	Min: 0 Max: 41.5 Mean: 1.91		

Table 6.3: Patient arrival regression input variables MG Mammography

The RFE code in the Python framework found that the optimal number of features to be included in the regression analysis for patient arrival patterns is six (Figure 6.4).

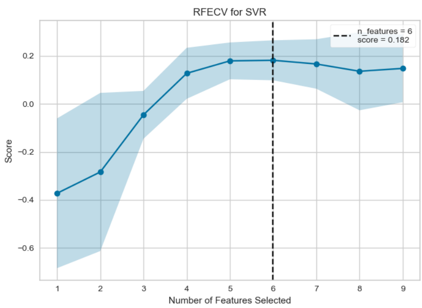


Figure 6.4: RFE Mammography

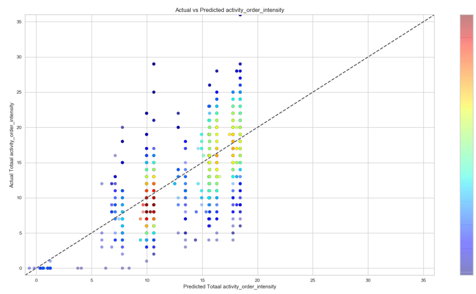


Figure 6.5: Regression output

These six features are Tuesday, Thursday, Saturday, Sunday, Holiday, SchoolHoliday (Table 6.4), which confirms and quantifies the finding in section 5.2. With the use of the derived variables and the corresponding coefficients, a prediction on the number of orders on a day can be derived.

Name variable	Coefficient	Standard deviation of Coefficient	P Value
Constant	10	0.1	0.000
Tuesday	8	0.1	0.000
Thursday	6	0.1	0.000
Saturday	-9	0.4	0.000
Sunday	-9	0.3	0.000
Holiday	-5	0.6	0.000
School Holiday	-3	0.1	0.000

Table 6.4: Regression coefficients patient arrivals MG Mammography

Using this model, a regression line as displayed in Figure 6.5 can be derived. The color scale blue to red represents the density of data points. This regression line can support the planning department with deriving the expected number of patients for a day. A Tuesday for example will most likely be 18, almost never less than 8, and almost never more than 25. Mondays, Wednesdays and Fridays will most likely be 10, almost never less than 4, and almost never more than 18. Depending on the service level the Elkerliek is aiming for the resource allocation for MG Mammographys can be set based on these numbers.

In the Python framework build in this research, this regression analysis can easily be performed for all other radiology examinations of the Elkerliek. MG Mammography examinations are often ordered by the surgery department and are often scheduled orders. CR Thorax examinations are often ordered by general practitioners and are mostly walk-in orders. Since the success of forecasting methods in hospitals can differ based on the ratio of planned and unplanned orders [16], the result of the regression on patient arrival patterns of CR Thorax examinations might be less conclusive.

In the case of CR Thorax examinations, the dataset consist of 67651 records and are distributed as depicted in Table 6.5.

Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
21%	19%	17%	19%	16%
Saturday	**Sunday**	**Holiday**	**Next Day Holiday**	**Prev Day Holiday**
4%	4%	1%	2%	2%
Reduction week	**Autumn**	**Spring**	**Summer**	**Winter**
18%	24%	26%	23%	27%
Weather 1	**Weather 2**	**Weather 3**		
43%	12%	45%		
MinTemp	**Wind**	**Rain**		
Min: -10.1	Min: 10	Min: 0		
Max: 23.6	Max: 180	Max: 41.5		
Mean: 6	Mean: 57	Mean: 2		

Table 6.5: Patient arrival regression input variables CR Thorax

In case of CR Thorax examinations, eight variables that influence patient arrival patterns can be defined, namely Monday, Saturday, Sunday, Holiday, NextDay Holiday, PrevDay Holiday, Reduction week, and Weather 3.

Name variable	Coef.	Std. Dev.	P Value
Constant	60	0.1	0.000
Monday	14	0.1	0.000
Saturday	-46	0.3	0.000
Sunday	-44	0.3	0.000
Holiday	-31	0.5	0.000
NextDay Holiday	5	0.4	0.000
PrevDay Holiday	1	0.3	0.000
Reduction week	-8	0.1	0.000
Weather 3	5	0.2	0.000

Table 6.6: Regression coefficients patient arrivals CR Thorax

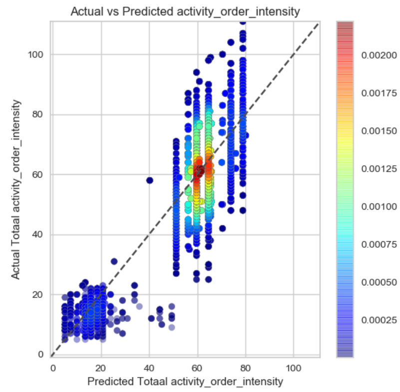


Figure 6.6: Regression output CR Thorax

For this model the regression line as displayed in Figure 6.6 can be derived. Again, the regression line can support the planning department with deriving the expected number of patients for a day.

6.1.4 Sub-conclusions

The unexplained variance in production times can barely be reduced by means of regression, this is most likely due to inconsistent manual logging of examination start and stop times. As a solution to this problem the exact scan times can be extracted from PACS. Alternatively, concrete agreements have to be made on how and when in the process the start and stop times are registered. After the quality of production time data is improved the regression analysis can easily be continued in the Python framework. Which in turn will explain some of the unknown variability in production times, which can be used to more accurately allocated timeslots to patients and thus to improve resource optimization.

The regression analysis approach provides more interesting results for explaining the variance in patient arrivals. The analysis on patient arrivals for MG Mammography and CR Thorax suggest to use the following formula to estimate the expected orders: $Constant_e + \alpha_e \text{Weekday}_{wd} + \beta_e \text{Season}_w + \gamma_e \text{Holiday}_{hd} + \delta_e \text{Reductionweek}_{hd} + \eta_e \text{Weather}_{wt} + \epsilon$. Where e is the examination at hand and $\alpha, \beta, \gamma, \delta, \eta$ the coefficients derived by the regression analysis.

The expected amount of orders of an entire modality is then $\sum_{c=1}^{i}$ *DemandPerExamination*, with c as a specific examination and i as the total of examinations in a modality.

There is, however, still a lot of variation unexplained (MG Mammography R-squared of 0.503, CR Thorax R-squared of 0.644). Although adding new variables into the mix or using different machine learning techniques might decrease the amount of unexplained behavior, it will not likely fully close the gap between expected an actual demand due to lacking insights into patient healthcare paths.

6.2 Process mining

As described, patient arrivals can be explained to some extent by the day of the week, holidays and sometimes the weather. However, to truly understand the demand for radiology, it is imperative to understand the healthcare processes in which radiology orders are embedded. This in-depth understanding is also crucial for the transition from a supply-driven to a demand-driven care system. Moreover, these insights can also indicate areas of attention for efficiency and effectiveness from a radiological perspective.

In this research process mining techniques are proposed as a method to gain more insight into this role and position of radiology in care paths. Benign neoplasm mamma healthcare paths are used as an example to test these techniques. This diagnosis was specifically chosen because the assimilated costs of these healthcare paths at Elkerliek are higher than at other comparable hospitals (see section 4.7).

Before committing to process mining, the relevant data should be collected and prepared. As described by [1], the core of process mining requires the data to be structured as event logs as shown in Table 6.7. Event logs contain essential data for process mining research: an event ID, an activity, a timestamp (start - stop), and possibly additional fields such as allocated resources and costs. Events are grouped as cases, a series of events, also known as trace.

Case ID	Event ID	Properties				
		Timestamp	Activity	Resource	Cost	...
1	1001	30-12-2019 11:02	Beleid Poliklinisch	Surgeon	10	...
	1002	31-12-2019 10:06	Radiologie aanvraag	Medical technician	30	...
2	1003	05-01-2019 15:12	Beleid Poliklinisch	Surgeon	10	...
	1004	06-01-2019 11:18	Radiologie aanvraag	Medical technician	30	...
	1005	07-01-2019 14:24	Opname	Nurcing	50	...

Table 6.7: Event log

The extraction of HIX orders for benign neoplasm mamma is performed with a SQL query that can be easily run for other diagnosis. However, the extracted data from HIX and RIS is not saved according to the event log format. Therefore, this data undergoes the following preparation steps in the Python framework.

- The data is dynamically converted into event logs. Different possible levels of abstraction can be used in this process. In this chapter the abstraction level "*ZorgtrajectNummer*" is used.
- *ZorgtrajectNummers* that have not yet been completed are excluded from the final dataset, to ensure that only completed paths are included.
- In consultation with a domain expert (medical specialist) irrelevant orders such as administrative procedures are removed.
- Similar assignments with minor deviations in the description of the activity, such as "Arrange aftercare" and "Aftercare", are brought together under one activity name.
- Activities that occur together with the same timestamp are often arranged in varying order, for example "policy outpatient, radiology order" and "radiology

order, policy outpatient". All these orders have been ordered alphabetically in this study, in order to avoid unnecessary complexity in the control flows.

With the event logs prepared, process mining techniques can be used to discover control flows. There are various algorithms for doing so. [24] found that the normally robust algorithm Heuristic Miner is not appropriate for healthcare applications. Due to the complex cross-functional nature of healthcare processes the inductive miner algorithm is often considered as more reliable. Therefore this algorithm is used to mine the control flows displayed in for example Figure 6.7 and Figure 6.8.

Of the 2411 benign neoplasm mamma healthcare paths that have started within the Elkerliek since 2008, 1654 have been completed. The average duration of these healthcare paths is 706.6 days or 2.1 years (median 449 days or 1.3 years). The longest path took 4,582 days or 13.6 years. The shortest path took 15 days.

During these 1654 healthcare paths, 8050 relevant orders were requested, including 2326 radiological investigations (17 internal radiology examinations, 2244 regular radiology examinations and 65 urgent radiology examinations). On average, a benign neoplasm mamma healthcare path therefore consists for 30% of radiological research. The treatment or rather monitoring of benign neoplasm mamma healthcare paths can be intensive or less intensive. The difference in the amount of radiology examination is therefore also significant. The maximum number of radiology examinations in a healthcare path is for example 19 and the minimum 0. To gain more insight into these deviations in intensity, a more in-depth analysis of these paths is required.

The largest chuck (48.04%) of the benign neoplasm mamma healthcare paths consist of only one outpatient clinical order and one radiology order, as depicted in Figure 6.7.

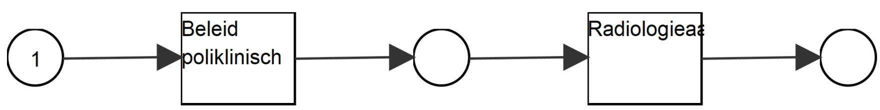


Figure 6.7: 48.04% of benign neoplasm mamma paths

The abstract benign neoplasm mamma process in Figure 6.7 can be enriched by adding the exact radiology orders to the eventlog. *Only radiology orders with a Zorgtraject-Nummer could be joined (see chapter 3).* This additional data provides a more detailed view on the control flow in Figure 6.7. 66% of the cases are MG Mammography C, 9% are MG Mammography control after BOBZ, 8% are regular MG Mammography, 8% are ultrasound mamma's, and 4% are MG Mammography annual controls (Figure 6.8)

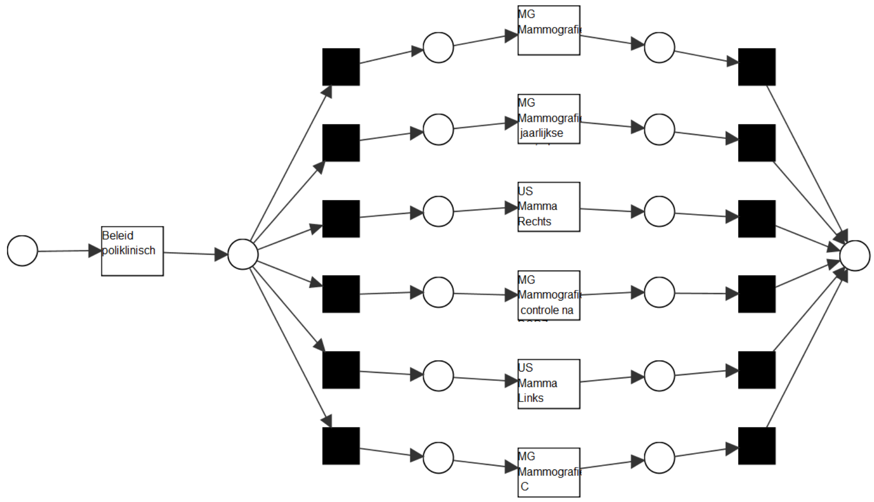


Figure 6.8: 48.04% of benign neoplasm mamma paths extended

The number of radiology examinations does not necessarily depend on the duration of a healthcare process. Take, for example, the two routes marked with large spheres in Figure 6.9.

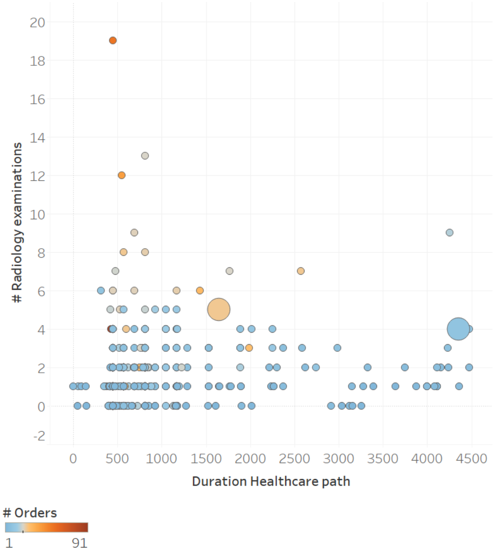


Figure 6.9: Radiology orders and duration

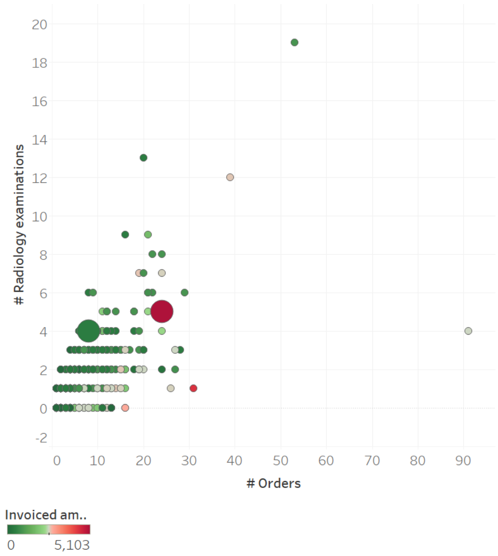


Figure 6.10: Cost of healthcare paths

One of these healthcare paths marked with a large sphere has a long duration ∼4500 days, relatively few (10) orders and relatively much (5) radiology orders. As turns out this path only consists out of a loop of outpatient clinical orders and radiology orders, as depicted in Figure 6.11.

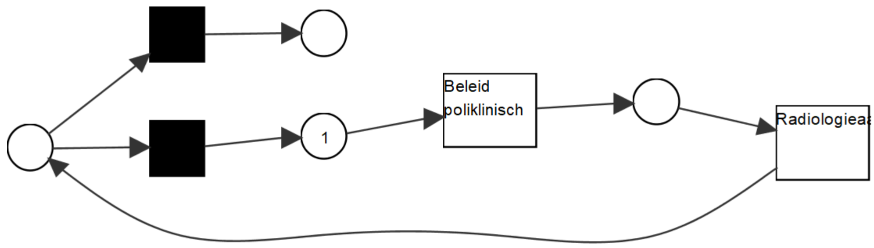


Figure 6.11: Petri Net of Long-Term Benign Neoplasm Mamma Paths

The other healthcare path marked with a large sphere is shorter in duration (∼1500 days) and consists of a lot of orders (24) and relatively few radiology orders (5). As depicted in Figure 6.12 this path is more complex, containing OR orders and hospitalization.

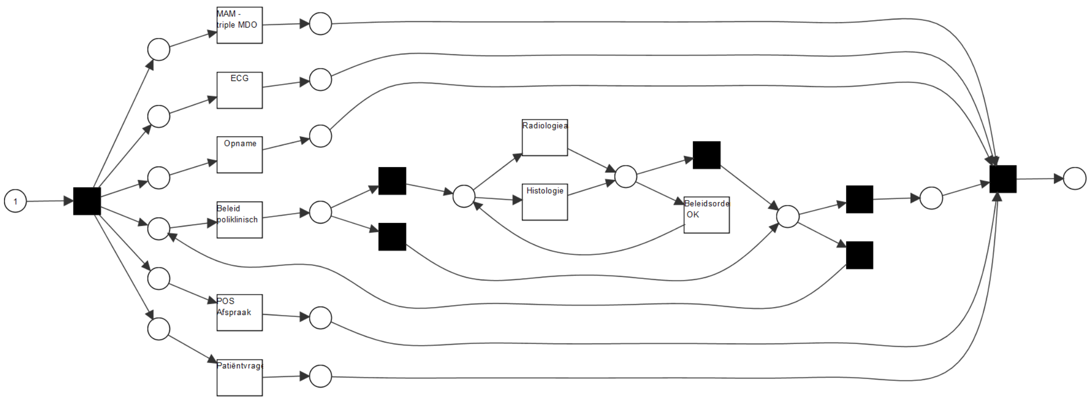


Figure 6.12: Petri Net of Short-Term Benign Neoplasm Mamma Paths

Only 6% of the benign neoplasm mamma healthcare paths have a complex character and contain more than 12 events. In most of these cases radiology orders, laboratory orders, MDO, hospitalization or OR (Operation Room) have a central position. In these cases, radiological examinations have probably given reason to take action.

From this point on a couple of paths can be taken.

1. The benign neoplasm mamma paths can be clustered in order to reduce complexity of the overall process [55], [26], [9] [53], [60].
2. The actual healthcare paths within the Elkerliek can be compared to text-book healthcare paths for benign neoplasm mamma, in order to find inconsistencies between what is actually conducted and what is considered useful [47],[2].
3. The differences in chosen healthcare paths between requesting specialists or practicing radiologist can be made insightful.
4. Choices going right or left so to speak in a healthcare path could be explained by decision point mining on patient characteristics and the clinical picture at hand [47],[2].
5. Score diagnostic choices in healthcare paths with the use of industry best practices, in order to recognize inappropriate radiology orders [35]. Ultimately to shift from volume-oriented healthcare to value-oriented healthcare [36].

Currently however there are several aspects that require attention before these paths can be taken. First, the data inconsistencies blur the outcome of the clustering algorithms. Second, text-book paths are typically not available in Petri net or BPMN format and have hence to be derived from domain knowledge. Literature [21], [35] can provide some basis for the creation of the text-book path Petri nets, but this approach requires revision by medical specialists. Third, difference between the chosen strategies of requesting specialist or practicing radiologist can be due to the fact that one specialist provides care for different type of patients than the other. Lastly, decision point mining requires in-depth information regarding the clinical picture of a patient which at this moment is not available nor can correctly be interpreted without assistance.

6.2.1 Conclusions

The basic process mining techniques prove to be able to derive a basic understanding of healthcare paths of specific diagnosis. In addition, technically the application of clustering, text-book path alignment and decision point mining is possible. Hence after the data is made completely reliable and extended with the required data fields, process mining applications can be of practical use for insights into healthcare processes, patient grouping and for the forecasting of radiology services.

The methodology on how the role and position of radiology affects the effectiveness of healthcare paths can be assessed still needs to be derived. However the differences in the healthcare paths with regards of radiology orders provide incentive to look into the underlying reasons for these choices more deeply.

6.3 Visualizations

As described in section 6.1 there is still quite a bit of unexplained behavior in radiology production times and patient arrival patterns. In addition, section 6.2 concluded that more research is needed to derive patient arrival patterns based on the clinical path and picture of a patient. This together makes estimating reliable production times and patient arrival distributions difficult.

Fortunately, the Elkerliek's radiology department has skilled medical technicians and is supported by an expertly facilitating management team. Together, the radiology department can handle the unexpected. However, in the hierarchical structure of a hospital, it can be difficult for operational personnel to communicate optimization opportunities and to request priority for those opportunities. Therefore, an interactive dashboard that is relevant and accessible for all layers of the hospital is created. The data in this dashboard is visualized in a way to support the use of data analysis in practice and to stimulate continues improvement within the radiology department.

It is important to think about the tasks one is going to perform with the data, before actually starting the visualization process [32]. This chapter will therefore first describe the research questions answered by this design, which specific tasks the design can perform, what functionality and design choices have been made, and lastly how the analysis layer can be used in practice.

In collaboration with the management of the Elkerliek's radiology department, research questions concerning this department are derived. At the highest level these questions touch upon four subjects, namely strategic, operational performance, patient arrival patterns and integral performance. In Appendix C the research questions, corresponding tasks and design choices are described.

The figures used throughout this research (such as 4.1, 4.5 , 4.6, 4.8, 4.17, 4.18, 5.1, and 5.4) are a result of the research questions stated and the design choices made. In section 4.8.1 the throughput times of various examinations are systematically visualised in Figure 4.15. Originally this figure was created with the process mining tool Disco. For ease of use this systematic visualization of throughput times is also implemented in the radiology dashboard (Figure 6.13).

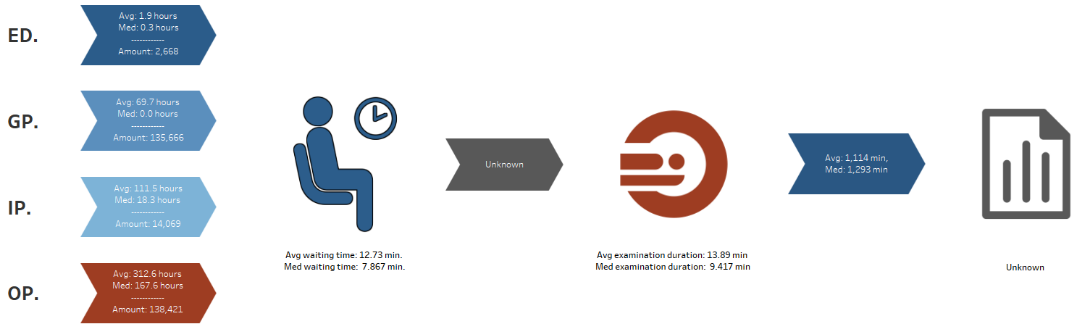


Figure 6.13: "Disco-like" representation of throughput times.

6.3.1 Use Cases

To put the radiology dashboard to the test use cases can be defined. Some of these use cases have already been tested. These cases are highlighted with an asterisk.

*** Corona pandemic**
On March 11, 2020 the spread of the Corona virus COVID-19 is officially announced a pandemic. Hospitals all over the Netherlands have to turn to emergency protocols. After the first large wave of infections the Elkerliek wanted to restart the "normal" healthcare processes, including conducting the radiology orders that have been in the backlog for quite some time. The analytical layer build in this research helped the management of the radiology department to create an image of what demand they could expect from the different requesting parties, and what capacity they should keep in reserve. This insight empowered the management of the radiology department to stand up to the demanding specialists.

Throughput time analysis
Once again, the radiology requests from the clinic proved to be challenging. Two walk-in patients came in for a CR Thorax. Both patients were strapped with IV making it hard to undress the patients. Meanwhile the scheduled patients had to wait until the clinical walk-in scans were completed. Afterwards the medical technicians had a look at the radiology dashboard to see what the impact was on the waiting time of the out-patient clinical patients that were imaged that day. To this end, they compare today with another similar Tuesday and found the wait times was twice as long as normal.

In addition, the examination time for clinical patients was significantly higher. With these findings the medical technicians went to the radiology manager to indicate the problem of not prepared clinical walk-in orders.

Time slot allocation
Again, two medical technicians worked overtime because the examinations took longer than expected. Out of curiosity the medical technicians took a look at the time slot allocation tap of the radiology dashboard. They searched for "CT Brain", which was the examination they performed the most that day. They selected the moment they started to notice additional pressure meeting the scheduled timeframe. The radiology dashboard provided them with a proposed timeslot which takes the change of overtime into account. They found out that the scheduled time for this examination is 5 minutes per examination less than the proposed timeslot by the radiology dashboard. The medical technicians discussed these findings with the planning department.

Long term capacity allocation
Increasingly often the reserved CT timeslots for internal medicine on Monday late afternoon are not filled. A quick call to the internal medicine department results in the insight that one specialist has retired hence reducing the required capacity on Mondays. To find out which department benefits the most of allocated CT timeslots on Monday later afternoon, the planning employee utilizes the radiology dashboard to view daily and hourly demand patterns for CT from different departments and concludes that neurology benefits the most from these timeslots.

Short term capacity allocation
The football world cup final is in three weeks and the personnel of the radiology department asks whether they could have additional free time during this day. To answer this question the radiology manager utilizes the radiology dashboard to look up historical dates of big sport events. A significant drop in demand can be viewed in these days and therefore the radiology manager concludes that a reduced occupation during the football world cup would be sufficient.

6.3.2 Conclusions

Supported with an accessible data analysis tool, the highly trained and experienced radiology team can harness the power of data analysis to improve alignment with the rest of the hospital, optimize capacity allocation and utilization, reduce access times, waiting times and the number of no-shows, ultimately providing the needed healthcare in a value-driven way.

Chapter 7

Conclusion

This chapter summarizes the most important conclusions of this research. Section 7.1 of this final chapter provides a summary of the research questions answered in this research. Section 7.2 describes the practical contribution of this research delivered to the Elkerliek for the identification of improvements areas in radiology. Section 7.3 and section 7.4 describe the limitations of this research and future work respectively. The final section of this report, section 7.5, describes the overall conclusion of this research.

7.1 Conclusions on research questions

Is relevant data available and of sufficient quality, and how can it be improved?
The directly available data for the radiology department is of insufficient quality to perform of-the-shelf data analysis on. The manual logging of process data such as timestamps for example is error prone and has serious consequences for the reliability of (key) performance analyses. Moreover, not all data relevant for the radiology department is available. Data such as consultation hours of other departments of the hospital are not suitable for analysis and reporting standpoints, and data regarding actual scan times or authorization times cannot be accessed due to system rights.

The whole radiology department will migrate to the HIX environment in two years. Getting familiar with the mechanics of HIX, making sure all the relevant data is present in HIX and already migrate all analyses and reporting practices of the radiology department to HIX will increase the connectivity with other systems and departments of the Elkerliek, ensures a smooth transition to HIX and provides a more mature analysis and reporting setup.

Concrete agreements on consistent and robust logging of examination duration and patient/process characteristics have to be made in order to accurately track performance and for planning purposes. Alternatively, the actual scan timestamps registered by the medical machines in PACS could be used, but this limits insights into examination preparation times.

How can patient arrival and production patterns, trends and performance be identified, and how does the planning process relate to this?
Based on literature, this research introduced some useful key performance indicators backed with relevant data to show how the current performance can be identified. In addition, a simply understandable regression methodology to predict production times

and patient arrivals is proposed in this research. Data quality issues make it however challenging to derive conclusions on the performance of the radiology department and to explain the differences in production times.

Patient arrival patterns on the other hand are predictable with the use of this methodology, explaining more than half of the variation that occurs. These insights can therefore be implemented to support the planning department in their daily practices. The role of consultation hours of medical specialists is of considerable importance on patient arrivals. Therefore, the concentration of consultation hours of departments with the same demand for radiology examinations requires attention.

How can the role and position of radiology in the flow effectiveness of a healthcare process be made transparent?
From the data present in systems of the Elkerliek event logs can be generated. Process mining shows actual behavior of healthcare paths and the role and position of radiology in these paths. Knowing the expected paths of patients and therefore the expected radiology demand can help close the gap between the known patient arrivals as derived by the regression analysis and the actual patient arrivals. Because process mining algorithms are sensible to order and time, the data quality issues make deriving conclusions at this moment in time challenging.

After improving the data quality and deriving the role and position of radiology in specific healthcare paths, trace clustering, text-book path alignment, and decision point mining can be used to explain differences in flow effectiveness and costs.

How can the data analysis insights be used in practice?
The bottom-up organizational structure of the radiology department requires all employees to be able to conduct data analysis. This research derived top of mind research questions, which overlap the KPIs somewhat, and a data visualization tool was set up, which enables data analysis on these research questions. The setup has yet to be brought into practice.

7.2 Practical contributions

In the previous section the observations of this research are described. This section summarizes the practical contributions to the Elkerliek and specifically the radiology department.

- An iterative radiology dashboard which enables data analysis and supports bottom-up improvement initiatives with facts;
- A Python framework for data preprocessing, regression analyses, and event log generation;
- An analysis of the current radiology department performance (all conclusions should be rectified when reliable data is available). The main takeaways for this analysis are:
  - CT and nuclear modalities are experiencing significant growth.
  - There is also a significant increase in all modalities from general practitioners.
  - Given the growth in CT demand and limited CT capacity, The CT machine capacity may become dire in the future.

  - The ultrasound machine capacity is overabundant.
  - Medical technicians are often over-specialized, but in general terms an acceptable medical technician utilization is achieved.
  - Examination durations are systematically underestimated.
  - The current radiology setting results in access times that are well below the imposed access time standard by the Dutch government.

7.3 Limitations of the project

As described, the regression analysis on production times did not yield fruitful insights. In addition, conclusions regarding performance and control flows could not be drawn with confidence. There are some root causes that have limited this research to more insightful and confident conclusions, namely:

- Such a broad project with high data analysis content requires a predefined high quality dataset, or excellent knowledge of the systems. During this project neither was available. This increased the amount of work and complexity of getting familiar with the data fields (e.g. status codes) and the processes (e.g. realistic event durations, order of events, decision points).
- In agreement with the Elkerliek the research approach was to first gain insights from the data and thereafter validate these insights with practical insights. This approach has proven to be inefficient in such broad projects if the author as no background in the sector. The impact of this not optimal approach increased during the COVID-19 pandemic because physical presence at the hospital was prohibited.
- Data on clinic occupation is not included in this research and outpatient clinic appointments have been of minor importance during this project. Both are however crucial for deriving forecast and integral planning purposes.

7.4 Future work

Despite the limitations, this research has stimulated the Elkerliek to take the first steps towards data science in radiology. This provides a fertile basis for (practical) future work as a follow-up to this research. Relevant future work includes:

- List all attributes required for management of the radiology department and task the IT and BI department with providing insight into that data.
- Make concrete agreements on consistent and robust logging of examination duration, or use scan timestamps from PACS to improve the data quality of production times. When the latter is chosen a methodology of the assignment of the time between the stop and the start of two consecutive examinations to events must be derived.
- After the data quality is improved, the regression analysis can be re-conducted on production times to quantify the effect of patient and process characteristics on production times. These insights can then be used to optimize appointment scheduling and timeslot allocation.
- After the data quality is improved, text-book paths are derived, relevant patient and process attributes are added and all *zorgtrajectNummers* are joined with radiology orders, the process mining steps can be redone in the Python framework.

Trace clustering, alignment analysis and decision point analysis should thereafter provide insight into the role of radiology in effective healthcare.
- Spread consultation hours of hospital departments which have the same demand for diagnostics such as radiology and laboratory by clustering hospital departments, gaining insight into general practitioner's demand patterns and defining a central and integral planning.
- The regression analysis can easily be transformed to estimate the chance of no shows and cancellations based on for example the weather.
- The patient arrival patterns and production times can be used in simulation models to test and optimize new integral planning setups, new walk-in policies, alternative capacity allocation and new appointment scheduling guides. It is important to note that these simulations should be ran for the entire radiology department because of competition of resources and additional demand that will be generated by other scans.

7.5 Overall conclusion

The initial goal of providing insight into how data analysis in radiology could be used to identify areas of improvement, exposed the structural problems in data quality and accessibility. These problems have put a constraint on basic identification of areas of improvement. Fixing these problems by consistent logging of process and patient attributes and starting the migration of reporting and analyses to the main information system of the Elkerliek will therefore improve the learning potential of the radiology department already quite a lot. This is essential to achieving part of the vision of the Elkerliek "quality and transparency in data exchange" between departments and hospitals as well.

Regression and process mining analysis can be of practical use for planning purposes in hospitals, however data quality issues blur the insights that are generated with these techniques. Once the quality of relevant data is improved, process mining techniques can shed light on the effect of the role and position of radiology in healthcare paths as well.

Within the Elkerliek the main driver of operational improvement is the supportive staff. In case of radiology these are the medical technicians, planning and administrative personnel. However, support in making a case for these operation improvement opportunities is not well established. Therefore, a radiology dashboard is proposed that compresses a multitude of different visualization techniques which will provide support for bottom-up improvement initiatives.

Appendix A

National Trends in Radiology Demand

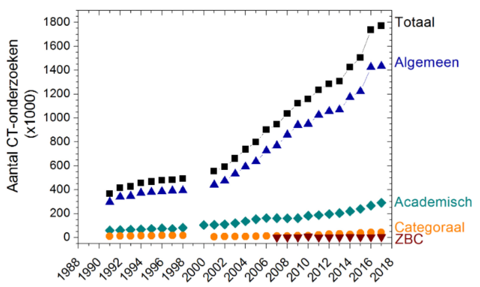


Figure A.1: National trend in CT examinations

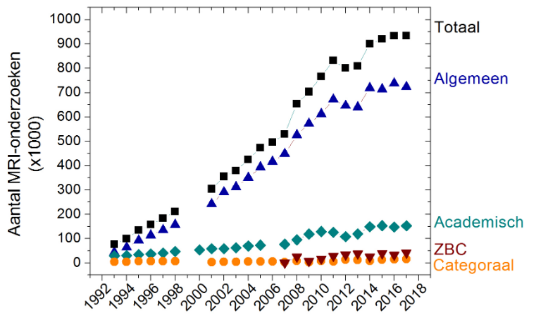


Figure A.2: National trend in MRI examinations

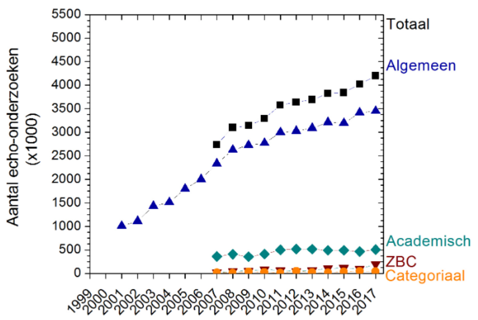


Figure A.3: National trend in Ultrasound examinations

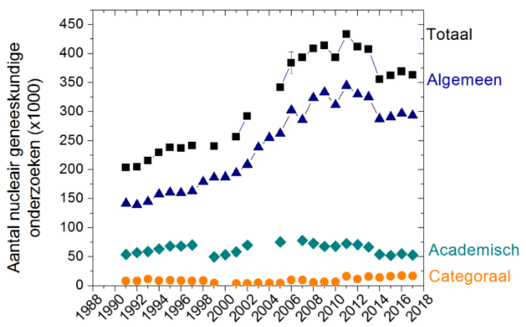


Figure A.4: National trend in Nuclear examinations

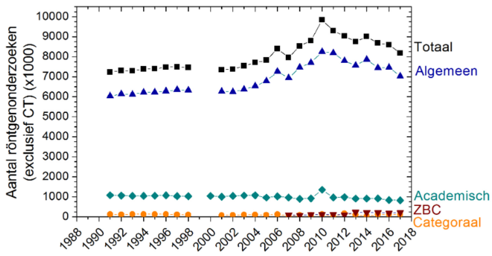


Figure A.5: National trend in X-ray examinations

Appendix B

Demographics Deurne and Helmond

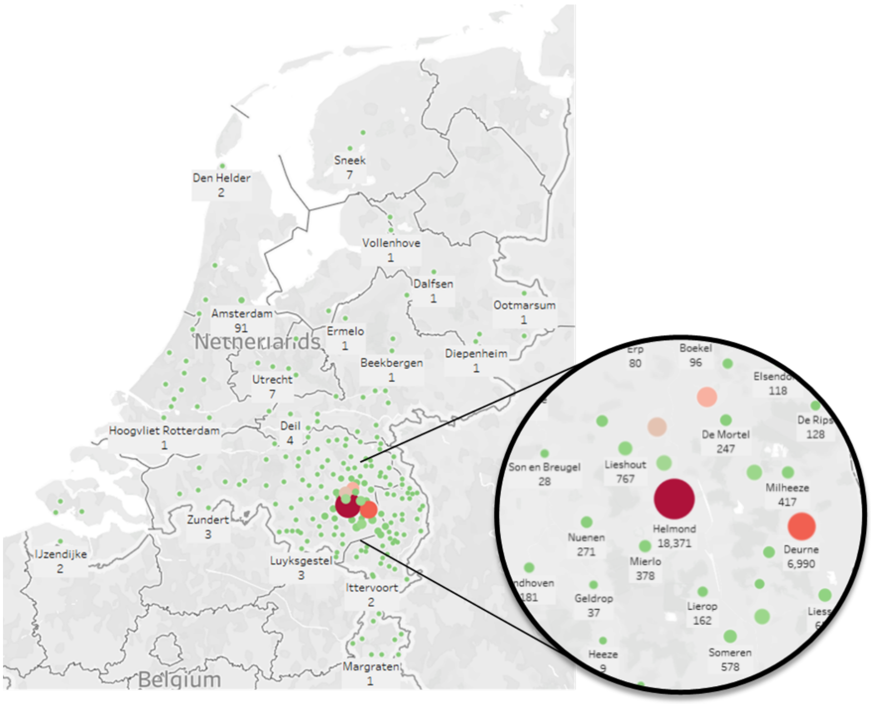


Figure B.1: Geo location of patients of the Elkerliek hospital

		Elder		Adult		Adolescent		Child	
		# Patients	COUNTD([Anoniem pati..	# Patients	COUNTD([Anoniem pati..	# Patients	COUNTD([Anoniem pati..	# Patients	COUNTD([Anoniem pati..
2016	M	7,664	20.92%	7,045	19.23%	1,216	3.32%	474	1.29%
	V	9,463	25.83%	9,004	24.58%	1,334	3.64%	431	1.18%
2017	M	7,841	20.52%	7,344	19.22%	1,290	3.38%	496	1.30%
	V	9,832	25.74%	9,637	25.23%	1,284	3.36%	480	1.26%
2018	M	7,669	20.11%	7,440	19.51%	1,364	3.58%	605	1.59%
	V	9,559	25.06%	9,615	25.21%	1,318	3.46%	568	1.49%
2019	M	7,690	19.96%	7,479	19.41%	1,369	3.55%	685	1.78%
	V	9,436	24.49%	9,922	25.75%	1,329	3.45%	620	1.61%

Figure B.2: Unique patients for radiology examinations at the Helmond location

		Elder		Adult		Adolescent		Child	
		# Patients	COUNTD([Anoniem pati..	# Patients	COUNTD([Anoniem pati..	# Patients	COUNTD([Anoniem pati..	# Patients	COUNTD([Anoniem pati..
2016	M	3,218	23.61%	2,456	18.02%	252	1.85%	124	0.91%
	V	3,974	29.16%	3,167	23.24%	336	2.47%	102	0.75%
2017	M	3,450	22.86%	2,796	18.53%	295	1.96%	138	0.91%
	V	4,322	28.64%	3,632	24.07%	335	2.22%	121	0.80%
2018	M	3,372	22.43%	2,789	18.55%	302	2.01%	157	1.04%
	V	4,296	28.58%	3,598	23.94%	370	2.46%	147	0.98%
2019	M	3,381	21.74%	3,032	19.49%	310	1.99%	158	1.02%
	V	4,329	27.83%	3,731	23.99%	448	2.88%	164	1.05%

Figure B.3: Unique patients for radiology examinations at the Deurne location

Appendix C

Visualization

In consultation with the radiology staff of the Elkerliek, the research questions stated in Table C.1 appear to be "top of mind" and should therefore ideally be incorporated in the radiology dashboard.

Strategic
What are our high turnover modalities and examinations?
What are our fastest growing modalities and examinations?
What radiology demand can we expect from (the extension of) the healthcare service portfolio?
Do we have sufficiently trained personnel for the coming years?
Operational performance / KPI's
How can throughput times be made insightful?
Where are the bottlenecks in our processes?
How are our production times distributed?
What is our capacity utilization rate?
Which outliers can be found and can the underlying reasons be identified?
How many times was a walk-in patient declined?
What was our utilization rate today and this week?
How many overtime hours have we worked?
Patient arrival patterns
Which department orders which examinations?
What trends to we see in the orders?
What is the outpatient clinic schedule?
What is the OR schedule?
What is the composition of the hospitalized patients?
What was the forecasted demand and the actual demand this day / week?
how high should our occupancy be tomorrow / next week?
Integral performance
Which (internal) applicant should receive more radiology capacity?
How often and in what healthcare paths is radiology the bottleneck?
Can (the position of) radiology speed up healthcare paths?
Can (the position of) radiology save costs of healthcare paths?

Table C.1: Visualisation Research Questions

From the research questions described in Table C.1, more specific tasks that the dashboard should be able to perform can be defined. For a radiology department the various ”streams” (clinical, outpatient clinical, general practitioner) of patients are important to compare and inspect. The dashboard should enable the user to filter on these streams. The same holds for appointment types (walk-in, appointment and emergency). For the Elkerliek hospital, and presumably all hospitals with multiple locations, the location (Deurne, Helmond) of a examination should also be a distinct feature in any dashboard aspect. Given the large amount of different examinations, it is easy to get lost in filters. Therefore the five most important examinations should be callable in every dashboard aspect (see Figure C.1.

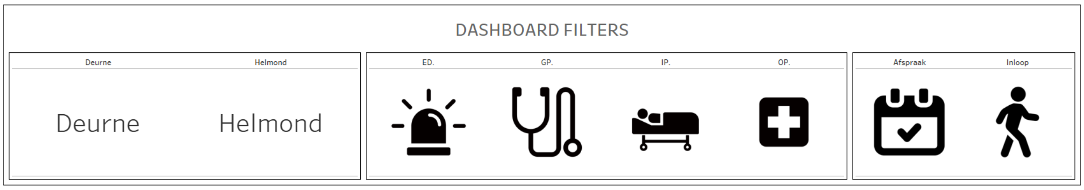


Figure C.1: ”Disco-like” representation of throughput times.

In addition, the management of the Elkerliek defined a special group of examinations consisting out of [Stereotactische mammografie, Coronaire, MRI Cardio] which should be callable as well.

Other tasks include:

- To put patterns into context it should be possible to filter the data based on a specific date or a period of time;
- To define the underlying reasons of outliers, process and patient characteristics should be brought up when inspecting specific outliers;
- Capacity utilization should be derived for both fixed agenda slots, examination time slots, medical machines, medical technicians and radiologists;
- Troughput times should provide insights into overall throughput of an examination or modality. On request addition insights into the access times, waiting times, production times and authorisation times should be brought up;
- Both daily and hourly patient arrival patterns should be insightful to support the 8 week capacity allocation.

The most important design choices in the radiology dashboard are depicted in Table C.2. For a full demo of the radiology dashboard please contact caspeeters26@gmail.com.

Task	Type of chart	Additional features
Provide insight into production times	Barchart & Boxplot	Supports brushing, Zoom-in function
Provide insight into the planned time slot and required time slot	Heatmap	
Display general overview of throughput times	Control Flow	Color-coding, Zoom-in function
Provide insight into access times	Barchart	
Display order frequencies	Heatmap & Linechart	Zoom-in function
Display order frequency per applicant and modality	Heatmap	
Display order growth per applicant and modality	Heatmap	
Provide insight into daily and hourly order patterns	Boxplot	Color-coding
Display geographical origin of patients	Worldmap	Color-coding
Display the time slot utilization	Heatmap	Parameter control
Find correlation between the weather and no shows	Scatter plot	Color-coding
Provide an overview of access times	Barchart	
Provide an overview of waiting times	Barchart	
Provide an overview of access times	Barchart	

Table C.2: Radiology dashboard design choices

Appendix D

Production distribution

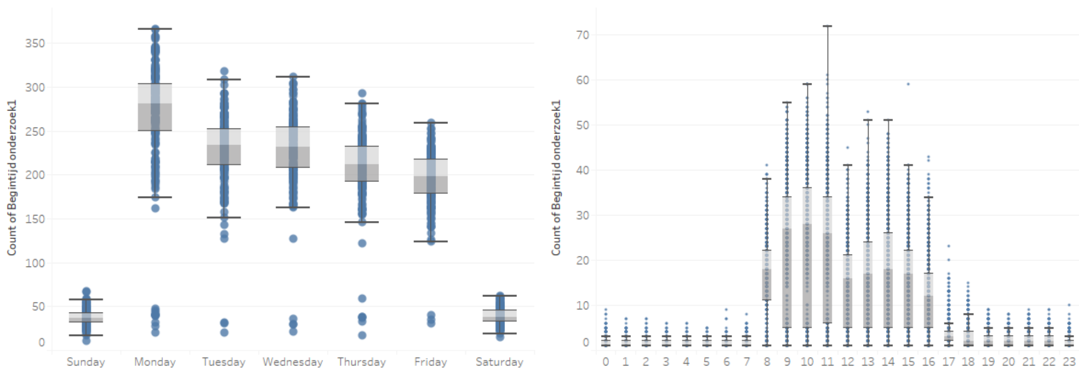


Figure D.1: Daily and Hourly X-Ray Examination Patterns

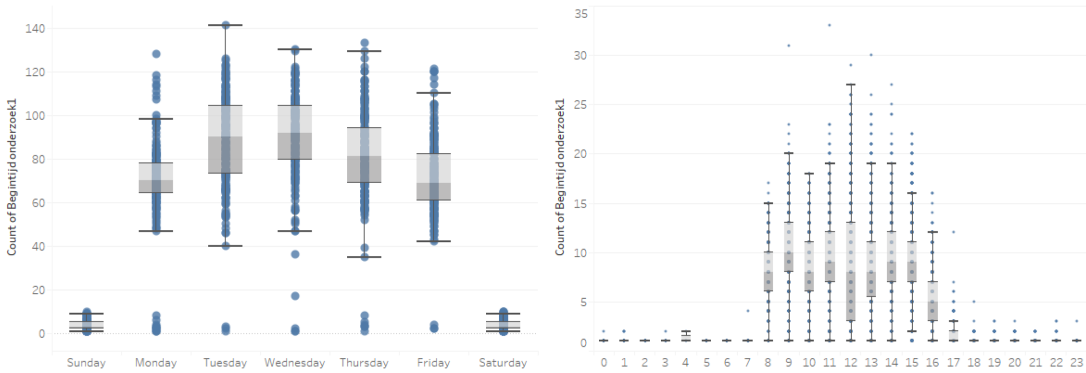


Figure D.2: Daily and Hourly Ultrasound Examination Patterns

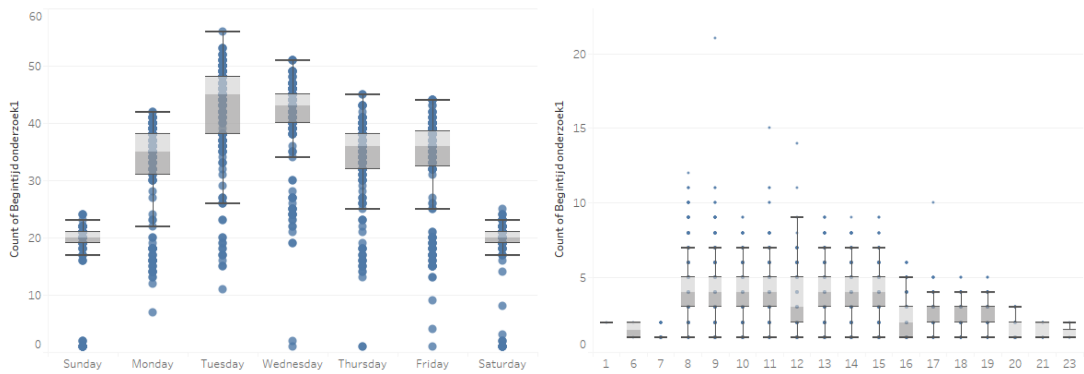


Figure D.3: Daily and Hourly MRI Examination Patterns

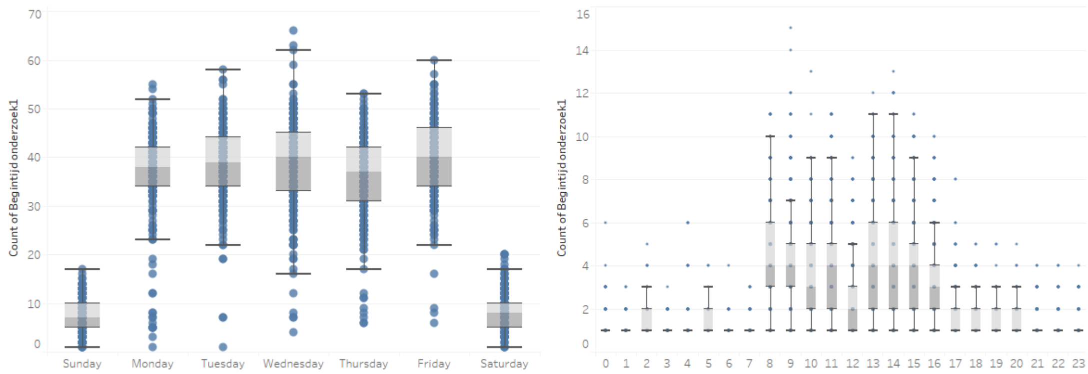


Figure D.4: Daily and Hourly CT Examination Patterns

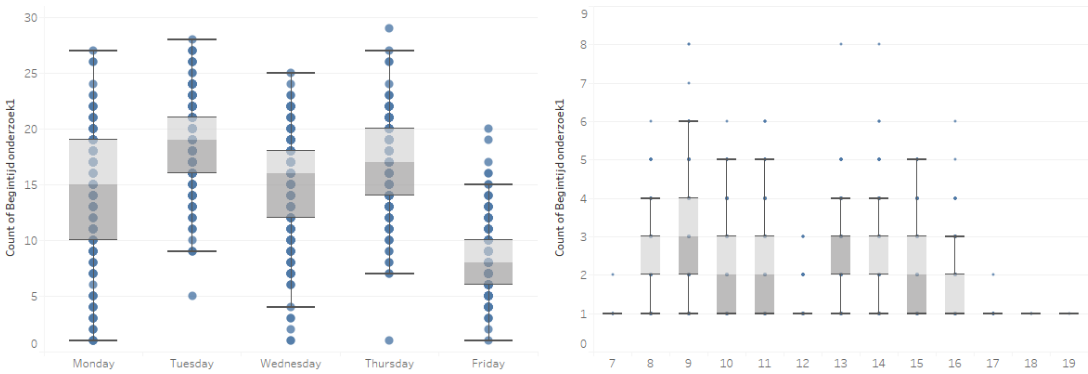


Figure D.5: Daily and Hourly Mammo Examination Patterns

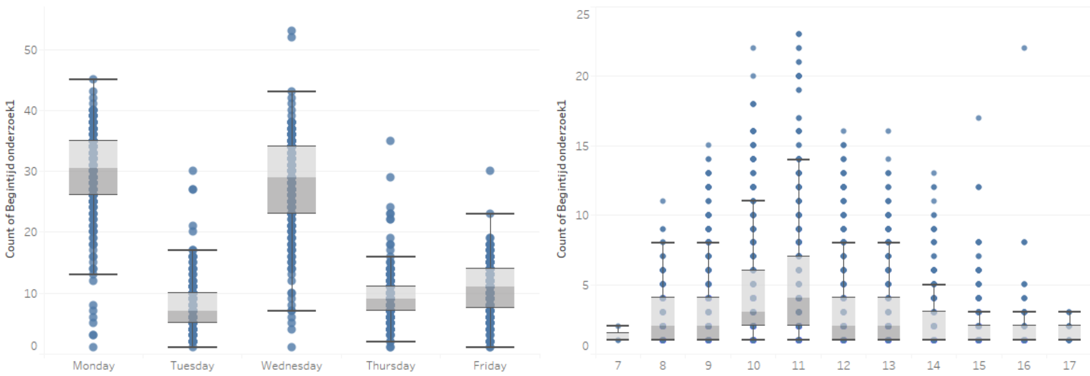


Figure D.6: Daily and Hourly Nuclear Examination Patterns

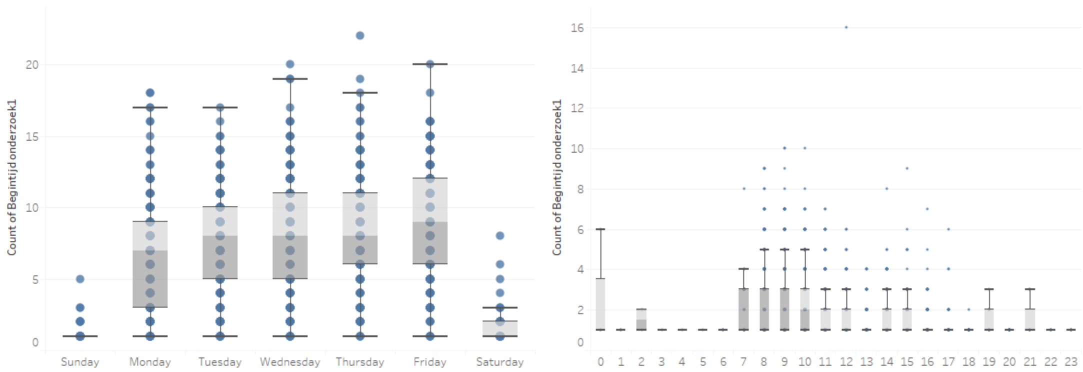


Figure D.7: Daily and Hourly Angio Examination Patterns

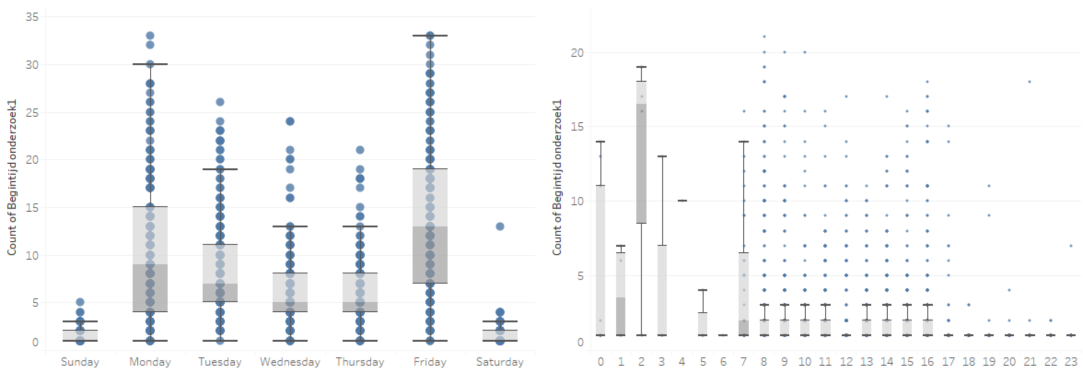


Figure D.8: Daily and Hourly Radioscopy Examination Patterns

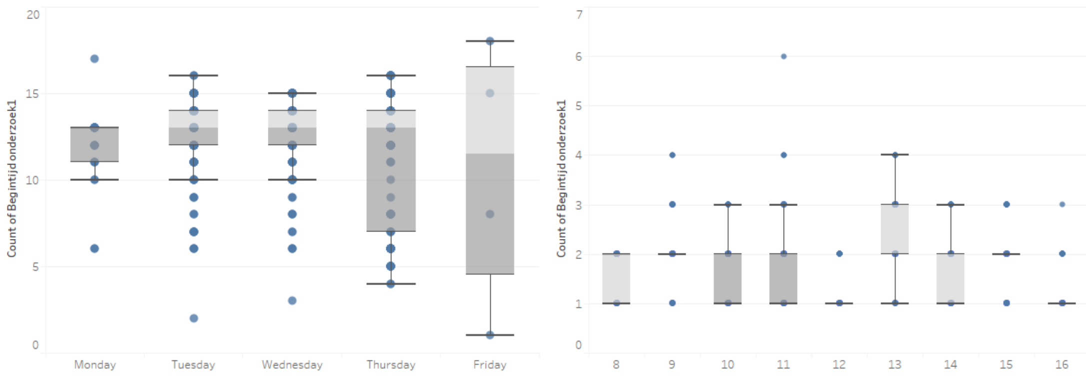


Figure D.9: Daily and Hourly DEXA Examination Patterns

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