Enabling measuring of the patient flow in an orthopaedic clinic

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Management summary

This research enables measuring of the patient flow in the orthopaedic clinic in the Sint Maartenskliniek (SMK). An in-depth understanding of the patient flow process is required in order to identify areas for improvement and by that make the patient flow process more efficient. Therefore, the following research goal is defined:

"Enabling measuring of the patient flow in an orthopaedic clinic."

Current knowledge about the patient flow in the SMK

The SMK is specialised in treatment of conditions related to the posture and movement of the human body. The SMK wants to improve their patient flow process and needs an accurate analysis of the access and processing times within the patient flow process. We identify and reflect the current routes that patients take to visit various departments. We create a flow scheme to determine what information needs to be acquired in order to gain a complete view of the processes of a patient in the SMK. Based on this flow scheme we identify what access and processing times are relevant to calculate for the analysis of the patient flow.

Methods to analyse the patient flow

The literature describes several approaches for analysing and assessing a patient flow. Based on a review of different studies and papers we created a classification matrix. The classification matrix reflects the sources of input data and the methods that are most commonly used in literature for analysation of the patient flow.

Data required to enable measuring of the patient flow

There are three important duration variables defined that we take into account when measuring the patient flow including: the external access time, the diagnostic process time, and the internal access time to the operating room (OR).

We define the external access time as the duration between referral by a specialist or a general practitioner (GP), until the first consultation takes place. The diagnostic process time is defined as the duration between the first consultation, until the moment that is decided that a patient needs surgery. The internal access time to the OR is defined as the duration that a patient has to wait for surgery after the decision is made that a patient receives surgery.

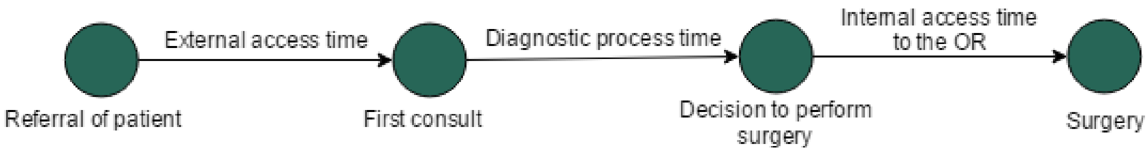

Figure 1 - Duration variables for measuring the patient flow

In order to make it possible to use the data which is recorded by the SMK for analysis and subsequently measure the variables, a conceptual data model is created to structure the data and show relationships between input data and output data.

Required steps to analyse the data

Firstly, we decided which data is required to calculate the durations in order to make the patient flow measurable. Secondly, we discussed the durations with the IT-department in the SMK and they created a dataset for us retrieved from three databases recorded data in the SMK. Thirdly, we checked the data on mistakes and removed data errors. Fourthly, we enriched the data by complementing missing data to the dataset. We wrote a script in R, a programming tool that enables us to convert timestamps of the data into durations. Finally, we created visualisations of the calculated durations.

Results

We measured the durations of the external access time, the diagnostic process time, and the internal access time to the OR.

The external access time is measured over the period 2012-2016 and has an average duration of **X** days. The diagnostic process time has an average duration of **X** days. The internal access time to the OR takes **X** days over the period 2013-2016.

We created a Sankey diagram that presents the relative amount of patients within the patient flow. After referral 100% of patients have a first consult at the outpatient clinic. An receipt to the OR is received by 36% of the patients. The relative amount of patients with an OR-receipt that receive surgery is 67%. From the patients that receive surgery is 84% an elective patient against 16% emergency patients.

Recommendations

Firstly, we recommend the SMK to train their employees in recording data correctly. Employees need to acquire knowledge and awareness about correctly recording of data. Secondly, recorded data in databases of the SMK must be linked to an episode number, this is a number for a specific healthcare process of a patient. This makes the data more reliable. Thirdly, we recommend the SMK to continue with the analysis of the patient flow to gain a more specific view of the patient flow process and identify areas for improvement.

Further research

The classification matrix includes the most commonly used input data and methods to analyse and assess the patient flow. Further research can incorporate literature in this classification matrix to gain a more complete classification matrix for discussion, analysis, and information retrieval.

More timestamps can be added to the patient flow. This enables measuring of more durations and thus a more complete view of the patient flow. Data can be registered in a way that it is possible to calculate the average external access time for patients of different origins separately.

The dataset that we used for this research can be used for further research about analysing and improving healthcare processes in the SMK.

Preface

With proud we present our bachelor thesis which serves as the final assignment to complete the bachelor Industrial Engineering and Management. It was great to be part of the 'Logistiek Bedrijf' in the SMK and be responsible for this multidisciplinary project that provides direct benefit to the 'Logistiek Bedrijf'. It was a good learning experience to execute this project within the Sint Maartenskliniek in Nijmegen, where we were able to meet doctors, nurses, and other employees of different departments.

We worked hard together, both at the university and within the Sint Maartenskliniek, and benefitted from the synergy that arose during the last months. It has become clear that we are well-attuned to each other and complemented one another. We have enjoyed the cooperation and even during periods of increased activity we respected and motivated each other.

We thank all the members of the team that together make up the 'Logistiek Bedrijf' in the Sint Maartenskliniek. Especially, we thank Rob Vromans, healthcare logistics consultant within the 'Logistiek Bedrijf'. In particular, his contagious enthusiasm, continuous support and direct involvement inspired and motivated us during this project. We want to thank Erwin Hans and Derya Demirtas as supervisors from the university. Their direct response and clear feedback made it possible for us to work independently. Especially the open door policy and interesting meetings were supporting and motivating.

Finally, we thank our family and friends for their tolerance and support during this project.

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Chapter 1 – Introduction

In 2006 the regulated market competition is introduced in the Dutch healthcare system. Hospitals have to lower their prices to market standards to stay competitive. This created an incentive for hospitals to improve the efficiency of their processes. In July 2015, the 'Logistiek Bedrijf' was founded in the Sint Maartenskliniek (SMK). The 'Logistiek Bedrijf' aims to coordinate the integral logistics in the SMK and aims to optimise the entire care pathway. In order to coordinate healthcare logistics and optimise the entire care pathway, insight in the processes is required to enable the identification of areas to improve. This research is about enabling measuring of the patient flow in an orthopaedic clinic. When we enable measuring of the patient flow and make visualisations of the patient flow based on measurements, the 'Logistiek Bedrijf' can use these insights to identify areas of improvement and improve the patient flow process. We *enable* measuring of the patient flow, which means that we not solely measure the current patient flow, but also create a measuring tool that gives the 'Logistiek Bedrijf' the opportunity to measure the patient flow in the future.

The first chapter describes the research plan: an introduction of the SMK (Section 1.1) followed by the motivation for research (Section 1.2), the research objective (Section 1.3), the scope (Section 1.4), and the research questions (Section 1.5).

1.1 Introduction SMK Nijmegen

The SMK has four locations in the Netherlands and this research is conducted at the location in Nijmegen. Founded in 1936, the SMK is of origin a catholic hospital. The SMK is specialised in the treatment of conditions related to the posture and movement of the human body. The SMK offers treatments on four different locations in the Netherlands and counted 1890 employees and 317 beds in 2013. Approximately 60,000 patients are treated yearly by the SMK[1].

The location in Nijmegen has an orthopaedic department, a rheumatology department, and a rehabilitation department. The orthopaedic department carries out hip, pelvis, upper leg, spine, knee, and lower leg diagnostics, surgeries and aftercare. The emergency department provides healthcare 24 hours a day, 7 days a week.

1.2 Motivation for research

The introduction of regulated market competition in the Dutch healthcare system in 2006 has consequences for the management of hospitals (Volmer, 2008). Dutch health insurers gained the opportunity to negotiate the healthcare premiums. In order to stay competitive in this new market system, hospitals have to lower their prices to market standards. The new system gives Dutch hospitals the incentive to improve the efficiency of their processes to be able to compete with other Dutch hospitals in the competitive environment.

The SMK strives to treat as many patients as possible using their limited resources while meeting quality standards. The 'Logistiek Bedrijf' aims to coordinate the integral logistics in the SMK and to optimise the entire patient care pathway. Before the 'Logistiek Bedrijf' started, every department in the SMK was responsible for their own healthcare logistics.

It is required to understand the integral processes in the SMK in order to improve the efficiency. The SMK asked us to enable measuring of the orthopaedic care processes by investigating the flow of the orthopaedic patients. When we enable measuring of the patient flow and make visualisations of the patient flow based on measurements, the 'Logistiek Bedrijf' can use this to identify areas of improvement and improve the patient flow process. By enabling measuring of the patient flow, we do not solely measure the current patient flow, but we create a measuring tool that gives the 'Logistiek Bedrijf' the opportunity to measure the patient flow in the future as well.

1.3 Research objective

The following problem statement is deduced from the motivation for research: 'To coordinate healthcare logistics and optimise the entire care pathway, it is required to understand the care pathway so that areas for improvement can be identified. An accurately measured patient flow contributes to the understanding of the care pathway.'

This results in the research objective:

"Enabling measuring of the patient flow in an orthopaedic clinic."

For this purpose, we identify the access and processing times of patients within their orthopaedic care process. The access time is the duration that a patient has to wait until the first consultation takes place and the process time is the duration of a process.

1.4 Scope

It is necessary to define a scope in order to reduce the complexity of this research regarding to the large number of patients that visit the SMK each year. We made the following demarcations to define the scope:

- We focus on patients of the orthopaedic care process
- We use data in the time range of 2012 until 2016
- We measure the following access and processing times:
    - The external access time
    - The time of the diagnostic process
    - The internal access time to the operating room (OR)

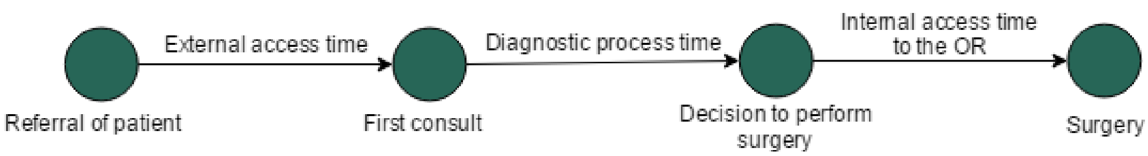


Figure 2 - Access and processing times within the scope

1.5 Research questions

The following research questions that contribute to the research objective are defined.

Research question 1: What is already known about the current patient flow in de SMK?
1.1 How is the patient flow process currently designed?
Chapter 2 provides a context analysis about the current patient flow process by identifying the different departments and different routes between the departments in the process.

Research question 2: What methods are used to analyse a patient flow in the literature?
2.1 Which approach is useful to identify the most commonly used methods?
2.2 What input data is used in these methods?
2.3 How are these methods defined?
Chapter 3 describes a classification matrix which includes the most commonly used methods to analyse and assess a patient flow and the input data used for these methods.

Research question 3: What data is required to enable patient flow measurement?
3.1 What variables are appropriate to make the patient flow measurable?
3.2 What data is required to calculate the variables?

3.3 How to create a conceptual data model to structure the data for analysis?
Chapter 4 describes the definition of the variables required to enable making the patient flow measurable and how to structure the required data in order to calculate the variables.

Research question 4: Which steps are required to analyse the data?
4.1 Where does the data originate?
4.2 How to properly implement the data?
4.3 How to clean the data?
4.4 How to analyse the data?
Chapter 5 describes the steps that are required to prepare the gathered data for analysis

Chapter 2 – Current knowledge about the patient flow in the orthopaedic clinic in the SMK

This chapter describes the patient flow process in the orthopaedic clinic. Based on our own observations and conversations with employees in the SMK, we have identified the different departments in the orthopaedic clinic and the different routes that patients follow to visit the departments. In this chapter, we depict the patient flow process in a flow scheme and explain the origin of patients, the routes of patients, and the departments. We need to understand the routes and departments to know what information about patients is stored, and where in the process this information is recorded. Section 2.1 describes the design of the patient flow process in the orthopaedic clinic and Section 2.2 presents a conclusion about the current knowledge of the patient flow process and what relevant information is still unknown.

2.1 Design of the current patient flow process

A known aspect of the patient flow process are the routes that patients follow to visit different departments in the orthopaedic clinic. Figure 3 reflects a flow scheme of the patient flow process in the orthopaedic clinic in the SMK. It includes the start of the process defined by the moment of referral until the end of the process when the treatment in the SMK is ended. The visual representation of the patient flow enables us to identify the access and processing times that we want to measure.

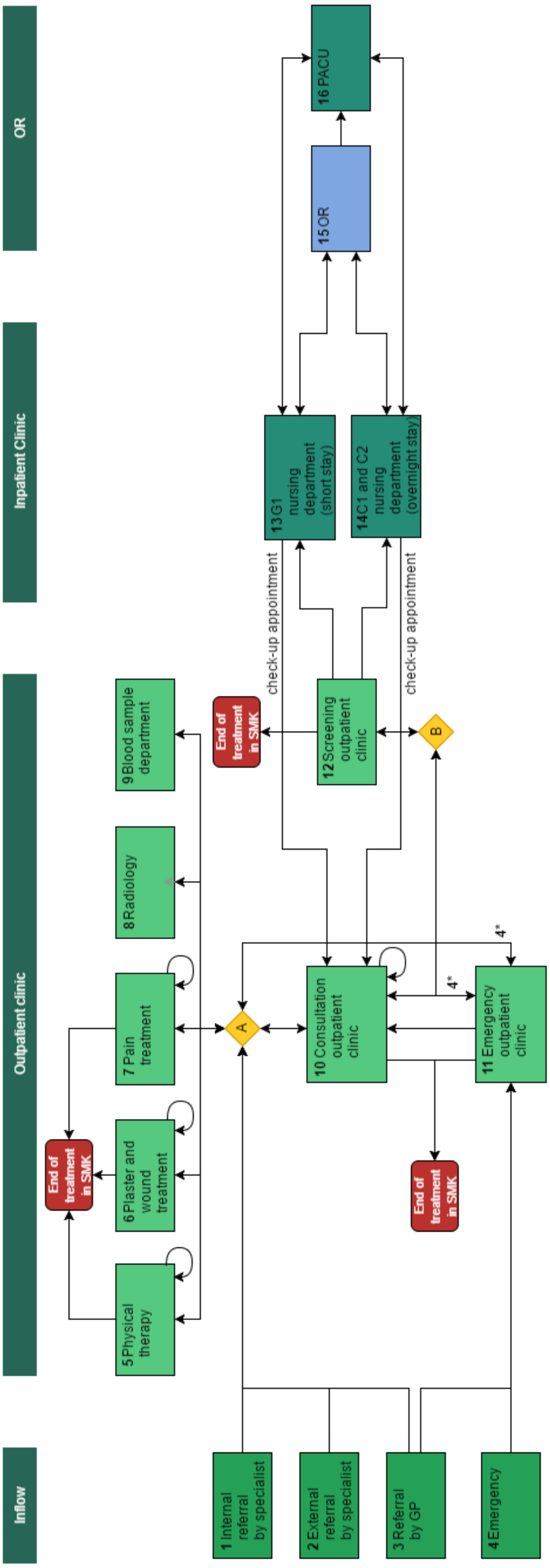
Patients without emergency are referred by a specialist (1-2) or a general practitioner (GP) (3). Patients are referred internally if another specialist within the SMK can provide better treatment to the patient. The waiting time for a first consultation after internal referral has a high priority with a maximum of five weeks. When a specialist from outside the SMK considers that the care for the patient is better in the SMK, external referral takes place. The external access time for patients referred by a GP or an external specialist has lower priority than the external access time of patients that are referred internally.

Within the outpatient clinic there are several departments that patients can visit with or without any consultation in advance. If a patient visits the radiology department (8) or the blood sample department (9) the patient always returns to the consultation outpatient clinic (10) to discuss the results. Physical therapy (5), plaster and wound treatment (6), and pain treatment (7) can serve as last departments visited by patients before the treatment ends. The diamond (A) indicates the decision which department is visited next by a patient during the diagnostic process.

Emergency patients (4) are referred by a GP or directly arrive in the SMK. Emergency patients are treated directly at the emergency outpatient clinic (11). They leave the SMK if the treatment is ended or are referred to visit a non-emergency department. Solely patients that arrive as emergency patients can return to the emergency outpatient clinic (4*).

The diamond (B) indicates the decision whether a patient needs surgery. Solely emergency patients can return to the emergency outpatient clinic after the decision that a patient is not in the right physical or mental state to receive surgery (4*). If surgery is not required, emergency patients can visit the consultation outpatient clinic as well. In case surgery is required, an OR-receipt is issued. This is a 'ticket' that allows a patient to receive surgery. After receiving the OR-receipt, the internal access time to the OR takes place. During this time the patient visits the screening department (12). If experts decide that the patient is not able to receive surgery, the patient returns to the outpatient clinic or the treatment ends or is revised.

When a patient is able to receive surgery a nursing department (13-14) is visited. The patient awaits the surgery and first preparations take place. When the surgery in the OR (15) is completed the patient returns to a nursing department or to the post anaesthesia care unit (PACU) (16). The PACU provides intensive observation and care of patients who have undergone procedures that require anaesthesia.[2] In general, patients who return to G1 leave the SMK the same day whereas patients that return to C1 and C2 stay at least one night. Leaving the nursing department after surgery is never the end of a treatment in the SMK. The patient always returns for a check-up appointment.



4* Only emergency patients

Figure 3 – Patient flow process in the SMK

2.2 Conclusion

In this chapter we reflected on what is currently known about the patient flow in the SMK. The goal of this chapter was to identify the patient flow process within the orthopaedic clinic. We need to understand the routes and departments to find out what information about patients is stored, where in the process this information is recorded, and where patients can arrive at the patient flow process and leave the process.

We found that a patient originates from referral by a specialist or GP, or arrives in the SMK as an emergency patient. A patient visits one or more departments within the outpatient clinic. Some departments can serve as the last visited department before the treatment in the SMK ends, whereas the visitation of other departments always require a check-up consultation to discuss the results. There are two different nursing departments and a PACU that provides intensive observation and care. A patient always returns to the outpatient clinic to discuss the results of the surgery.

Based on the current information, we investigate where the information about the origin of a patient is stored, how long a patient stays at the outpatient clinic before leaving the SMK or until the decision takes place that a patient receives surgery, how the information is stored that a patient receives surgery, and how long a patient awaits the surgery by investigating how the start of the surgery is recorded.

Chapter 3 – Literature review on methods used to analyse a patient flow

In the literature there are several studies about methods that are used to analyse a patient flow. We identified and reflected the most commonly used methods by reviewing different studies and papers. In this chapter we explain where the data originates that is used in a study to analyse the patient flow and we explain the different methods that are most commonly used to analyse a patient flow. The most commonly used input data sources and methods to analyse a patient flow are depicted in a classification matrix. Section 3.1 explains the classification matrix as an approach to identify the most commonly used methods. Section 3.2 explains the sources of input data that are used in the methods to analyse the patient flow. Section 3.3 gives a definition of the most commonly used methods and Section 3.4 presents a conclusion about the most commonly used methods and what input data and method is appropriate to use in this research.

3.1 Classification matrix as approach to identify the most commonly used methods

In the literature we searched for current knowledge about approaches for analysing and assessing a patient flow. We encountered a lot of different methods that are used to analyse a patient flow. Different studies and papers are reviewed to identify the most commonly used methods. Table 1 presents the two-dimensional framework that we created based on the literature review. Appendix B includes the bibliography of the papers and a description of how we searched for relevant literature.

The vertical axis reflects the sources that are most frequently used for input data and the methods in what the input data is used. The horizontal axis distinguishes the studies and papers that either consider solely emergency patients or both consider elective and emergency patients. We did not find articles that solely focus on elective patients and this group is therefore excluded from the framework. The two-dimensional framework is a classification matrix for literature about analysing the patient flow. We applied the matrix to several articles and selected fifteen articles that cover all of the input data sources and methods in the classification matrix. Table 1 presents what input data is used and which methods are applied in the researches. The classification matrix is a conceptual framework for discussion, analysis, information retrieval, and provides structure for research about analysing and assessing the patient flow. The sources of input data and the methods on the vertical axis are further explained in the next paragraphs.

3.2 Input data used in the methods

I1: Failure mode and effects analysis

"Failure mode and effects analysis is a systematic technique to identify potential errors or system failures"(de Silva, 2013). According to de Silva (2013) this type of analysis tends to be qualitative and involves reviewing as many components and subsystems as possible to identify failures, causes and effects. This approach is particularly used in patient flow research to address aspects of patient safety.

I2: Feedback from staff

Another method for identifying the patient flow is collecting systematic feedback from staff. A popular method to gain feedback from staff is using a survey (van Lent *et al*., 2012). However, "caution is advised when relying on staff feedback to prioritise patient flow initiatives" (de Silva, 2013). Researchers found that staff may not have accurate insight into the most important areas for improvement. As a result, staff perceptions do not always correlate well with real-time analysis.

I3: Information system data

Many health services routinely collect data about the usage of health services by patients. This data can be used to identify patterns in service usage and search for trends based on particular times of the day or the types of care or staff involved. When this information system data is collected it can be used as input data for a research. Based on the articles, we concluded that this data is not always collected by the health service. In this case information system data is generated by the researchers themselves.

I4: Structured observations

Ethnography is a qualitative methodology for a detailed study of healthcare issues in the context in which they occur. It can utilise a range of qualitative and quantitative methods and uses participant observation. Ethnography can be useful in a predesign stage of research and can generate questions for research that can be followed up by other methodologies (Savage, 2000).

According to Erickson & Stull (1997), ethnographies provide detailed descriptions and observations about environments and interactions. Ethnographies aim to be holistic and include a history of the issue and an analysis of the terrain, habitat, and relationships in a specific site.

As an alternative to ethnography a more simplistic structured observation is also possible. This provides a less in-depth observation, but it can still provide valuable insights into how emergency care is operating and potential areas to improve patient flow.

I5: Predictive analytics

”Predictive analytics is the process of using modelling and data analysis techniques on large data sets to discover predictive patterns and relationships for business use”(Dale Hall, 2014). Predictive models emerged that incorporate new techniques to help guide business decisions and opportunities. “More than ever, it has been financial services firms, healthcare providers and all levels of government agencies getting into the predictive analytics mix”(Dale Hall, 2014).

Predictive analytics is used in healthcare for the practice of large-scale machine learning and statistical analysis. It provides deeper insights and understanding in big data volumes. Predictive analytics in healthcare can be used for example to calculate the probability that a patient should be transferred to a specific unit and the length of stay in a unit.

Predictive analytics is not solely useful to calculate input data but can serve as a method to analyse the input data as well. This method is especially applicable to large data sets. Meaningful relationships among variables are explored and responding variables are predicted.

3.3 Definition of the methods

M1: (Computer) simulation

Managers of healthcare institutions need to make decisions about the patient flow based on subjective information if “hard data” is not available. In this case, a simulation of the real-world can help. A computer simulation is the process of building an abstract model that mimics the behaviour of a real-world or theoretical system, executing the model on a computer and analysing the output. (Law, 2006)

M2: Mathematical programming

Mathematical programming uses optimisation methods that allow a mathematically representation of a decision problem. Values of a set of decision variables are bounded and defined as constraints. The objective function is maximized or minimized depending on the desired optimal solution. (Bradley, Hax, & Magnanti, 1977). Mathematical programming is used in hospitals to schedule nursing personnel for example.

M3: Qualitative analysis

Qualitative analysis is the interpretation of not measurable input data that originates from interviews, surveys and experiences. It is used to understand people, contexts and interactions. The data relates to concepts, opinions, values and behaviours of people in a social context and is not easily reducible to numbers.

M4: Queuing theory

"Queuing theory is the study of waiting lines, or queues. Usually a mathematical model is constructed to predict queue lengths and waiting times. Historical data is analysed to explore how to provide optimal service while minimising waiting, thus providing an objective method of determining staffing needs during a specific time period"(de Silva, 2013)**.** Queuing theory is applicable on a queuing system, for example a hospital. "Queuing systems consist of entities being processed through a series of service stages, with the opportunity for queues to form between each stage in case of insufficient processing capacity at a server unit"(Eitel, Rudkin, Malvehy, Killeen, & Pines, 2010).

M5: Spreadsheet analysis

The most widely used business intelligence and reporting tool used for spreadsheet analysis is Microsoft Excel. It acts as a tool for data collection, data integration, data analysis, and data reporting. Fieldston et al., (2012) describe the use of Excel in their article: "Direct Observation of Bed Utilization in the Paediatric Intensive Care Unit". They used Excel as a recording tool to collect data and as an analysis tool with the objective to identify when a room was being used for any critical care.

M6: Statistical analysis

Statistical analysis is a method that enables a researcher to draw conclusions about data that is collected through observation, experimentation or a survey. Statistical analysis involves the collection and analysis of data by using data samples. A sample is a representative reflection of the total population that is analysed.

Table 1 reflects the proposed classification matrix which includes the input data sources and the most commonly used methods to analyse and assess a patient flow on the vertical axis. The horizontal axis separates the 15 articles in considering either emergency or both elective and emergency. For each article (1-15) an 'x' is placed when particular input data or a method is used in the research described in the article.

Table 1 - Proposed classification matrix

Classification matrix for literature about patient flow analysis		**Elective and emergency**							**(semi) Emergency**							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Input data	I1: Failure mode and effects analysis										x					
	I2: Feedback from staff								x					x		x
	I3: Information system data	x	x	x		x			x	x	x	x	x	x	x	
	I4: Structured observations				x		x						x			
	I5: Predictive analytics							x								
Method	M1: (Computer) simulation		x		x			x								
	M2: Mathematical programming												x			
	M3: Qualitative analysis															x
	M4: Queuing theory									x						
	M5: Spreadsheet analysis						x		x						x	
	M6: Statistical analysis	x		x		x			x		x	x		x		x

3.4 Conclusion

To conclude this chapter we provide an answer to our research question: “What methods are used to analyse a patient flow in the literature?”. Based on the review of different studies and papers a classification matrix is created. The classification matrix reflects the sources of input data and the methods that are most commonly used in literature about analysing the patient flow. It can be used for discussion, analysis, and information retrieval. We conclude from table 1 that the most commonly used input data originates from an information system. The most commonly used method to analyse data is statistical analysis.

This research aims to analyse the patient flow by creating a visualisation of the patient flow of both emergency and elective patients within the orthopaedic clinic. When we apply the classification matrix to our own research, the input data originates from information system data. The method used to analyse the patient flow is statistical analysis.

Chapter 4 – Data required to enable patient flow measurement

This chapter explains how we made a selection of data that we consider as valuable to enable patient flow measurement. Section 4.1 describes the appropriate variables that we defined to make the patient flow measurable. Section 4.2 explains what data is required to calculate these variables. Section 4.3 introduces a conceptual data model to structure the data for analysis. It explains the definition of a data model, the necessity of a data model, and the creation of a conceptual data model for this research. Section 4.4 presents a conclusion about the data that is required to enable patient flow measurement.

4.1 Appropriate variables to make the patient flow measurable

We defined durations in order to enable measuring of the patient flow. These variables, depicted in Figure 4, are based on the patient flow process as described in Chapter 2.

External access time

The first variable that we defined is the external access time. *This is the duration that a patient waits after referral by a GP or specialist until the first consultation takes place.* It is interesting to know how long the external access time for patients is and whether the external access time for patients referred internally is shorter than for patients that are referred externally. If a patient is referred internally and awaits the start of a new treatment, a new external access time is included.

Diagnostic process time

The diagnostic process time is the duration between the day that the first consultation takes places and the day that is decided to perform surgery. Not all patients need to receive surgery but they have a diagnostic process time as well. Identifying all the timestamps other than an OR-receipt that can be the end of a diagnostic process time makes the research more complex. We chose to reduce the scope and focus solely on the diagnostic process time for patients for whom is decided that they receive surgery.

Internal access time to OR

The internal access time is the duration between the decision to perform surgery and the start of the surgery. Desired limits of internal access time to the OR are defined by the SMK depending on the level of emergency. Emergency patients are divided into four categories. The highest level of emergency is 'acute', followed by 'emergency' and sequential '1 month' and '2 month'. 'Acute' patients receive surgery within **X** hours, 'emergency' patients within **X** weeks and for the '1 month' and '2 month' patient categories is a maximum access time set on respectively 1 month and 2 months. The desired internal access time to the OR is not defined for elective patients. We are curious to discover if the real access time for each patient category corresponds to the desired limits of access time set by the SMK depending on the level of emergency.

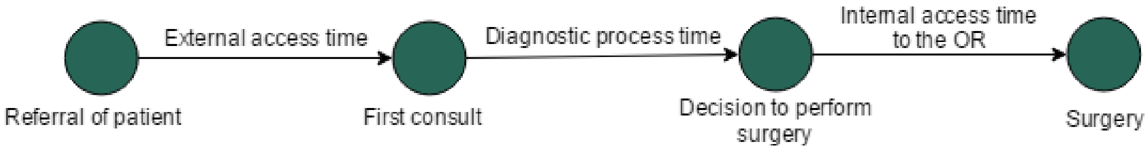


Figure 4 - Access and processing times within the scope

4.2 Data required to calculate the variables

In order to measure the defined variables we need data of the activities that we defined as the beginning or end of the duration of a variable. We defined entities to reflect these activities and relate these activities to each other. "In data modelling, which means the first step in the creation of a database, an entity is some unit of data that can be classified and have stated relationships to other entities."[3] The timestamps we defined to represent the start and end activities are, with respect to the circles in Figure 4, the time of referral, the first consultation, the OR-receipt and the start of the surgery.

4.3 Conceptual data model to structure the data for analysis

In order to make it possible to use the data for analysis and subsequently measure the variables, a conceptual data model is required to structure the data and show the relationship between input data and output data.

Definition of a data model

A data model is a diagram, using text and symbols, to represent what data is collected and stored in a database. It depicts the dataflow and logical interrelationships between different elements of data. A data model can be used to document a complex software system design. It can serve as a blueprint for the construction of new software or for re-engineering a legacy application.[4,5]

The necessity of a data model

A data model provides structure and overview of the data recorded in the data set. Errors in the data structure and oversights are caught by making a data model which eventually reduces time and therefore costs. Identifying errors in an early stage results in fewer application errors and fewer data errors.

Data models are helpful to define the problem and enable consideration of different approaches to structure the data and choose the best one. This results in a data set of higher quality. Data models provide focus for determining a scope and can be used to estimate the complexity of software.

In order to start with data mining, which means analysing data from different perspectives and summarizing it into useful information,[6] creating a data model is a good starting point. The documentation inherent in a model serves as starting point for analytical data mining. It is possible to load day-to-day business data into a dedicated database known as a "data warehouse".[7]

Creation of a conceptual data model for this research

Figure 5 presents the conceptual data model that we created for our research. We used the template from the 'Logistiek Bedrijf'. A conceptual data model is a concept version of the data structure that is made before working with the data. The content of the data model can change on operational level during the programming. The conceptual data model is more important than the final data model, because the goal of making a data model is to plan the structure of the final product.

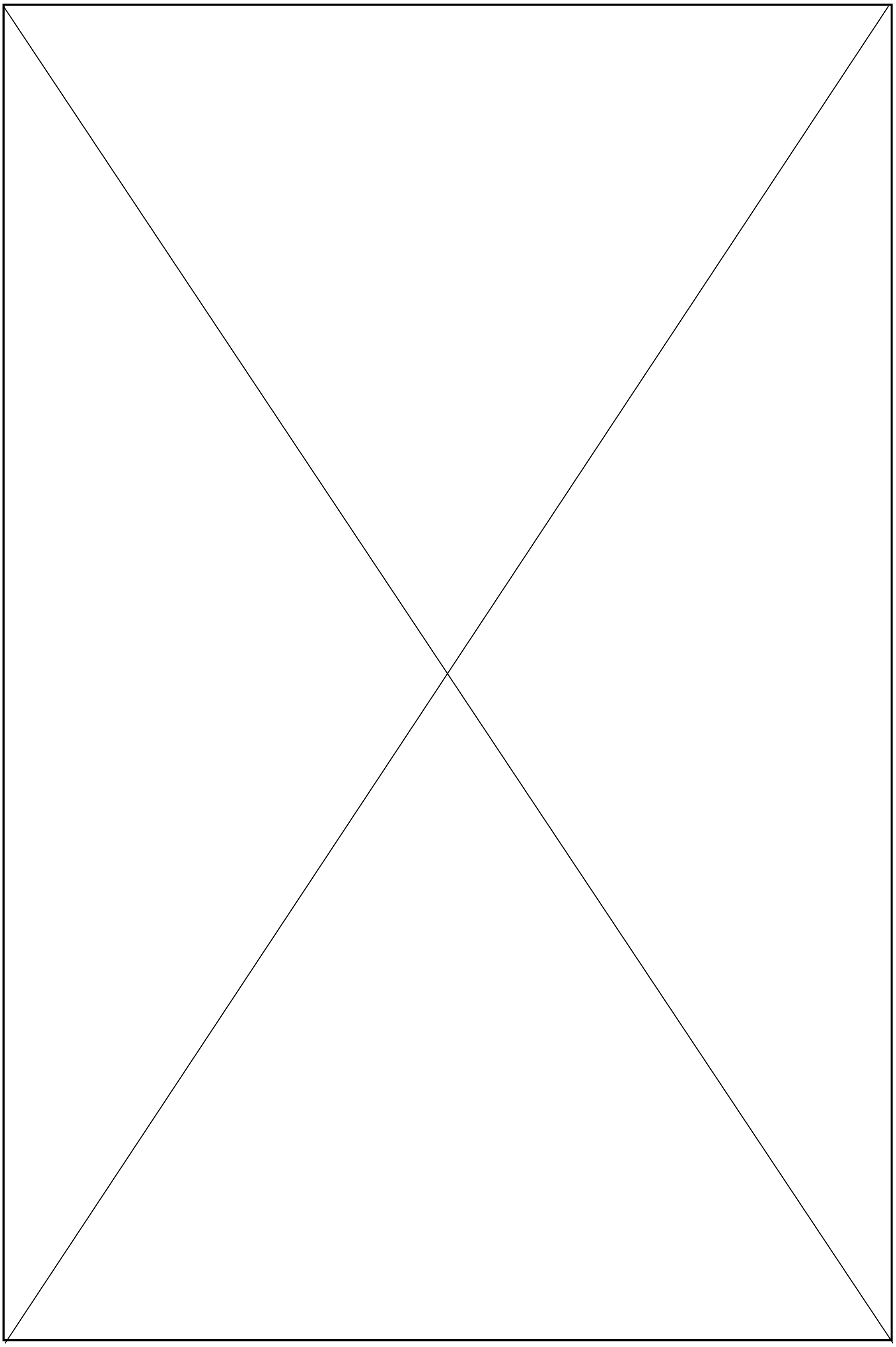


Figure 5 - Conceptual data model

We created the conceptual data model based on the desired output; a dataset that shows the external access time, diagnostic process time, and the internal access time to the OR of a patient. The dataset is created by combining three data subsets that consists of the calculation of the respective times.

The data subsets are retrieved from our main dataset. The main dataset consists of merged data retrieved from three databases of the SMK: the referral data, the outpatient clinic data, and the OR data. After merging the databases, we cleaned our dataset by identifying and removing errors.

The enriching process of the data starts after the cleaning of the dataset. Enriching data means adding relevant information to the dataset based on existing information. An example of enriching the dataset is the addition of the week numbers based on the dates in the dataset. The enriching process is further explained in Chapter 5.

When the desired output data is created, it is necessary to transform the datafile into the right format. We use Spotfire for the analysis of the data. Therefore, the format from our data will be transformed into a comma separated values (CSV) format, which is a suitable format for data analysis.

4.4 Conclusion

The conclusion answers the question: “What data is required to enable measuring of the patient flow?”. We identified three durations that we measure in order to enable measuring of the patient flow. We conclude that the durations of the external access time, the diagnostic process time, and the internal access time to the OR are required to enable measuring. Data of four different timestamps is required to calculate the three durations. We need data about the time of referral of patients, the time that a first consultation takes place, the time it is decided that a patient receives surgery, and the time that a surgery starts.

To structure the data and combine the data into a dataset, we created a conceptual data model. This model gives insight in the relationship between the input data and the output data. The conceptual data model shows the transformation of raw data into data that is formatted for analysis. A data model helps to overcome errors in the data structure. We cannot say retrospectively if errors are prevented by using a conceptual data model.

Chapter 5 – Required steps to analyse the data

This chapter describes the steps that are required to analyse the data. Section 5.1 describes the data gathering process. Section 5.2 describes the data implementation into R, a programming language. Section 5.3 describes the cleaning of the data. Section 5.4 focuses on the data analysis. Section 5.5 presents the conclusion about the required steps for data analysis.

5.1 Data gathering

We defined activities that represent the start and end of the variables. Chipsoft, the information system used by the SMK, registers the timestamps of all the activities of patients in the SMK. Chipsoft is a software package that is used by the SMK for the registration and planning of activities, the registration of patient data, admission and discharge registration, and to keep track on the electronic patient record. In order to interpret the recorded data and to consider the validity of the data, we need to know how and when a certain activity is registered in Chipsoft by the SMK staff.

We observed the various departments where the activities are executed and we had conversations with different employees in the SMK to find out how they register the activities in Chipsoft. The referral of patients within or to the SMK is processed in the outpatient clinic. A GP refers a patient by using the digital referral application called 'ZorgDomein'. This application makes it easy for a GP to electronically refer a patient to a healthcare institution. A specialist refers a patient, internally or externally, by sending a letter per email to the desired healthcare institution. Employees of the outpatient clinic process these referral requests in Chipsoft within a maximum of three working days.

When a patients arrives at the outpatient clinic after referral, the patient announces his arrival at the department desk, this time is registered. When a patient visits the outpatient clinic more than once, each visiting time is registered.

A patient has a patient number and one or more registered episode numbers. The same episode number is linked to all of the activities within one healthcare program of the patient. If a patient visits the SMK for two different medical complaints, there are two episode numbers and one patient number registered in Chipsoft. All the activities within one episode are reported. We consider the first registered visit to the outpatient clinic within one episode as the first healthcare contact within an episode in the SMK.

A specialist decides if a patient needs surgery. Based on the patient screening, an OR-receipt is issued. When the surgery takes place, the actual start of the surgery is registered in the operating room. Both, timestamps of writing the OR-receipt and the start of the surgery is registered in Chipsoft.

The IT-department in the SMK has access to all the recorded data in Chipsoft. We defined what data is relevant to our research and discussed this with the people working for the IT-department. A database was created by the IT department containing all the relevant data for our analysis.

5.2 Data implementation

The data from the dataset is loaded into R. This language is suitable for statistical computing. The benefits of the implementation of the data in R is discussed in this paragraph.

Automation is necessary in order to find mistakes in the large data set. R is one of the programming languages that is able to compare all the different rows and columns of a table at once. This is more efficient than a language that requires an individual comparison of data points.

Implementing the data in R has the benefit that repeating analysis is possible. Because the code is stored in different modules, repeated analysis with different subsets of data is possible. The possibility to repeat the analysis is relevant for this data set, because the data gets constantly updated with recent data.

5.3 Data cleaning

The next step in the data preparation process is the cleaning of the data. The data set of the SMK was raw and unstructured at the time of receiving. Furthermore, we directly noticed obvious mistakes. For example, according to the data some patients had their first consult after their surgery.

The dataset that we use is a combination of different databases and this results in mistakes in the dataset. All the databases have different structures, which leads to a loss of information after joining them together. Fortunately, it is possible to match existing data with missing data by adding the missing data based on the information of a whole episode.

We also encountered some fundamental flaws in the data set. The OR-receipt is issued before the screening of a patient. However, this was not the case in our initial data set. About 94% of the available episode data includes an OR-receipt with the same date as the screening. This cannot be true because most of the times the screening takes place a few weeks after the specialist decides to perform surgery. We found that the cause of this error was a misinterpretation of one of the used databases.

Another flaw in the data is the unreliable outpatient clinic data. Since we are evaluating a whole episode of a patient, it is important that the data of an episode is complete. This is not always the case. We solved this problem by adding all registered data that was stored in the outpatient clinic data base. After filtering the unnecessary data and enriching the input with the episode number, a more complete data set is constructed.

The dataset had to be improved to perform a reliable analysis. Therefore, the fundamental flaws in the dataset were solved by the IT-department in the SMK by adding episode numbers to activities of patients and by adding a number which make it possible to match the right OR-receipt with the corresponding surgery. The dataset is updated five times by the IT-department during the process of making the dataset more reliable.

The first version of the dataset contained over **X** rows, whereas the last version of the dataset contained **X** rows. The last version of the dataset contained more patient data by adding data that was missed in earlier versions to the existing data.

We were not able to identify and solve all the flaws during this research. We filtered data that contained errors using logical checks. An example of a logical check is checking if an activity of a patient that serves as timestamp, used to calculate a duration, is linked to the same patient.

5.4 Data analysis

The data analysis is divided into different procedures within the programming code, known as methods. We started the data analysis with a method that makes a summary of the data. The summary gives an overview of the data by calculating different quantities of the data set. The summary provides the used parameters for the data (for example to filter data over one or more specific years), the amount of input data (for example the amount of episodes), and presents parameters that indicate possible errors in the data. The summary is used for data verification and to interpret the results of the data analysis. Part of the summary is presented in Table 2.

Table 2 – Part of the summary of the analysed data

Amount of rows	**X**
Amount of episodes	**X**
Amount of patients	**X**
Amount of start surgery	**X**
Amount of emergency surgery's	**X**

The next step in our data analysis is calculating the defined variables in the episodes of the patients. We calculate the external access time to the SMK by matching the referral date with the date that a patient has a first consultation in the outpatient clinic. We calculate the duration between the timestamps. The method that calculates this duration performs checks and filters incorrect data.

We calculate the diagnostic process time by measuring the duration between the timestamp that a patient has a first consult and the timestamp that an OR-receipt is issued for this patient.

The last duration we calculate is the internal access time to the OR. The method calculates the duration between the timestamp that the OR-receipt is issued and the timestamp of the start of the surgery. When a patient receives more than one surgery, we consider the first timestamp as the start of surgery. An extensive description of the used scripts can be found in Appendix C.

The output of the different methods is visualised in Spotfire, a software for the visualisation of structured data. Using the visualisations we can analyse the data and draw conclusions.

5.5 Conclusion

The conclusion answers the question: "Which steps are required to analyse the data?". Firstly, relevant data is gathered and connected to an episode number. Connecting data to an episode number was complicated because the data was often incomplete or incorrect. Secondly, the data is loaded into the data analytics program R and correctly formatted. The advantage of using R for the analysis is that repeated analysis is possible. Thirdly, the data is cleaned by separating data that consists of mistakes and by complementing missing data to the data set. The last step is calculating the defined variables.

The results of the calculations and analysis are visualised in Spotfire. The analysed data contains **X** episodes from **X** patients. An extensive description of the used scripts can be found in Appendix C.

Chapter 6 – Results

This chapter describes the results of the research. It presents visualisations of the three different durations and provides interpretations of these visualisations. The average of the data of 2016 is not reliable due to the use of historic data which is only available for the first half year of 2016 at this moment. However, we added 2016 because the average external access time just gives an indication. We enabled measuring of the patient flow over time, because it is possible to update the graphs when more recent data is available.

Section 6.1 presents the results of the data analysis. Firstly, visualisations of the average external access time are presented and analysed. Secondly, the visualisations of the diagnostic process time are reflected and analysed. Thirdly, the results of the internal access time to the OR are reflected in graphs for elective and emergency patients together and separately. Finally, the durations of the external access time, the diagnostic process time, and the internal access time to the OR are combined in the same graph. The last figure is a Sankey diagram that visually represents the patient flow.

6.1 Results of the data analysis

External access time

Figure 6 presents the average external access time over the period 2013-2016. We defined the average external access time as the average time that patients have to wait for a first consult after referral. The average external access time is fluctuating between **X** days during the period 2013-2015. The data of 2016 is still incomplete, so this average is not reliable.

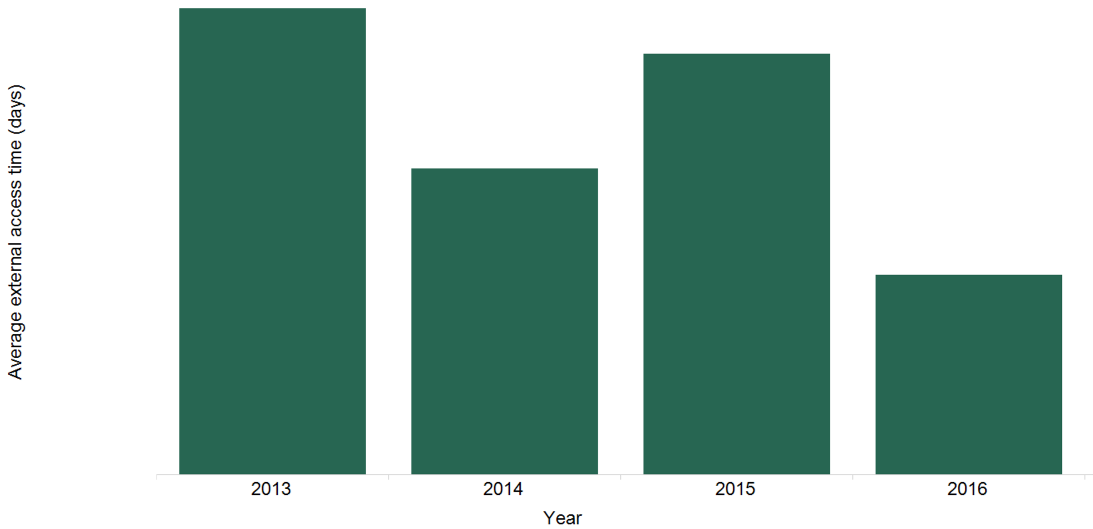


Figure 6 - Average external access time 2013-2016

Figure 7 presents the average external access time in days over the same period (2013-2016) in months. In this graph we overcome the problem that the data of the second half year of 2016 is missing. The bar chart illustrates upward and downward trends in certain waves. The maximums are lower during 2015, compared to the maximums in 2013. Both 2014 and 2016 show a dip compared to the peaks in 2013 and 2016. This is reflected as well by the average internal access time per year in Figure 6. The extreme peak in the first month of 2015 is probably a result of a mistake in the data recording.

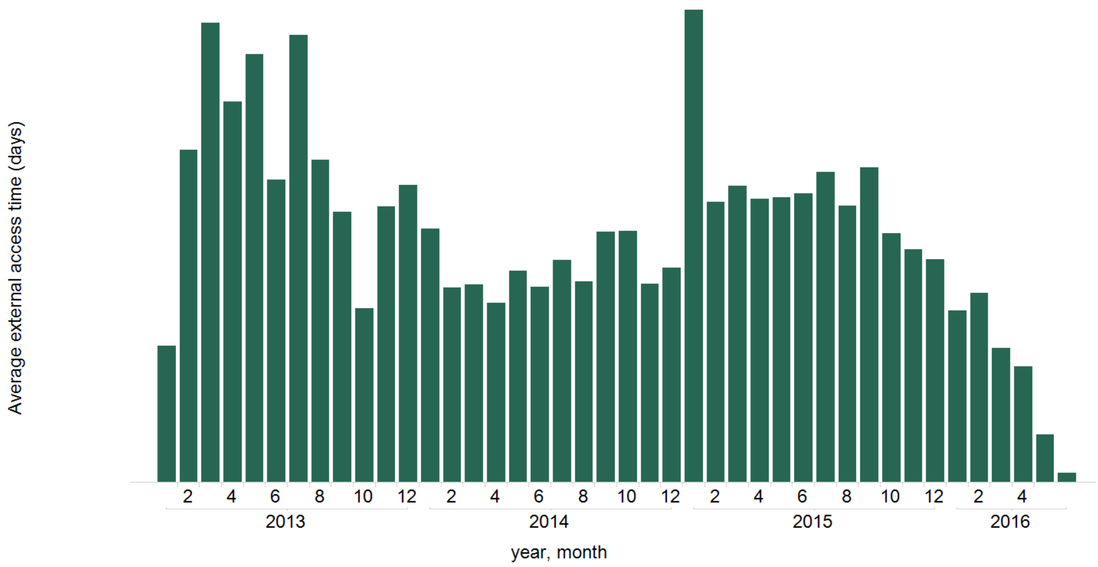


Figure 7 - Average external access time per month (2013-2016)

Diagnostic process time

Figure 8 presents the average diagnostic process time. We defined the average diagnostic process time as the duration between the first consultation and receiving the OR-receipt. The average diagnostic process time is expressed in days over the period 2014-2015. The years 2013 and 2016 are not reflected due to the lack of data during these years. The average duration of the diagnostic process has lower maximums in 2015 compared to 2014.

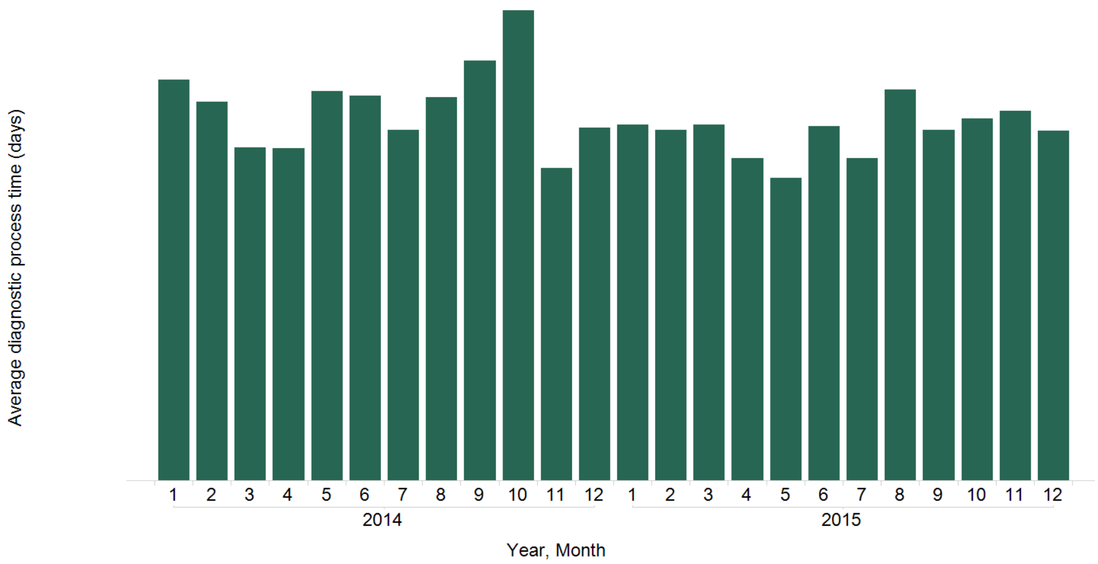


Figure 8 - Average duration of the diagnostic process in 2014 and 2015

Internal access time to OR

Figure 9 describes the average internal access time to the OR per year. The average internal access time in days is calculated for all of the patients together. In this figure we do not distinguish between elective patients or emergency categories. The figure shows that the average internal access time remains relatively constant during the reflected period, fluctuating between approximately **X** days.

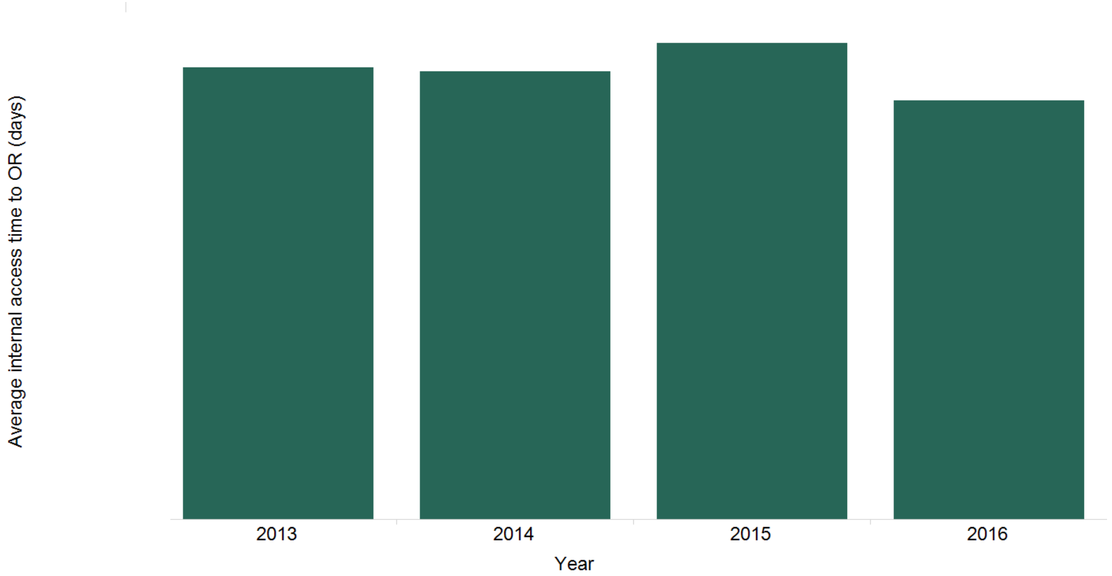


Figure 9 - Average internal access time to OR per year

Figure 10 presents the average internal access time to the OR in 2015 per month. In Figure 9 we have already seen that the average internal access time to the OR in 2015 was **X** days. The average internal access time to the OR in 2015 is during months two until seven below average and during months eight until eleven above average.

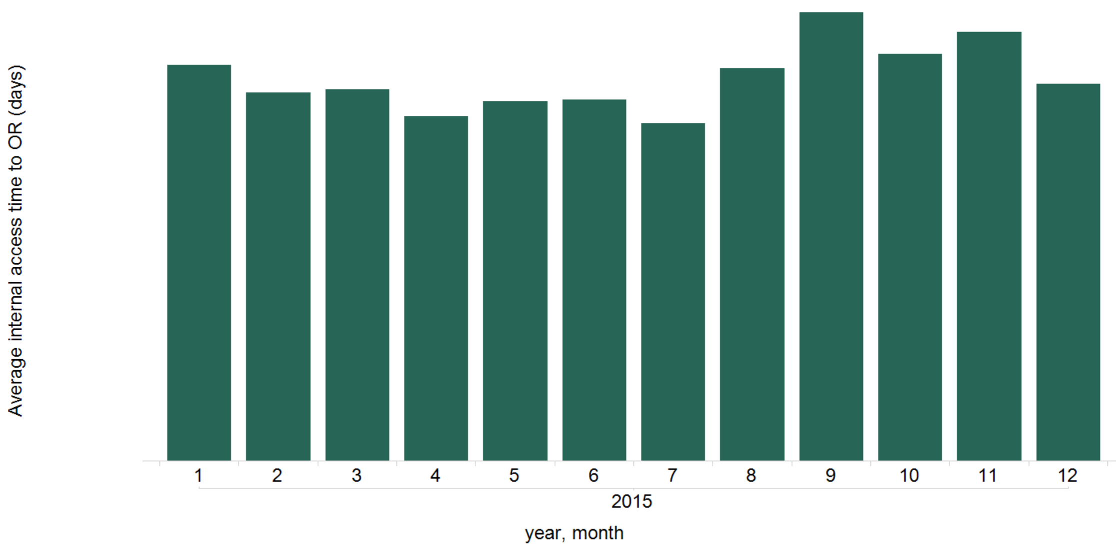


Figure 10 - Average internal access time to OR in 2015

Figure 11 presents the average internal access time to the OR for elective patients. For this patient category, in contrast to the emergency categories, is a certain limit for the access time not defined by the SMK. We are curious to explore this average internal access time to the OR for elective patients. Approximately, the average internal access time to the OR for elective patients is between the **X** and **X** days. The emergency category with the highest limit of waiting is the '2 month' category which means an average internal access time to the OR with a maximum of **X** days. We expected that the access time for elective patients is higher. Our expectations were confirmed upon analysis of the data.

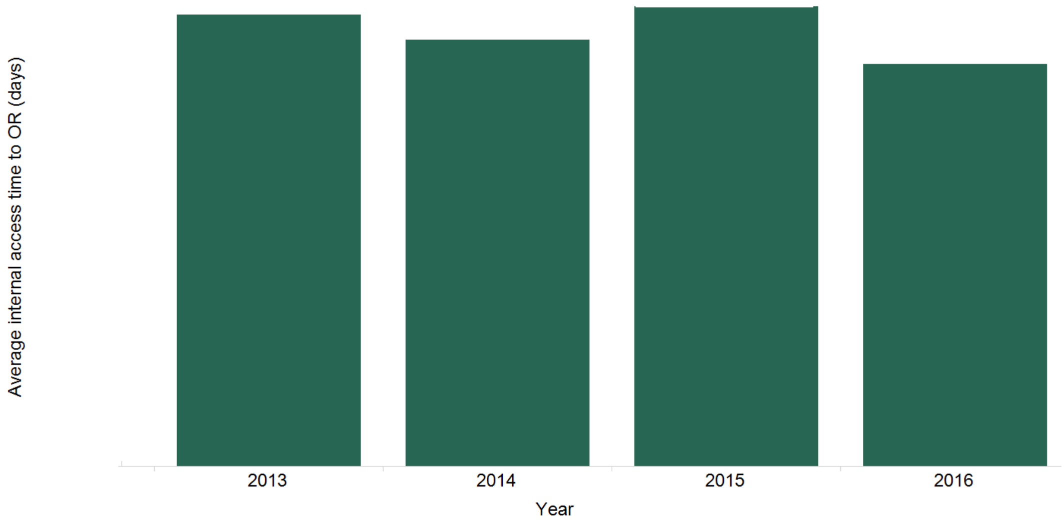


Figure 11 - Average internal access time to OR for elective patients

Figure 12 presents the average internal access time to the OR for solely the 'emergency' patients, we excluded the emergency categories 'acute', '1 month' and '2 months'. The first thing we conclude is that this average internal access time for emergency patients is significantly lower than that for elective patients. Elective patients have an average internal access time to the OR of approximately **X** days whereas emergency patients have an average internal access time of approximately **X** days.

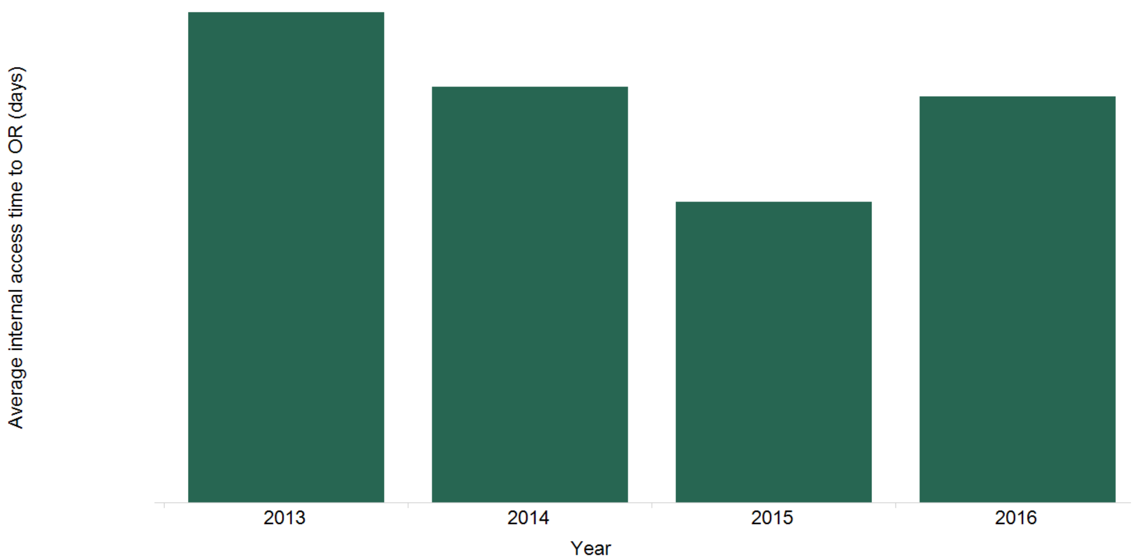


Figure 12 - Average internal access time to OR for solely emergency patients

The SMK defined a desired limit of **X** days as maximum average internal access time to the OR for emergency patients. The second thing we conclude from the graph is that the average internal access time to the OR is only within the limit during the years 2015 and 2016. However, the data of 2016 is not complete so maybe the average of 2016 changes and ends above the limit.

Figure 13 presents the average internal access time to the OR for all of the four emergency categories separately. A certain limit for the internal access time is stated for each emergency category as described in Chapter 4. This limit for 'acute' patients (A) is an average internal access time to the OR within **X** days. The figure presents that the average internal access time for 'acute' patients is not within this limit each year. The limit of average internal access time to OR is set for the '1 month' category (1 m) on 30 days and for the '2 month' category (2 m) on 60 days. For both categories the average internal access time to the OR is relatively stable and around the limits, respectively **X** days and **X** days. The average internal access time for 'emergency' patients (E) is already analysed in Figure 11.

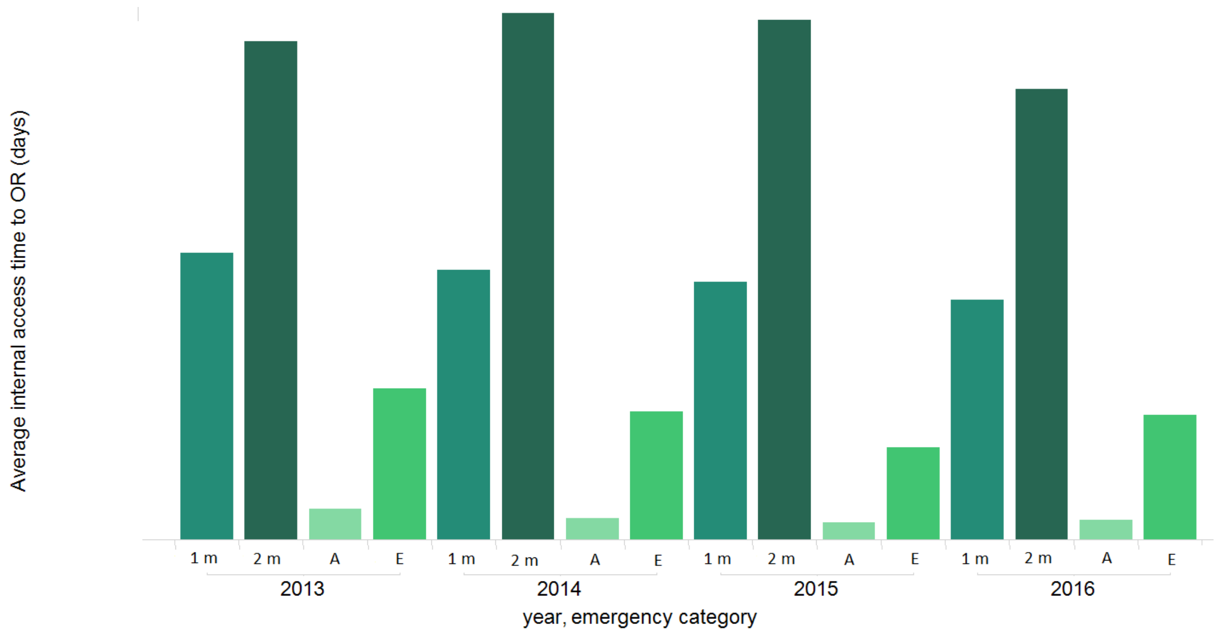


Figure 13 - Average internal access time to OR per emergency category

Figure 14 presents the amount of surgeries in the period of 2013-2016. The amount of surgeries is significantly less in July 2013, August 2014, and in August 2015. During other months of the year the amount of surgeries is fluctuating with no certain repetition. We have seen in Figure 9 that during the end of the year the duration is above average. In 2013 there is a peak wave during month nine, ten and eleven. In 2014 there is a peak during month nine and ten and in 2015 there is a peak during month nine, ten and eleven. However, there are more relative maximums separated over the year. We assume that the peaks during the end of the year result from the minimums in months seven and eight.

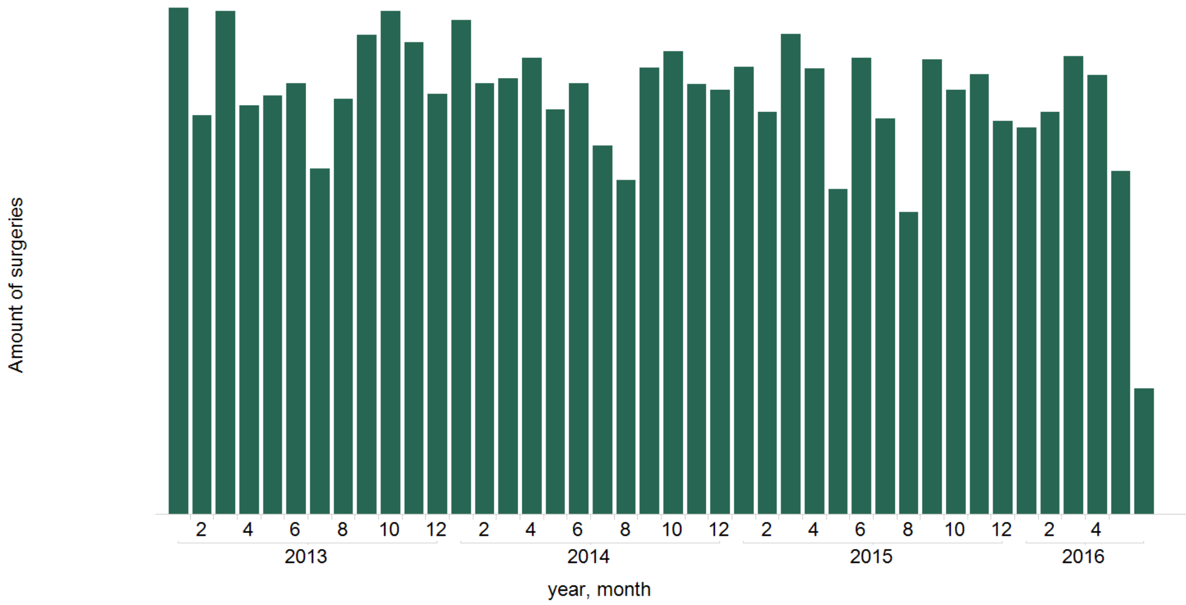


Figure 14 - Amount of surgeries in 2013-2016

Combined durations

In this paragraph we show the duration of the external access time, the diagnostic process time, and the internal access time to the OR combined in one bar chart. In order to compare these three durations with each other, we use solely data from complete episodes. It is possible to calculate the average external access time for all patients together. However, not all of these patients receive surgery and thus have an internal access time to OR. By using complete episodes, we can compare the durations. We can show them in the same proportion as experienced by patients.

Figure 15 presents the average duration of the external access time, the diagnostic process time, and the internal access time to the OR calculated over the period 2012 until 2016. There is a significant difference between the three durations. The external access time is the shortest duration within the whole duration of an episode. The average duration of **X** days corresponds to the duration of **X** days reflected in Figure 6. The average diagnostic process time takes more than **X** days and corresponds to Figure 8. The internal access time to the OR is around the **X** days and corresponds to Figure 8.

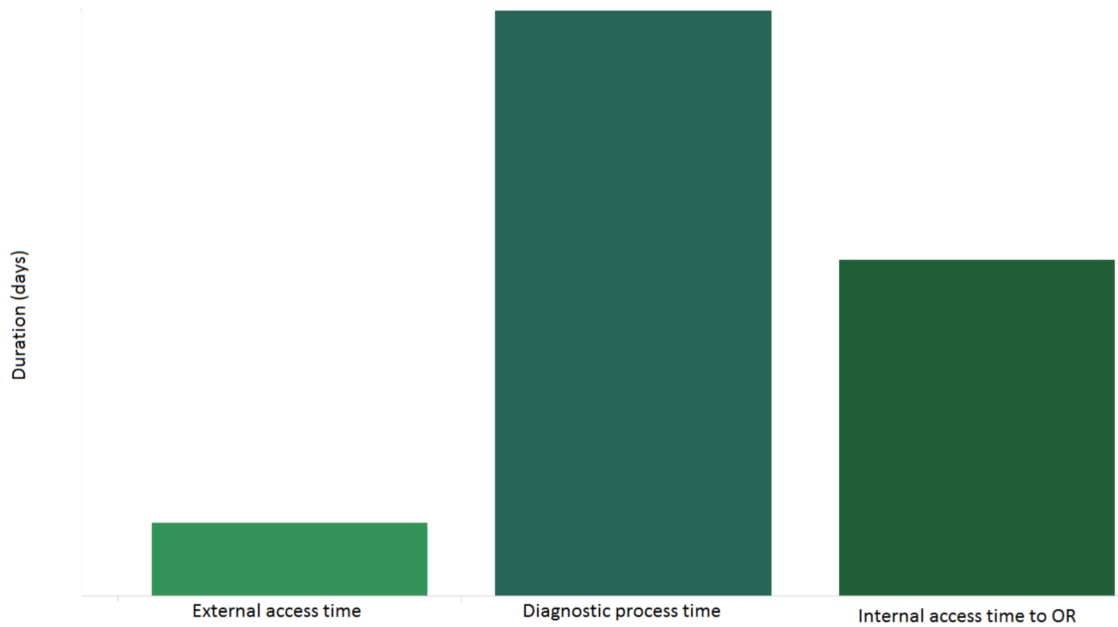


Figure 15 - Average of the three durations over the period 2012-2016

Figure 16 presents the average duration of the external access time, the diagnostic process time, and the internal access time to the OR per year. Each duration is reflected over the period 2012 until 2016. The graph shows that the external access time is a bit reduced over the reflected period. The diagnostic process time followed a downward trend during the reflected period. This trend is possibly non-existent, since the registration of the diagnostic process time in 2012 and 2013 is affected by the introduction of the data registration system Chipsoft in 2012. The Internal access time to the OR remained relatively constant.

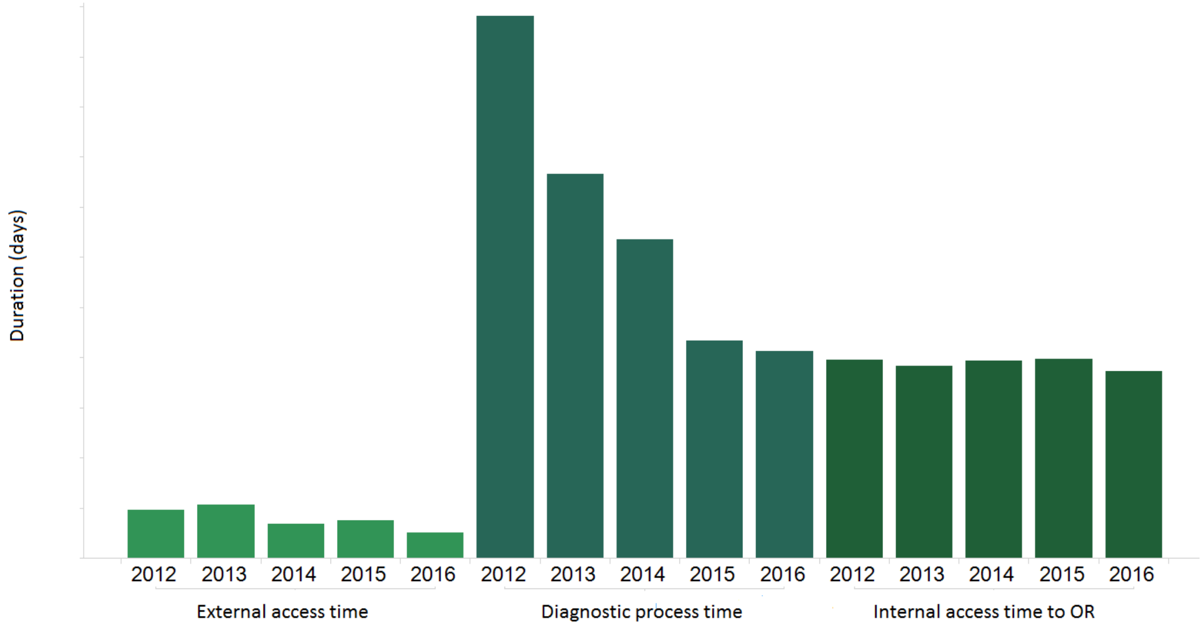


Figure 16 - Average of the three durations per year over the period 2012-2016

Figure 17 presents the Sankey diagram of the patient flow. Data from the period 2012-2016 is used. 100% of the patients is initially referred to the first consult outpatient clinic where the 100% arrives. 64% of the patients do not receive an OR-receipt against the other 36% of patients that receive an OR-receipt. From the patients that receive an OR-receipt only 67% percent receives surgery. The other 33% cannot receive surgery based on the results of the screening. 16% of the patients that receive surgery are patients within one of the four emergency categories. 84% of the patients that receive surgery are not emergency patients.

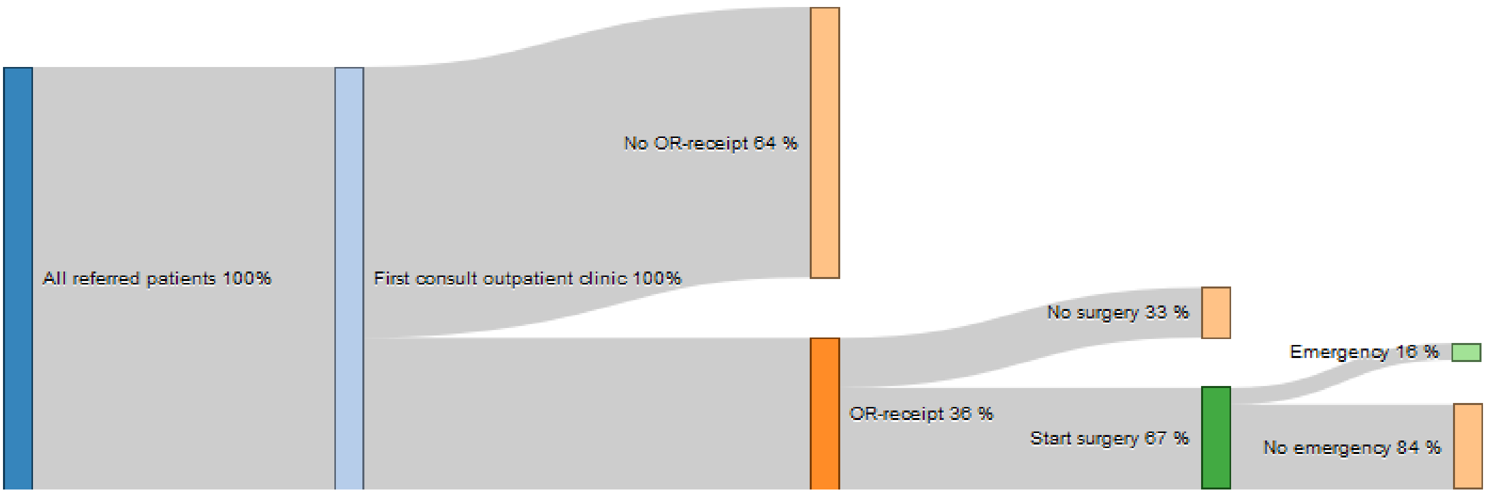


Figure 17 – Sankey diagram of the patient flow

6.2 Conclusion

We enable measuring of the patient flow by expressing the three durations in bar charts. The average external access time is fluctuating between **X** days during the period 2013-2015. The average external access time in 2013 is approximately equal to the average external access time in 2015. However, we noticed that the maximums in 2013 are almost **X** days higher than the maximums in 2014 and 2015. We also notice waves in average external access time with minimums in month ten during 2013 and 2014. However, in 2015 there is no minimum in month ten, but the average external access time falls down during the first months of 2016 and is reduced more significant until now.

We were only able to reflect the average diagnostic process time for the years 2014 and 2015 due to the lack of data in 2013 and 2016. We assume a relationship between the average external access time and the duration of the diagnostic process time. If the average external access time is high, we assume that there are more patients in the diagnostic process which makes the duration of the diagnostic process time higher. Based on Figure 7, patients that are finished with the diagnostic process in month ten had a diagnostic process of **X** days. So, these patients had their first consultation approximately six months ago, in month four. Figure 6 presents the average external access time per month, so the average external access time for patients that have their first consultation during that month. Month three and four are peaks which means that the higher the average external access time, the more patients, thus the longer the diagnostic process time.

The average internal access time to the OR for all patients together fluctuates between the **X** days. We expect the average internal access time to the OR for elective patients higher than **X** days and for emergency patients lower. Fortunately, the average access time to OR for elective patients is **X** days and for 'emergency' patients (one of the four emergency categories) **X** days.

For the emergency patients (all the emergency categories) a desired maximum of internal access time to the OR is set. The limit of average internal access time to OR is set for the '1 month' category on 30 days and for the '2 month' category on 60 days. For both categories the average internal access time to the OR is quite stable and around the limits. The average internal access time to the OR for 'acute' patients and 'emergency' patients is not each year below the desired maximum.

The visualisations of the combined data presents an overview of the results of the three durations. The diagnostic process time has the longest duration. The downward trend in the diagnostic process time is possibly non-existent, since the registration of the diagnostic process time in 2012 and 2013 is unreliable. The external access time has the shortest duration with an average of **X** days. The internal access time to the OR is relatively constant over the period 2012-2016 with an average of **X** days.

The Sankey diagram presents the relative amount of patients within the patient flow. After referral 100% of patients have a first consult at the outpatient clinic. An OR-receipt is received by 36% of the patients. The relative amount of patients with an OR-receipt that receive surgery is 67%. From the patients that receive surgery is 84% an elective patient against 16% emergency patients.

Chapter 7 – Conclusion

This chapter describes the conclusion of our research. Section 7.1 provides the conclusion of our research. Section 7.2 describes the limitations of our research. Our recommendations are discussed in Section 7.3. Section 7.4 proposes further research on patient flow analysis in the SMK.

7.1 Conclusion

In this thesis we enable the measurement of the patient flow in the SMK. For this purpose we did research concerning aspects, critical for effective measurement of the durations of the patient flow.

Firstly, we have identified three duration variables to calculate, to enable measuring of the patient flow in the orthopaedic clinic. These variables include: the external access time, the diagnostic process time, and the internal access time to the OR. To quantify these durations we identified four critical timestamps. These critical timestamps are: the referral of a patient, the first consult at the outpatient clinic, the decision to perform surgery, and the start of the surgery.

Secondly, for the interpretation of the data in the information system (Chipsoft), in-depth knowledge regarding the patient flows within the SMK is required. An overview of the patient flows is presented in Figure 3, and was constructed based on conversations with employees in the SMK.

Thirdly, we conducted a literature review to identify the most commonly used methods to analyse and assess the patient flow. We have created a classification matrix that reflects the sources of input data and methods. It can be used for discussion, analysis, and information retrieval. We can conclude that the most commonly used input data originates from an information system and the most commonly used method is statistical analysis. Therefore we have used these methods in this research.

For our analysis we used the data from the internal information system, Chipsoft. We need a dataset that contains data of the four timestamps that we have identified. Since this data was available in three separate databases we have created a conceptual data model to structure the data and merge the information into a single dataset.

To prepare this raw dataset for analysis different steps have to be completed. The most important steps include the cleaning and complementing of the data. The cleaning and the complementing of the data is performed using the programming language R. Calculations and analysis of the durations of the patient flow process are visualised. The reliability of our dataset is dependent of the database where all the data is manually recorded by employees of the SMK. This probably restrains results from complete accuracy.

The visualisations of the results enables analysis of the data. The external access time is between the **X** days and is a bit reduced over the period 2012-2016. The diagnostic process time is between **X** days. The internal access time to the OR is between **X** days over the period 2013-2016.

7.2 Limitations

Our research had several limitations. First, the lack of available and reliable data. Chipsoft is introduced in April 2012. Therefore, the data of 2012 is not reliable due to the lack of data in the beginning of 2012 and the failures in the data due to the introduction of a new data information system. Another limitation related to the lack of available and reliable data is that only the data of the first half year of 2016 is available.

The second limitation is the existence of failures and errors in the data. For example, we calculated a negative average access time to the OR. The reason for this data error was the bad registration in Chipsoft by employees of the SMK.

The last limitation of our research is that we did not analyse all the diagnostic process times but only the ones that we could link to an OR-receipt. This gives a skewed image of the diagnostic process time.

7.3 Recommendations

Firstly, we want to recommend the SMK to train their employees in recording the data correctly. Employees need to acquire knowledge about the recording of data and acquire awareness that accurate recording of data is required for the analysis and improvement of healthcare processes.

Secondly, all the recorded data in the databases must be linked to an episode number. When the recorded data is linked to an episode number, it makes the database more reliable.

We also recommend the SMK to continue with the analysis of the patient flow. The program we created can be used by the 'Logistiek Bedrijf' to perform further analyses in the future. We recommend to develop our program further to gain a more specific view of the patient flow process.

Finally, the results of our research can be used to identify areas for improvement in the patient flow. This enables the coordination of the integral logistics in the SMK and improvement of the entire care pathway.

7.4 Further research

We solely include literature about analysis and assessing the patient flow in our classification matrix. Further research can incorporate literature about improving the patient flow to gain a more complete classification matrix for discussion, analysis, and information retrieval.

To improve the measurability of the patient flow in the SMK, we propose to measure more durations by adding timestamps. For example, the screening can be included in the third duration that calculates the average internal access time to the OR. Then the duration between issuing the OR-receipt and the screening can be calculated, and the duration between the screening and the start of the surgery. Including more timestamps in the process makes it possible to calculate more durations which results in a more accurate view of the patient flow.

The second duration, about the diagnostic process time, expands by including more timestamps that reflect the end of the diagnostic process. We solely calculated the diagnostic process time for patients for who is decided that they receive surgery. Issuing the OR-receipt reflects the end of the duration of the diagnostic process time. It is possible to identify more activities that represent the end of the diagnostic process time, even for patients for which an OR-receipt is not issued.

The first duration, about the average external access time to the SMK, expands when the data is registered in a way that it is possible to calculate the average external access time for the patients of different origins separately.

It is possible to use the dataset that we used for this research, created in cooperation with the IT-department in the SMK, for further research. The 'Logistiek Bedrijf' can use our dataset for further research about analysing and improving healthcare processes in the SMK.

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Appendix A – List of abbreviations

GP = general practitioner

OR = Operating room

SMK = Sint Maartenskliniek

Appendix B – Articles used to create classification matrix

Searching process

In our analysis of patient flow literature we tried to get an overview of the most commonly used methods to analyse the patient flow. The literature study was carried out from April 2016 until June 2016 and covers literature about the patient flow from an operation research perspective.

We used different keywords in our online search for patient flow literature. We used the network of the University of Twente to gain access to the articles at the websites. Table 3 presents how many articles we analysed per search term.

In the process of the literature analysis we noticed that patient flow literature sometimes focuses on solely emergency departments. Our research includes both elective and emergency department. Therefore, this literature is not suitable for our research and we tried to exclude these articles with the "-" command.

We were looking for the most commonly used methods to analyse and asses the patient flow. During the searching process we found out that more specific terms were required to find articles that are scarce for certain methods.

Table 3 - Frequency of analysed articles per search term

Keywords	**Estimated amount of analysed articles (without doubles)**
Patient flow	20
Patient flow -emergency	10
Patient flow -emergency - acute	2
Patient Flow Operation Research	10
Patient flow simulation	5
Patient flow staff perspective	5
Patient flow theory	5
Patient flow queuing	1
Process mining healthcare	5

Bibliography of articles in classification matrix

Table 4 - Proposed classification matrix

Classification matrix for literature about patient flow analysis		**Elective and emergency**							**(semi) Emergency**							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Input data	I1: Failure mode and effects analysis										x					
	I2: Feedback from staff								x					x		x
	I3: Information system data	x	x	x		x			x	x	x	x	x	x	x	
	I4: Structured observations				x		x						x			
	I5: Predictive analytics							x								
Method	M1: (Computer) simulation		x		x			x								
	M2: Mathematical programming												x			
	M3: Qualitative analysis															x
	M4: Queuing theory									x						
	M5: Spreadsheet analysis						x		x						x	
	M6: Statistical analysis	x		x		x			x		x	x		x		x

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Appendix C – Scripts in R for patient flow analysis

(confidential)