Optimizing the planning of regular multi-disciplinary checkups in Isala using discrete event simulation

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Preface

This report is the result of my graduation project, at the internal medicine department of Isala Clinics in Zwolle, which I executed for the final part of my Industrial Engineering & Management master program. I am grateful that I was able to study at the University of Twente. I am thankful that I could perform my graduation project at Isala Clinics Zwolle. I have been interested in healthcare logistics ever since I started this master, and I really enjoyed taking part in such an assignment. Specifically, I want to thank Jelmer, who offered great feedback and insights when I needed it the most. Furthermore, I want to thank my supervisors from the University of Twente, Gréanne and Sebastian. Gréanne, it was incredible to see how quickly you always were up to speed with my progress. Whenever I tried to ask something, you always immediately understood what I was trying to say, no matter how unclear my question were. Sebastian, your feedback helped me improve my modelling skills and find smart solutions for problems I encountered. I also want to thank my supervisors from Isala, Titia and Ingrid. Titia, your knowledge of the process and drive to find improvements got me right on track from the first day onward. Ingrid, your connections and quick thinking often got me out of situations where I was lost. I also wish to extend my thanks to my Isala companions, Ruben and Stan, who stood by me throughout the research journey, consistently brainstorming and providing assistance during my moments of difficulty. Finally, I want to thank my girlfriend, friends and family for supporting me the past eight years. I have learned a lot in these years, about operations research and about myself, and I look forward to what the future will bring!

Jur Horstman
Zwolle, November 2023

Management summary

Problem definition

This research is performed at the internal medicine department of Isala Clinics in Zwolle (Isala), with a special focus on the diabetes center in Zwolle. The diabetes center treats diabetes people of all ages with diabetes. These patients have an annual multidisciplinary checkup, called the IDEAAL checkup. Currently the department finds themselves in a situation where it is too hard to plan IDEAAL checkups for every patient on one day respectively. Therefore, we formulate the following research question: *How can the number of scheduled hospital days for the IDEAAL checkup per individual patient be minimized without increasing the overtime for staff and while minimizing the waiting time between appointments?* In the current situation the planners do not plan every element (appointment) of the checkup, resulting in partly scheduled IDEAAL checkups. Also, these different appointments are not planned on a single day, resulting in more pressure on the logistics of the hospital and calendars of patients. The reason for not planning complete IDEAAL checkups on a single day finds its roots in the low availability of caregivers and the need for rescheduling a complex combination of appointments after a potential cancellation. Both of these problems are influenced by the booking horizon, which thus became the focus of this research.

We start by determining how well the current situation performs, in which we found that 0.4% of the IDEAAL checkups got carried out entirely in a single day. This is mostly caused by the planners not being instructed to plan complete IDEAAL checkups nor them being instructed to plan them on a single day. All based on the presumption of IDEAAL checkups being impossible to plan on a single day.

Solution Design and Evaluation

We design a solution approach for the analyzed problem. We formulated a discrete event simulation (DES) to test different booking horizons and see how changing this booking horizon impacts the potential to plan complete IDEAAL checkups in a single day. To first proof planning IDEAAL checkups in a single day is possible, a mathematical model has been developed. Thereafter, by using the DES we can give a more specific advice, related to the focus of this research, the booking horizon. The DES contains several heuristics, to approach reality as much as possible. Examples of the use of these heuristics are: finding appointment dates, sequencing appointments and changing availability. The Key Performance Indicators (KPIs) used to measure results from the DES are: “Fraction of single day checkups”, “Fraction of not scheduled patients”, “Throughput time of patients” and “Delta weeks”. With the first KPI “fraction of single day checkups” being the most important measure to take into account.

Results

We executed a base case analysis of the diabetes department in which the instruction for the planners would be changed to: try to plan as many complete IDEAAL checkups on a single day as possible. The results of this base case experiments were not in line with the expectations of Isala. In these results we see that taking a booking horizon of twelve weeks is optimal and results in an average of 88.5% patients scheduled on a single day. From this we conclude that it is possible to plan most IDEAAL checkups on a single day. By varying the demand rate, cancellation rate, availability of caregivers and assignment of preferred caregivers we found that the results found from the base case are robust. Less impactful changes like increasing or decreasing the cancellation rates, having a small (7.8%) demand increase or equalizing the demand rate over the year, still resulted in twelve weeks being optimal with a single day fraction of 88.6%, 88.6%, 89.1% and 88.4% respectively. Only extreme changes to the settings would change the single day fraction, the

twelve-week optimal booking horizon would remain the same. We also analyzed extreme settings in which cancellation rates and patients outside IDEAAL checkups, fair workloads, smart pairing of caregivers and an extreme demand increase. These experiments resulted in single day checkup fractions of $99.8\%, 91.7\%, 95.2\%$ and 84.3% respectively. The results of the experiments show that it is possible to start planning IDEAAL checkups on a single day and that there is still room for improvement aside from 'simply' starting to instruct planner to plan on a single day. We see small differences between experimental results, but although these difference are small, they are statistical significantly different.

A drawback with regards to the results is for the employees to work with changes. People, with a health care background, are taught to work in a risk-averse manner. They learn to first thoroughly test before implementing. This makes it harder for them to implement and accept changes suggested to their work.

The large difference between the results of the experiments and the current situation is explained by the work instruction for planners and Covid regulations. Due to Covid regulations, Isala stopped planning IDEAAL checkups on a single day in 2020. After ending the Covid regulations, Isala did not adjust the work instruction accordingly. Resulting in planners still planning IDEAAL checkups on multiple days and leaving out some appointments. Instructing planners to plan appointments spread over multiple days directly explains the low single day checkup fractions in the current situation.

Practical contribution
The practical contribution of this research is that the diabetes center in Isala can almost half the visiting days for IDEAAL checkups (from 0.4% checkups on a single day to 88.5% on a single day) of patients. In the current situation the researched patient group has a total of 1112 hospital visits ($= 0.996 \cdot 557 \cdot 2 + 0.004 \cdot 557$). When comparing this to the base case, where the patient group has a total of 621 hospital visits ($= 0.885 \cdot 557 \cdot 2 + 0.115 \cdot 557$), we reduced the number of hospital visits by 44% ($= 1 - \frac{621}{1112}$). Changing the work instructions greatly reduces the pressure on patient calendars and hospital logistics created by IDEAAL checkups.

If Isala would implement the changes to combinations of caregivers, number of hospital visits will be reduced to 48% ($= \frac{(0.952 \cdot 557 \cdot 2 + 0.048 \cdot 557)}{1112}$). The fact that the department can simply start steering on the reductions by changing instructions for planners makes it easily implementable.

Scientific contribution
We show that a large complex problem can be split into multiple smaller and more solvable problems. Approaching problems in such a matter, makes it possible for future researchers to tackle greater and more complex problems than before. Also, our DES and its heuristics give us insight in how gaps in knowledge and/or data can be overcome. An example would be the way we overcame the lack of data on availability. By categorizing small portions of data, we created fewer portions with more data. This made us able to still analyze the data and gain valid data from a small database. We also showed that a complex and hard to solve problem for a mathematical model can still be solved by implementing a DES.

We combined the results of an mathematical model into a DES by using heuristics to approach the results found by the mathematical model. This thesis shows how multiple advanced solution approaches can be combined into one and these can be adjusted so they complement each other and make the results of both more valid. To the author's knowledge, no solution approaches are found in the literature that compare exactly to the approach proposed in this thesis. Few approaches are close, but applied on less complex circumstances.

Contents

1 Introduction

This chapter introduces Isala, as the problem owner. Here we identify the problem experienced by Isala. In the current situation they find it impossible to plan IDEAAL checkups in one day. Finally, we describe the research plan to find a solution to improve the current situation.

1.1 Problem definition

This research took place at Isala Clinics in Zwolle, as a graduation assignment of the master program Industrial Engineering & Management of the University of Twente.

1.1.1 Hospital description.

This research is conducted at the internal medicine department of Isala Clinics in Zwolle, with a special focus on the diabetes centrum in Zwolle. Further references to Isala Clinics in Zwolle will be mentioned as Isala. Isala has five locations situated in Zwolle, Meppel, Steenwijk, Kampen and Heerde. It has about 7,000 employees, 1,250 beds and a yearly turnover of about 824 million euros (Isala, n.d.).

The diabetes center at Isala is one of the largest diabetes centers of the Netherlands and treats people of all ages with diabetes. The treatment team is located at a single location to be able to deliver the correct customized care, where pediatricians and internists work alongside. Having the diabetes nurses, podiatrists, and dieticians at the same department makes it easy for specialists to discuss cases (Isala, n.d.).

1.1.2 Problem description

The diabetes center at Isala aims to deliver value-driven care. According to Porter & Lee (2013) five steps to achieve value-driven care, are: forming a multidisciplinary team, optimizing care pathways within the care chain, defining outcome measures, learning and improving at three levels, and measuring costs and making payment agreements per care chain based on quality.

This study will focus on the second step, “optimizing care pathways within the care chain”, because that is the expertise of the researcher. More specifically, this means re-evaluating the planning process and finding a way to decrease the number of hospital visits for patients. Children and young adults with diabetes type 1 visit the hospital annually for the *Isala Diabetes Extensive Annual All-in Loop* (IDEAAL) checkup during their birth month. The IDEAAL checkup is a multistage checkup, consisting of several disciplines. First, blood and urine samples are sent to the lab. Thereafter the blood pressure of the patient will be measured. This could be followed by routine questions about the patient's quality of life and satisfaction involving the delivered care and reading out the devices. Thereafter, the patient has an appointment with the diabetes nurse and is required to have a retina photo taken if needed. Once this is done, the patient also visits a podiatrist and/or a dietician depending on their diagnosis. Finally, the patient visits the internist or pediatrician to discuss all the results of the yearly checkup. Figure 1 provides a visual overview of this multistage checkup.

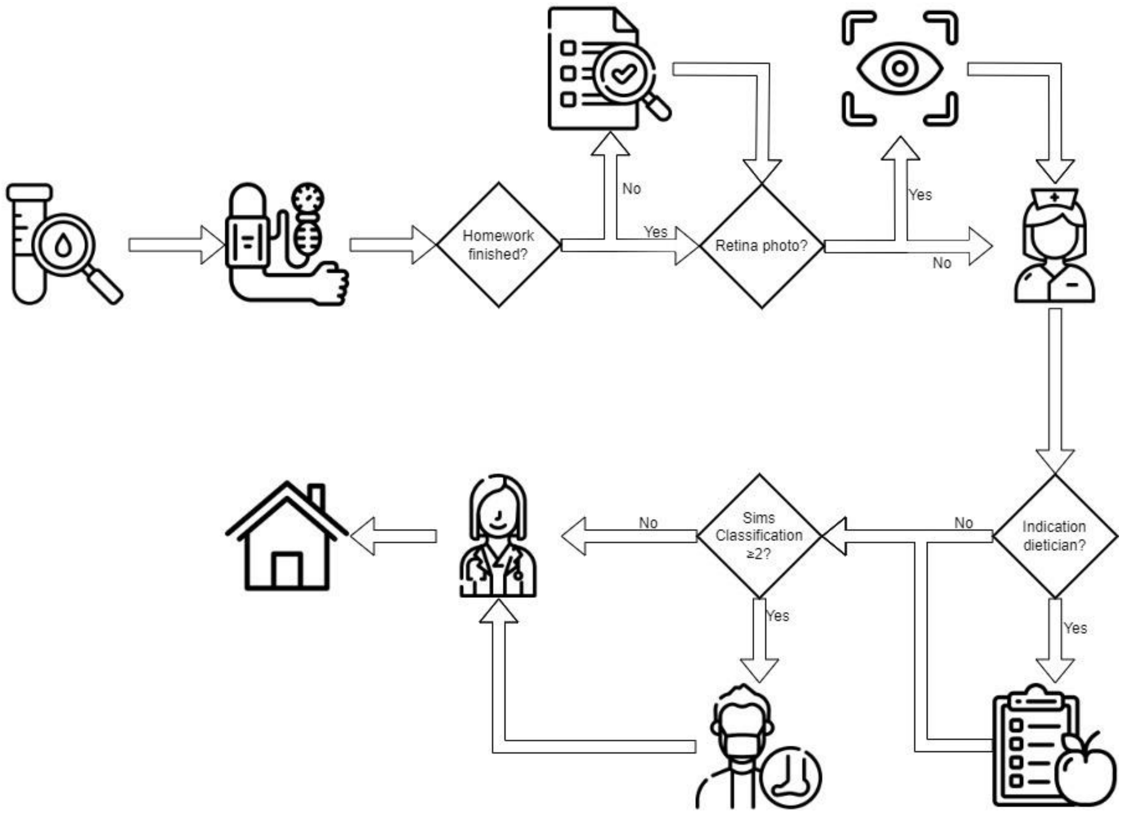


Figure 1 IDEAAL checkup

Figure 1 contains four directional questions, influencing the care pathway of a patient. The first question is “Homework finished?”, checking whether patients filled out the questionnaire and read out their devices at home or if that still has to be done at the hospital. The second question “Retina photo?” refers to whether the patient needs to have a retina photo taken. Depending on the patient this photo is either never, yearly, once every other year or once every three years taken. This photo will be evaluated by an eye doctor and in the future possibly by an AI. At the time of planning the IDEAAL checkup, it is known whether the patient needs a retina photo taken or not. The third directional question is “indication dietician?”, where it is checked whether the patient has an indication for a dietician. The last question is “Sims Classification ≥2?”, which is determined by the diabetes nurse during the prior IDEAAL checkup. The Sims classification is a model developed to indicate the stage of the foot issues of a diabetes patient and determine the necessary care. The higher the classification the bigger the risk of foot wounds to arise (voetencentrum wender, 2023).

Note that there is a minimum fixed time period of two weeks for evaluation of the retina photo at Isala. This time period cannot be reduced and is considered fixed in the optimization of the planning.

1.1.3 Action problem

The action problem is the problem as identified by Isala. In general terms, the action problem can be described as a situation that is not as it is desired to be (Heerkens & Van Winden, 2021). In the current situation, it is not possible to complete the IDEAAL checkup for all patients in a single day, which means that the patient has to visit the hospital multiple times. This is an undesirable situation for both the patient and the caregiver, in this case Isala. For patients, visiting the hospital multiple times results in more absenteeism from work, more travel time and higher costs. Isala benefits in form of pressure release on the hospital facilities in case patients limit their visits.

1.1.4 Problem identification

In order to understand the root cause of the action problem, a problem cluster is created. This problem cluster is depicted in Appendix A: Problem cluster. The problem cluster was established based on discussions with stakeholders in the process. Based on the previously described action problem, the problem cluster was further developed.

This problem cluster shows that the action problem has multiple connected causes. The staff working on the IDEAAL checkup have extremely full agendas, and combining this with appointments taking more time than planned makes it currently impossible for the planners to manually schedule the IDEAAL checkup in one day for every patient. To receive results of the lab research in time, every lab research is set to a rush order to ensure the results arrive in time, making the planning process for the planners more complex. One more thing making the planner having to schedule multiple days are no-show patients. But to keep the research focused, it is chosen to leave the no-show patients out of scope.

A possible root cause that is left out of scope is the evaluation of the retina photos by the eye doctor. According to internists these results are not essential for the IDEAAL checkup on the day itself. Leaving the root causes “shifting booking horizons” and “incorrect and incomplete planning rules” as the main focus for this research. As a result of these two root causes there is not a standardized planning method, every patient is manually planned into the agendas of the different staff by the planners. The requisite for the planners is to make sure that the lab appointment is the first appointment and the appointment with the internist or pediatrician the last appointment, this planning process not optimized.

In despite of a standardized planning method for how the appointments are placed in the calendars, the booking horizon is also not standardized. The booking horizon is the time between planning of an appointment and the date of the appointment itself. Varying booking horizons have different impacts on the plannability of an appointment and should therefore also be considered when finding an optimal standardized planning method.

1.2 Research plan

1.2.1 Research objective & Scope

The aim of this research is to find a way to maximize the number of patients that can be scheduled for the IDEAAL checkup in a single day, without requiring the staff to work extra overtime and by minimizing waiting times between appointments. This objective contributes to the goal of Isala to optimize care pathways within the care chain.

The research will be conducted at the diabetes center of Isala. To limit scope, it will solely focus on patients with diabetes type 1, between 0-26 years old. This is a patient group that participates in the IDEAAL checkup. However, that, the solution approach will be kept generic in order to maintain applicability. The research is conducted in approximately half a year.

This problem is considered complex due to the following:

- We are dealing with a multistage problem where multiple calendars and availabilities play a role.
- The duration of appointments is stochastic, but to fit it to different agendas the durations can be assumed to be deterministic.
- There are multiple unique care pathways that patients take, which can alter depending on the patient going through the care pathway.

To the authors' knowledge no literature is available on a planning problem with all these issues combined, making this an assumed valuable contribution to the established literature.

1.2.2 Research Design

This section lists the research questions, which will form the structure of this research. All research questions will relate to the main research question:

How can the number of scheduled hospital days for the IDEAAL checkup per individual patient be minimized without increasing the overtime for staff and while minimizing the waiting time between appointments?

The sub-questions together will result in an answer to the main question and will be based on the following structure: current situation description, literature review, solution design, solution evaluation and recommendations.

1. **How are the IDEAAL checkups currently planned and how does it perform?**
   This sub question will describe the current situation both in text and numbers. It will describe how the planning is currently made and how it performs. The performance of the planning will be based on "Number of single day IDEAAL checkups". The goal of this research question is to get a good grasp on how the IDEAAL checkups are currently planned. The staff involved will be interviewed and the past data, generated by Isala, will be reviewed. A final goal of this part is to identify potential bottlenecks in the process.
2. **How are optimal booking horizons found according to the literature?**
   A systematic literature review will be conducted to find out what types of solutions have been found in the literature for similar problems and how this solution could help in finding a solution for the diabetes center of Isala. This part will also determine which method is going to be used to solve the issues at hand.
3. **How to find the optimal planning approach for the IDEAAL checkups?**
   The method to solve the IDEAAL checkup planning problem will be developed. A simulation optimization approach will be used to determine an optimal IDEAAL checkup booking horizon and a mathematical model will be developed to optimize the blueprint planning.
4. **How does this new planning approach impact the planning of the IDEAAL checkup?**
   An extensive sensitivity analysis will be carried out in which the newly developed planning method will be tested. The current situation will function as a benchmark to show whether and how the newly developed method is better than the current situation. The new planning method will also be tested for changing circumstances such as an in- or decrease in patients or hiring/leaving staff.
5. **What are the recommendations that can be given to Isala with regards to planning of the IDEAAL checkup and how can a solution be implemented?**
   An implementation plan will be formulated, accompanied by the conclusions that can be drawn from the results and recommendation for the future.

2 Current Situation

The sub-question *"How are the IDEAAL checkups currently planned and how does it perform?"* is elaborated and reflected upon the current situation regarding the IDEAAL checkup by the following section. The goal of this section is to describe the way patients are currently planned, and how this method performs. This chapter demonstrates why Isala needs a new way of planning and will give a benchmark to compare solution results with.

2.1 Description of diabetes department

2.1.1 Aim of the department

The diabetes department only treats patients with diabetes. They treat patients that experience inconveniences as a result of them being a diabetic. Since diabetes is a chronic disease, diabetic patients also receive their regular checkups at the diabetes department.

The diabetes department in Isala is aiming to improve the quality of care. To accomplish this to the best of their abilities the department is implementing the steps of "value driven care". Optimizing the IDEAAL checkup planning is one of the examples of this. Optimizing the planning of IDEAAL checkups contributes to the goal of optimizing care pathways within the care chain.

2.1.2 Care pathways

As the IDEAAL checkup has a flexible care pathway, there are different pathways a patient could take to do their checkup. The entire care pathway with, including all their possible branches, is shown in Figure 1. From this figure we can deduce the "standard care pathway", which every patient has to follow in order to have undergone a complete IDEAAL checkup.

The standard care pathway consists of the following planned appointments: Laboratory research, a blood pressure test, consultation with a diabetes nurse and a consultation with an internist. Important to note is that for every IDEAAL checkup the laboratory research always has to be scheduled first and the consultation with an internist last. The other appointments do not have a fixed sequence.

An IDEAAL checkup has three variable appointments, namely: a retina photo, consultation with a dietitian, and consultation with a podiatrist. These appointments all occur independent of each other. At the end of every IDEAAL checkup the internist determines the care pathway the patient will undergo the following year. Which consists of the standard care pathway, plus any, all or none of the variable appointments.

2.1.3 Appointments and their specialists

Since the IDEAAL checkup is a multidisciplinary appointment combination, there are a couple of different specialists involved. The most noteworthy are the internist, pediatrician and diabetes nurse. These specialists are always included in every IDEAAL checkup, carrying out the appointments of the standard care pathway. Whether the patient sees a pediatrician or internist is based on age, once the patient becomes an adult they will switch away from the pediatrician to an internist.

In Table 1 an overview of all appointments and their specialists is given. The percentage given in the frequency column are the fraction of IDEAAL checkups that contain the appointment. The numbers are retrieved by analyzing the current situation. Since the podiatric consult is not yet included in the IDEAAL checkup, no frequency is known. Despite the results of the current situation, the standard care pathway appointments are given a frequency of 100%. In the desired situation these appointments should be part of every IDEAAL checkup.

Table 1 Overview of appointments and their specialists

Appointment	Caregiver	Department	Why	Current frequency	Input frequency
Lab	Lab worker	Laboratory	To check health values	90.0%	Yearly (100%)
Bloodpressure	Doctor assistant	Diabetes	To check bloodpressure	81.7%	Yearly (100%)
Nurse consult	Diabetes nurse	Diabetes	Check current health status	37.5%	Yearly (100%)
Retina photo	Doctor assistant	Diabetes	Check the eyes	45.6%	Health dependent (45.6%)
Dietician consult	Dietician	Diabetes	Education on carb counting and carb/insuline ratio	2.4%	Health dependent (2.4%)
Podiatric consult	Podiatrist	Diabetes	Patient is in care profile 1 or higher	0.0%	Health dependent 0.0%)
Doctor	Internist/pediatrician	Diabetes	Discuss the results of prior appointments	91.4%	Yearly (100%)

2.1.4 Current planning strategy

Currently all appointments are planned manually by planners. The diabetes department has its own team of planners that focus on planning appointments on the diabetes department only. Not all young adult type 1 diabetes are currently included in the IDEAAL checkup.

The planners are planning IDEAAL checkups both on long-term and short-term. The long-term planning is done according to the following steps:

1. **Pick from the list of "need to plan patients";**
   Patients that require an appoint will automatically be placed on this list by HiX. The planners can open this list and work through it, planning appointments.
2. **Check the prescribed appointments;**
   The doctor creates an order at the end of their appointment, which includes the desired appointments for next year's IDEAAL checkup.
3. **Combination of the prescribed appointments;**
   The planner creates an appointment combination, including all prescribed appointments from the doctor's order. This appointment combination is seen as one appointment.
4. **HiX checks availability in the calendar;**
   The planner gives a time period for HiX to search in. HiX checks for the availability in the calendars of the service providers to find timeslots where the appointment can be scheduled. This system looks for timeslots in the IDEAAL raster. The planner chooses one of the available slots, if there is no time slot available one more step will be taken.
5. **Manual planning of the combination.**
   If the system is not able to find a date for the combination of appointments, the planner looks for a way to plan the combination anyways. This for example can be done by overwriting freed blocks for certain appointment types, by looking in another time period or planning the appointment over more than one day.

Now the appointment combination is planned in the agenda of all caregivers and also the patient will be informed automatically. This results almost always in an IDEAAL checkup planned on one day.

The short-term planning is where it becomes more complicated for the planners. There are several reasons for changes in the IDEAAL checkups. These reasons will be discussed in Section 2.2.3. In the short-term, planning all appointments is a lot harder to accomplish than when planning further ahead. Almost all calendars, especially those of the doctors, are completely filled up. This forces the planners to improvise, there are no standardized planning rules for planning on the short-term.

2.2 Current performance

To describe the current situation, the data has to be reviewed. This chapter will show how the current situation is described based on the relevant Key Performance Indicators (KPIs). This started by ensuring the privacy protection of patients, followed by preparing the data and finally the most important findings are visualized. The method used to retrieve all the data can be found in Appendix E: Data retrieval.

We retrieved data from 629 patients, age 0-26, that visited Isala between January 1st 2020 and December 31st 2022 for one or more appointments. Not every IDEAAL checkup in the past included the entire standard care pathway and not every appointment retrieved from the data is part of an IDEAAL checkup. Therefore, we decided to divide them into five different categories. These categories are demonstrated in Table 2.

Table 2 Categories of combination appointments

	Combination of appointments in a period of six weeks
Complete	IDEAAL check-up that contains at the entire standard care pathway
Mediocre	IDEAAL check-up that lacks one of the standard care pathway appointments
Bad	IDEAAL check-up that lacks at least two of the standard care pathway appointments
No	Not an IDEAAL check-up
Unlikely	Very unlikely to be an IDEAAL check-up

As their category description shows, the categories “No” and “Unlikely” are not IDEAAL checkup. Therefore, these appointment combinations are not included when defining the numbers, shown in Section 2.2.2. We still have these categories in the data, because finding the actual IDEAAL combinations had go step by step. The categorizing is done based on the logic shown in Appendix B: Categorizing logic.

Another part of the preparation is defining the KPIs on which the results will be analyzed. These KPIs are:

- **Fraction of IDEAAL checkups carried out in one single day;**
  This is the most important indicator, since goal of this research is to maximize the number of IDEAAL checkups carried out in one day and to find out whether this is a realistic goal to set for the Department. This KPI will give us insight into exactly this aspect.
- **Fraction of not scheduled patients;**
  For every patient we expect to find an appointment date. But sometimes this will be impossible. This KPI will give us insight into the plannability of the patients for set circumstances. It will give an indication for the effectiveness of the chosen planning strategy or method. It will also notify us if we need to figure out other reasons why the planning strategy or method does not work as intended.
- **Throughput time per patient;**
  When it is possible to plan a patient in one day, it is desirable for the patient to be in the hospital for as short as possible. Thus, a low throughput time would be good. Although this is not the main objective of the research. When an IDEAAL checkup is split up, the throughput time will not be taken into account, because the time between appointment days does not have to be optimized.
- **Time between expected and realized schedule weeks (delta weeks)**
  Every patient has an expected appointment week, which is a random week in their birth month. It is possible the patient will be scheduled in a different week as a result of the

caregivers' availabilities or as a result of rescheduling due to the cancellation of their checkup. This KPI should give insight in the ease of planning for IDEAAL checkups. We will refer to this KPI as the Delta Weeks.

2.2.1 Availability results

Since the IDEAAL checkup is planned in both a long time in advance and on the short term, it is relevant and interesting to analyze the availabilities of the different care givers in the process.

The data is gathered through a period from week 34 – 40 in 2023. Every week the data availability of the caregivers is monitored for up to sixteen weeks in advance. A maximum horizon of sixteen weeks was chosen, because availability data for 2024 was not available at the time of data gathering and sixteen weeks should be sufficient for testing a wide variety of booking horizons.

Since we only recorded data for seven weeks, every caregiver has seven data points available per horizon length. One data point is "*the fraction of expected outpatient clinic time still available for a caregiver weeks in advance, where* $caregiver\ weeks\ = \{1, \ldots, 16\}$". Due to this issue with limited data, we categorized the calendars of the caregivers into three groups. The three groups are *"slow filling calendars"*, *"average filling calendars"* and *"fast filling calendars"*.

Caregivers are assigned to one of these groups, based on their average filled fraction over the sixteen weeks period. To clarify this: The average availability of the seven data points per week is taken, giving every caregiver sixteen averages, one for each week in advance. If every average availability fraction is greater than 0.5, we consider the caregiver part of the *"slow filling calendars"* group. If every average availability fraction is smaller than 0.3, we consider the caregiver part of the *"fast filling calendars"* group. The rest of the patients are part of the *"average filling calendars"* group. This resulted in nine caregivers in the Slow group, nineteen caregivers in the Average group and six caregivers in the Fast group.

The data for all caregivers in a group are combined to and fitted to the most suitable probability distribution. This probability distribution will generate the fraction of time available for every caregiver in the group. In Appendix F: Distribution fit, we give a visual representation how the different weeks per category are fitted. From these we found that for most weeks the normal distribution was the best fit according to test statistics. The few weeks where the normal distribution was not the best fit according to the test statistics, the results were very close. Therefore, to stay consistent, we decided to take a normal distribution for every week. Choosing a normal distribution also makes analyzing results the most straight forward.

2.2.2 IDEAAL planning results

Categorizing was the last step before the data could be visualized. The most important statistic from the current situation is how often an IDEAAL checkup is actually is carried out in one day. These results are shown in Table 3. As shown in Table 2 the categories Complete, Mediocre and Bad are the three categories that actually were IDEAAL checkups carried out.

Table 3 Performance current situation

IDEAAL checkup		Count	Percentage	Total
Complete	One day	2	**0.4%**	18.7%
	Other lab/fundus day	13	2.6%	
	Multiple days	77	15.7%	
Mediocre	One day	13	**2.6%**	67.2%
	Multiple days	317	64.6%	
Bad	One day	27	**5.5%**	14.1%
	Multiple days	42	8.6%	

The percentages shown in this table are the fraction of the number of IDEAAL checkups over a period of 3.5 years. Since January 2020 Isala has carried out 491 IDEAAL checkups for 257 unique patients. Of these 491 checkups 92 checkups are fully carried out and two of those were on one day. There were 330 checkups that lacked one standard care pathway appointment and 69 checkups that lacked at least two standard care pathway appointments.

At the start of the corona crisis the planners had to stop planning laboratory appointments on the same day as the IDEAAL checkup. These appointments could probably still have been planned on one day, but the planners had the assignment to plan the laboratory appointment on another day. This was because of the restriction surrounding the corona crisis. In a normal time period this measure should not have been taken by the hospital. The appointment with the diabetes nurse is not yet considered part of the standard care pathway. Currently the diabetes nurse is only included if the internist gives an order to include that appointment.

With this in mind we can say that 14.1% of the appointments are not planned as intended. With appointments "planned as intended" we mean that the appointments are planned in the way the planners were instructed to plan. But those instruction do not meet the criteria the department wants to work towards. Since it depends on the order of the internist, it is assumed that the remaining part (85.9%) of the appointments is planned as intended.

2.2.3 Problem identification

As described in Section 2.1.4 most IDEAAL checkups can effectively be planned on one day. As long as the long-term planning is unchanged. But as the data from the current situation implies, which is shown in Section 2.2.1, this long-term planning almost never holds up. Almost none of the IDEAAL checkups actually are carried out in one day, despite (almost) all of them being planned on one day.

There are several reasons for an appointment to change after it being set by the long-term planning. When an appointment has to be canceled, the IDEAAL combination ends up in a buffer list. This buffer list is overseen by the planners, who will have to reschedule any appointment or combination of appointments that end up on this buffer list manually. Reasons for as of why appointments end up on this buffer list are derived from the Isala database, but no data on fractions of these reasons are available. The reasons for an appointment to end up on the buffer list are:

- **Day off by the caregiver;**
  A day off can be requested until three months in advance.
- **Holiday;**
  Doctors have to request their holidays at least six months in advance and diabetes nurse at least three months in advance.
- **Sickness of a caregiver;**

When a caregiver is ill, or absent due to personal reasons their whole calendar must be scraped and rescheduled.

- **Raster changes;**
  New rasters replacing or overwriting rasters containing appointments.
- **Work shift changes;**
  There are different types and locations for the work shifts of the caregivers. The type of shift or location of the shift can change until three months in advance.
- **Caregivers swapping shifts;**
  This can be done any time by caregivers. By swapping shifts they do not take over the patients of the one they switched with. The planners have to reschedule patients, to make sure the patients and their care givers see their own patients. This is for comfort of the patient and to make that caregivers do not need to read-up on every patient they see.
- **Patient cancellations;**
  Some patients call the hospital prior to their appointment to notify the hospital that they are unable to show up. The appointments that are canceled by the patient more than 24 hours before the appointment is considered to be patient cancellations.
- **No-show patient**
  This can occur because of a wide variety of personal reasons, on which the hospital has no influence. No-shows are patients that are either canceled within 24 hours of the appointment or do not show up unannounced.

Another issue that arose from the data is that only 0.4% of the IDEAAL checkups is actually fully carried out. The majority of checkups lacks at least one appointment. This is due to the fact that up until now the planners work under the instructions of planning three, instead of all four of the standard care pathway appointments. The IDEAAL checkup with a diabetes nurse is in the current situation not considered part of the standard care pathway.

If we include the IDEAAL checkups that are not carried out correctly, it can be seen that 8.5% of the appointments are carried out on one day. This means that 8.5% of the patients that came in for an IDEAAL checkup only needed to visited the hospital one day.

2.2.4 Mutation of appointments

When an appointment is canceled, it will be mutated in the system. The number of mutations for all appointment in the IDEAAL check-ups have been analyzed from 2019-2023. Table 4 shows the resulting mutation rates.

Table 4 Mutation rates for IDEAAL appointments in 2019-2023

Year	Appointments	Mutated	Fraction	>1 Mutation	Fraction
2019	1359	227	0.167	17	0.013
2020	823	313	0.380	22	0.027
2021	528	179	0.339	18	0.034
2022	480	226	0.471	36	0.075
2023	518	229	0.442	39	0.075
Average	742	235	**0.317**	26	**0.036**

In Table 4 we see that the fraction of appointments that needed at least one mutation is evenly distributed, aside from the positive outlier in 2019. On average 31.7% of the IDEAAL appointments needed rescheduling for this five-year period. In Appendix E: Data retrieval the method for retrieving and calculating these mutation fractions is described.

The two most right columns of Table 4 give insight in the appointments that underwent more than one mutation. We see that on average 3.6% of the IDEAAL appointments needed rescheduling more than once. We note that the data for 2023 is for the period from January until July, as no more data was available at the time of the research. The number of appointments over the years is notable. We see that after 2019 the number of IDEAAL appointment became much lower than in 2019. This is a result of changes made by Isala to comply with the Covid regulations from 2020 onward. We see an increase in IDEAAL appointments in 2023, as the Covid regulations are being lifted.

2.3 Conclusion

In Section 2.1.4 the planning method is described. The planning is done on two levels, long-term and short-term. Long-term planning mostly follows the desired conditions and goes according a structured method. The short-term planning has to be done manually by the planner, working around full calendars of the different caregivers.

The number of IDEAAL checkups carried out in one day is extremely low. In the current situation only 8.5% of the checkups are fully carried out in one day, meaning that currently the planning performs very poorly. As Section 2.2.3 suggests, the most likely reasons behind these low number are the agreed planning method for planners to plan a standard care pathway without the diabetes nurse. There was a time that they had to plan retina and/or laboratory appointments at least two weeks prior to the rest of the appointments. Both making it impossible for full IDEAAL checkups to occur in one day. This is due to the short-term planning being extremely hard to optimize for the planners manually.

Furthermore, the mutation rates shown in Section 2.2.4 tell us that the planners indeed often have to reschedule IDEAAL check-ups, since 31.7% of the appointments needed rescheduling. If at least one appointment from the checkup is cancelled, the complete checkup needs rescheduling for it to still be scheduled in one day. There is not really data on the difference between the expected appointment date and the actual appointment date. But with such high mutation rates it is likely that the hospital does not perform well on this aspect.

3 Literature

In this chapter literature related to finding an optimal booking horizon will be discussed. The goal of this chapter is to describe the problem type, according to the literature. This chapter will also provide insight in how similar problems have been solved in the past, whether those approaches are suitable for the problem of this research and how this research will contribute insights to the established literature. This chapter will answer the sub question: *"How are optimal booking horizons found according to the literature?"*. The scope of the literature review is focused on the papers written in the health care sector.

3.1 Booking horizon

This section will describe booking horizons and why and how these are used to optimize scheduling in outpatient clinics.

3.1.1 Definition

The booking horizon determines how much time in advance an appointment can be planned, and is an input parameter to an appointment system (Leeftink et al., 2021). When the booking horizon is determined, there is no information on actual patient arrivals, as typically only historical data on the patient population is known. Therefore, the booking horizon optimization problem is considered at the tactical level of control (Hans et al., 2012). The booking horizon is the number of business days from the current date to the date of the latest available appointment slot (Leeftink et al., 2021).

The relationship between scheduling interval and the cancellation rates is well-studied. The scheduling interval is in the literature also referred to as lead time, planning horizon, appointment age or appointment intervals. This is expressed as the number of business days from the creation of the appointment to the date the appointment is scheduled for (Leeftink et al., 2021).

Akin et al. (2013) considers three major groups in patient scheduling and capacity management: single-class patients with single resource, multi-class patients with single resource, and multi-class patients with multiple resources. The multi-class patients with multiple resources can be divided into two subgroups: systems with multiple resources used during a single patient visit and the systems with a single resource that is chosen from a set of resources based on the appointment type. The patient group considered for this research falls in the subgroup "systems with multiple resources used during a single patient visit".

3.1.2 Characteristics and predictors of cancellations

Ever since the increasing focus on efficient healthcare operations, clinics started to evaluate their no-show and cancellation rates (Leeftink et al., 2021). Cancellations result amongst other things in reduced productivity and efficiency for hospitals. Furthermore, cancellations increase the waiting lists, by reducing the available appointments. Therefore, it reduces patient access to care (Davies et al., 2016). To be able to assess this reduction in access to care, it is important to not only take the amount, but also the timing of cancellations into account. By quantifying the cancellation behavior, the effects of interventions can be measured (Leeftink et al., 2021).

Leeftink et all. (2021) considers patients that are rescheduled more than 24 hours in advance to be cancelled. For cancellations we have either patients that need rescheduling and patients that disappear from the system. In this research we consider cancellation to be appointment that need rescheduling, caused by the hospital.

When focusing on predictive studies, Bean and Talaga (1992) and Norris et al. (2014) found that the scheduling interval is the most significant predictor of patient non-attendance. Denney et al. (2019) use machine learning techniques to forecast no-show and cancellation behavior. They showed that the scheduling interval was the top feature for prediction both no-show and cancellations. According to Whittle et al. (2008) has a large effect on cancellation rates. Liu (2016) showed that adopting an optimal appointment scheduling window resulted in substantial efficiency gains. Patients that have a longer scheduling interval tend to have a higher probability of no-show and cancellation. However, when the scheduling interval becomes very long, these effects may fade out (Bean & Talaga, 1992).

3.1.3 Minimizing the effect of cancellations

There are several scheduling strategies that aim to minimize the adverse effect of cancellations, including overbooking, open access scheduling, panel sizing and reducing the booking horizon. As Section 3.1.2 describes, the booking horizon has the largest impact on cancellations. Therefore, the focus of this section will be mostly on the reducing booking horizon strategies.

Both Leeftink et al. (2021) and Liu (2016) propose a queuing model to find an optimal booking horizon. Liu (2016) focusses on the no-show behavior of patients and developed an M/M/1/K queuing model that maximizes the long-run average net reward for providers, which depends on the rewards collected from patients served and the penalty paid for those who cannot be scheduled. Leeftink et al. (2021) proposes a way to improve efficiency of clinics by minimizing the impact of no-shows and cancellations. An analytical model with balking and reneging is proposed, to determine the optimal booking horizon. Which is being verified through simulation experiments. Akin et all. (2013) proposes a discrete event simulation model to analyze the effects of allowing different appointment windows. They use capacity utilization, patient access and financial rewards as performance indicators.

These works come closest to the proposed approach in this thesis. Due to the complicated nature of the system considered in this paper, we use simulation to analyze the effects of changing appointment windows for patients in the clinic, similar to Akin et al. (2013).

3.2 Blueprint scheduling

When finding an optimal booking horizon, a planning strategy still has to be determined. This section will describe what a blueprint planning is and how to develop a blueprint planning for a multi-disciplinary multi-stage appointment combination.

3.2.1 Definition

According to Leeftink et al. (2020), multi-disciplinary planning can be considered at different hierarchical levels. In this research the focus is on capacity planning. Capacity planning specifies the results of capacity dimensioning decisions into a division of the resource capacity to patient groups or time slots (Hans et al., 2007). Blueprints are created in which resources are allocated to different tasks (Leeftink et al., 2020).

A blueprint schedule in the healthcare environment is the amount of capacity on a set time that can be used for specific patient types in the operational planning (Leeftink et al., 2020). Zomer (2022) describes that there are different types of blueprints. This thesis considers “Slots filled with patients” as a blueprint planning. The objective of using a blueprint schedule for appointment planning is to combine appointments on one day (Dharmadhikari & Zhang, 2013) and to minimize waiting time on the day of the appointments (Liang et al., 2015). The blueprint can also prescribe what the best appointment hours are for caregivers (Liang et al., 2015).

3.2.2 Designing a blueprint

Suitable methods to design blueprints are mathematical programming or heuristics, in combination with robust optimization or computer simulation to ensure robustness. Stochastic programming can also be used, which takes robustness to several scenarios into account (Leeftink et al., 2020). The preference of both the patients and hospital is often to combine several appointments on a day. In a blueprint, slots are kept open in order to plan combinations of appointments (Dharmadhikari & Zhang, 2013).

Numerous studies used exact optimization methods to schedule appointments (Benzaid et al., 2020). Simulation and approximate methods, on the other hand, can handle large and complex systems with difficult constraints (Bouras et al., 2021). Most of these researches focus on the development of a blueprint planning to minimize for example makespan, workload of nurses, overtime or total excess workload (Bouras et al., 2021).

Condotta & Shakhlevich (2014) proposes a mathematical programming approach to design a blueprint. They modeled the key stage of the scheduling process as a linear program and solved it using CPLEX solver. Their solution is based on the concept of a multi-level template schedule, with minimizing patients' waiting times and nurses' workload as main objectives. Hesaraki et al. (2019), developed an integer programming model using makespan suppression cost coefficients in the objective function. They developed a template planning to serve as a link between planning on a tactical level and online scheduling on an operational level.

There are also examples of papers discussing approximation methods for scheduling problems. Bouras et al. (2021) presents a tabu search inspired algorithm to obtain a better solution especially suitable for large instances. Turkcan et al (2012) developed an operations planning and scheduling method for chemotherapy patients by minimizing the deviation from optimal treatment plans. They used a two-stage rolling horizon approach to solve the problems sequentially. An advantage of their heuristic is that it has a short computational time.

The mathematical formulation of Bouras et al. (2021) comes closest to the approach we propose in this thesis. To develop a blueprint Bouras et al. (2021) minimizes their mathematical model on the makespan. The makespan is the time until the last operation is completed (Bouras et al., 2021). In this research we name this throughput time. Similar to our case, Bouras et al. (2021) has to use other methods to actually solve the entire instance of their problem due to complexity. They still formulated the mathematical model to determine the lower bound of their solution.

3.3 Conclusion

In this section the most suitable solution approach selection is described. This chapter also answers the sub question: "*How are optimal booking horizons found according to the literature?*"

3.3.1 Relevance

The approach proposed in Akin et al. (2013) comes closest to the approach of this paper. The focus of Akin et al. (2013) is on specifically finding an optimal booking horizon for different patient types within a clinic. This paper will go one step further and combine an optimal booking horizon with an optimized blueprint for a complex appointment combination. To the best of the authors knowledge there is no prior research on optimizing appointment scheduling on both appointment method and booking horizon.

3.3.2 Approach

The approach chosen for this will be a combination of the most suitable approaches found in the literature for finding an optimal booking horizon and determining an optimal blue print. As discussed in their respective sections, the most suitable approach for finding the optimal booking horizon will be developing a discrete event simulation due to the complexity of the system. The most suitable approach for determining an optimized blueprint planning will be mathematical modeling. As the literature shows this is an appropriate way to minimize the makespan of the patients, which is the main objective set for blueprint scheduling in this system.

4 Solution approach

In this chapter the third sub question will be answered, namely: "*How to find the optimal planning approach for the IDEAAL checkups?*". The goal of this chapter is to describe how to get to a fitting solution for the current situation of Isala, based on mathematical modelling (Section 4.1) and discrete event simulation (Section 4.2).

4.1 Mathematical modelling

As discussed in Section 3.2.2 a mathematical model is a suitable approach to develop a blueprint planning. This chapter will describe the mathematical model developed for the problem at hand and describe what steps are to be taken with the mathematical model.

4.1.1 Model overview

In order to make an optimized blueprint planning, a model needs to be constructed. The objective of the model is to make sure that as many patients, needing the IDEAAL checkup, only needs to visit the hospital once to complete the checkup. The number of patients and the appointments needed for a complete IDEAAL checkup are known one year in advance. The objective is to minimize the throughput time of patients, meaning that the time a patient is present in the hospital, should be minimized. At the same time, a larger number of patients that visit the hospital multiple days, should be penalized. The model needs different parameters as input, which are inputs that can be changed when the situation at the hospital changes or to test different potential situation. Section 4.1.2 **Error! Reference source not found.**gives an overview of the model on paper.

4.1.2 Model definition

Sets

$Patients\ (p = 1, \dots, P).$
$Doctors\ (doc = 1, \dots, Doc).$
$Diabetes\ nurses\ (dn = 1, \dots, Dn).$
$Slots\ (s = 1, \dots, S).$

Parameters

$PrDoc_p$	$Prefered\ Doctor\ of\ patient\ p$
$PrDn_p$	$Prefered\ Diabetes\ nurse\ of\ patient\ p$
Fun_p	$1\ if\ the\ patient\ p\ needs\ to\ have\ a\ retina\ photo\ appointment,$ $0\ otherwise$
$LabTime$	$Time\ until\ lab\ results\ are\ available\ in\ number\ of\ slots$
$PoliDoc_{doc,s}$	$1\ if\ the\ doctor\ doc\ is\ available\ on\ slot\ s,$ $0\ otherwise$
$PoliDn_{dn,s}$	$1\ if\ the\ diabetes\ nurse\ dn\ is\ available\ on\ slot\ s,$ $0\ otherwise$

Variables

$W_{p,doc,s}$	$1\ if\ the\ consultation\ of\ patient\ p\ is\ carried\ out\ by\ doctor\ doc\ at\ time\ slot\ s,$ $0\ otherwise$
$Z_{p,dn,s}$	$1\ if\ the\ consultation\ of\ patient\ p\ is\ carried\ out\ by\ Diabetes\ nurse\ dn\ at\ time\ slot\ s,$ $0\ otherwise$
$Lab_{p,s}$	$1\ if\ the\ laboratory\ appointment\ of\ patient\ p\ is\ carried\ out\ at\ time\ slot\ s,$ $0\ otherwise$
$AB_{p,s}$	$1\ if\ the\ bloodpressure\ appointment\ of\ patient\ p\ is\ carried\ out\ at\ time\ slot\ s,$ $0\ otherwise$

$Ret_{p,s}$	1 *if the Retina appointment of patient p is carried out at time slot s,* 0 *otherwise*
C_{max}	*Maximum completion time of all patients*

Objective function

$\min C_{max}$

Subject to

$$\sum_{p=1}^{P} W_{p,doc,s} \leq 1 \qquad \forall doc, s \qquad (1)$$

$$\sum_{p=1}^{P} Z_{p,dn,s} \leq 1 \qquad \forall dn, s \qquad (2)$$

$$\sum_{s=1}^{S} W_{p,PrDoc,s} = 1 \qquad \forall p \qquad (3)$$

$$\sum_{s=1}^{S} Z_{p,PrDn,s} = 1 \qquad \forall p \qquad (4)$$

$$\sum_{s=1}^{S} \sum_{dn=1}^{Dn} Z_{p,dn,s} = 1 \qquad \forall p \qquad (5)$$

$$\sum_{s=1}^{S} Lab_{p,s} = 1 \qquad \forall p \qquad (6)$$

$$\sum_{s=1}^{S} AB_{p,s} = 1 \qquad \forall p \qquad (7)$$

$$\sum_{s=1}^{S} Ret_{p,s} \leq 1 \qquad \forall p \qquad (8)$$

$$\sum_{p=1}^{P} Ret_{p,s} \leq 1 \qquad \forall s \qquad (9)$$

$$Fun_p = \sum_{s=1}^{S} Ret_{p,s} \qquad \forall p \qquad (10)$$

$$\sum_{s=1}^{S} Lab_{p,s} \cdot s + 1 \leq \sum_{s=1}^{S} AB_{p,s} \cdot s \qquad \forall p \qquad (11)$$

$$\sum_{s=1}^{S} AB_{p,s} \cdot s + 1 \leq \sum_{s=1}^{S} W_{p,PrDoc,s} \cdot s \qquad \forall p \qquad (12)$$

$$\sum_{s=1}^{S} Ret_{p,s} \cdot \left(\sum_{s=1}^{S} Lab_{p,s} \cdot s + 1 \right) \leq \sum_{s=1}^{S} Ret_{p,s} \cdot s \qquad \forall p \qquad (13)$$

$$\sum_{s=1}^{S} Ret_{p,s} \cdot s + 1 \leq \sum_{s=1}^{S} W_{p,PrDoc,s} \cdot s \qquad \forall p \qquad (14)$$

$$\sum_{s=1}^{S} Lab_{p,s} \cdot s + 1 \leq \sum_{s=1}^{S} Z_{p,PrDn,s} \cdot s \qquad \forall p \qquad (15)$$

$$\sum_{s=1}^{S} Z_{p,PrDn,s} \cdot s + 1 \leq \sum_{s=1}^{S} W_{p,PrDoc,s} \cdot s \qquad \forall p \qquad (16)$$

$$\sum_{s=1}^{S} (Lab_{p,s} \cdot s) + LabTime + 1 \ \leq \sum_{s=1}^{S} W_{p,PrDoc,s} \cdot s \qquad \forall p \qquad (17)$$

$$Lab_{p,s} + \ AB_{p,s} + \ Ret_{p,s} + \ Z_{p,PrDn,s} + \ W_{p,PrDoc,s} \ \ \leq 1 \qquad \forall \mathrm{p,s} \qquad (18)$$

$$PoliDoc_{doc,s} \ \geq \ W_{p,doc,s} \qquad \forall \mathrm{p,doc,s} \qquad (19)$$

$$PoliDn_{dn,s} \ \geq Z_{p,dnc,s} \qquad \forall \mathrm{p,doc,s} \qquad (20)$$

$$\sum_{s=1}^{S} \sum_{doc=1}^{Doc} W_{p,doc,s} \cdot s - \sum_{s=1}^{S} Lab_{p,s} \cdot s + 1 \leq C_{max} \qquad \forall p \qquad (21)$$

$$C_{max} \in \ \mathbb{Z}$$

$$W_{p,doc,s}, Z_{p,dn,s}, Lab_{p,s}, AB_{p,s}, Ret_{p,s} \in \{0,1\}$$

4.1.3 Model description

The mathematical model will optimize a blue print planning for IDEAAL checkup appointments by minimizing the throughput time (C_{max}) of the patients. Constraints (1) and (2) ensure there will be only one patient per slot per doctor and one patient per slot per diabetes nurse, respectively. Constraints (3), (4), (6) and (7) make every patient have exactly one appointment with their preferred doctor, preferred diabetes nurse, at the lab and a blood pressure appointment respectively. Constraint (5) prohibits the model from assigning patients to appointment slots for diabetes nurses that are not their preferred diabetes nurse. Constraint (8) ensure that every patient has not more than one retina photo taken. Constraint (9) ensures that not more than one patient is planned at the same slot, because there is only one retina photo machine. Constraint (10) if the retina photo is part of the IDEAAL checkup a patient will get a retina appointment. Constraints (11), (13) and (15) ensure that the Lab appointment is always the first appointment. Note here that constraint (13) has an extra summation on the left. This is because not every patient will have a retina photo taken. Constraints (12), (14) and (16) ensure that the doctor appointment is always the final appointment. Constraint (17) makes sure there are at least “*LabTime*” slots between the first and last appointment. Since the time it takes the lab to yield results is at most “*LabTime*” slots. Constraint (18) ensures that all appointments of one patient are on different slots. Constraints (19) and (20) ensure that only available slots for the doctors and diabetes nurses can have an appointment planned. Finally, constraint (21) calculates the throughput time of a patient and also prevents the model from planning more than one doctor for every patient.

4.2 Discrete event simulation model

We discuss to find the optimal booking horizon for IDEAAL checkups. The various booking horizons will be scored based on the KPIs, to determine which booking horizon would be the best fit for our situation. In this research the booking horizon is defined as the number of weeks from the current date to the date of the latest available appointment slot. A week consists of five business days and weekends will not be considered.

4.2.1 Simulation process logic

A visual representation of the simulation process logic can be found in Appendix C: Process flowchart.

This simulation model uses a list of all IDEAAL patients as input to determine how many patients need an appointment for any given week in a year. This patient list contains the following information per patient

- **Patient name**
  The anonymized name of the patient.
- **Expected plan week**
  A random week within the birth month of the patient, used by the simulation to check whether the patient needs scheduling.
- **Preferred doctor**
  The anonymized name of the doctor that treats the patient and will carry out the doctor appointment. This is an internist for adults or a pediatrician for children.
- **Preferred nurse**
  The anonymized name of the nurse that generally carries out the nurse appointments of the patient. For adults, this is a diabetes nurse and for children a child nurse.

Based on that list, the patients will be planned on slots of their preferred caregivers at least a booking horizon in advance. We will experiment with the booking horizon over the different runs of the simulation model.

Every week a number of regular patients will arrive to fill up the available slots of every care giver in the system. The purpose of these patients is to simulate the occupancy of the different caregivers' schedules. After planning all appointments, the availability changes occur. As described in Chapter 2 there are multiple reasons for changed availability. With a larger booking horizon, it will be more likely that the availability changes due to patient cancellations or caregiver unavailability.

When the actual appointment day of the patient occurs, the patient goes to the hospital and undergoes their appointments. The IDEAAL patients will go through the appointments needed, corresponding to their individual checkup. In reality this is determined by the doctor after the previous IDEAAL checkup. In the simulation this included appointments are based on the probabilities from Table 1 i.e., 2.4% chance to have a diabetes appointment and 45.6% chance to have a retina photo. Every patient will always at least have the entire standard care pathway as a part of their checkup. The lab appointment is always the first appointment and the doctor appointment is always the last appointment. After undergoing their final appointment, patients go home and leave the system.

4.2.2 Routing logic

This section highlights some of the most prominent and

One day appointment logic
The appointment logic is different for regular patients and IDEAAL patients. As the focus of this research is on the IDEAAL patients, the appointment logic for these patients is improved and the appointment logic of regular patients will just follow a randomized first come first serve (FCFS) logic. This means that the appointment slot assigned to a regular patient is randomized within their appointment week. But the arrivals are FCFS in the sense that if the week is filled, no new patients can get an appointment in that particular week. We will elaborate further on filling the sub calendars

in Section 4.2.3. A sub calendar is defined as: "*The calendar of the (preferred) caregiver that will carry out an appointment type"*. In general, the FCFS method is being implemented for the IDEAAL patients as well, but with the following changes.

A visual representation of the IDEAAL patients' appointment logic can be found Appendix D: Logic flowchart. At the start of a week, the IDEAAL patients that need an appointment one booking horizon in the future will be scheduled. The IDEAAL patients get an appointment at the lab within the first hour of the morning or afternoon. The doctor appointment will be planned closest to the last appointment of the checkup. The other appointments are all planned in between the lab and doctor. In Section 4.2.6 we elaborate on how the sequence of the appointments is determined.

If a patient cannot be planned in one day, following the previously described logic, the same logic will be applied to the next day. To determine how many days will be checked for available slots we introduce Checking Horizon. We define Checking Horizon as: "*The maximum number of weeks from the original appointment date will be checked on their availability"*. The simulation will keep looking for a day to schedule the entire checkup until a day is found where the patient can get all their appointments on one day with or until the Checking Horizons has expired. The Checking Horizon is set to four weeks, as this gives the best representation of reality. Currently planners look in the entire birth month of a patient to find an appointment date. A four week Checking Horizon will therefore give the best representation of reality.

When no appointment date is found for the patient, the patient's information will be stored in a separate table to remember it for calculating the "*Fraction of not scheduled patients*"

Filling sub calendars

All sub calendars will be followed by generating regular patients. These regular patients will be generated based on the likelihood that the caregiver's sub calendar will be full at a given point in time. These patients will be planned in these sub calendars to make them decrease their availability. These regular patients will be generated following a probability distribution. This distribution is based on historical data of the availability of the caregivers in the diabetes department. An overview of the arrivals is discussed in Section 2.2.1. Here we described how every sub calendar is divided into one of three groups. Where every group has their own arrival distribution per week for 1- 16 weeks in advance.

Since a normal distribution has been fitted on every week of all three group, the only distribution inputs we need are a mean and a standard deviation per week per group. An overview of these inputs is shown in the tables in Appendix F.2 Tables. Every Monday the simulation tries to fill all sub calendars based on a random fraction derived from one of these tables, based on which week it is trying to fill. For example, on Monday of week 1 the simulation will fill the sub calendars of a fast-filling calendar of week 17 based on a random number drawn from a normal distribution with a mean of 0.75 and a standard deviation of 0.18.

Before the simulation starts filling the sub calendar it will check the current fraction of slots that is occupied. The simulation will only generate regular patients until the sub calendar will be filled up to the fraction drawn from the distribution. If the current fraction is higher than the fraction drawn from the distribution, the simulation will not create any new regular patients. The filled fraction will than remain the same.

Two-day appointment logic

If all days of the Checking Horizon have been checked, but no appointment date is found, we will split up the IDEAAL checkup in two separate checkup days. We then attempt to schedule the checkup spread over two days instead.

The split of appointments will always be the same. The first day always includes the laboratory appointment, since this appointment always must be the first appointment. Also, the appointment with the nurse will be on the first day since this is, just as the doctor, the hardest to schedule since the patients has to be scheduled with their preferred nurse. The last appointment that will be included in the first day is the retina photo, if the IDEAAL checkup contains a retina photo. The retina photo has to be reviewed by the eye doctor; it makes sense to carry this out on the first day so that it is more likely that the results are known during the doctor appointment.

The blood pressure will be measured on the appointment date of the doctor, as it will give the most recent and thus accurate results for the doctor to discuss with the patient. Also, if the checkup contains a dietician appointment, the dietician will be scheduled on the second day. This is to spread the number of appointments more evenly over the two appointment days, making the likelihood of the appointments finding a suitable spot more likely. Once an appointment date is found for the first day, we start looking for an appointment date for the second day. The starting date on which the simulations start looking for the second appointment is $first\ appointment\ day\ +\ 1$. Regular patient appointments will never be split over two days. Since they are not real patients, they never have more than one appointment.

The Checking Horizon for both the first and second combination of appointments is twice as long as the Checking Horizon for the one-day appointment. We chose to take twice the Checking Horizon of the single day checkups, to increase the chance to find suitable dates for the first- and second day checkup. The maximum time in advance an appointment can be scheduled is sixteen weeks, therefore it is possible that no appointment date will be found in the simulation. The sixteen-week period is how far in advance the simulation fills the calendars of every caregiver. The simulation will never check a day that is more than 16 weeks in advance, counted from the current day in the simulation.

Cancellation of appointments

As the focus of this research is on the IDEAAL checkups, only IDEAAL appointments can be canceled in the simulation.

To simulate the cancellation of IDEAAL checkups we use the probability of an appointment in the IDEAAL checkup being cancelled. Rodríguez-Garcia et al. (2016) found a function to fit the probability of a cancelation, based on the booking horizon. The different equations they found are shown in Table 5. IDEAAL checkups are always with established patients and since we want to reschedule the checkups, following the results of Rodriguez-Garcia et al. (2016) the logarithmic equation used in this research will be: $Y = 0.0694 \cdot ln(x) + 0.0432$.

Table 5 Characteristics of the best-fit function. Y is the cancelation probability and x are the booking horizon in weeks Source: (Rodríguez-García et al., 2016)

Type of Patient	Patient Outcome	Logarithmic Equation	R^2
New Patients	No-show	Y=0.0680ln(x)+0.0402	0.85502
	Cancelation without Reschedule	Y=0.0600ln(x)+0.0283	0.82339
	Cancelation with Reschedule	Y=0.0637ln(x)+0.0685	0.81365
Established Patients	No-Show	Y=0.0513ln(x)+0.0397	0.90034
	Cancelation without Reschedule	Y=0.0561ln(x)+0.0306	0.94416
	Cancelation with Reschedule	Y=0.0694ln(x)+0.0432	0.91919

At the time of scheduling the IDEAAL checkup, the probability check will be done. As described in Section 2.2.4 only 3.6% of the appointments in IDEAAL checkups get cancelled more than once. Therefore, we chose to only do a cancellation check at the first scheduling date. An appointment will never be cancelled after rescheduling in the simulation. If the checkup is not cancelled, the checkup will be carried out on the planned date. When the checkup gets cancelled, a cancellation date needs to be set.

To determine a cancellation date, we must determine the cancellation interval. The cancellation interval is the number of business days from the creation of an appointment to the date the appointment is cancelled (Leeftink et al., 2021).

Figure 2 shows a normalization of the scheduling intervals on the interval $[0,1]$, with 0 being the date on which the appointment is created, and 1 the appointment date. The frequencies from the bimodal distributions will be used to determine the cancellation date. This way, for every appointment that will be cancelled, the simulation will immediately determine the cancellation date. At the cancellation date, we assume that the entire checkup will be rescheduled on the cancellation date. At the start of every day the simulation will check whether the cancellation date of any checkup has been reached. If that is the case, the checkup will then be rescheduled within a Checking Horizon from the initial appointment date according to the planning logic from both Section 4.2.2 and Section 4.2.4. Regular patients will never have their appointments cancelled.

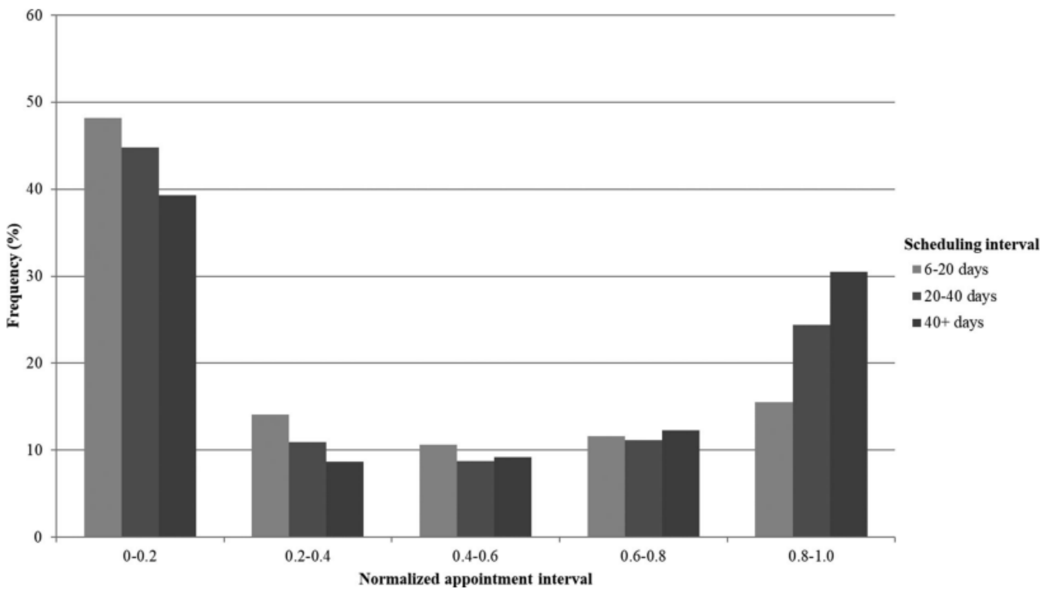


Figure 2 Probability of the timing of a cancellation for a given scheduling interval. Source: Leeftink et al., (2021)

Sequencing appointments within a checkup

As we discussed in Section 1.1.4, the sequence in which the appointments are carried matters. The lab appointment always has to be the first appointment and the doctor appointment always has to be last. There have to be at least two hours in between the lab and doctor appointment, because it takes up to two hours for the lab to get results.

To determine the sequence of appointments, we developed a heuristic within the simulation which is being called once a potential appointment day is found. A potential appointment day is defined as "A day *in which at least one slot is available for every sub calendar included in the checkup"*.

The sequencing heuristics creates separate lists of available slots for every sub calendar during the potential appointment day in ascending sequence. Once creating the lists is done, the heuristic will start comparing the available slots of the doctor in descending sequence with the rest of the sub calendars in ascending sequence. This makes sure that, when no doctor slot is smaller than all the sub calendars, the check can immediately be cancelled. Furthermore, the heuristic makes sure that none of the sub calendars receive the same slot.

If a suitable slot has been found for every sub calendar, the heuristic will first identify the sub calendar with the smallest available slot, meaning that it identifies which appointment will be carried out first. This is essential, to check whether the time between the first appointment and the doctor appointment is at least two hours to make sure the lab results will be available at the time a patient has their doctor appointment.

To minimize the throughput time of the patient, as a final optimization, the heuristics starts looking for a doctor appointment slot that is closer to the second to last appointment, without making the difference between the first appointment and doctor appointment smaller than two hours. The doctor appointment will also always remain the last slot in the sequence. The doctor appointment slot that minimizes the throughput time will be chosen, after which the simulation will continue.

If the heuristic is not able to find a sequence that meets the set conditions, the simulation will start looking for a new potential appointment date following the logic described in Section 4.2.2.

4.2.3 Experimental design

To determine the replication and warm-up period we used the hospital data as input. This means that the arriving patients, their preferred caregiver and their appointment week are not random, but known. The only randomized aspect is whether the patient will need a retina photo appointment and/or an appointment with the dietician.

Replications

The number of replications is determined based on the confidence interval of a KPI of choice. The KPI chosen to find the number of replications is "*The fraction of IDEAAL checkups carried out in one day, during a one run time period".* We chose this, because maximizing the fraction of IDEAAL checkups carried out in one day is the most important goal for the hospital. The statistics calculated for this approach are shown in Appendix G: Number of Replications. The logic for this method is to perform replications until the width of the confidence interval, relative to the average, is sufficiently small. We decide to take a confidence interval of 95%, meaning that the maximum relative error has to be smaller than 0.05 for the simulation to yield valid results. The results shown in Appendix H show that only two replications are needed to make the simulation results valid.

To find the results, shown in Appendix H, the simulation is run on the highest potential settings with regards to booking horizon. The booking horizon was set the fifteen weeks and the Checking Horizon to four. For the run length, namely the number of days for one run, we chose 325 days. One year consists of $52 \cdot 5 = 260$ days, the booking horizon consists of $15 \cdot 5 = 75$ days and together this is a total of $260 + 75 = 335$ days. For these settings we did twenty replications, of which the results are shown in Appendix G: Number of Replications.

A reason so few replications are needed to make the results valid, is that it is relatively easy to plan the IDEAAL checkups on one day, which is also demonstrated in Section 5.1.1. As the IDEAAL check ups are such a small part of the calendars of the different caregivers, there are many different solution yielding an optimal outcome. Therefore a heuristic is likely to also find the optimal solution and thus does not need multiple replications to give a valid solution. Another reason would be that the input patient list is the same for every run, reducing the randomness in the input of the model.

The simulation has a very low runtime per replication. Therefore, we chose to use ten replication per experiment despite two experiments already resulting in a valid answer. By using ten replications, the other test statistics, gained from the experiments, will also increase in validity. Since the run time is so low, runtime is not a constraining factor for this research. So, to increase the validity of the test statistics, we carry out ten replications per experiment.

Warmup period

The warmup period is determined with the MSER heuristic. To find the warmup period we ran the system once with the same settings as when we determined the number of replications. As output KPI we use a similar number. Since we now only have one run, we take "*The number of IDEAAL checkups carried out in one day, per week"* instead. We run the system for 335 days, which will result in 75 weeks $(= \frac{335}{5})$ with data points.

These data points are used in the MSER heuristic and the results are shown in the table and graph from Appendix H: Warmup period. From the MSER heuristic we know that the warmup period is found by taking the period with the lowest MSER value minus one. Since week thirteen is the period with the lowest MSER, as shown in the table from Appendix H: Warmup period, the warmup period for the simulation is twelve weeks.

We have to keep in mind that this is determined with the settings described before. When taking a smaller booking horizon, the warmup period will also decrease. As we will run the simulation for different settings, including smaller booking horizons, the warmup period can be different per experiment. Despite that, we chose to always take a warmup period of at twelve weeks for all experiments. Fifteen weeks will be the largest booking horizon, we will always take exactly the necessary or a larger booking horizon. Therefore, the result for every experiment will be equally valid and taking a constant warmup period will keep the experimentation consistent.

Experimentation strategy

As described before, the goal of the simulation is to find which planning decisions should be made with the IDEAAL checkups. Every experiment is going to determine an optimal booking horizon for the settings that are being tested. Since we will test a booking horizon of 1 - 15 weeks, every experimental setting described below will always be tested for all these booking horizons.

We started by testing a base case scenario in which the instructions of the planners are changed to: try to plan as many complete IDEAAL checkups on a single day as possible. This will function as a base case to which every other experiment will be compared.

Every experiment will output the different KPIs per booking horizon described in Section 2.2. Afterwards the booking horizon that has the best KPI outcomes will the recommended booking horizon. The different experiments we conducted are the following.

- **Demand**

  In the category of demand we will analyze two separate experiments. The first experiment will be "*Equal demand distribution*" and the second experiment will be "*Increased demand*". We consider an equal demand distribution as: "*Distributing the demand equally over the time period, depending on the expected availability of caregivers*". This means that the demand will be spread in such a way that vacation periods have a smaller demand and non-vacation periods a larger demand. As described in Section 1.1.2 the patient demand is currently distributed over the year by assigning the birth month of patients as their preferred appointment month.

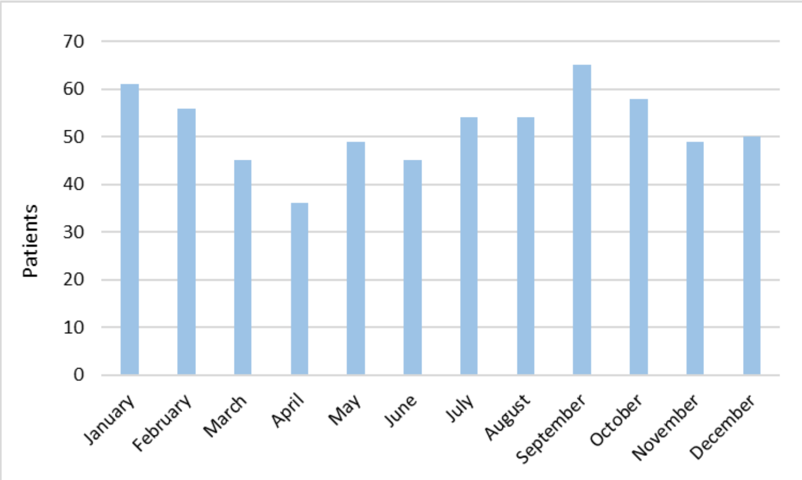


Figure 3 Demand per month

  Figure 3 shows the demand distribution over a year following that appointment logic. These results are not considered a fair distribution. Therefore, we looked into ways to smoothen the demand over the year. For simplicity in modelling, we decided to exclude vacation from the availability of caregivers. So, to get a fair distributed demand over a year, for the simulation, the demand per month or per week will be equalized. This means that the weekly demand will be 10.7 patients $(= \frac{557}{52})$. Since it is impossible to treat decimal patients, 30% of the weeks have eleven patients to treat and 70% of the weeks have ten patients to treat, when equalizing the demand per week.

  Figure 4 gives an overview of how the demand over time changes when it is being equalized over the weeks. The green line shows the current demand per week, based on assigning random weeks within birth months to patients. The equalized demand shown in this figure will be used as input of the equalized demand experiment.

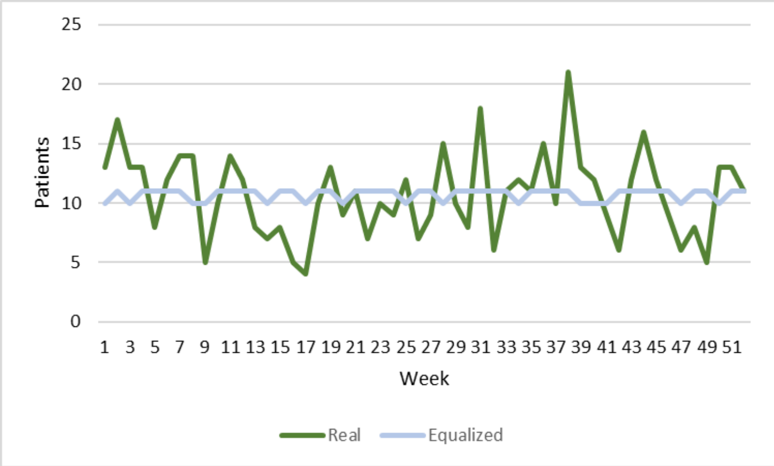


Figure 4 Comparison between equalized demand and real demand

The second demand experiment "*Increased demand*" will be based on the increase in patients expected according to Rossing & Visee (2018). The expected increase in patient demand for 2029, 2034 and 2039 are respectively 3.7%, 6.7% and 7.8% (Rossing & Visee, 2018). As these are very small increases in demand, we expect no difference in results between those future demands. We chose to take the 7.8% demand increase as an experiment, as this is the largest increase. We will also experiment with an extreme situation to see how the planning strategy will hold in an extreme case. This resulted in two experiments, the first one with 600 patients ($= 557 \cdot 1.078$), to simulate the expected demand increase. Secondly the demand will be doubled to 1114 patients ($= 557 \cdot 2$), to simulate an extreme setting.

Increasing the demand results in new patients for which no birth month, preferred nurse or preferred doctor is known. For the demand increases we used the current data to determine how many of every preferred caregiver should be included among the newly created patients. The decision logic is described in Appendix I: Preferred caregiver logic.

- **Caregiver tuning**
  Another interesting restriction for the current situation are the preferred caregivers for every patient. To deliver the best possible care, it makes sense to have a dedicated caregiver for any patient. That way the caregiver needs less or no time to prepare an appointment. Less time of the appointment will go towards getting to know each other. Also, the communication between caregiver and patients that are familiar with each other will be easier.

  But, for planning convenience this is a restriction that can result in harder to schedule patients and therefore worse performance of the planning strategy. That is why we came up with two ways to adjust the caregiver patient combinations to quantify the impact of this restriction.

  The first experiment will be "*Every caregiver doing a fair amount of IDEAAL checkups*". The demand then will be distributed based on their expected available time. Some caregivers work more hours than others in the outpatient clinic, making them a more suitable caregiver to carry out IDEAAL checkups.

  The second experiment will be "*Smart pairings of doctors and nurses*". Currently doctors and nurses are somewhat randomly paired to be the preferred caregivers of a patient. When a patient arrives as a new patient, the planners look for a nurse and a doctor that still have available calendar slots for new patients and those will be scheduled accordingly. By developing a smarter way to pair doctors and nurses that are assigned to deliver care for the patient, we can test whether this improves the plannability of the IDEAAL checkups. For this experiment, we will be looking at doctors and nurses that are often expected to be available on the same day.

- **Cancellation and availability**
  From our analysis of the current situation we concluded that the cancellations of appointments and the availability of the caregivers are the most prominent causes of the inability to plan IDEAAL checkups on one day. This set of experiments gives us insight whether this is actually the case. First, we will check whether excluding either and both cancellations and availability from the planning will impact the results.

  Afterwards we will also do a more thorough inspection of a changing cancellation rate on plannability of the IDEAAL checkups. The cancellations will be more thoroughly investigated since the data used to determine the cancellation rate is actually taken from literature research. If the data for cancellation will become known in the future for Isala it is useful to know whether the planning decisions for the IDEAAL checkups should change or that they would remain the same.

  We tested a doubled cancellation equation by increasing the variables in the equation found in the literature. This resulted in a new cancellation rate equation of $Y = 0.1388 \cdot ln(x) + 0.0864$. Changing the equation will result in different probabilities per booking horizon, the probabilities per booking horizon are visualized in Figure 5.

  The reason for increasing the cancellation rates is that we see that in the base case, an appointment scheduled fifteen weeks in advance only has a cancellation rate of 12.4% ($= 0.0694 \cdot ln(15) + 0.0432$). This is much lower than the average mutation rate of 31.7% found in the data. To see if the cancellations have any impact, we also experimented with no cancellations.

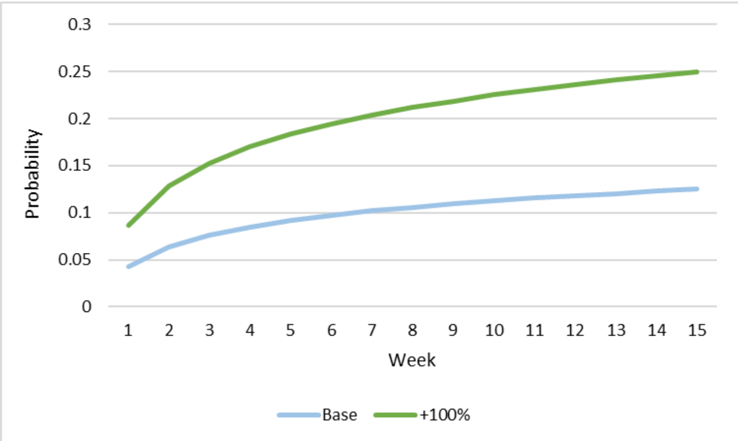


Figure 5 Cancellation probability per booking horizon for the base case and a doubled equation

4.3 Conclusion

We developed a mathematical model and an DES model. The mathematical is able to give an exact blueprint in a static time frame, where the DES model will be able to evaluate a move time horizon with changing randomized input value. We will be experimenting with both these models, where the focus of the DES model will be on finding an optimal booking horizon and the focus of the mathematical model to find an exact blueprint for the IDEAAL checkups. We will experiment with different demands, cancellation rates and caregiver assignments. And a base case study will be done in which the work instruction for the planners is changed to planning all appointments and try to plan them on a single day.

5 Results and analysis

This section will answer the sub-question: "*How does this new planning approach impact the planning of the IDEAAL checkup?*". Thereby a variety of changes on the panning method is elaborated based on the analysis of the results from the experiments described in Section 4.2.7. This chapter is split into a section for the mathematical model results (Section 5.1) and a section for the discrete event simulation model (Section 5.2). The section for the discrete event simulation model contains four sub sections, the first elaborates on the base case and the other three elaborate on the three experiments respectively.

5.1 Mathematical model

For the mathematical model we used the actual caregivers and their calendars as input over a time horizon of two weeks (one odd and one even week), the other inputs are shown in Table 6.

Table 6 Input for the mathematical model

Name	Input	Set
Patients	P = 22	{p1, …, p22}
Doctors	Doc = 12	{doc1, …, doc12}
Diabetes nurses	Dn = 16	{n1, …, n16}
Slots	S = 400	{1, …, 400}

We limited the time horizon so that the model would be able to run the system. We choose 22 patients, because on average 22 patients arrive every two week period. And a two week period consists of 400 appointment slots (40 slots per day). There are 12 doctors and 16 nurses in Isala that carry out the IDEAAL checkups in scope of this research.

5.1.1 Results

The results of the mathematical model confirm the constatation of the planners that, when the IDEAAL checkup is planned months in advance, there is always more than enough room in the calendars of the caregivers to have every IDEAAL checkup be done in one day. When inputting the actual patient demand for a given week, with the availability of the caregivers during that week, the model can find multiple solutions in which every patient has the minimum throughput time, namely the time it takes for the lab to output its results.

This is due to the fact that when the calendar is still empty, which is the case when an IDEAAL checkup is planned months in advance. The different caregivers have more than enough time available in their calendars to fit the IDEAAL patients. The total time any caregiver is seeing an IDEAAL patient is a very small fraction of their total available time. By analyzing the regular planning for caregivers, we found that all doctors combined have 489.5 slots available. There are 12.1 IDEAAL checkups ($= \frac{557^{1}}{46^{2}}$) on average per week. This results in approximately $\frac{12.1}{489.5} \approx 2.5\%$ of their outpatient clinic time spent on IDEAAL checkups. The planning issues will start to arise and increase once more and more appointment slots are occupied. To imitate the actual availability of the caregivers, a simulation model is made. This model can be used to find the ideal booking horizon for patients, while ensuring appropriate planning performance, meaning the moment in time with the

[1] The number of patients between 0 – 26 being treated for diabetes
[2] The number of working weeks for doctors at Isala after subtracting vacation

least chance for changes to the planning, but with still enough room in all calendars to plan the complete checkup in one day.

5.2 Discrete event simulation model

Throughout this chapter various figures will be shown with confidence intervals of the KPIs "single day fraction" and "not planned fraction". These confidence intervals are a result of every experiment being run for ten replications; outputting ten unique outcomes plotted in the figures. For the "single day fraction" figures, the higher the results the better. For the "not planned fraction" figures, lower results are better. The difference between experiments can be verified by studying the p values, see Appendix J: Experimentation. When a p value is below 0.05 we can presume that the mean values are different with a probability of 95%. The experiment number, shown on the horizontal axis of the confidence interval figures, corresponds with the booking horizon i.e., experiment 1 (Exp 1) refers to a booking horizon of one week and Experiment 12 (Exp 12) refers to a booking horizon of twelve weeks.

The other two KPIs, "Throughput time of patients" and "Delta Weeks" will be analyzed based on boxplots. The boxplots are derived by taking all data points per experiment into account. Based on the boxplots we can determine whether the mean and standard deviation of the experiments change over the different booking horizons.

For the DES model we used the actual caregivers and their calendars as input over a time horizon of a year. We include all 557 patients, 100 slots per week (5 working days consisting of 40 slots each). There are 12 doctors and 16 nurses in Isala that carry out the IDEAAL checkups in scope of this research. To anonymize the input data the patients are $\{p1, \dots, p557\}$, the doctors are $\{doc1, \dots, doc12\}$ and the nurses are $\{n1, \dots n16\}$.

5.2.1 Optimal booking horizon

Prior to analyzing the various impact factors, the current situation was tested in order to check if it is possible to apply planning IDEAAL checkups on a single day at the diabetes department. Tests were performed via simulation.

The test results shown in the figures throughout this section are for a booking horizon of 1-15 weeks, where every booking horizon is analyzed on the fraction of patients that have a single day checkup, the fraction of total patients having no appointment, the throughput time per patient and the difference between the expected planned week and the realized plan week.

Single day fraction

As can be seen in Figure 6 the confidence intervals are close to one another and have small intervals. Only the result for a booking horizon of fifteen weeks is not close to the other results. This shows us that any booking horizon of 1 - 14 weeks will give about a similar result. However, there is a small upwards trend towards for the larger booking horizons, where a booking horizon of twelve and thirteen have a significant increase in contrast to the other booking horizons. This suggests that the impact of higher cancellation rates for these booking horizons is a bit smaller compared to the impact of availability.

The results for Experiment 15 are (most likely) due to the maximum of sixteen weeks we set for patients to be scheduled in. Note that only data on the availability of up to sixteen weeks is available. This means that with a booking horizon of fifteen weeks, the simulation only has one week to plan the patients. As shown, this is clearly not enough to uphold the high single day fraction standards found for the other fourteen experiments.

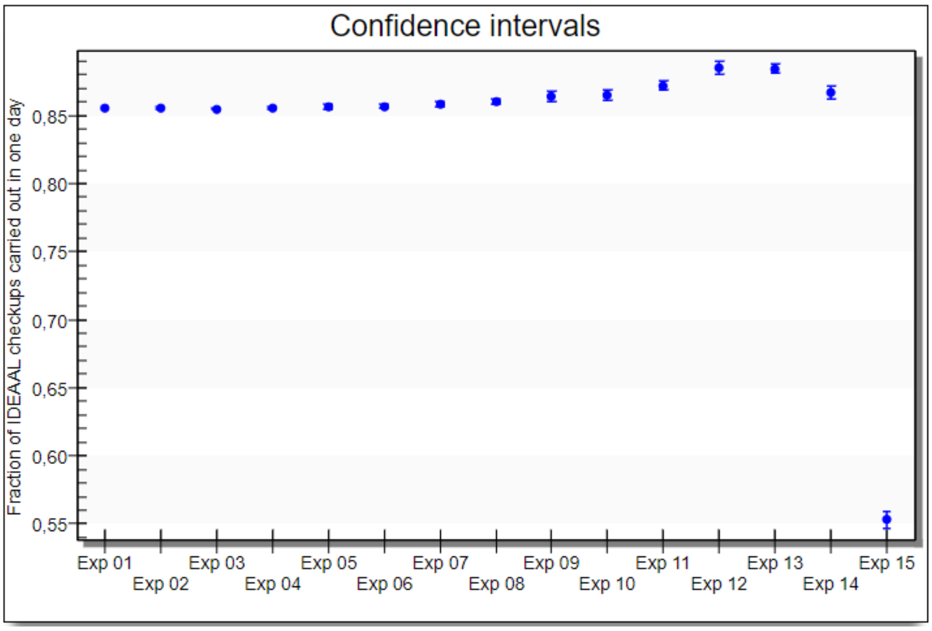


Figure 6 Confidence interval of the single day fraction patients per booking per horizon (exp 01 – exp 15 translates to booking horizon 1 – 15)

As can be read from Table 7, most experiment results are not significantly different. In contrary to the other experiments, the mean from Experiment 14 is significantly different from every other experiment. This suggests that the booking horizon has a significant impact on the results. As shown in Table 8, 1.11% of the patients are not scheduled when taking a booking horizon of fourteen weeks. This is higher compared to the booking horizons one up to thirteen. Note that a booking horizon of fourteen has a maximum Checking Horizon of two weeks, making it harder to find an appointment.

Table 7 p values between experiments, based on the not scheduled fraction for the base case

Not Scheduled	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14	Exp 15
Exp 01	0.467	0.243	0.098	**0.03**	**0.022**	**0.022**	**0.04**	**0.022**	0.054	0.467	**0.015**	**0**
Exp 02		0.618	0.247	0.056	**0.035**	**0.035**	0.08	**0.035**	0.122	1	**0.006**	**0**
Exp 03			0.418	0.069	**0.033**	**0.033**	0.11	**0.033**	0.19	0.618	**0.004**	**0**
Exp 04				0.33	0.191	0.191	0.466	0.191	0.647	0.247	**0.003**	**0**
Exp 05					0.697	0.697	0.749	0.697	0.568	0.056	**0.002**	**0**
Exp 06						1	0.451	1	0.335	**0.035**	**0.002**	**0**
Exp 07							0.451	1	0.335	**0.035**	**0.002**	**0**
Exp 10								0.451	0.777	0.08	**0.002**	**0**
Exp 11									0.335	**0.035**	**0.002**	**0**
Exp 12										0.122	**0.002**	**0**
Exp 13											**0.006**	**0**
Exp 14												**0**

Not scheduled patients

Figure 7 shows the results of the KPI "fraction of not scheduled patients". This figure shows the same impact of the different booking horizons as the previous KPI. We can see that once again Experiment 15 performs a lot worse than the other experiments. The result for a booking horizon of fifteen is an outlier to the rest of the experiments. This is most likely caused by the maximum of sixteen weeks we set to plan appointments.

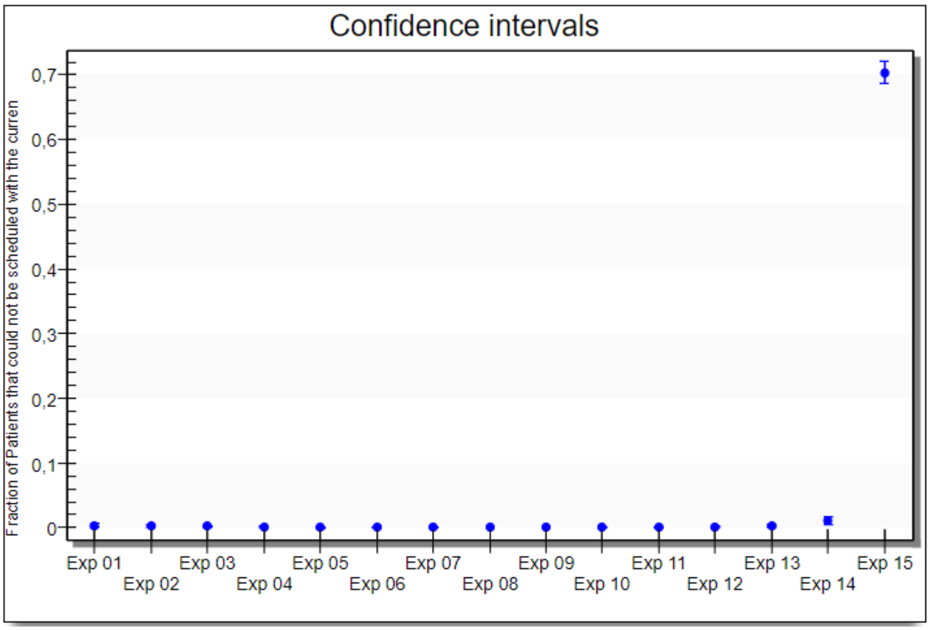


Figure 7 Confidence interval of the not scheduled patients fraction per booking per horizon (exp 01 – exp 15 translates to booking horizon 1 – 15)

For Exp 1 up to 14 a more detailed analysis is performed by p value comparison. Table 7 gives an overview of the p values, where values lower than 0.05 are marked green. Experiments 8 and 9 are not taken into account in this overview, as every replication in their respective experiments yielded the same outcome i.e., zero patients not scheduled. Due to this there is no error in the results for these experiments and hence no p value. Table 8 shows the average results per experiment.

Table 8: Mean of the single day fraction and not scheduled fraction per booking horizon per KPI for the base case

Booking Horizon	One day	Not scheduled
1	85.5%	0.36%
2	85.5%	0.25%
3	85.5%	0.20%
4	85.6%	0.13%
5	85.6%	0.05%
6	85.7%	0.04%
7	85.8%	0.04%
8	86.0%	0%
9	86.4%	0%
10	86.5%	0.07%
11	87.2%	0.04%
12	**88.5%**	**0.09%**
13	88.4%	0.25%
14	86.7%	**1.11%**
15	55.3%	70.4%

Figure 6 Experiment 12 shows a small increased mean value. In Table 8 the booking horizon is also highlighted. With an average of 0.09%, Experiment 12 has one of the best performing booking horizons, when considering the fraction of not scheduled patients. On average for 0.5 patients ($= 557 \cdot 0.0009$) no appointment day was found. Hence for every other patient no appointment day was found. In contrary, the average fraction of patients that is planned on a single day is also the highest for Experiment 12. Table 9 shows us that this percentage is significantly different from all

other experiments, except for Experiment 13. Table 9 also shows us that most results of experiments from seven up to fifteen are significantly different to one another.

Table 9 p values between experiments, based on the single day fraction for the base case

Single Day	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 09	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14	Exp 15
Exp 01	1	0.451	0.571	0.18	0.095	0.003	0	0.001	0	0	0	0	0	0
Exp 02		0.356	0.532	0.159	0.082	0.002	0	0.001	0	0	0	0	0	0
Exp 03			0.202	0.063	0.033	0.001	0	0	0	0	0	0	0	0
Exp 04				0.389	0.221	0.007	0	0.001	0	0	0	0	0	0
Exp 05					0.712	0.06	0.002	0.002	0.001	0	0	0	0.001	0
Exp 06						0.127	0.005	0.002	0.001	0	0	0	0.001	0
Exp 07							0.102	0.011	0.004	0	0	0	0.002	0
Exp 08								0.084	0.033	0	0	0	0.012	0
Exp 09									0.665	0.002	0	0	0.272	0
Exp 10										0.006	0	0	0.477	0
Exp 11											0	0	0.062	0
Exp 12												0.832	0	0
Exp 13													0	0
Exp 14														0

Throughput time

Furthermore, we analyzed the throughput time of the patients over the different experiments. An overview of these throughput times is shown in the boxplot in Figure 8. It shows that when increasing the booking horizon up to fourteen weeks, the throughput time of patients becomes more consistent, but the mean remains the same. This is because when we have a larger booking horizon, the caregivers will have more available slots in their calendars. Making it more likely that the throughput time can be minimized further.

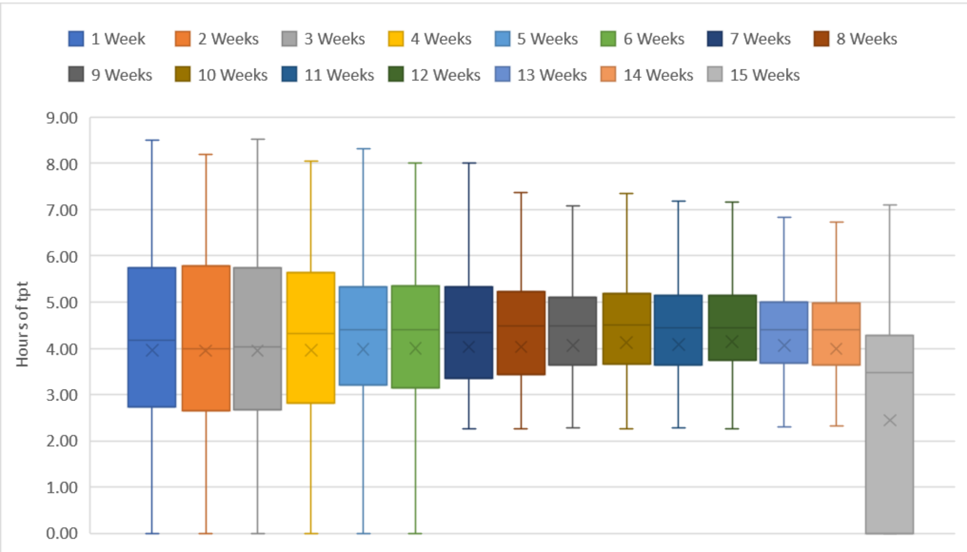


Figure 8 Boxplot of throughput time per patient over fifteen experiments when considering the base case

Delta weeks

The final KPI we take look at is the Delta Weeks, which is shown in the boxplots in Figure 9. From this figure we can conclude that a higher booking horizon is better. The standard deviation of Experiment 13 and 14 are decreasing by a fair amount. This can be explained by the increase in not planned patients. In the lower booking horizons, the patients can have a larger Delta Week, as a result of a longer Checking Horizon. The patients that still find an appointment, but with a higher Delta Week, might not be scheduled when the booking horizon increases. Therefore, the Delta Weeks standard deviation decreases.

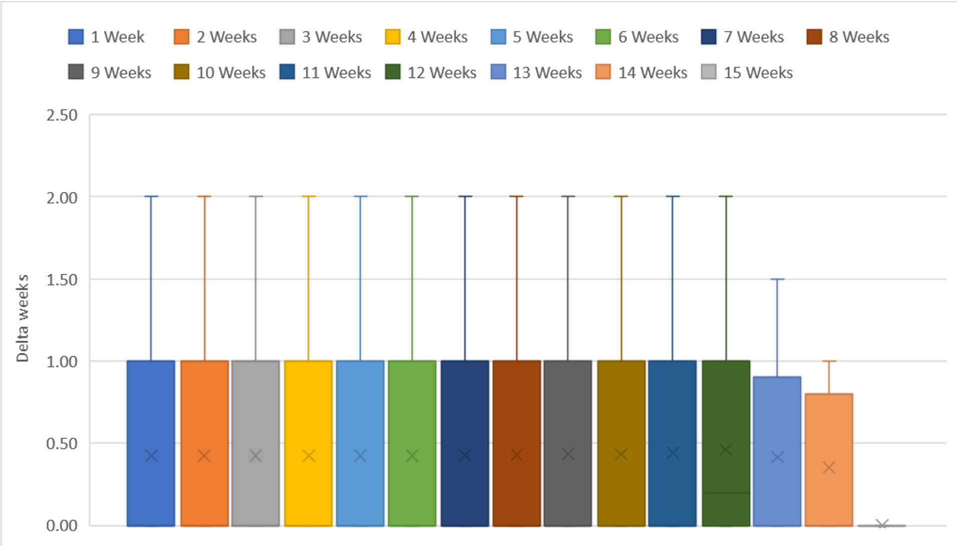


Figure 9 Boxplot of Delta Weeks per patient over fifteen experiments when considering the base case

Conclusion
Concluding from all this we can say that having a larger booking horizon in general will be better than a smaller booking horizon. From the perspective of this research, and ignoring the limitations, we could say that a booking horizon of twelve weeks is recommended. Overall, this booking horizon performs better in relation to the booking horizons. Note however, the difference in the results is small and hence taking a different booking horizon might have little impact.

We cannot be sure whether a fourteen-week booking horizon is actually worse than a smaller booking horizon. Just as a fifteen-week booking horizon, they are hindered by a smaller Checking Horizon to give sensible outcomes.

5.2.2 Demand

We changed the demand distribution and increased the demand. The booking horizon of fifteen weeks (Exp 15) is excluded from these experiments. We will be executing the same analysis for these different settings as we did for the base case. We will analyze the impact of one up to fourteen week booking horizon for an equal demand distribution, an expected demand increase and an extreme increase in demand.

<u>Equal demand Distribution</u>

Single day fraction
As can be seen in Figure 10 the confidence intervals are close to one another and have small intervals. Only the result for a booking horizon of fifteen weeks is not close to the other results. This shows us that any booking horizon of 1 - 14 weeks will give about a similar result. However, there is a small upwards trend towards for the larger booking horizons, where a booking horizon of twelve and thirteen have a significant increase in contrast to the other booking horizons. This suggests that the impact of higher cancellation rates for these booking horizons is a bit smaller compared to the impact of availability.

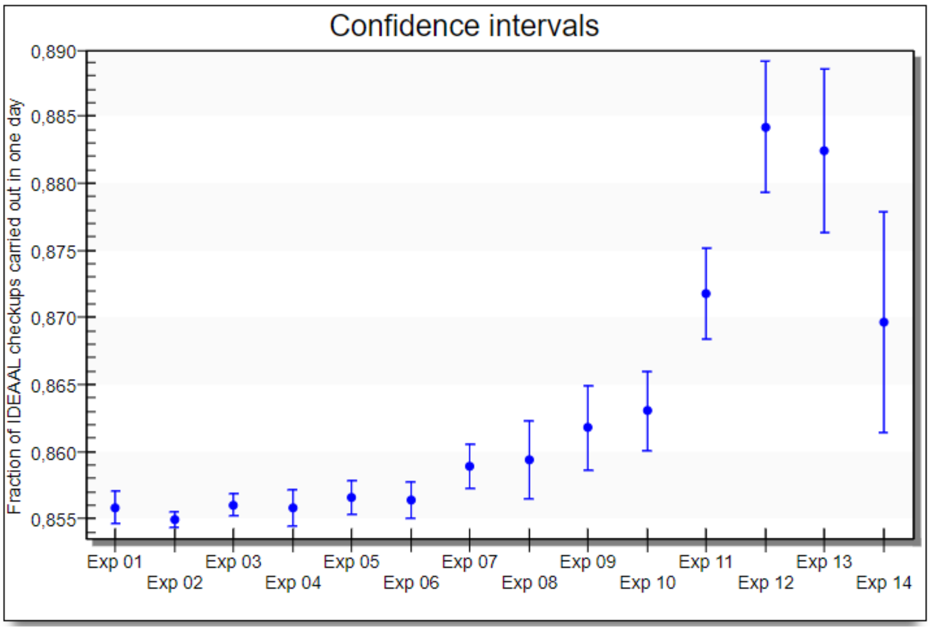


Figure 10 Confidence interval of the single day fraction patients per booking per horizon for equalized demand (exp 01 – exp 14 translates to booking horizon 01 – 14)

Not scheduled fraction

Figure 11 shows the results of the KPI "fraction of not scheduled patients". This figure shows the same impact of the different booking horizons as the previous KPI. A booking horizon of four up to eleven weeks give the best results in terms of not scheduled patients, as the lower this fraction the better the booking horizon.

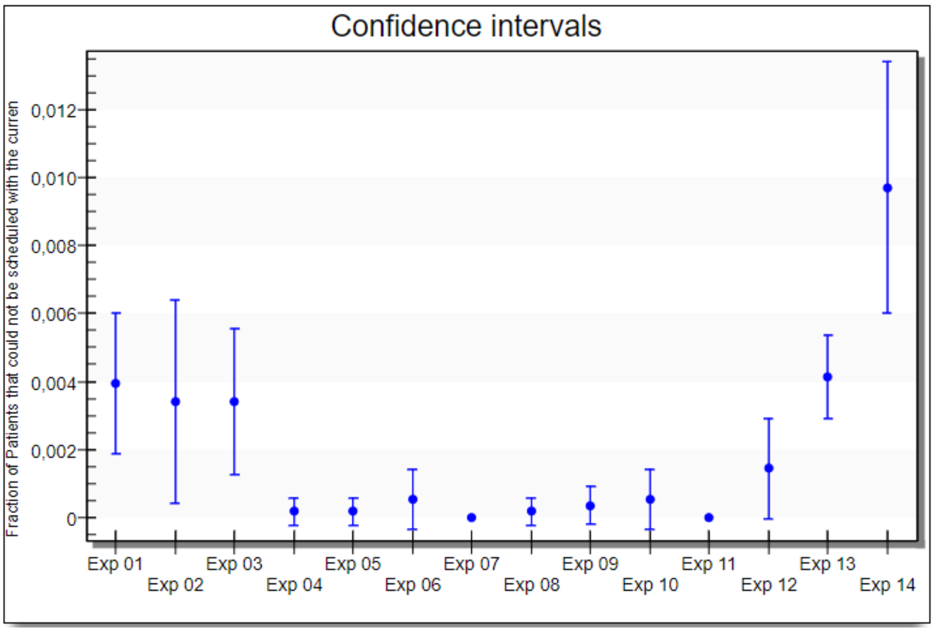


Figure 11 Confidence interval of the not scheduled patients fraction per booking per horizon (exp 01 – exp 14 translates to booking horizon 01 – 14)

Table 10 gives an overview of the p values, where values lower than 0.05 are marked green. Experiments 7 and 11 are not taken into account in this overview, as every replication in their respective experiments yielded the same outcome i.e., zero patients not scheduled. Due to this there is no error in the results for these experiments and hence no p value. Table 8 shows the average results per experiment.

Table 10 p values between experiments, based on the not scheduled fraction for an equalized demand

Not scheduled	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 08	Exp 09	Exp 10	Exp 12	Exp 13	Exp 14
Exp 01	0.743	0.688	**0.003**	**0.003**	**0.005**	**0.003**	**0.003**	**0.005**	**0.04**	0.869	**0.008**
Exp 02		1	**0.038**	**0.038**	0.062	**0.038**	**0.048**	0.062	0.203	0.624	**0.008**
Exp 03			**0.008**	**0.008**	**0.016**	**0.008**	**0.01**	**0.016**	0.103	0.519	**0.005**
Exp 04				1	0.412	1	0.557	0.412	0.089	**0**	**0**
Exp 05					0.412	1	0.557	0.412	0.089	**0**	**0**
Exp 06						0.412	0.697	1	0.25	**0**	**0**
Exp 08							0.557	0.412	0.089	**0**	**0**
Exp 09								0.697	0.144	**0**	**0**
Exp 10									0.25	**0**	**0**
Exp 12										**0.005**	**0.001**
Exp 13											**0.008**

As can be read from Table 10, most experiment results of booking horizon four up to eleven are not significantly different from one another. The mean from Experiment 14 is significantly different from every other experiment. This suggests that the booking horizon has a significant impact on the results. As shown in Table 11, 0.97% of the patients are not scheduled when taking a booking horizon of fourteen weeks. This is higher compared to the booking horizons one up to thirteen. Note that a booking horizon of fourteen has a maximum Checking Horizon of two weeks, making it harder to find an appointment.

Table 11 Mean of the single day fraction and not scheduled fraction per booking per KPI for equalized demand

Booking Horizon	One day	Not scheduled
1	85.6%	0.39%
2	85.5%	0.34%
3	85.6%	0.34%
4	85.6%	0.02%
5	85.7%	0.02%
6	85.6%	0.05%
7	85.9%	0%
8	85.9%	0.02%
9	86.2%	0.04%
10	86.3%	0.05%
11	87.2%	0%
12	88.4%	0.14%
13	88.2%	0.41%
14	87.0%	0.97%

Throughput time

Furthermore, we analyzed the throughput time of the patients over the different experiments. An overview of these throughput times is shown in the boxplot in Table 13. It shows that when increasing the booking horizon, the throughput time of patients becomes more consistent, but the mean remains the same.

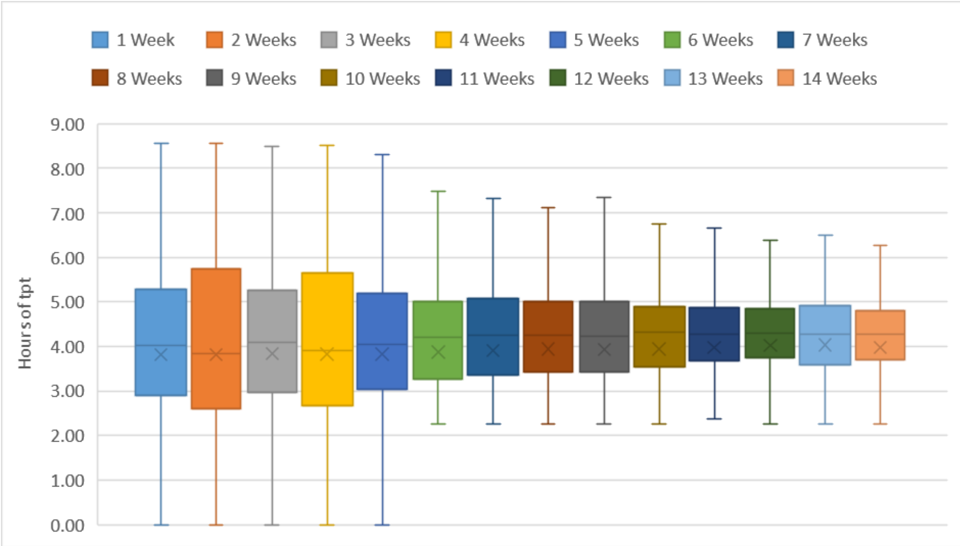


Figure 12 Boxplot of throughput time per patient over fourteen experiments when considering an equalized demand

Delta weeks

The final KPI we take look at is the Delta Weeks, which is shown in the boxplots in Table 14. From this figure we can conclude that a higher booking horizon is better. The standard deviation of Experiment 14 is lower than the other experiments. This can be explained by the increase in not planned patients. In the lower booking horizons, the patients can have a larger Delta Week, as a result of a longer Checking Horizon. The patients that still find an appointment, but with a higher Delta Week, might not be scheduled when the booking horizon increases. Therefore, the Delta Weeks standard deviation decreases.

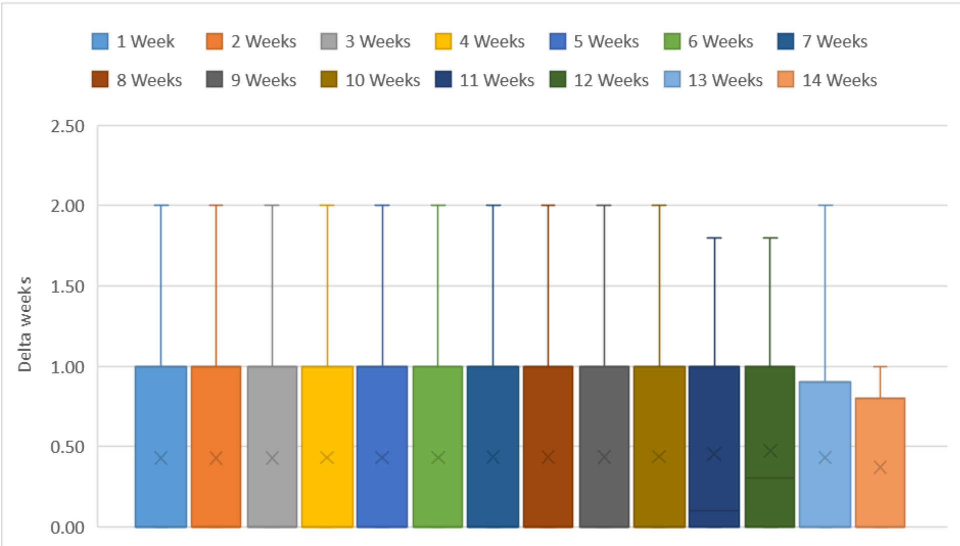


Figure 13 Boxplot of Delta Weeks per patient over fourteen experiments when considering an equalized demand

Conclusion

Equalizing the demand over the year has no impact on the outcomes of the experiments, compared to the base case. This is explained by the small impact of the IDEAAL checkups on the individual sub calendars discussed in Section 4.1.3.

Increased demand

Two different amounts of increase in demands are used in this section, an increase of 7.8% and an increase of 100%. Where 7.8% is the expected increase in demand and 100% an extreme increase in demand. The expected increase in demand did not impact the plannability of the IDEAAL checkups at all, the results of these experiments can be found in J.1 Expected demand increase. This is because the increase was so small that the demand rate did not yet reach a critical level in which it starts significantly impacting the sub calendars.

Extreme demand increase

To test what happens when the demand will impact the sub calendars, we experimented with an extreme increase of the demand. This extreme increase gave some interesting insights in the performance of the planning of IDEAAL checkups over the different booking horizons.

Single day fraction

In Figure 14 we observe that an extreme increase in demand strongly impacts the results of the simulation. The system is way less stable, as the confidence intervals vary a lot more than with the actual demand rate. When evaluating the results in Figure 14, we conclude that a booking horizon of twelve weeks, perform significantly better than any other booking horizon. The p values to proof the significance are shown in J.2.1 p values.

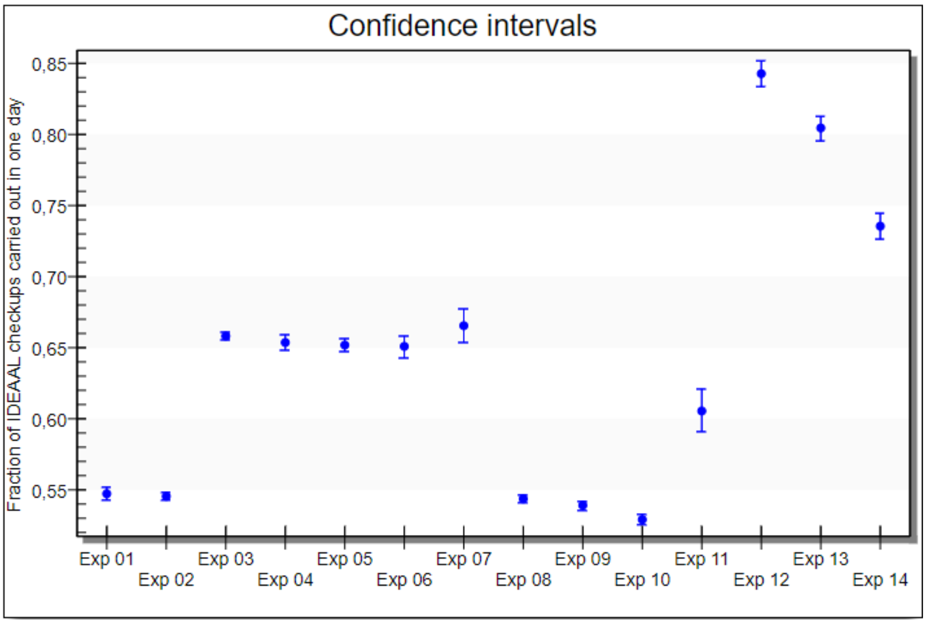


Figure 14 Confidence interval of the single day fraction patients per booking per horizon with an extreme demand (exp 01 – exp 14 translates to booking horizon 01 – 14)

Not scheduled fraction

Figure 15 leads us to a similar conclusion as Figure 14 did. We observe that the fraction not scheduled patients is significantly lower when choosing a booking horizon of twelve weeks. For both KPIs it is still hard to compare Experiment 12 with Experiment 13 and 14, for the same reasons mentioned earlier. Experiments 13 and 14 are more limited by the 16 weeks maximum planning horizon.

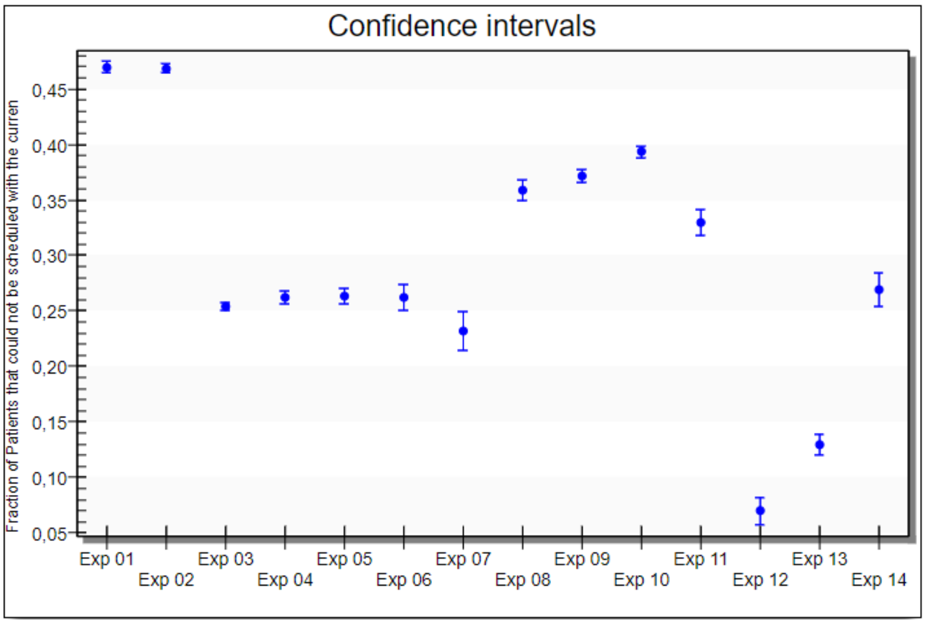


Figure 15 Confidence interval of the not scheduled patients fraction per booking per horizon with an extreme demand (exp 01 – exp 14 translates to booking horizon 01 – 14)

Throughput time

The boxplot in Figure 16 shows that for the Throughput time we cannot statistically say that there is a difference between any of the experiments. We only see somewhat of a decline in average throughput time for a higher booking horizon and the throughput time becoming somewhat more consistent.

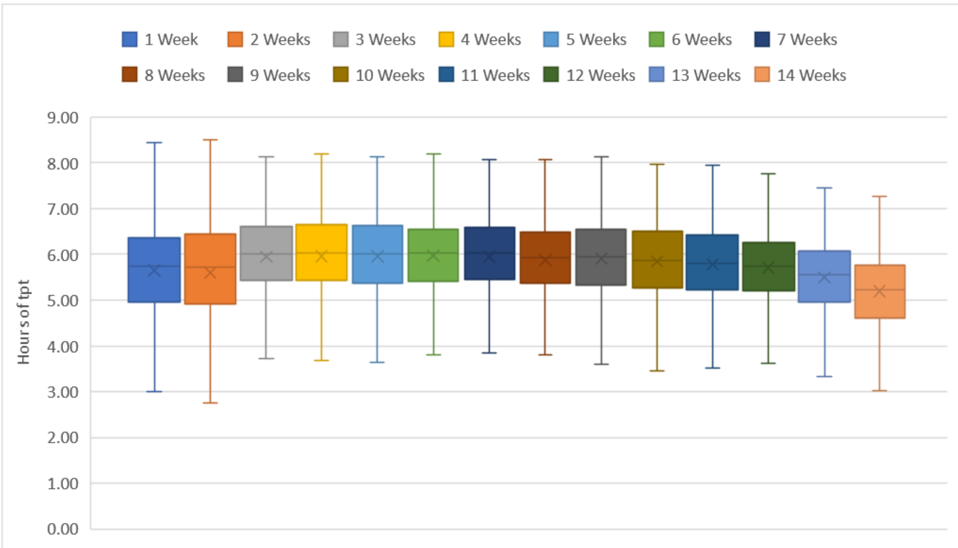


Figure 16 Boxplot of throughput time per patient over fourteen experiments when considering an extreme demand increase

Delta weeks

The boxplot in Figure 17, shows that for the Delta weeks we cannot statistically say that there is a difference between any of Experiment 3 up to 13. The Delta weeks of a booking horizon of one and two weeks is both 0, meaning that every scheduled appointment, is scheduled in the expected appointment week. As Table 12 shows, the not scheduled fraction of these booking horizons are 47.0% and 46.8% respectively, heavily influencing the results shown in this table. Half of the appointments did not find an appointment at all.

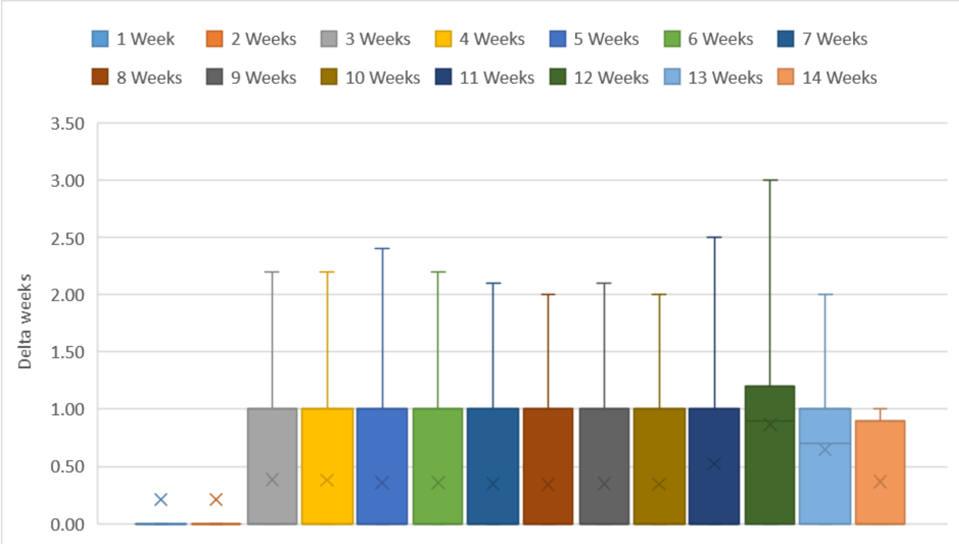


Figure 17 Boxplot of delta weeks per patient over fourteen experiments when considering an extreme demand increase

Conclusion

Table 12 gives an overview with the means of the results shown in Figure 14 and Figure 15. Both the mean for the one-day fraction and not scheduled fraction score best when planning with a booking horizon of twelve weeks. We can say that a booking horizon of twelve weeks is the best booking horizon with an extreme demand of IDEAAL patients, as there is a significant difference when considering the KPIs shown in Table 12.

Table 12 Mean of the single day fraction and not scheduled fraction per booking per KPI with an extreme demand

Booking Horizon	One day	Not scheduled
1	54.8%	47.0%
2	54.6%	46.8%
3	65.8%	25.4%
4	65.4%	26.2%
5	65.2%	26.3%
6	65.1%	26.2%
7	66.6%	23.2%
8	54.4%	35.9%
9	53.9%	37.1%
10	53.0%	39.3%
11	60.6%	33.0%
12	**84.3%**	**6.97%**
13	80.5%	13.0%
14	73.6%	26.9%

5.2.3 Cancellation rates

We changed the cancellation rates of appointments and availability setting of the caregivers. The booking horizon of fifteen weeks is excluded from these experiments. The first experimentations are with the exclusion of cancellations and the exclusion of other patients. Furthermore, we experimented with the cancellation rate, to determine the impact of cancellations.

<u>**Excluding cancellations and availability**</u>

Single day fraction / not scheduled patients

Excluding cancellations and availability results in constant KPI values for Experiments 1 to 13. Since there are no difference, we do not need to determine either the p values nor the confidence interval. In Table 13 the results mean fraction of the single day checkups and the mean fraction of not scheduled patients.

Table 13 Mean of the single day fraction and not scheduled fraction per booking per KPI when excluding cancellations and availability

Booking Horizon	One day	Not scheduled
1	99.8%	0%
2	99.8%	0%
3	99.8%	0%
4	99.8%	0%
5	99.8%	0%
6	99.8%	0%
7	99.8%	0%
8	99.8%	0%
9	99.8%	0%
10	99.8%	0%
11	99.8%	0%
12	99.8%	0%
13	99.8%	0%
14	99.2%	0%

We observe that almost every patient (99.8%) now finds an appointment on a single day and every patient will be planned (0% not scheduled). This is notable, we would expect that every patient now finds a date on which their IDEAAL checkup can be carried out in one single day. But since that is not the case, we will take a further look at the patients that did not find such a day to find the cause. Table 14 contains an overview of the patients that got a split-up checkup when considering a booking horizon of fourteen weeks.

Table 14 Patients that did not get a single day checkup when excluding cancellations and availability

Patient	First day	Second day	Initial Week	First week	Second week	Preferred doctor	Preferred Nurse
p094	Monday	Tuesday	25	25	25	doc4	n9
p420	Monday	Tuesday	39	39	39	doc5	n15
p490	Monday	Tuesday	39	39	39	doc5	n15
p561	Monday	Tuesday	39	39	39	doc5	n15

There are no days on which both doc4 and n9 work in the outpatient clinic at the same time. Doc5 and n15 only have one day every two weeks in which both of them work half a day in the outpatient clinic. Due to a lack of available outpatient clinic working days among the preferred caregivers, it is not possible to schedule patients for a single day. This explains the single day fractions being 99.8% and 99.2% instead of 100%.

<u>Changing the cancellation rate</u>

As described in Section 4.2.7 we experimented by doubling the cancellation rate and only excluding the cancellations. Appendices J.4 No Cancellations and J.5 Doubled Cancellation Rate contain all statistics about these experiments. From these statistics we can see that both increasing and excluding the cancellation rates has close to no impact on outcome of the experiments. From that we conclude that the cancellation rate does not or barely impact the plannability of the IDEAAL checkups. As a result, we conclude that the availability of the caregivers is the main issue. As shown in the experiments, where we excluded the availability as well as the cancellations, almost every patient got their checkup planned on one single day. the “Caregiver Tuning” experiments will be used to further investigate if it is possible to reduce impact of the availability of caregivers on the fraction of single day checkups.

5.2.4 Caregiver tuning

We spread the demand in a fair way over the caregivers and determine smart pairings of preferred caregivers. The booking horizon of fifteen weeks is excluded from these experiments.

Fair workload

In Appendix J.6.1 Workload distribution we describe how the workload is distributed over the caregivers. Distributing the demand in such a way resulted some interesting changes in the KPI outcomes.

Single day fraction

In Figure 18 the confidence intervals of the single day fraction per experiment are shown. The lower- and upper bounds of these fraction are noticeably higher than the results from the base case, shown in Figure 6. We observe the same impact of booking horizons on the single day fraction as in the base case, where the higher the booking horizon, the better the single day fraction becomes. Up until a booking horizon of twelve weeks. These results lead us to the conclusion, that a booking horizon of twelve weeks yields the best single day fraction results when planning the IDEAAL checkups.

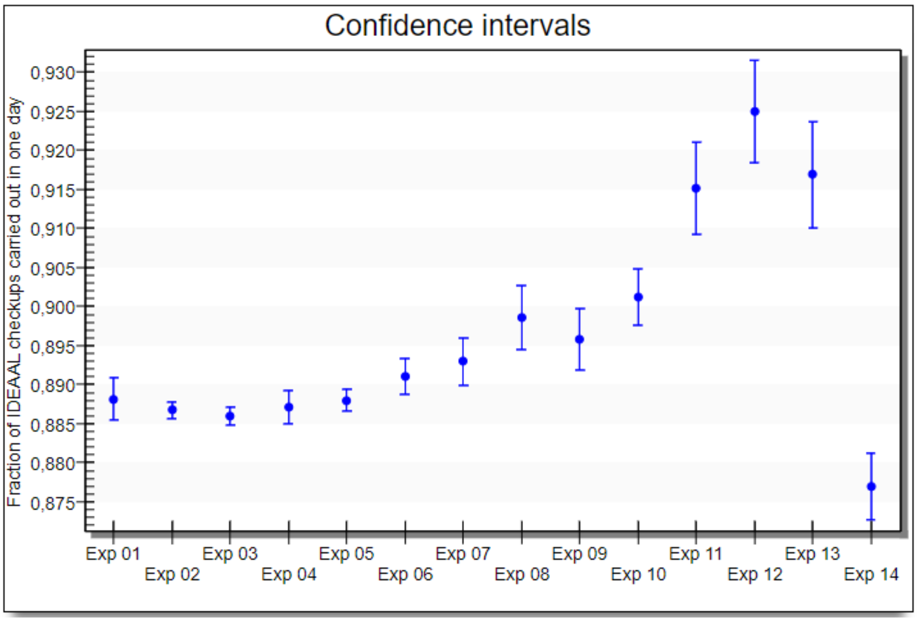


Figure 18 Confidence interval of the single day fraction per booking per horizon with a fair workload (exp 01 – exp 14 translates to booking horizon 01 – 14)

Similar to the conclusion in Section 5.2.1, in reality a booking horizon of more than twelve weeks might be superior. But with the limitations of the simulation model, we can say that a booking horizon of twelve weeks has a significantly better single day fraction compared to all other booking horizons except a booking horizon of thirteen weeks. J.6.2 p values shows us that the p value compared to most other booking horizons is smaller than 0.05, proving this significant difference. Only the p value of the results between Experiment 12 and 13 is higher than 0.05 (0.069), indicating that we cannot say that the difference between these experiments is statistically significant.

Not scheduled fraction

When analyzing the results in Figure 19, we observe that increasing the booking horizon up until ten weeks, lowers the standard deviation of the not scheduled patients and with a booking horizon of more than ten weeks this standard deviation increases again. J.6.2 p values, shows that the results from Experiment 10 are significantly different from any other Experiment with all p values being zero. This suggests that a booking horizon of ten weeks would be the best fit when considering a fair workload.

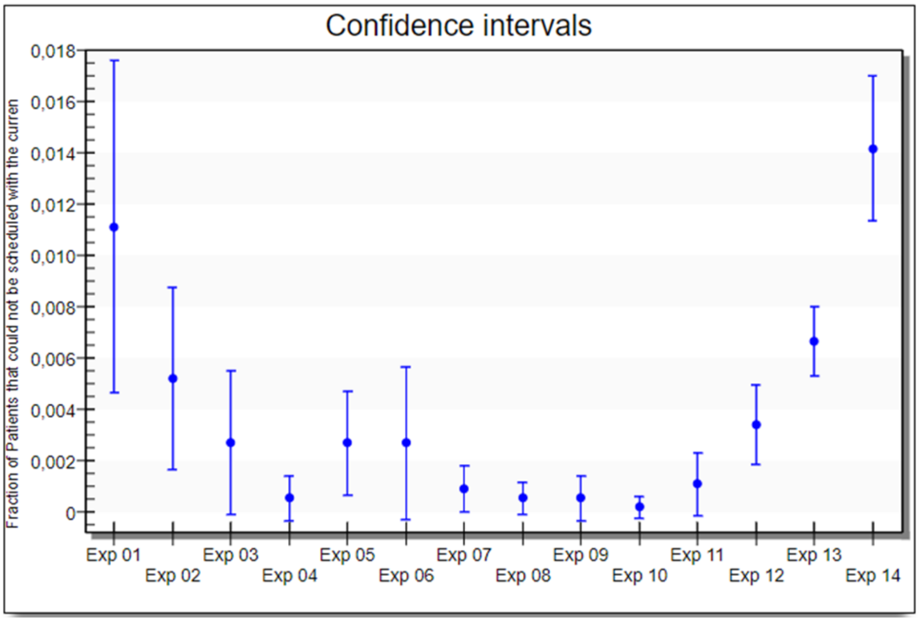


Figure 19 Confidence interval of the not scheduled patients fraction per booking per horizon with a fair workload (exp 01 – exp 14 translates to booking horizon 01 – 14)

Throughput time

Considering the results of the throughput time per experiment, we can merely conclude that taking a booking horizon of five weeks or more will not impact the throughput time of patients. As we see in Figure 20, the standard deviation of the throughput time for more than four weeks stays almost the same. Therefore, we can conclude that based on the throughput time any booking horizon higher than four weeks performs similar.

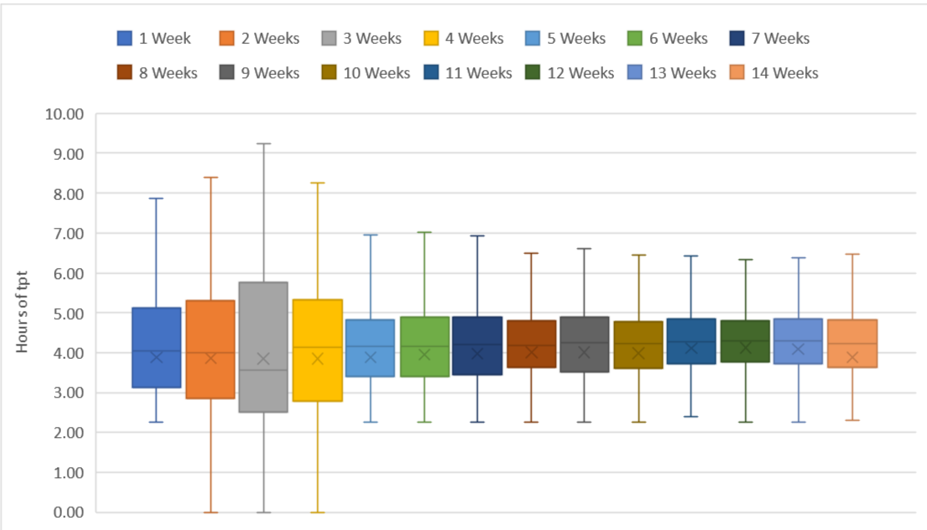


Figure 20 Boxplot of throughput time per patient over fourteen experiments when considering a fair workload

The boxplot for the delta weeks of a fair workload is shown in J.6.3 Delta weeks. This figure shows that there is close to no difference in the delta weeks between the experiments.

Conclusion

Concluding the results of the second day fair workload experiments, we can say that either a booking horizon of twelve weeks or ten weeks is the best booking horizon when considering a fair workload. Since the fraction of patients scheduled on one day is the most important indicator, we would advise a booking horizon of twelve weeks. In reality patients will be scheduled no matter what, where in this simulation we are limited to a sixteen-week period for which availability is known. It is fair to assume that every patient will always be scheduled in reality, no matter what.

Smart pairings

In Appendix J.7.1 Smart pairing logic we describe how the caregiver are paired. Pairing caregivers some interesting changes in the KPI outcomes.

Single day fraction

In Figure 21 the confidence intervals of the single day fraction per experiment are shown. The lower- and upper bounds of these fraction are noticeably higher than the results from the base case, shown in Figure 6. We observe the same impact of booking horizons on the single day fraction as in the base case and fair workload distribution. A longer booking horizon results in a better single day fraction, up until a booking horizon of twelve weeks. These results lead us to the conclusion, that a booking horizon of twelve weeks yields the best single day fraction results when planning the IDEAAL checkups.

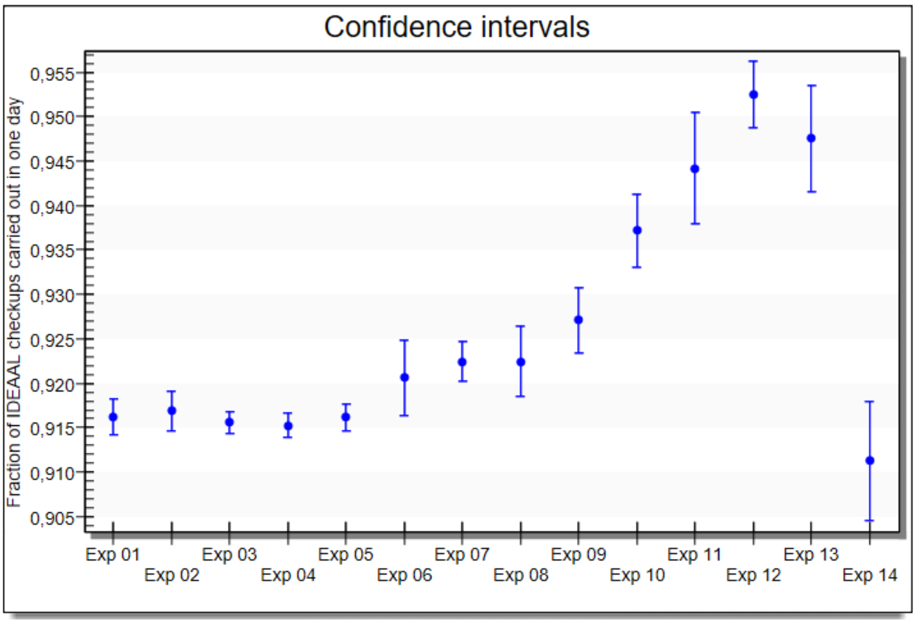


Figure 21 Confidence interval of the single day fraction per booking per horizon with smart pairings (exp 01 – exp 14 translates to booking horizon 01 – 14)

Similar to the conclusion to the fair workload distribution experiments, in reality, a booking horizon of more than twelve weeks might be superior. But with the limitations of the simulation model, we can say that a booking horizon of twelve weeks has a significantly better single day fraction compared to all other booking horizons except a booking horizon of thirteen weeks. J.7.2 p values shows us that the p value compared to most other booking horizons is smaller than 0.05, which proves the difference is significant. Only the p value of the results between Experiment 12 and 13 is higher than 0.05 (0.873), indicating that we cannot say that the difference between these experiments is statistically significant.

Not scheduled fraction

When analyzing the results in Figure 22 we observe that a booking horizon of five or seven weeks performs best. J.7.2 p values, shows that the results from these experiments are not significantly different from the other experiment. These p values proof that there is no statistical difference between most experiments with regards the fraction of not scheduled patients. Only a booking horizon of one week and a booking horizon of fourteen weeks are significantly different from all other experiments. A booking horizon of thirteen weeks is significantly different to most other experiments. But as we can see in Figure 20, a booking horizon of one week, thirteen weeks and fourteen weeks perform significantly worse than the other experiments. Therefore, we can conclude that there is no significant difference between choosing any booking horizon of two to twelve weeks, when considering the fraction of not scheduled patients.

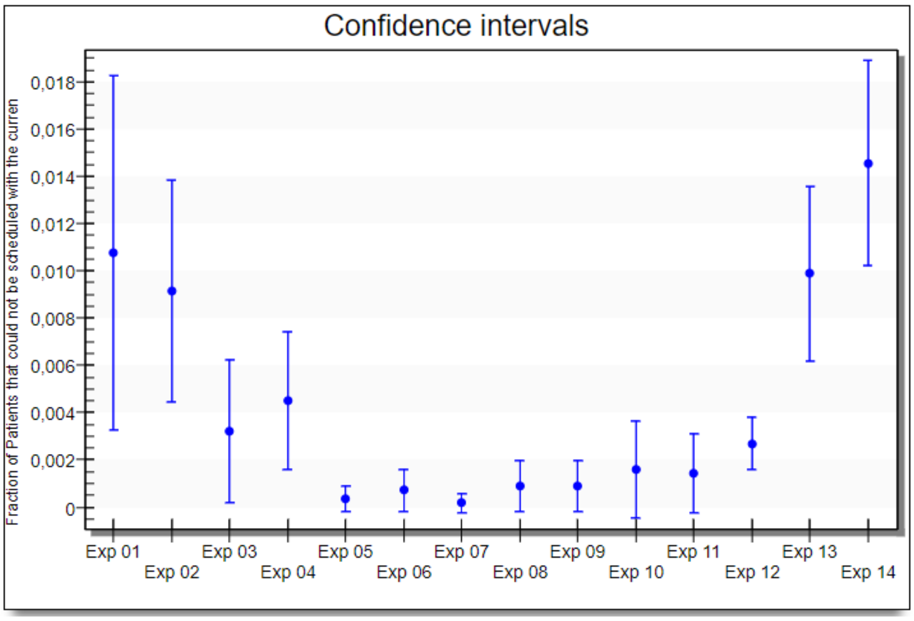


Figure 22 Confidence interval of the not planned fraction per booking per horizon with smart pairings (exp 01 – exp 14 translates to booking horizon 01 – 14)

Throughput time

Considering the results of the throughput time per experiment, we can merely conclude that taking a booking horizon of seven weeks or more will not impact the throughput time of patients. As we see in Figure 23, the standard deviation of the throughput time for more than six weeks stays almost the same. Therefore, we can conclude that based on the throughput time any booking horizon higher than six weeks performs similar.

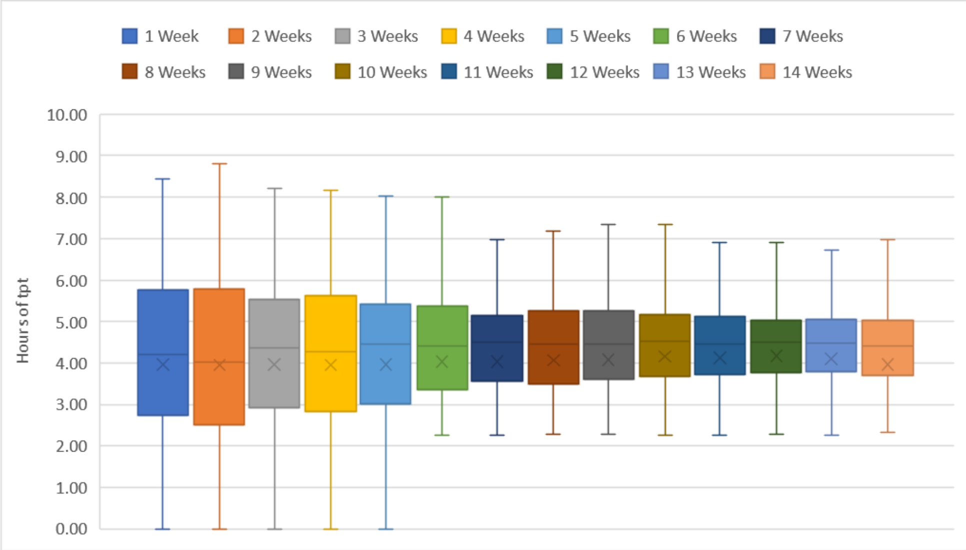


Figure 23 Boxplot of throughput time per patient over fourteen experiments when considering smart pairings of caregivers

The boxplot for the delta weeks of a fair workload is shown in J.7.3 Delta weeks. This figure shows that there is close to no difference in the delta weeks between the experiments.

Conclusion
Concluding the results of the smart pairing experiments, we can say that a booking horizon of twelve weeks when considering smart pairings of caregivers. Since the fraction of patients scheduled on one day is the most important indicator, we would advise a booking horizon of twelve weeks. In reality patients will be scheduled no matter what, where in this simulation we are limited to a sixteen-week period for which availability is known. Therefore, a higher booking horizon might still be better in reality.

5.3 Conclusion

From the results of the mathematical model we conclude that there are many different solutions giving an equally good result. From that we can conclude that a heuristic is very likely to also always find the optimal solution. This is also confirmed by the throughput times being so consistent over the different experiments and booking horizons.

The overall best choice to make is changing the work instructions to have the planners always try and plan all appointments of an IDEAAL checkup on a single day. Then start planning twelve weeks in advance, as this yields the highest single day fraction regardless of the experiments. From this we can conclude that making both these discissions results in robust planning rules, that will give a constant and good performing planning.

6 Conclusion and Discussion

This chapter shows the conclusions of our research (Section 6.1) and argues the limitations of our study and suggests further research directions (Section 6.2).

6.1 Conclusion

In Chapter 1, we formulated the following research question: *How can the number of scheduled hospital days for the IDEAAL checkup per individual patient be minimized without increasing the overtime for staff and while minimizing the waiting time between appointments?*

We analyzed the current situation of Isala and their problems, and concluded that there were three essential causes of the planning problems:

1. Wrong work instructions
2. Cancellation and rescheduling of appointments
3. Availability of the caregivers

Since the last two of these issues are influenced by the booking horizon, we investigated the impact of the booking horizon on the plannability of the IDEAAL checkups. For the measuring method, we designed a discrete event simulation that measures the impact of varying booking horizons. This discrete event simulation showed us that planning patients on a single day, which is the minimum number of scheduled hospital days, is already possible for 88.5% of the patients in the current situation, when changing the work instructions. Our experiments show us that the planning method is very robust, as most experiments did not cause large changes in the fraction of patients that could be scheduled on a single day. Our experiments did show that there is still room for improvement on the current situation. By assigning patients to caregivers based on their working hours in the outpatient clinic, we will be able to plan up to 92.5% of the patients on a single day, when choosing a booking horizon of twelve weeks. By making smart pairings for nurses and doctors we can even improve this number up to 95.2% of the patients when we choose a booking horizon of twelve weeks. As expected, we can both see in our experimentation and base case that the booking horizon impacts the number of scheduled hospital days for IDEAAL patients. Although we can also see that this impact is relatively small, as the lowest percentage in the base case is 85.5%. From this we can conclude that the booking horizon does not need to be followed extremely strict, but when optimizing the chance for a patient to have a minimal number of hospital days it is advised to choose plan with a booking horizon of twelve weeks. Even an extreme increase in demand does not impact the percentage of patients with all appointments on a single day, proving the robustness of their current planning method. As long as the appointments are scheduled with a booking horizon of twelve weeks, the diabetes department can achieve a percentage of 84.4% patients planned on one single day. We can therefore conclude that when the diabetes department sticks with the current method of assigning caregivers and planning the patients, they should be able to plan 88.5% of the patients in one day. Since we are limited to a maximum of sixteen weeks in which we can actually plan patients, we are not able to give a conclusive answer on which booking horizon is the best. The best booking horizon might be higher than fourteen weeks. If we consider our research scope, we advise the department to adjust the instruction for planners and start planning the IDEAAL checkups on one day. At the same time it is advised to try and always plan with a booking horizon of twelve weeks, as this maximizes the chance for the patient to have their checkup carried out in one single day.

6.2 Discussion

Notable results

Notable are the resulting boxplots for the throughput time and the delta weeks for all executed experiments, with the delta weeks being the most notable. Regardless of the experimental settings, the average delta weeks for any booking horizon is below one, which means that practically every patient can be scheduled in the week we initially tried to plan them. This implies that planning the IDEAAL checkups is relatively easy and is not complicated at all. If the complexity with multiple sub calendars, availabilities and cancellations had more of an impact, we would see more variation in these numbers, which is not the case. It is possible that this is caused by the model, not really representing the complexity of the different calendars correctly. Currently a caregiver is categorized in one of three groups of availability. Where in reality, within these groups, there is still a lot of variety in availability. Since the sub calendars now all fill according only one of three distributions, the variation in availability is not entirely exact represented. This will most likely result in similar availabilities over the weeks for the different caregivers, making it more likely for patient to have get an entire checkup planned on one day. Another aspect that influenced this constant result in delta weeks is the expected weeks being randomized over the month of birth. By doing this, the IDEAAL checkups are even more equally spread over the year, making it even more likely for them to be scheduled in a single day.

This directly correlates with the next point of discussion, being the bias in the found data for availability. We now based the availability of the caregivers merely on their availability in the period from week 34-40. Which does not represent their actual availability over an entire year.

Other notable results are that no matter the experiments over booking horizons nor other variations in inputs we see that more than 80% of the patients always can be planned in one day. This is a noteworthy conclusion, as the diabetes department used to be under the impression that planning these complex checkups on one day was practically impossible. We think this is not the case because the IDEAAL checkups take up such a small portion of the different sub calendars. As the IDEAAL checkups make up such a small portion of the sub calendars, they are hardly impacted by the availability of the caregivers. As shown in the experimentation section, we see that the cancellations have such a small impact on the plannability that they can almost be negated. Since the IDEAAL checkup has such a small impact on the availability of the caregivers, they do not form as much of a problem as the diabetes department initially thought.

Equalizing the demand did not impact the results over the booking horizons compared to the base case. As we explained in Section 5.2.2, this has to do with the small impact of the IDEAAL checkups on the sub calendars. As demonstrated in other experiments, changing factors outside the IDEAAL checkups, like the availability, did have an impact on the results. Just like extremer cases like doubling the demand of IDEAAL checkups. Equalizing the demand can still have a more significant impact on the results, but then we will have to combine it with an experiment like doubling the demand. In that situation, you would have the quantity of IDEAAL checkups impact the plannability of checkups, making it a more suitable circumstance for equalizing demand to have an impact on the results. Since the total number of patients (not limiting the scope with only Type I, and age 0 -26 patients) that go through IDEAAL checkups is much closer to 1500 in reality, equalizing demand could be a beneficial approach for the diabetes department.

Assumptions and limitations

We did not include absence of caregiver due to vacation, conferences or other obligations during a year. In the discrete event simulations, it is now assumed that the base availability of every even week is always the same and the base availability of every odd week is also always the same. This is somewhat taken into account with the cancellation rates, as appointments can be cancelled due to these reasons. But we never clear the entire calendar of a caregiver for any period as a result of vacation. This could impact the fraction of patients that are planned on one day, but we do not think this will be a significant impact. This could have a significant impact on the delta weeks KPI, as there will be less availability over the year for the caregivers, making it not as likely that checkups are planned in the expected week.

For the current model, cancellations of regular patients are not included. In reality, patients outside the IDEAAL checkup also cancel their appointments. This could in practice result in more availability for IDEAAL checkups, as a cancelled appointment frees up an appointment slot for an IDEAAL checkup. For example, a patient that is scheduled over multiple days, could get their appointments moved to one single day if another patient cancels their appointment, freeing a slot needed for that patient to have their checkup carried out in one day.

For the sake of simplicity, we chose to have the split in appointments always be a two-day split and this split is always the same. In reality we could a schedule all but the one bottlenecking appointment on one day, or distribute the appointments over more than two days. The first option could result in more IDEAAL checkups carried out in one day, when combined with cancellations of regular patients. As it is easier to fit one appointment than three appointments on a day at later moment in time. The second option will most likely make the fraction of not scheduled patients even lower than the fractions are now in the different experiments. Making the splitting of appointments more flexible would also give a better representation of reality than the current model.

Currently, when a checkup is planned over two days the second appointment can be planned the following day. It is interesting to see results of forcing at least two weeks between the first and second appointment. These two weeks guarantee that the retina photos are always analyzed before the doctor's appointment. For the current model this was not realistic to implement as a result of the limited data on availability. We limited the model to not plan further than sixteen weeks in advance. This limitation makes splitting an appointment for higher booking horizons a lot less likely, as we will "run out of weeks to plan in". With more elaborate data we could also implement this and experiment with it.

Another limitation of the model is that patients are only scheduled from their expected week into the future. So, if for a patient their expected plan week is 36, they can only be planned in weeks $36, 37, ..$ etcetera. In reality a patient does not have one exact week in which they are planned, but they are attempted to be scheduled in their month of birth. To prevent IDEAAL checkups to always be planned in the same weeks, which would be the case when using the first week of a month, we randomized the expected plan week over the patient's month of birth. This results in a deviation from reality as a patient with the last week of a month as their expected plan week is now more likely to be planned in the month after their birth than in the month of birth.

Initially we saw a possibility to experiment with dedicated caregivers for IDEAAL checkups. This would mean that only a select group of caregivers would carry out IDEAAL checkups and this group would be selected based on whether with their calendars it would make sense to carry out these checkups. But with the way the simulation is model has been structured, results from experimenting with this will not be realistic. In reality availability will be tweaked for such an assignment and as we have no data on how the availability of the chosen caregivers would change, we cannot make a realistic estimation of how results of this choice will turn out.

Relation to literature

As stated in Section 3.3.1, the approach proposed in Akin et al. (2013) comes closest to the approach of this paper. Akin et al. (2013) finds that an appointment window (booking horizon) of twelve weeks is for established patients is optimal. As IDEAAL checkups are only carried out with established patients, this booking horizon would also apply to the IDEAAL checkups. We also concluded that twelve weeks is the optimal booking horizon according to our experimentation. This strengthens the validity of the results and therefore the conclusion drawn from this research that a booking horizon of twelve weeks is the optimal booking horizon.

Future research

Something interesting for the diabetes department to look at next is the necessity of the IDEAAL checkups, or other regular checkups for diabetes patients. Most of the patients currently have a standard half year and a standard annual checkup in the hospital. Research could be done whether it is even necessary for patients to come to the hospital this often. As described before, the IDEAAL checkups is best scheduled in one day to relieve the pressure on the hospital logistics and planning of patients. By reevaluating the necessity of these checkups, they might conclude that fewer checkups are needed, relieving the pressure on the hospital logistics and planning of patients even more.

Another thing to consider is extending the scope of the research. For now, the research was limited to a portion of the IDEAAL checkups. This smaller portion was chosen, because these patients have very similar care pathways, without a lot of variety. Also, the syndrome of these patients is very similar, making the patients relatively interchangeable and therefore easier to research. It will be interesting for the hospital to take a look at all patients with diabetes, to extend to finding from this research. They could research how similar these out-of-scope patients are to the researched patient group to determine how applicable the findings from this research are on the out-of-scope patients. When it turns out these patients are too different, they can try and find a way adjust the results and method of this research in such a way that they can also optimize the planning of these patients. As the total number of patients going through IDEAAL checkups is around 1500, we analyzed $\approx 38\% \left(= \frac{1500}{572}\right)$ of the patients with IDEAAL checkups in Isala.

The current method of caregivers is based on simple logic steps developed in this research. Although the optimal combination of caregivers can be found in far more exact mathematical methods. Therefore, it can be interesting to see what the optimal combination of caregivers would be and see how this perfect combination would perform. It could also be researched how the basic availability should look like to create perfect caregiver combinations. Sometimes small changes in basic availability can lead to great improvements in planning optimization for any department.

The final and more basic recommendation is for Isala as whole. It would be beneficial to look into how data is stored and how this can be optimized to have better and more data available. This would make researching different aspects of the hospital much easier and realistic, giving far more reliable results. As we also encountered in this research, data on cancellations and availability of the caregivers is hard to extract. Making data like this more obtainable would be a great step in the right direction for Isala to modernize and improve as a hospital.

A follow-up to this research could be to implement simulation optimization. For the current question and scope the mathematical model is not needed to find the optimal solution. As we found in the results of the mathematical model, there are numerous solutions that yield the same objective value. This means that, for the current question, a heuristic can consistently find an optimal solution that perform just as good as any other solution. When extending or changing the scope the problem become more complex making it harder to find the optimal solution. When this will be the case, simulation optimization could be a suitable approach to find the optimal solution regardless of the complexity. In that case the mathematical model would be implemented into the simulation, instead of heuristics, resulting in a simulation optimization approach.

References

Akin, G., Ivy, J. S., Huschka, T. R., Rohleder, T. R., & Marmor, Y. N. (2013). Capacity management and patient scheduling in an outpatient clinic using discrete event simulation. *43rd Winter Simulation Conference - Simulation: Making Decisions in a Complex World.* Rochester. https://doi.org/10.1109/WSC.2013.6721598

Bean, A. G., & Talaga, J. (1992). Appointment Breaking: Causes and Solutions. *Marketing Health Services, 12*(4), 14.

Benzaid, M., Lahrichi, N., & Rousseau, L. (2020). Chemotherapy appointment scheduling and daily outpatient-nurse assignment. *Health Care Management and Science, 23*, 34-50.

Bouras, A., Masmoudi, M., El Houda Saadani, N., Bahroun, Z., & Abdeljaouad, M. A. (2021). Multi-stage appointment scheduling for outpatient chemotherapy unit: a case study. *RAIRO Operations Research, 55*, 589-610.

Condotta, A., & Shakhlevich, N. V. (2014). Scheduling patient appointments via multilevel template: A case study in chemotherapy. *Operations research for health care, 3*(3), 129-144.

Davies, M. L., Goffman, R. M., May, J. H., Monte, R. J., Rodriguez, K. L., Tjader, Y. C., & Vargas, D. L. (2016). Large-Scale No-Show Patterns and Distributions for Clinic Operational Research. *Healthcare, 15*.

Denney, J., Coyne, S., & Rafiqi, S. (2019). Machine Learning Predictions of No-Show Appointments in a Primary Care Setting. *SMU Data Science Review, 2*(1), 211-213.

Dharmadhikari, N., & Zhang, J. (2013). Simulation optimization of blocking appointment scheduling policies for multi-clinic appointments in centralized scheduling systems. *International Jounral of Engineering and Innovative Technology (IJEIT), 2*(11).

Hans, E. W., Van Houdenhoven, M., & Hulshof, P. J. (2012). A framework for healthcare planning and. In *Handbook of healthcare system scheduling* (pp. 303-320). Springer.

Hans, E., Herroelen, W., Leus, R., & Wullink, G. (2007). A hierarchical approach to multi-project planning under. *Omega, 35*(5), 563-577.

Heerkens, H., & Van Winden, A. (2021). *Solving Managerial Problems Systematically.* Routledge.

Hesaraki, A. S., Dellaert, N. P., & de Kok, T. (2019). Generating outpatient chemotherapy appointment templates with balanced flowtime and makespan. *Eur. J. Oper. Res., 275*, 304-318.

Isala. (n.d.). *Diabetescentrum*. Retrieved from Isala: https://www.isala.nl/specialismen-en-centra/interne-geneeskunde/over-de-afdeling/diabetescentrum/

Isala. (n.d.). *Over Isala*. Retrieved from Isala: https://www.isala.nl/over-isala/

Leeftink, A., Bikker, I., Vliegen, I., & Boucherie, R. (2020). Multi-disciplinary planning in health care: a review. *Health Systems*, 95-118.

Leeftink, G., Martinez, G., Hans, E. W., Mustafa, Y., & Pasupathy, K. S. (2021). Optimising the booking horizon in healthcare clinics considering no-shows and cancellations. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2021.1913292

Liang, B., Turkcan, A., Ceyhan, M., & Stuart, K. (2015). Improvement of chemotherapy patient flow and scheduling in an outpatient oncology clinic. *International Journal of Production Research, 53*(24), 7177-7190.

Liu, N. (2016). Optimal Choice for appointment scheduling window under patinet no-show behavior. *Production and Operations Management, 25*(1), 128-142.

Norris, J. B., Kumar, C., Chand, S., Moskowitz, H., Shade, S. A., & Willis, D. R. (2014). An Empirical Investigation Into Factors Affecting Patient Cancellations and No-shows At Outpatient Clinics. *Decision Support Systems, 57*, 428-443.

Porter, M. E., & Lee, T. H. (2013). The Strategy That Will Fix Health Care. *Harvard Business Review*, 3-19.

Rodríguez-García, M., McLean-Carranza, A. A., Prado-Prado, J. C., & Domínguez-Caamaño, P. (2016). Managing Waiting TImes to Predict No-shows and Cancelations at Children's Hospital. *Journal of Industrial Engineering and Management, 9*(5), 1107-1118. https://doi.org/http://dx.doi.org/10.3926/jiem.2075

Rossing, H., & Visee, H. (2018). *Toekomstige vraag naar medisch specialisten.* Regioplan.

Tan, J., Zhang, L., Li, M., & Wang, Y. (n.d.). Multi-resource fair sharing for multiclass workflows.

Turkcan, B., Zeng, & Lawley, M. (2012). Chemotherapy Operations Planning and Scheduling. *IIE Transactions Healthcare Systems Engineering, 2*(1), 31-49.

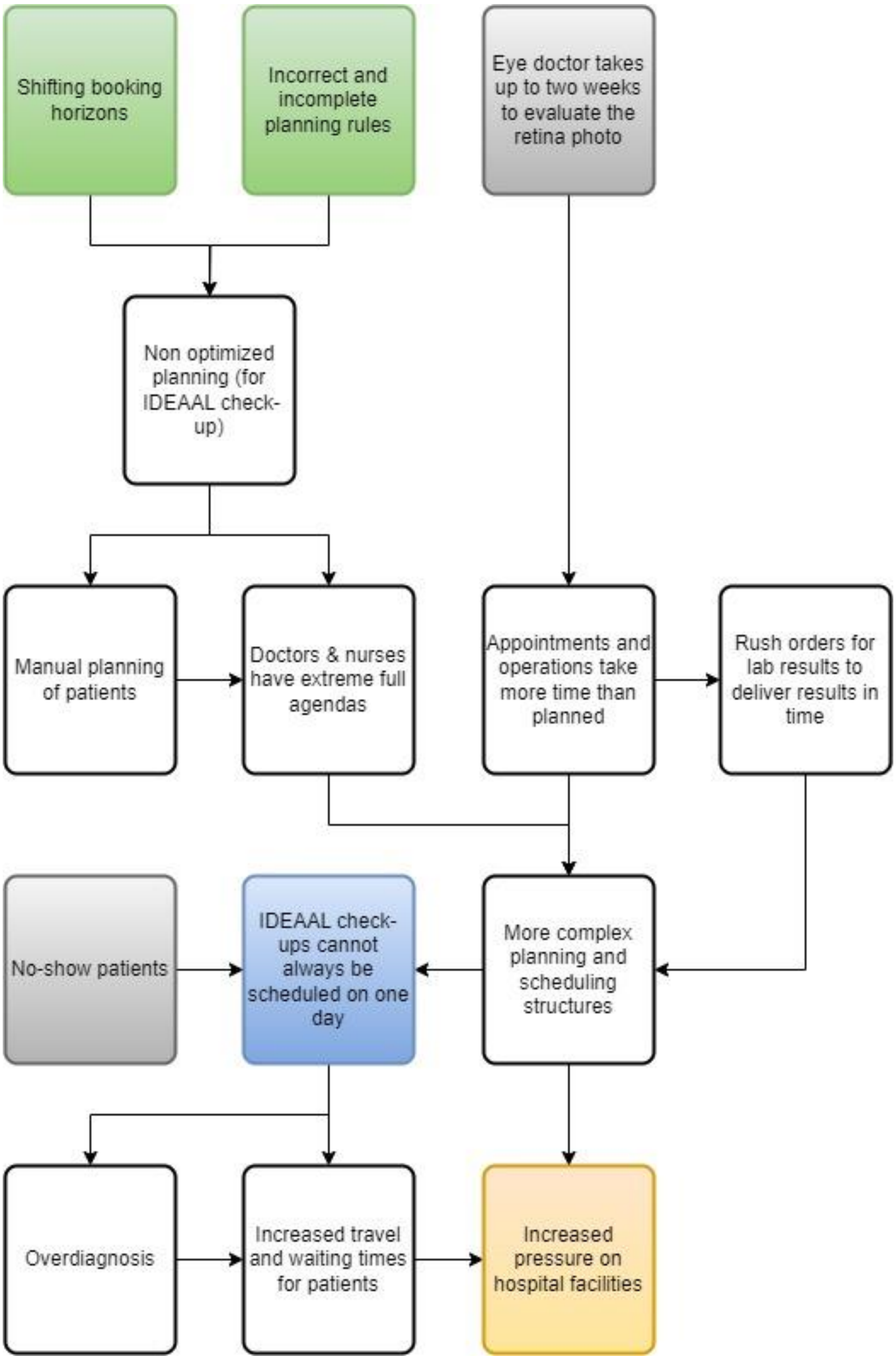
voetencentrum wender. (2023). *Wat is de Sims classificatie?* Retrieved from podotherapeut: https://podotherapeut.nl/voetproblemen-bij-diabetes/sims-classificatie-en-zorgprofielen/

Whittle, J., Schectman, G., Lu, N., Baar, B., & Mayo-Smith, M. F. (2008). Relationship of Scheduling Interval to Missed and Cancelled Clinic Appointments. *The Journal of Ambulatory Care Management, 31*(4), 290-302.

Zomer, V. (2022). *Increasing the number of outpatients treated within the access time norm by implementing a blueprint schedule.* University of Twente.

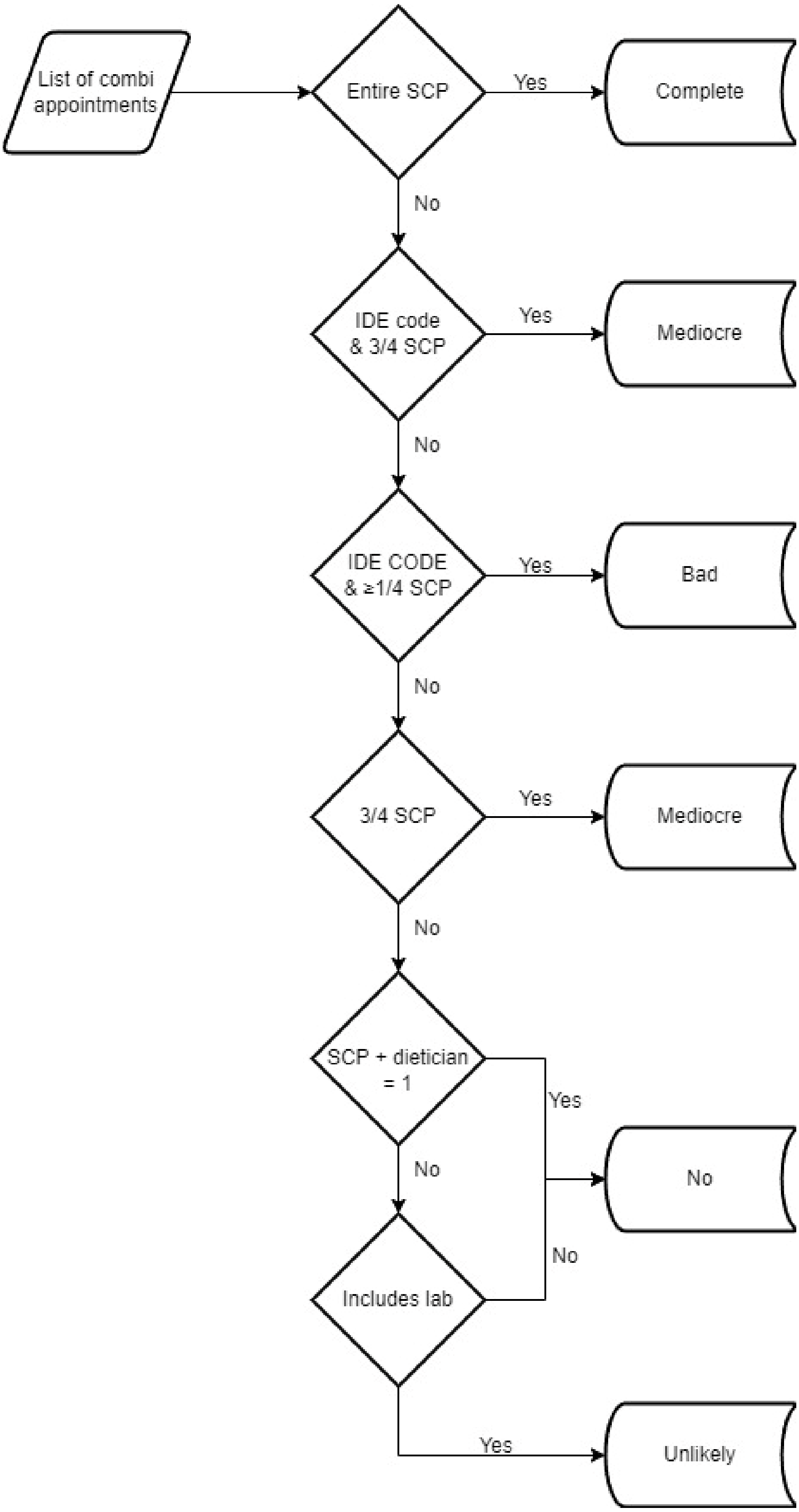
Appendix A: Problem cluster

The orange block indicates the consequence of the action problem. The white blocks represent intermediate causes that contribute to the action problem. The grey blocks are core problems that are outside the scope, and the green block is the root cause where this research will focus on.

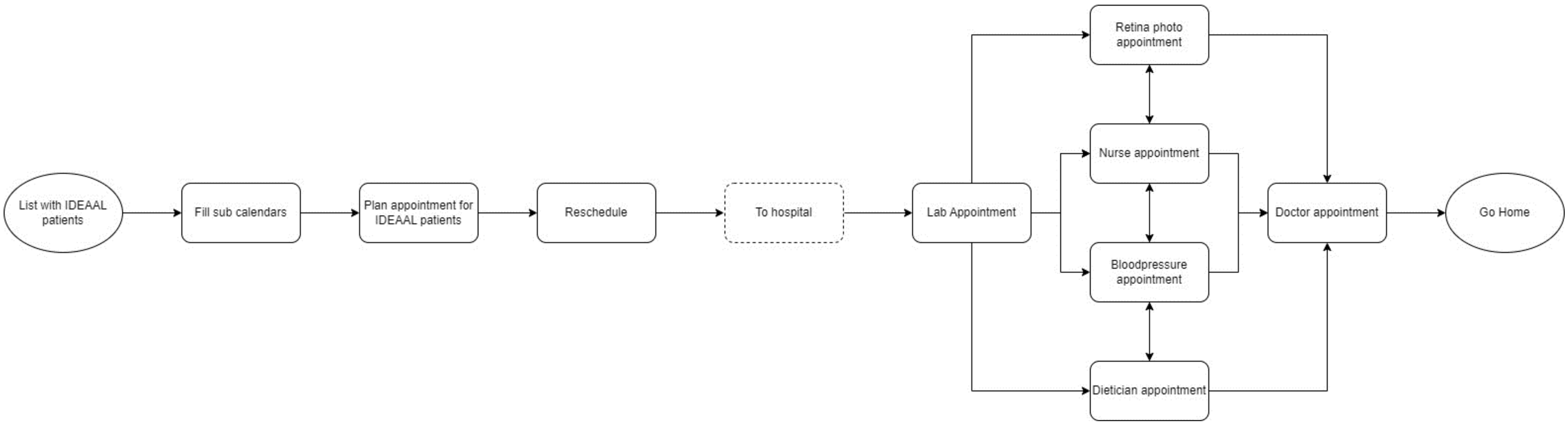


Appendix B: Categorizing logic

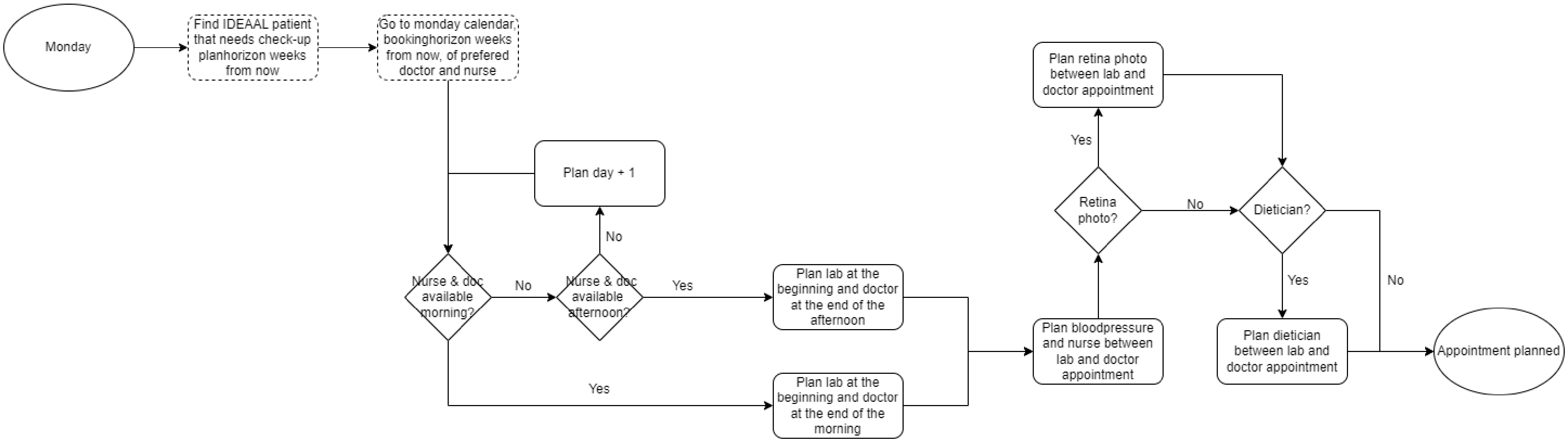
A list of combination appointments is categorized based on the following logic. Note, SCP stands for Standard Care Pathway.



Appendix C: Process flowchart



Appendix D: Logic flowchart



Appendix E: Data retrieval

E.1 Privacy protection

To extract data from HiX, data first has to be anonymized. The appointments extracted from HiX are real appointments, from real patients. To protect the privacy of these patient the appointments are made untraceable back to the patient by hiding the date of birth and encrypting the patient ID. This way the patient can still be retraced by the hospital itself, but not by others. The extraction of data is done by using CTCUE. This program is able to extract most data from HiX and will encrypt the privacy sensitive parts.

Preparation

There is no indicator in HiX that allows one to always know for sure if an appointment is part of an IDEAAL checkup. This makes it complicated to find out which appointments a patient had, actually were part of an IDEAAL checkup. To still find data on the current situation, with regards to the IDEAAL checkup, some assumptions had to be made and with a detour still reliable description of the current situation can be given.

Finding the IDEAAL checkups, carried out in the past, started by setting appropriate CTCUE criteria. These criteria dictate for which group of patients and what data will be extracted. In CTCUE only diabetes type 1 patients of the age between 0 and 26 are included. From them the appointment data is extracted based on appointment codes, for: internist consultation, retina photos, blood pressure, diabetes nurse, laboratory and the dietician.

This resulted in a long list of appointments. All appointments within a time period of six weeks (42 days), are bundled together. Those bundles are considered possible combination appointments and thus possible IDEAAL checkups.

Mutation data

For the mutation data, the years 2019 – 2023 have been analyzed. Particularly the appointments from these years which have been a part of the IDEAAL check-up. From HiX a list of all appointments is generated and of every appointment the number of mutations is noted.

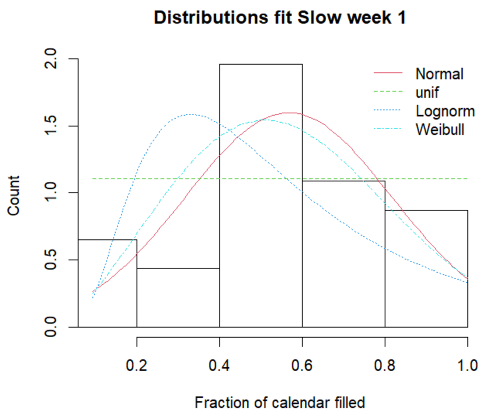
Some appointments have been rescheduled more than once. Every rescheduled appointment will be considered as a new appointment, meaning that if for example an appointment is rescheduled twice, this appointment contributes three appointments towards the total appointment count and two times towards the mutations count. The total results over the years are shown in Table 4.

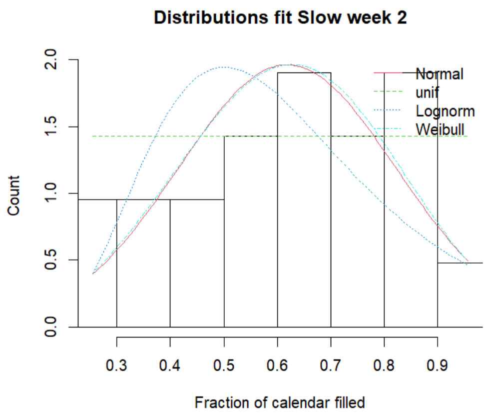
Appendix F: Distribution fit

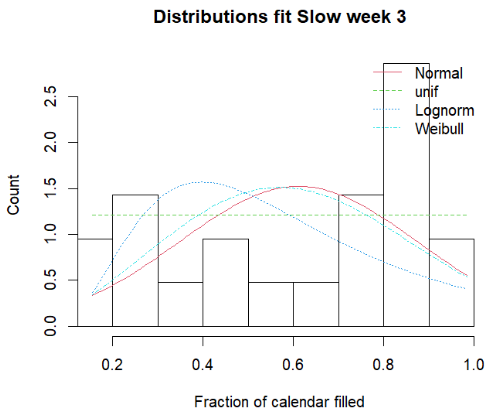
This appendix is split up into two separate sections. The first section, Graphs, contains the visualization of fitting different distribution on the different weeks per group. The second section, Tables, contains an overview of the standard deviation and mean corresponding to the distribution chosen per week per group.

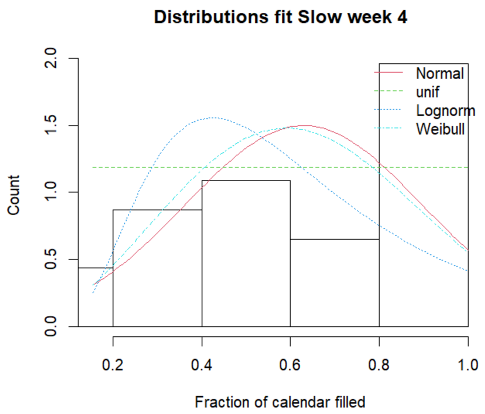
F.1 Graphs

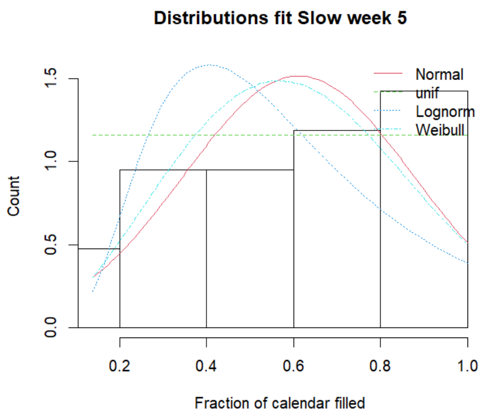
F.1.1 Slow weeks visual fit

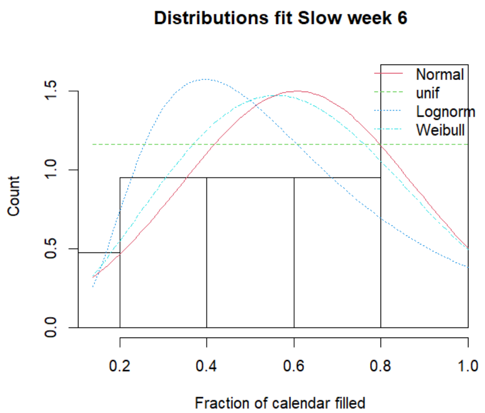


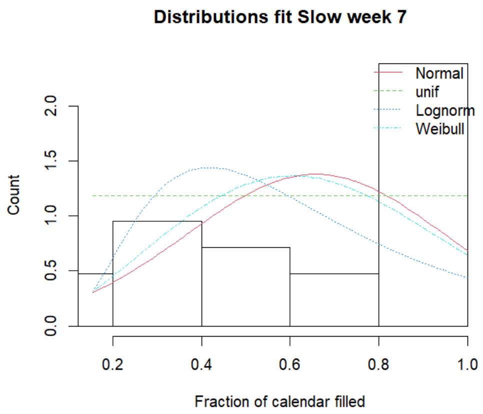


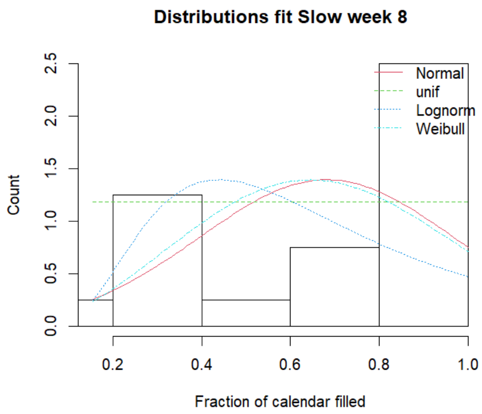









Distributions fit Slow week 7
Normal
unif
Lognorm
Weibull
Count
Fraction of calendar filled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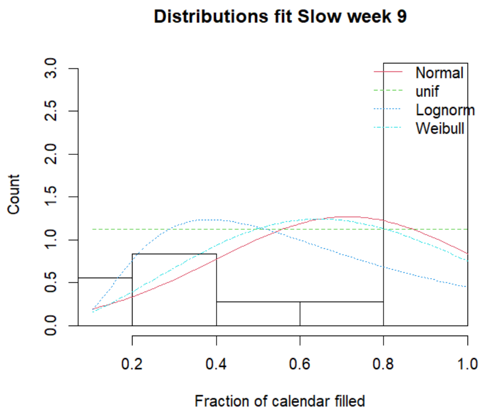
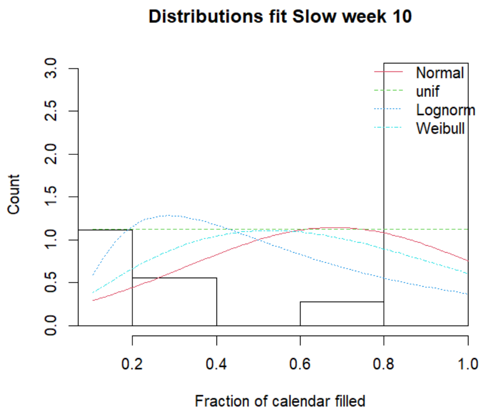
Normal
unif
Lognorm
Weibull
Count
Fraction of calendar filled


Distributions fit Slow week 9
Normal
unif
Lognorm
Weibull
Count
Fraction of calendar filled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Normal
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Lognorm
Weibull
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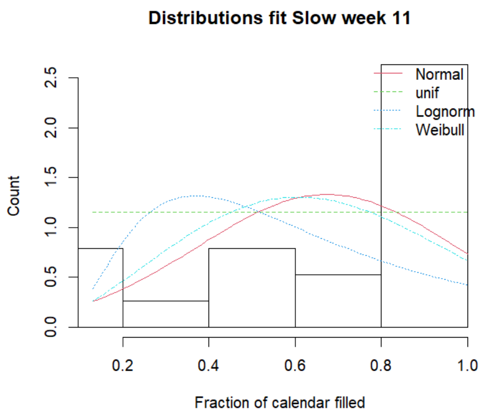
Fraction of calendar filled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Normal
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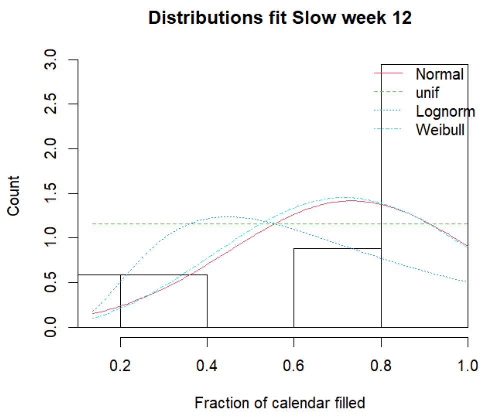
Lognorm
Weibull
Count
Fraction of calendar filled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Lognorm
Weibull
Count
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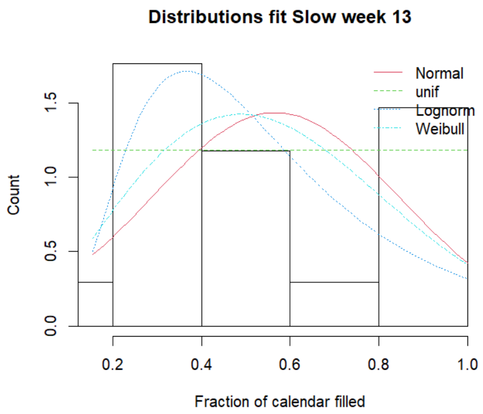
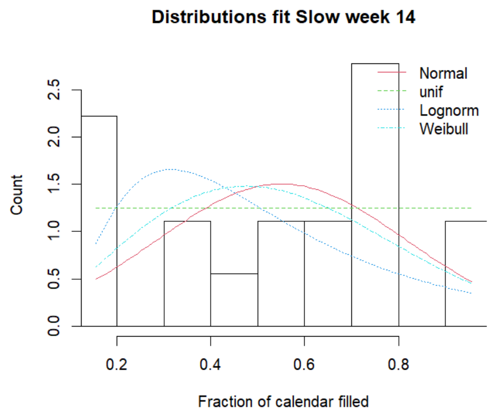
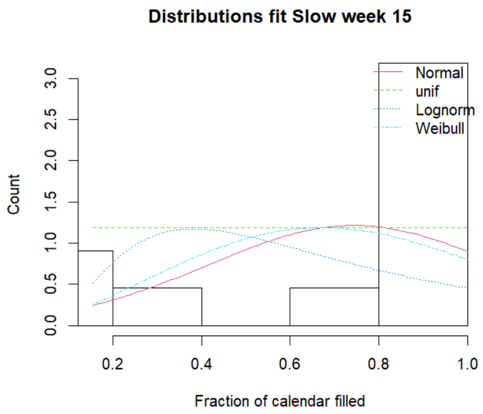
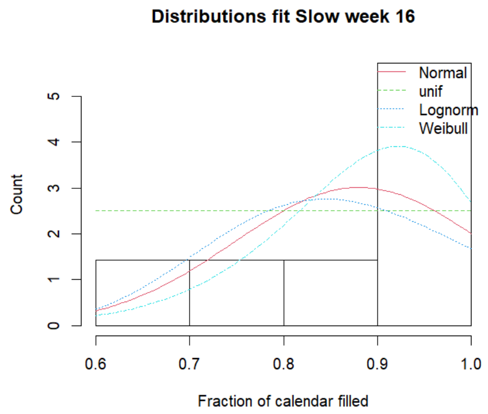
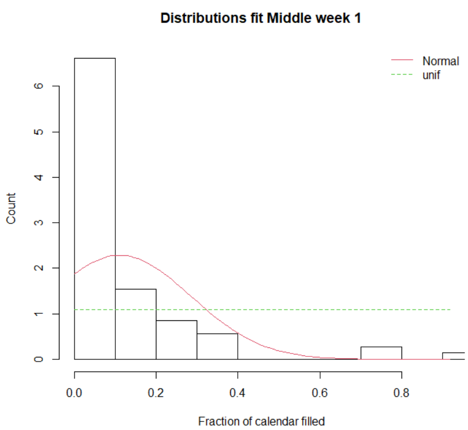


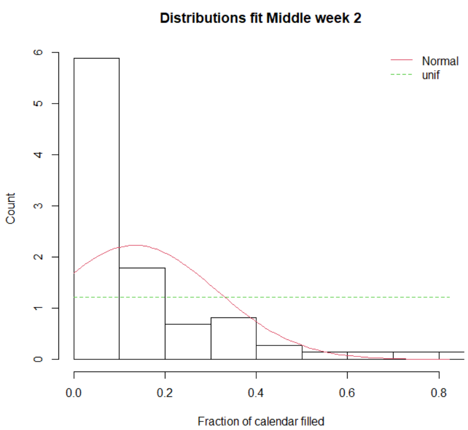




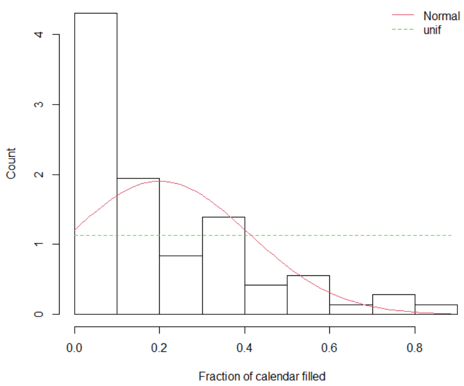


F.1.2 Average fast weeks visual fit

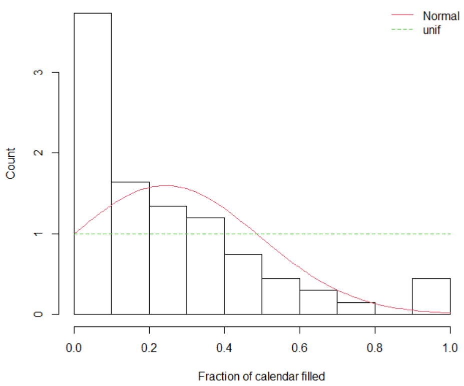




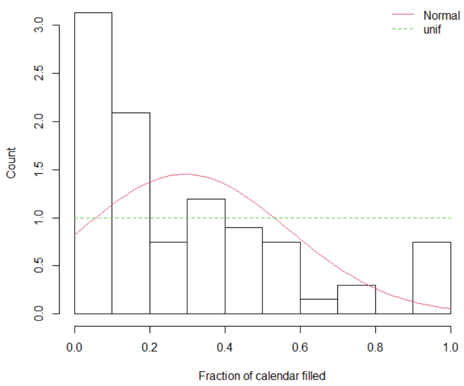
Distributions fit Middle week 3



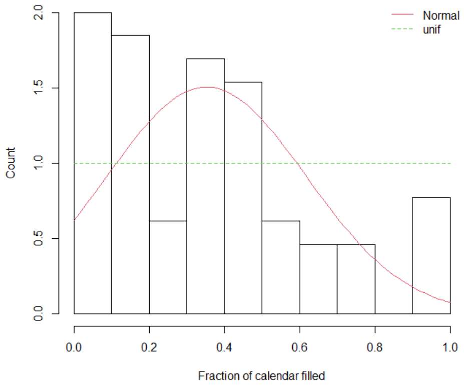
Distributions fit Middle week 4



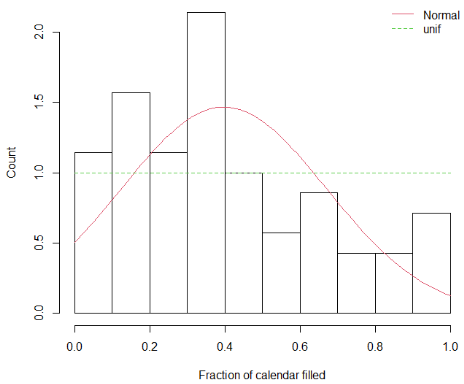
Distributions fit Middle week 5



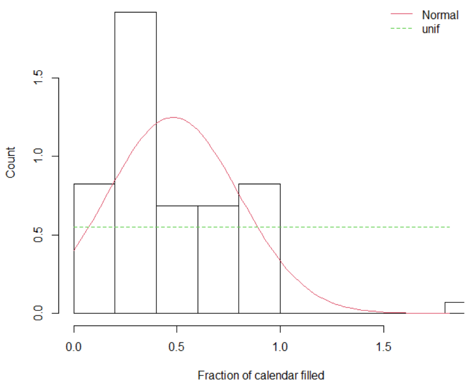
Distributions fit Middle week 6

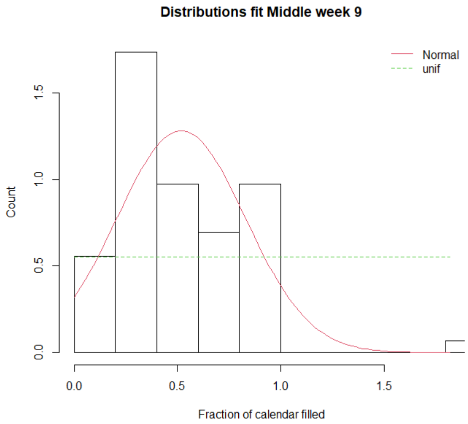


Distributions fit Middle week 7



Distributions fit Middle week 8




Distributions fit Middle week 9
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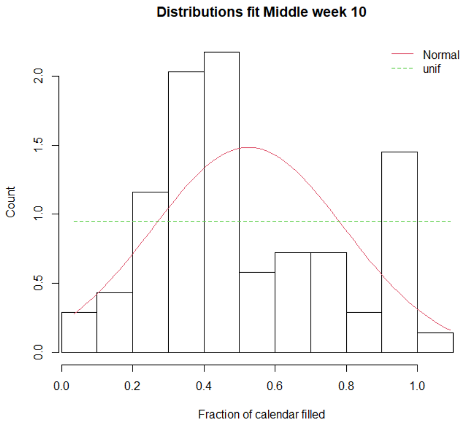
unif
Count
Fraction of calendar filled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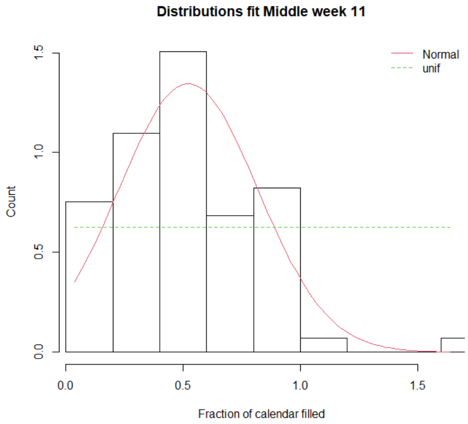
Count
Fraction of calendar filled


Distributions fit Middle week 11
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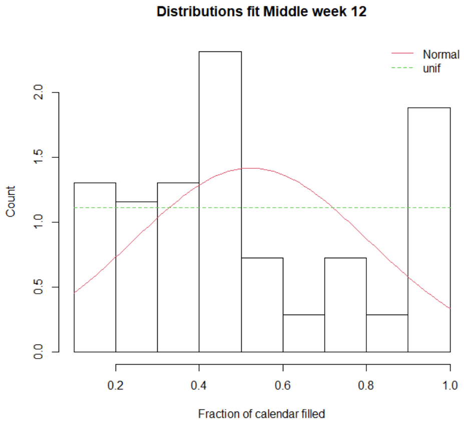
Distributions fit Middle week 12
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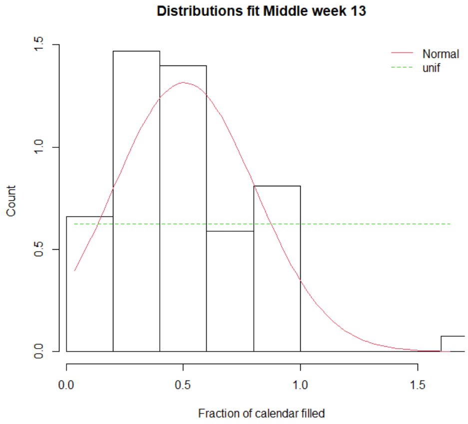
unif
Count
Fraction of calendar filled


Distributions fit Middle week 13
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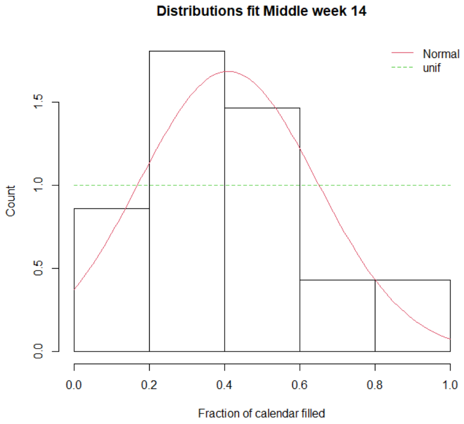
Count
Fraction of calendar filled


Distributions fit Middle week 14
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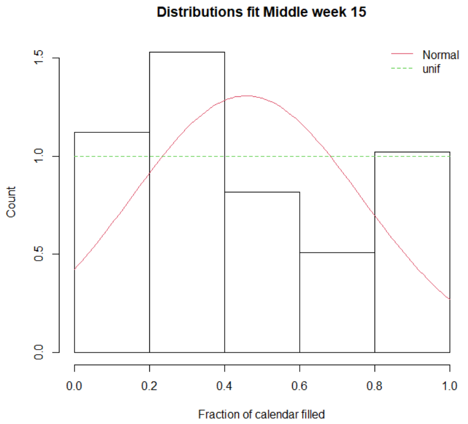
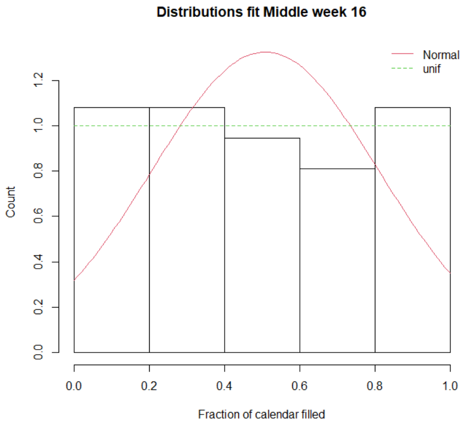
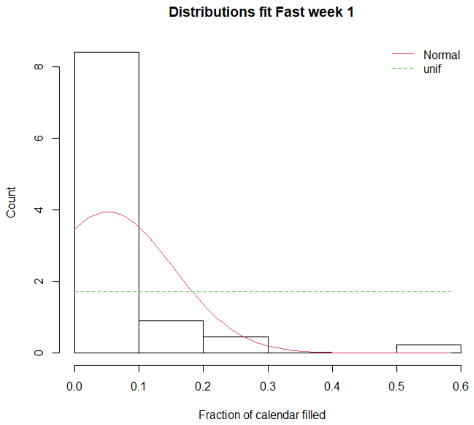
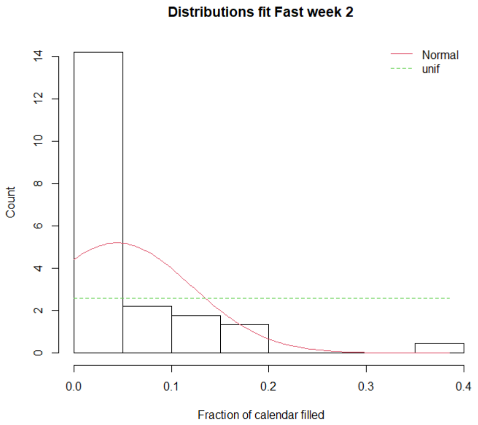
unif
Count
Fraction of calendar filled

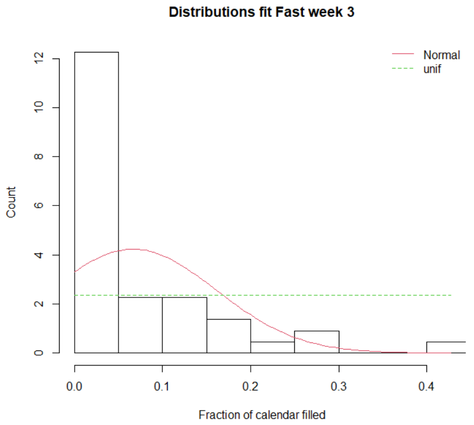


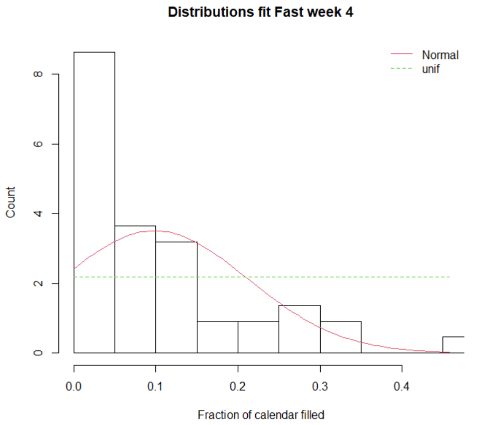


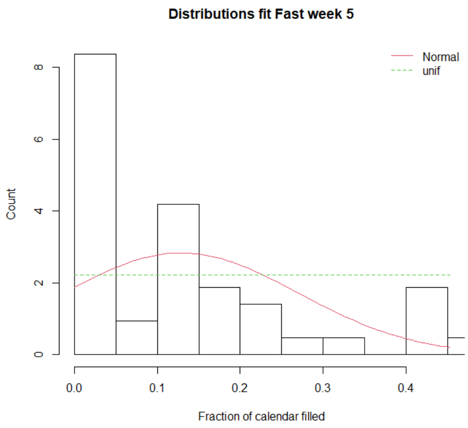
F.1.3 Fast weeks visual fit

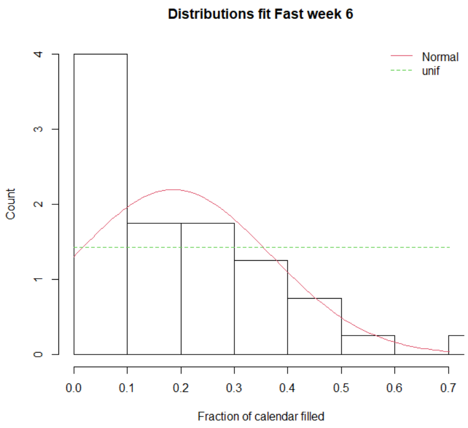









Distributions fit Fast week 5
Normal
unif
Count
0
2
4
6
8
0.0
0.1
0.2
0.3
0.4
Fraction of calendar filled


Distributions fit Fast week 6
Normal
unif
Count
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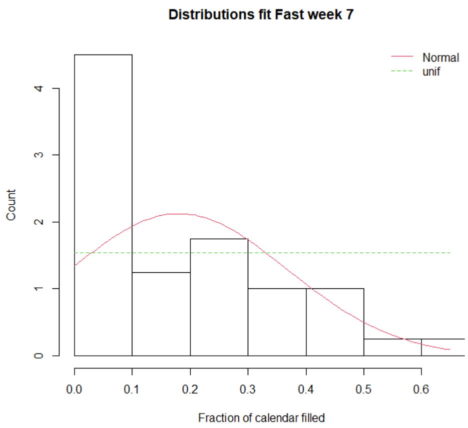
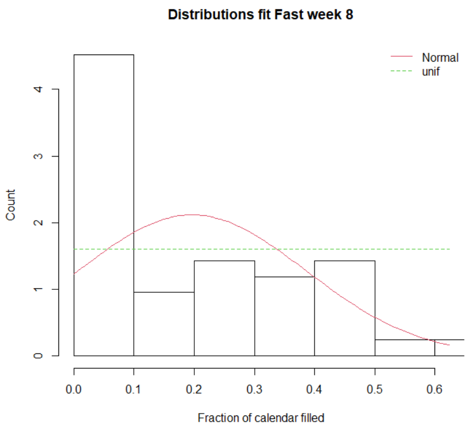
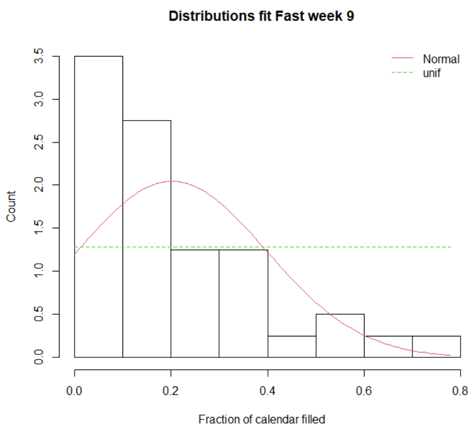
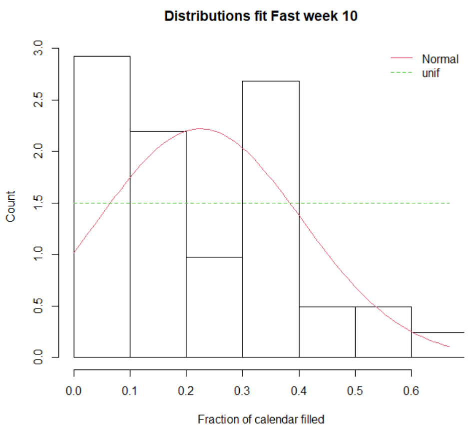
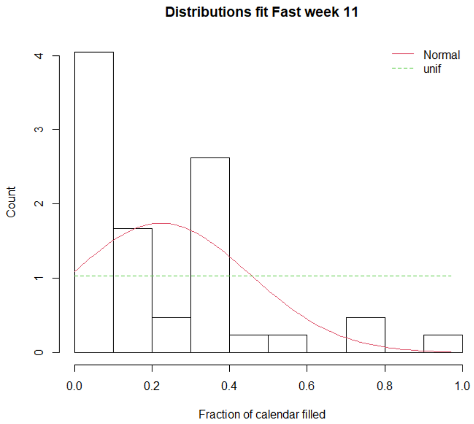
2
3
4
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Fraction of calendar filled

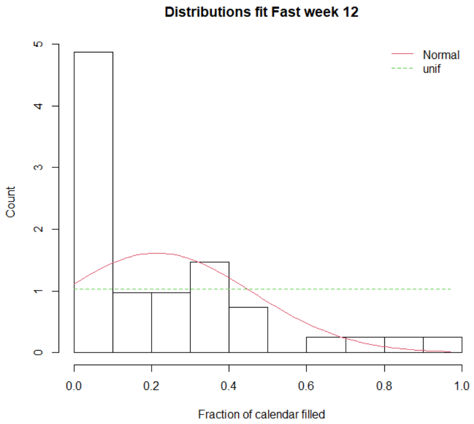

Distributions fit Fast week 7
Normal
unif
Count
0
1
2
3
4
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Fraction of calendar filled

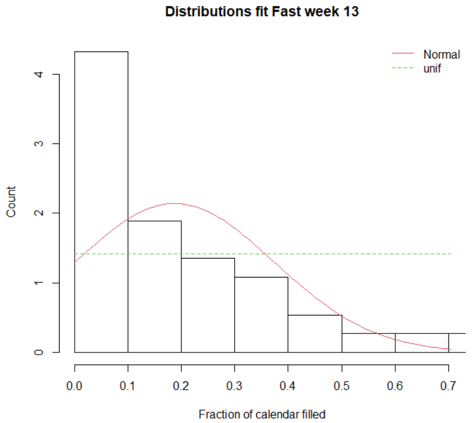

Distributions fit Fast week 8
Normal
unif
Count
0
1
2
3
4
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Fraction of calendar filled

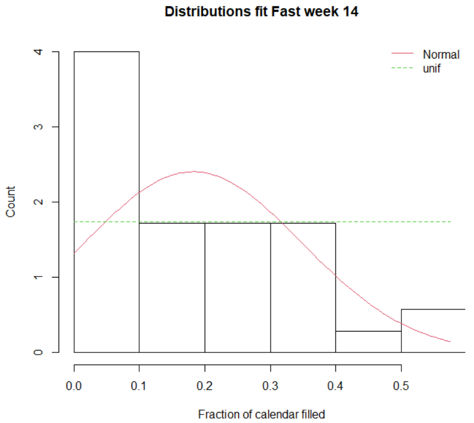

Distributions fit Fast week 9
Normal
unif
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.0
0.2
0.4
0.6
0.8
Fraction of calendar filled

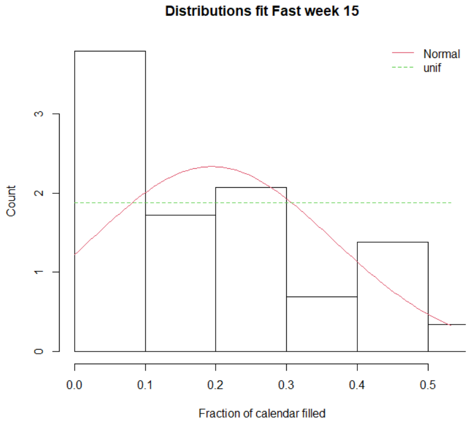

Distributions fit Fast week 10
Normal
unif
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Fraction of calendar filled

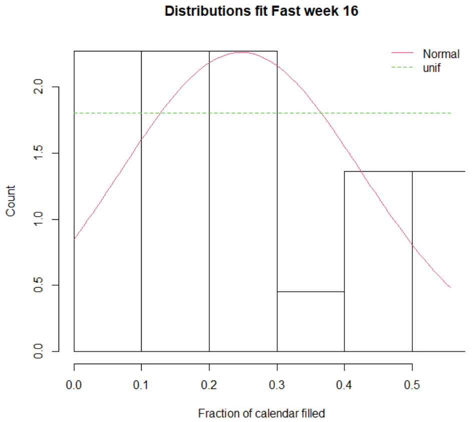












F.2 Tables

Slow weeks

Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Mean	0.43	0.38	0.39	0.37	0.39	0.39	0.34	0.32	0.29	0.32	0.33	0.27	0.43	0.45	0.26	0.12
Standard deviation	0.26	0.21	0.27	0.27	0.27	0.27	0.30	0.29	0.32	0.36	0.31	0.29	0.29	0.27	0.34	0.14

Average weeks

Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Mean	0.89	0.87	0.80	0.76	0.71	0.65	0.60	0.52	0.48	0.47	0.48	0.48	0.50	0.59	0.54	0.49
Standard deviation	0.18	0.18	0.21	0.25	0.28	0.27	0.27	0.32	0.31	0.27	0.30	0.28	0.31	0.24	0.31	0.31

Fast weeks

Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Mean	0.95	0.96	0.93	0.90	0.87	0.81	0.82	0.80	0.80	0.78	0.78	0.79	0.81	0.82	0.81	0.75
Standard deviation	0.10	0.08	0.10	0.12	0.14	0.18	0.19	0.19	0.20	0.18	0.23	0.25	0.19	0.17	0.17	0.18

Appendix G: Number of Replications

The number of replications is sufficient as soon as the maximum relative error is smaller than 0.05, since we take a confidence interval of 95%.

Reps	One day Count	Mean	Var	Tvalue	CIHW	Error	Sufficient Reps
1	0.560						
2	0.560	0.560	0	12.71	0.000	0.00	YES
3	0.549	0.557	0	4.30	0.015	0.03	YES
4	0.562	0.558	0	3.18	0.009	0.02	YES
5	0.555	0.557	0	2.78	0.006	0.01	YES
6	0.546	0.555	0	2.57	0.007	0.01	YES
7	0.553	0.555	0	2.45	0.006	0.01	YES
8	0.544	0.554	0	2.36	0.006	0.01	YES
9	0.539	0.552	0	2.31	0.006	0.01	YES
10	0.564	0.553	0	2.26	0.006	0.01	YES
11	0.576	0.555	0	2.23	0.007	0.01	YES
12	0.564	0.556	0	2.20	0.007	0.01	YES
13	0.575	0.557	0	2.18	0.007	0.01	YES
14	0.587	0.560	0	2.16	0.008	0.01	YES
15	0.535	0.558	0	2.14	0.008	0.01	YES
16	0.564	0.558	0	2.13	0.007	0.01	YES
17	0.583	0.560	0	2.12	0.008	0.01	YES
18	0.548	0.559	0	2.11	0.007	0.01	YES
19	0.562	0.559	0	2.10	0.007	0.01	YES
20	0.540	0.558	0	2.09	0.01	0.01	YES

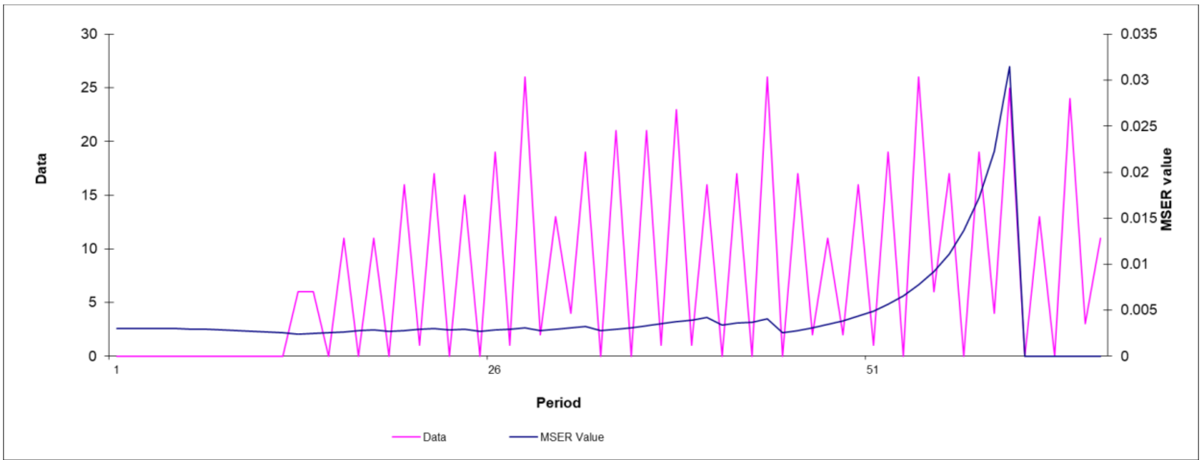
Appendix H: Warmup period

The first section of this appendix gives a table that contains the MSER values per week of the experimental run to find the warmup period. The second section gives a visual representation corresponding to the table.

H.1 MSER heuristic Table

Week	Data	MSER Value
1	0	0.0030
2	0	0.0030
3	0	0.0030
4	0	0.0030
5	0	0.0030
6	0	0.0029
7	0	0.0029
8	0	0.0029
9	0	0.0028
10	0	0.0027
11	0	0.0026
12	0	0.0025
13	6	**0.0024**
14	6	0.0025
15	0	0.0026
16	11	0.0027
17	0	0.0027
18	11	0.0029
19	0	0.0027
20	16	0.0028

H.2 MSER heuristic graph



Appendix I: Preferred caregiver logic

This appendix contains the logic used to determine the preferred caregiver for newly created patients in the demand experiments.

The logic for the experiment on the expected demand increase is as follows: first the number of patients treated per caregiver was determined. This number is divided by the total number of patients in the current situation and that fraction is then multiplied by the difference in patients between the new situation and current situation. An example to demonstrate this: Doc10 treats 82 patients in the current situation, therefore this doctor treats a fraction of $\frac{82}{557} = 0.147$ of the current situation's patients. Multiply this by the difference in patients with the experiment, for the first experiment $600 - 557 = 43$ patients, gives us $0.147 \cdot 43 = 6.33$ patients. In this experiment at least six of the newly created patients will be treated by Doc10.

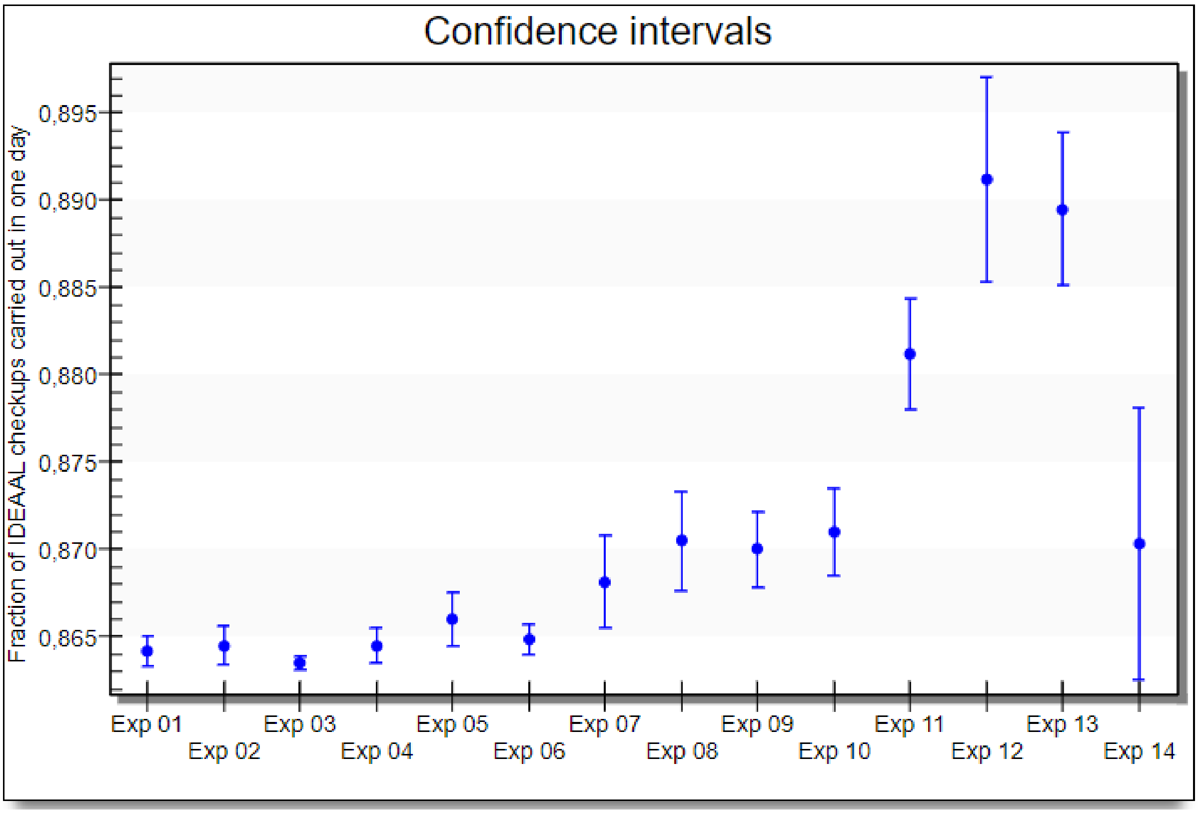
After that we are still left with a couple of patients without a preferred nurse and/or preferred doctor. So, we take the fractions left per caregiver and use that as a probability for that doctor to treat one more patient. Taking the same example: three patients are treated by Doc10, and of every other patient that still has no preferred doctor assigned will have a $6.33 - 6 = 0.33$ patients will have Doc10 as their preferred doctor. By summing all the leftover fractions of every doctor, we will find the number of patients without a preferred doctor. For every leftover patient a random doctor will be drawn based on these probabilities. The exact same method will be used to find the preferred nurses for every newly added patient.

The logic for the experiment on an extreme demand increase is much more straight forward. The existing patients are duplicated to form the new patients.

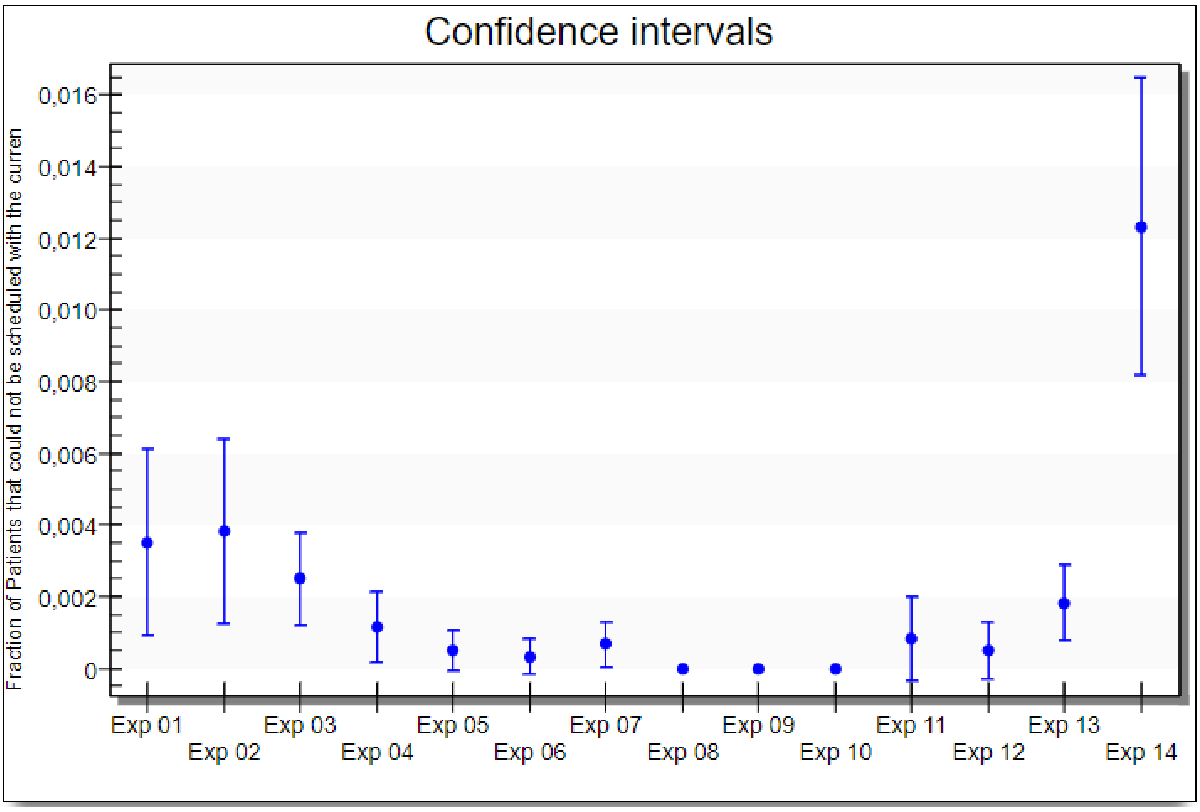
Appendix J: Experimentation

J.1 Expected demand increase

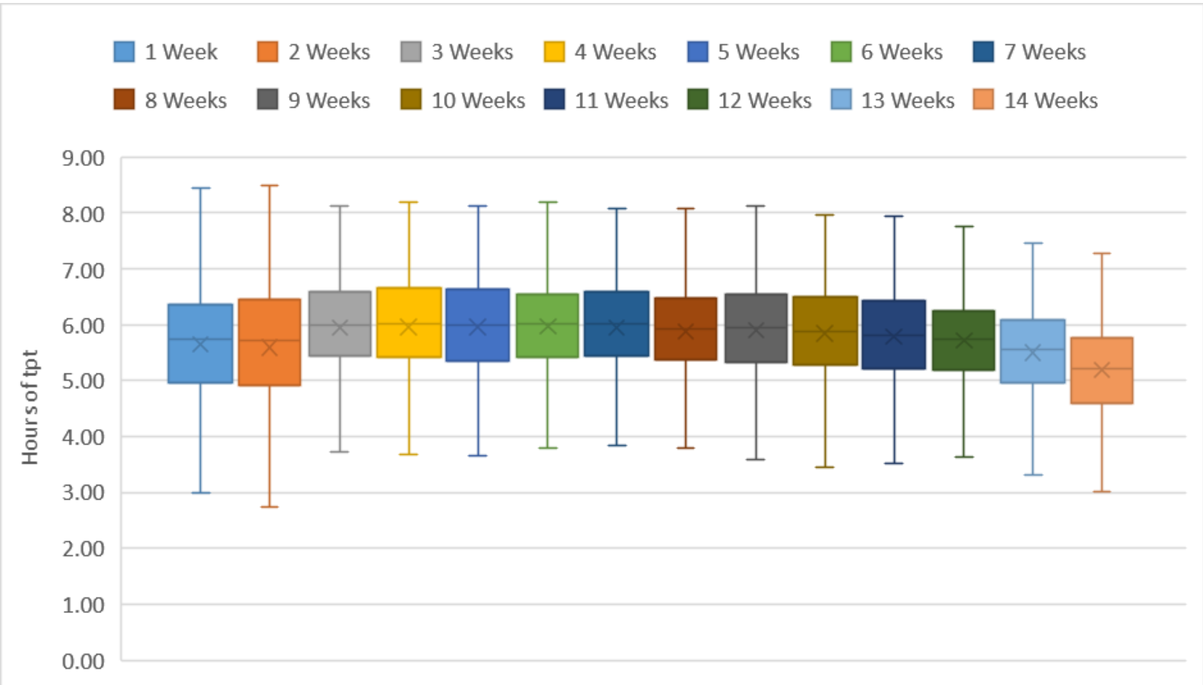
J.1.1 One Day



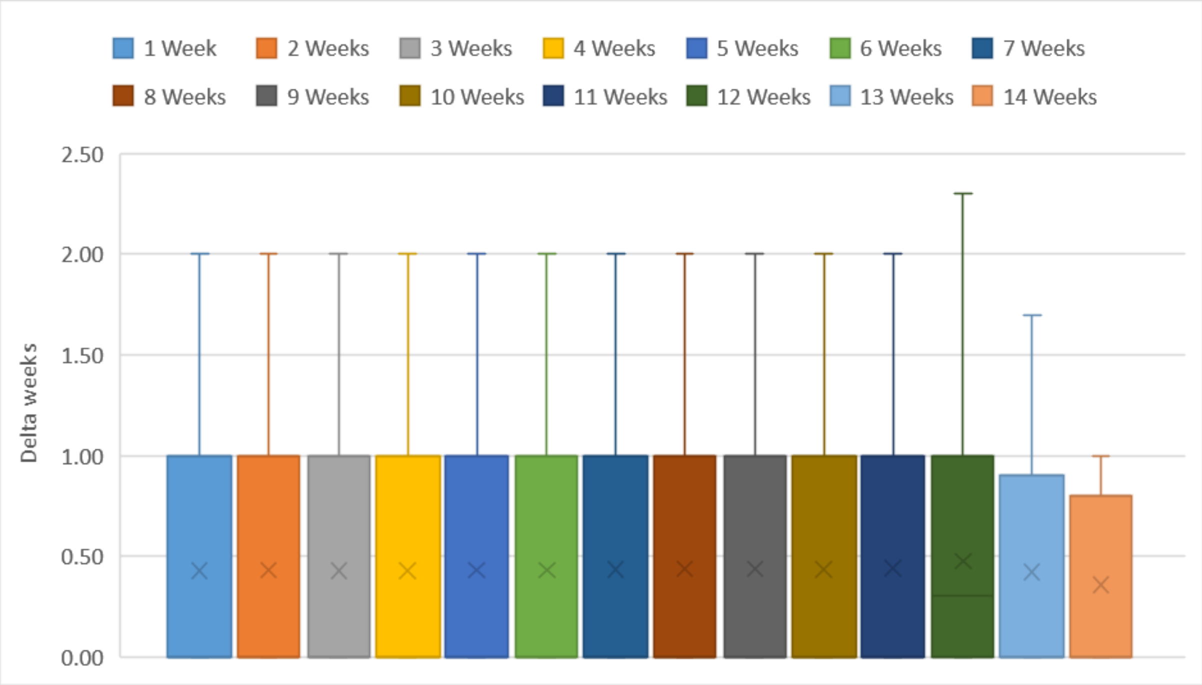
J.1.2 Not Scheduled



J.1.3 Throughput time



J.1.4 Delta Weeks



J.2 Extreme demand increase

J.2.1 p values

One day fraction

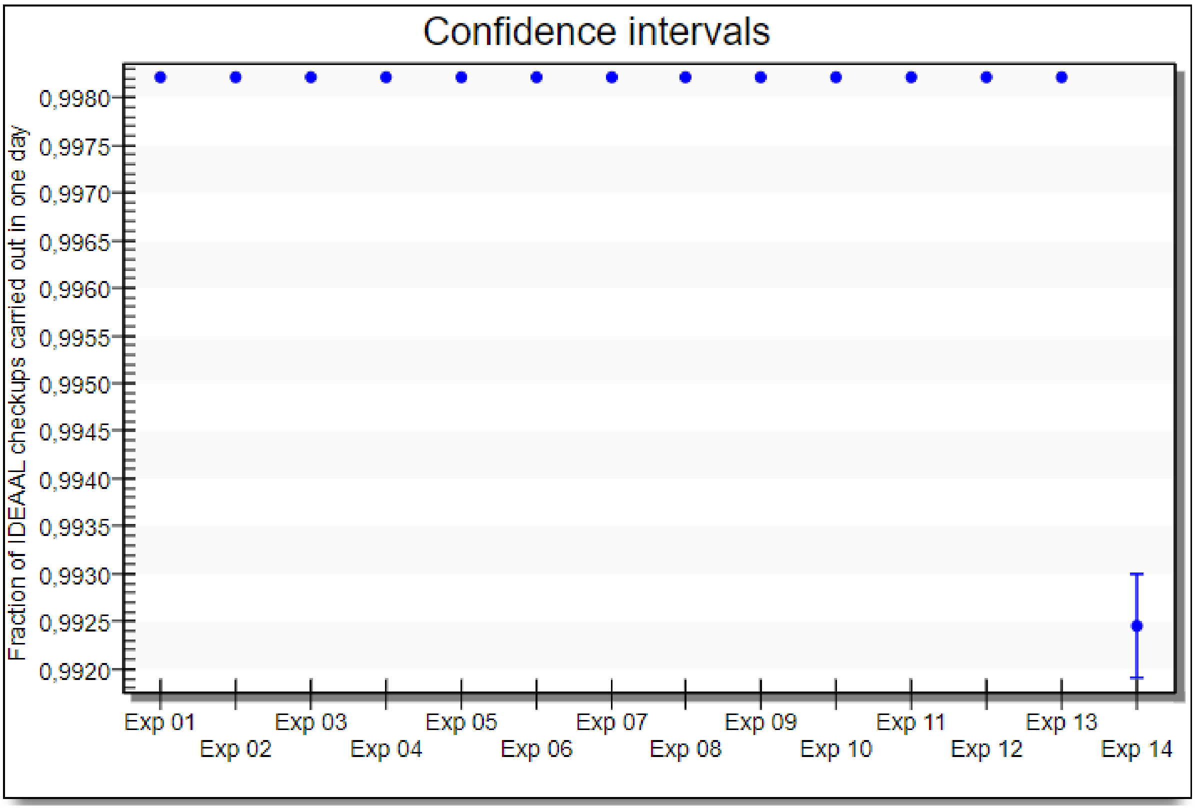
Single Day	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 09	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14
Exp 01	0.527	**0**	**0**	**0**	**0**	**0**	0.141	**0.003**	**0**	**0**	**0**	**0**	**0**
Exp 02		**0**	**0**	**0**	**0**	**0**	0.221	**0.001**	**0**	**0**	**0**	**0**	**0**
Exp 03			0.137	**0.025**	0.069	0.175	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 04				0.57	0.459	0.057	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 05					0.74	**0.03**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 06						**0.028**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 07							**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 08								**0.01**	**0**	**0**	**0**	**0**	**0**
Exp 09									**0**	**0**	**0**	**0**	**0**
Exp 10										**0**	**0**	**0**	**0**
Exp 11											**0**	**0**	**0**
Exp 12												**0**	**0**
Exp 13													**0**

Not scheduled fraction

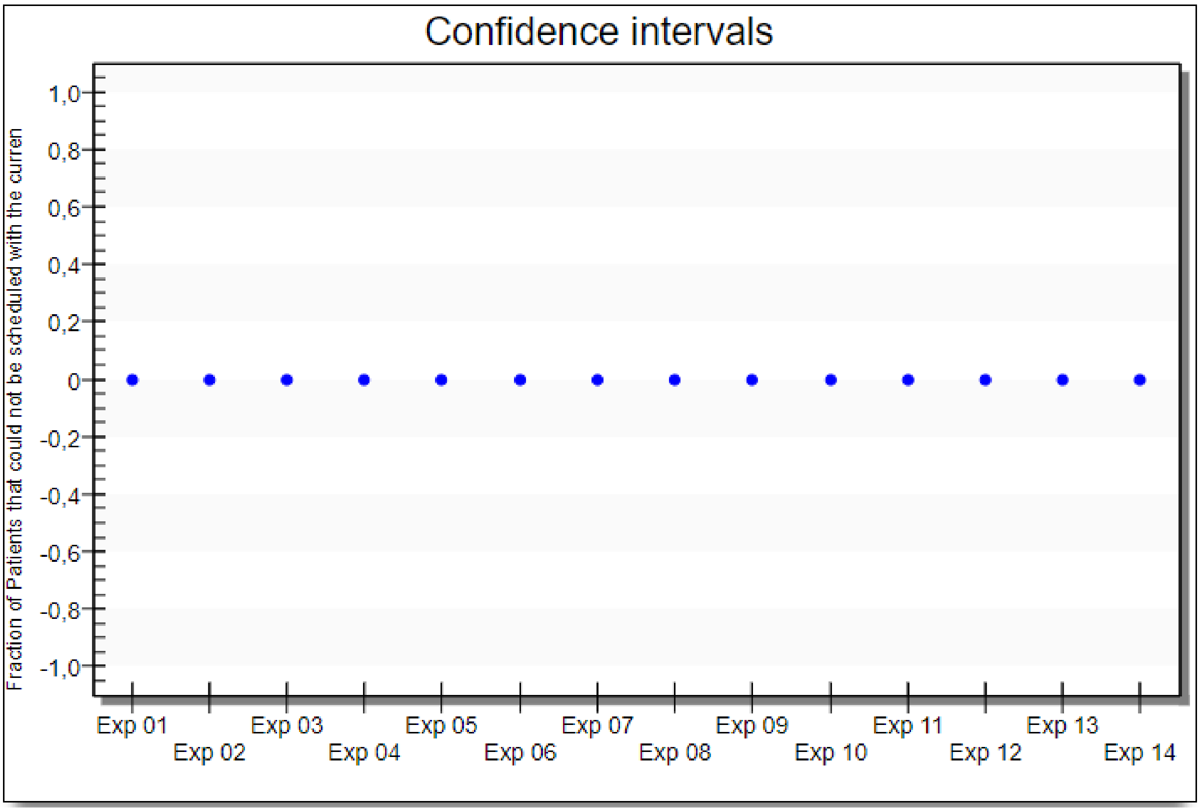
Not Scheduled	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 09	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14
Exp 01	0.664	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 02		**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Exp 03			**0.017**	**0.023**	0.19	**0.016**	**0**	**0**	**0**	**0**	**0**	**0**	0.052
Exp 04				0.763	0.951	**0.003**	**0**	**0**	**0**	**0**	**0**	**0**	0.332
Exp 05					0.794	**0.002**	**0**	**0**	**0**	**0**	**0**	**0**	0.434
Exp 06						**0.005**	**0**	**0**	**0**	**0**	**0**	**0**	0.381
Exp 07							**0**	**0**	**0**	**0**	**0**	**0**	**0.002**
Exp 08								**0.016**	**0**	**0**	**0**	**0**	**0**
Exp 09									**0**	**0**	**0**	**0**	**0**
Exp 10										**0**	**0**	**0**	**0**
Exp 11											**0**	**0**	**0**
Exp 12												**0**	**0**
Exp 13													**0**

J.3 No cancellations and empty calendars

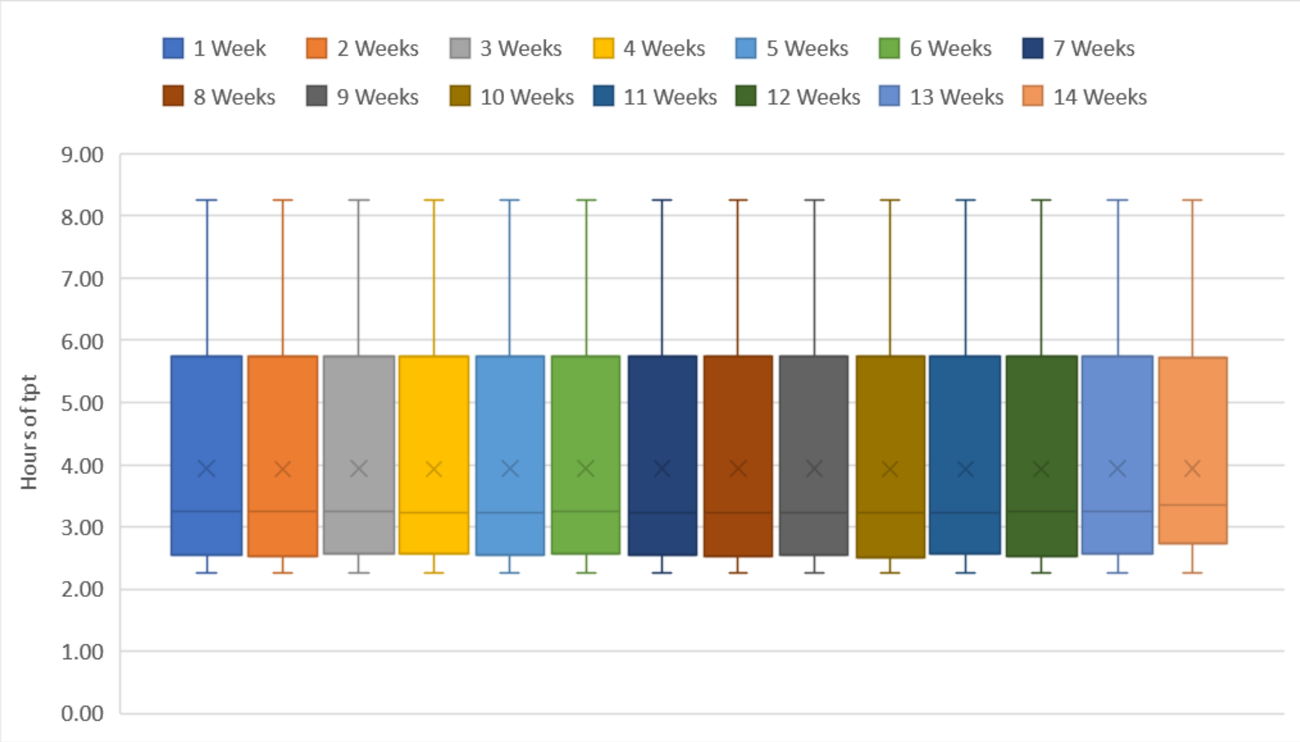
J.3.1 One Day



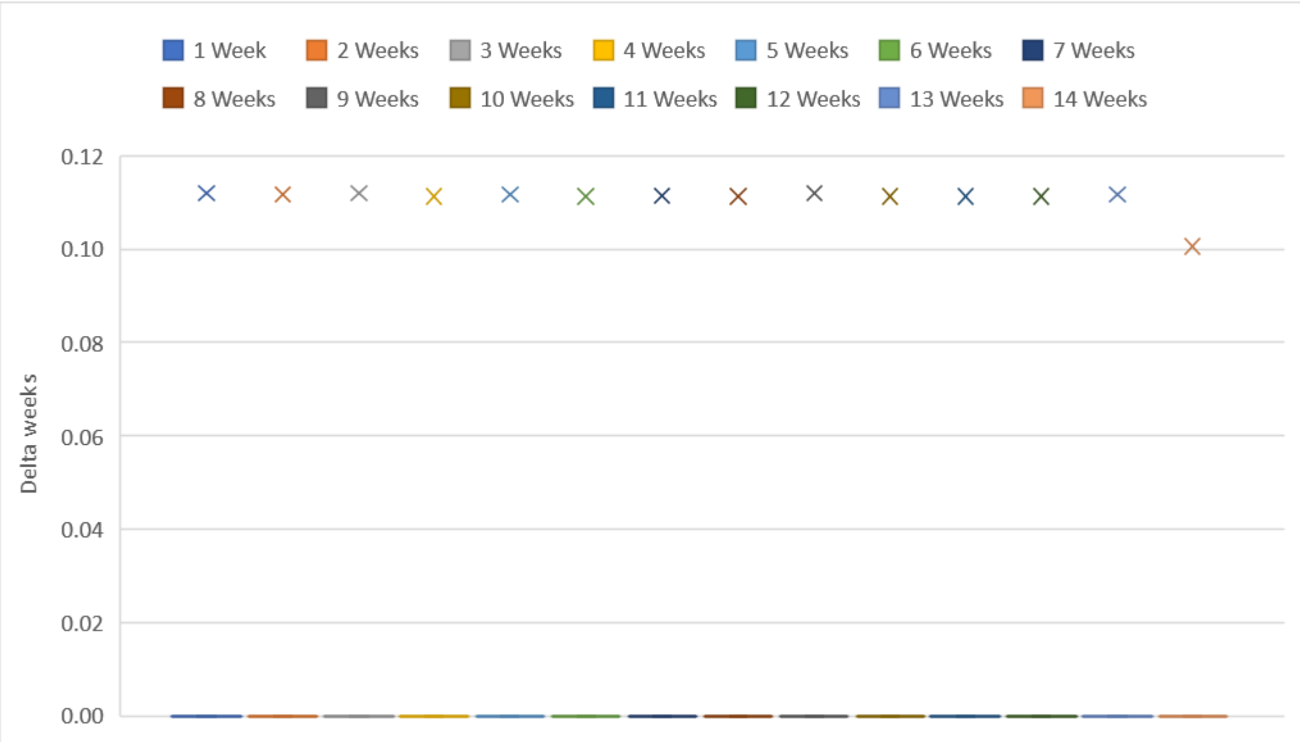
J.3.2 Not Scheduled



J.3.3 Throughput time

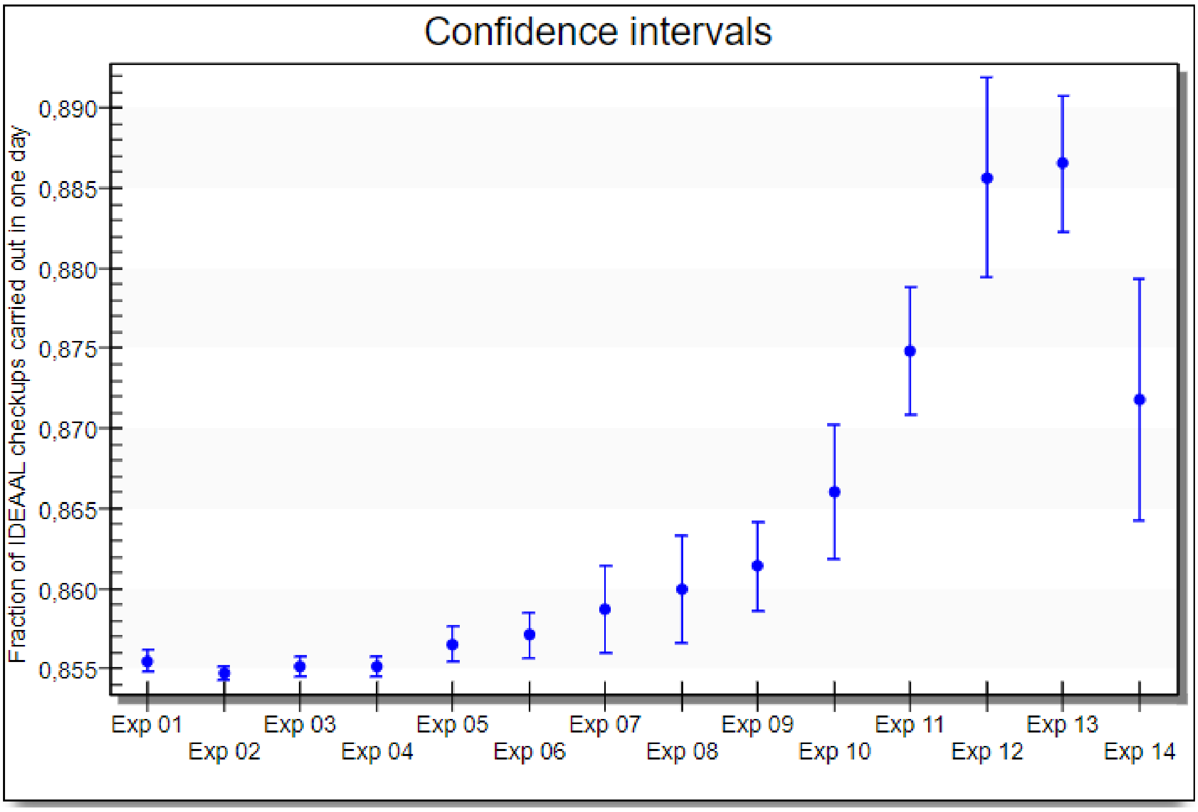


J.3.4 Delta weeks

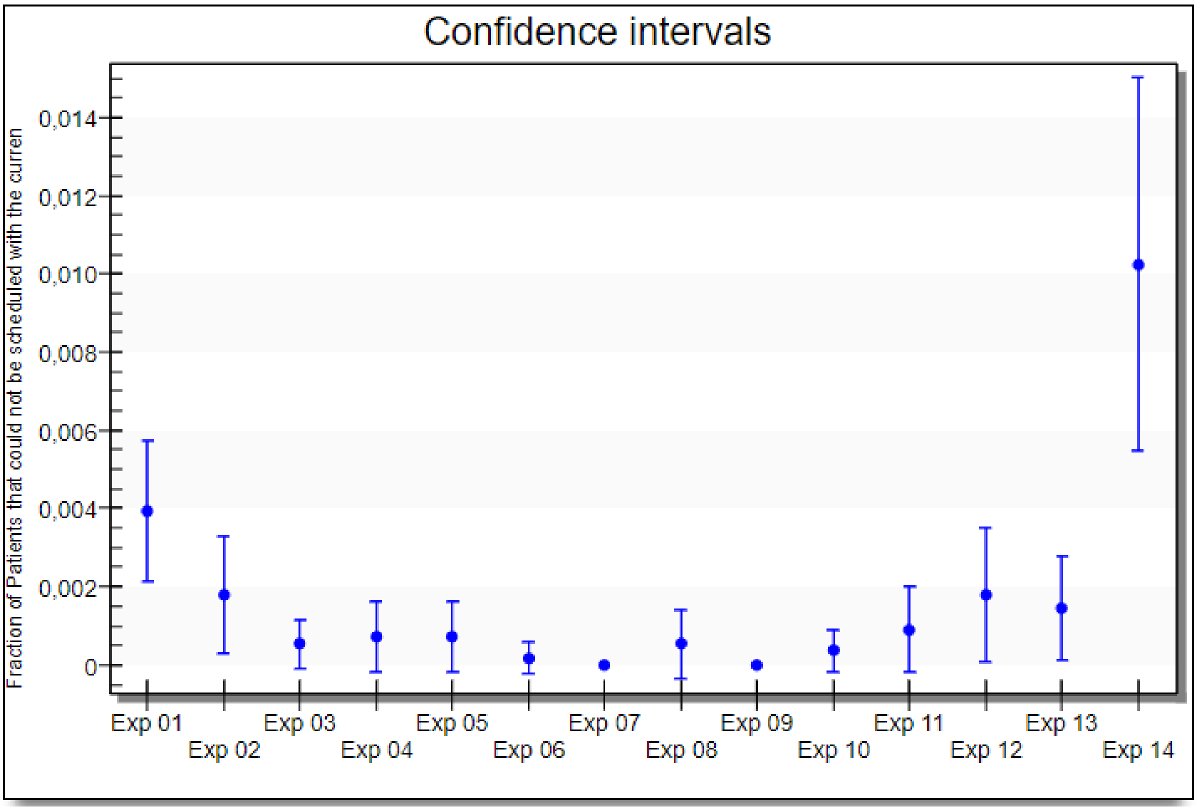


J.4 No Cancellations

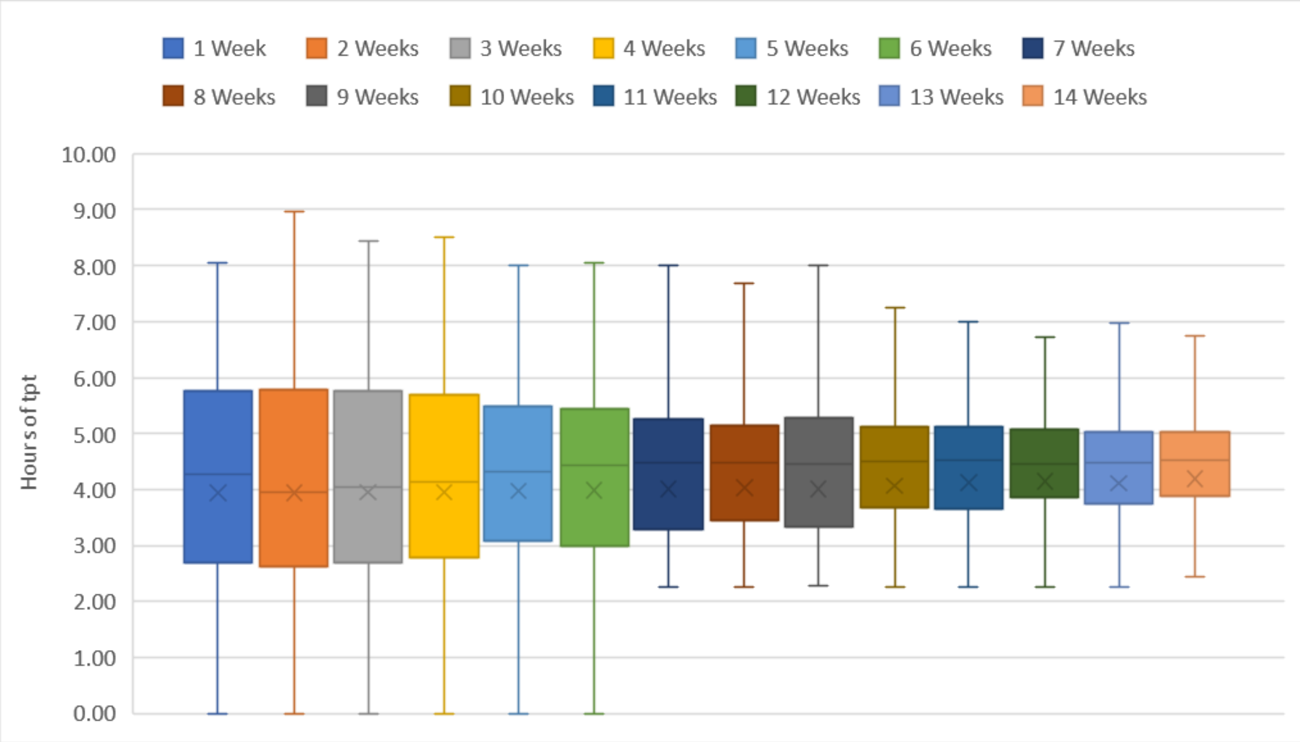
J.4.1 One Day



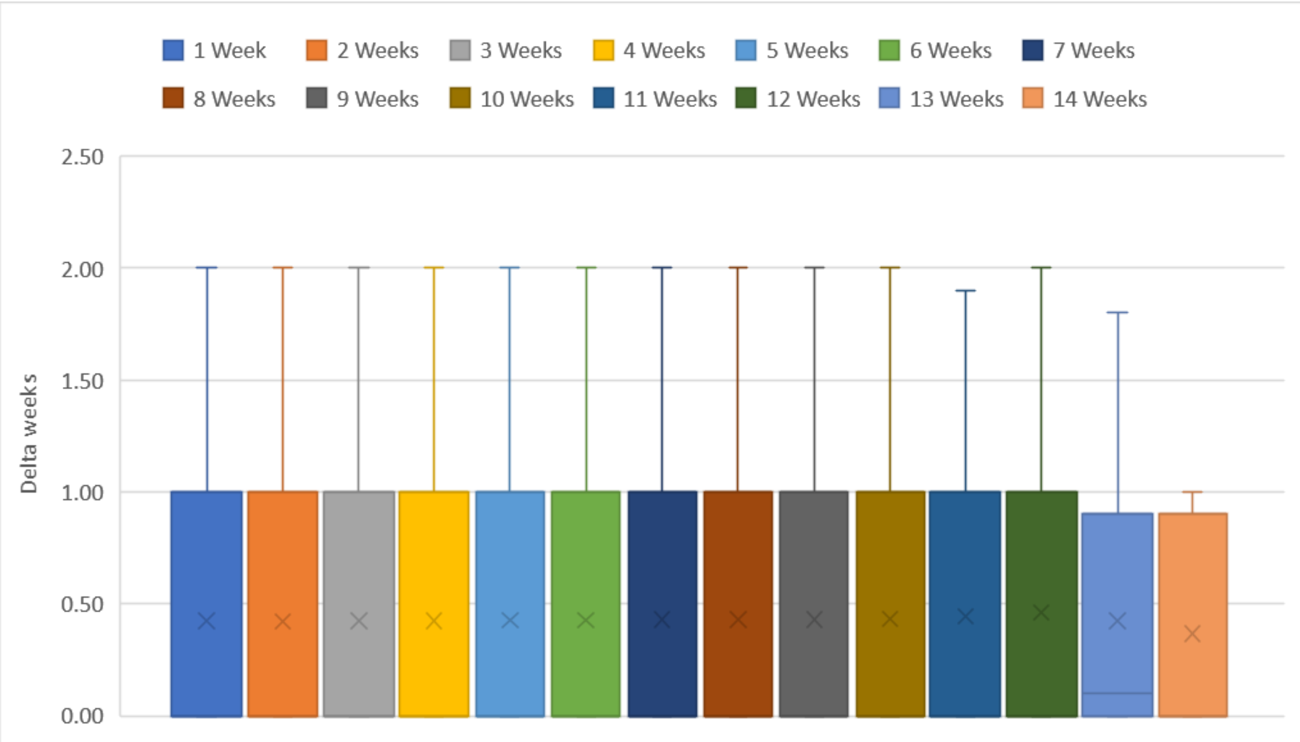
J.4.2 Not Scheduled



J.4.3 Throughput time

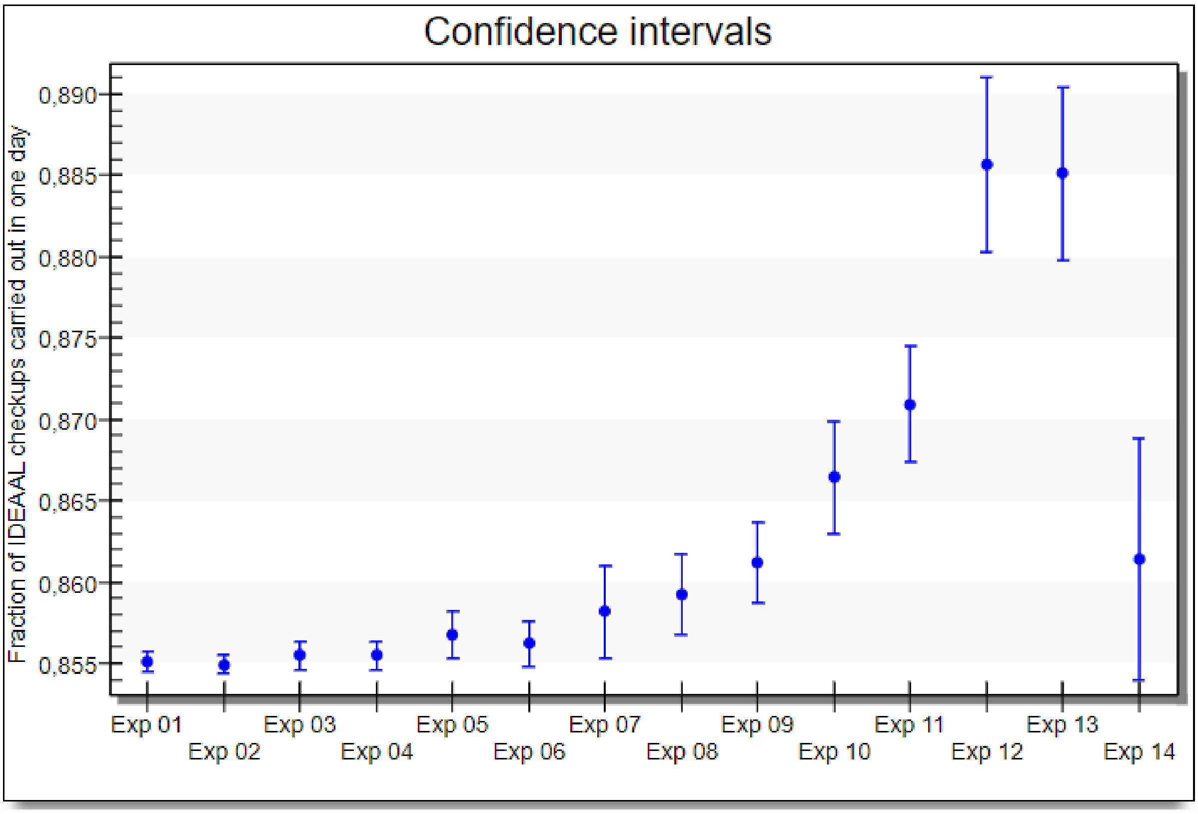


J.4.3 Delta weeks

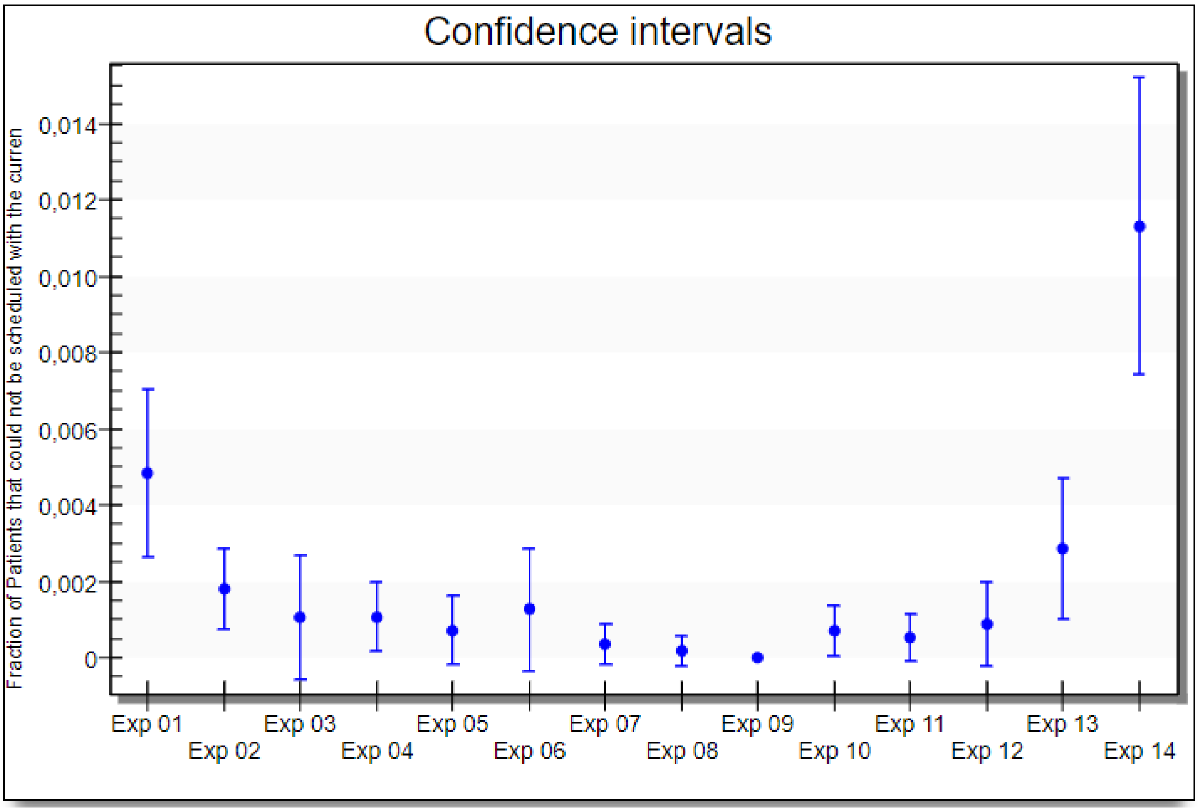


J.5 Doubled Cancellation Rate

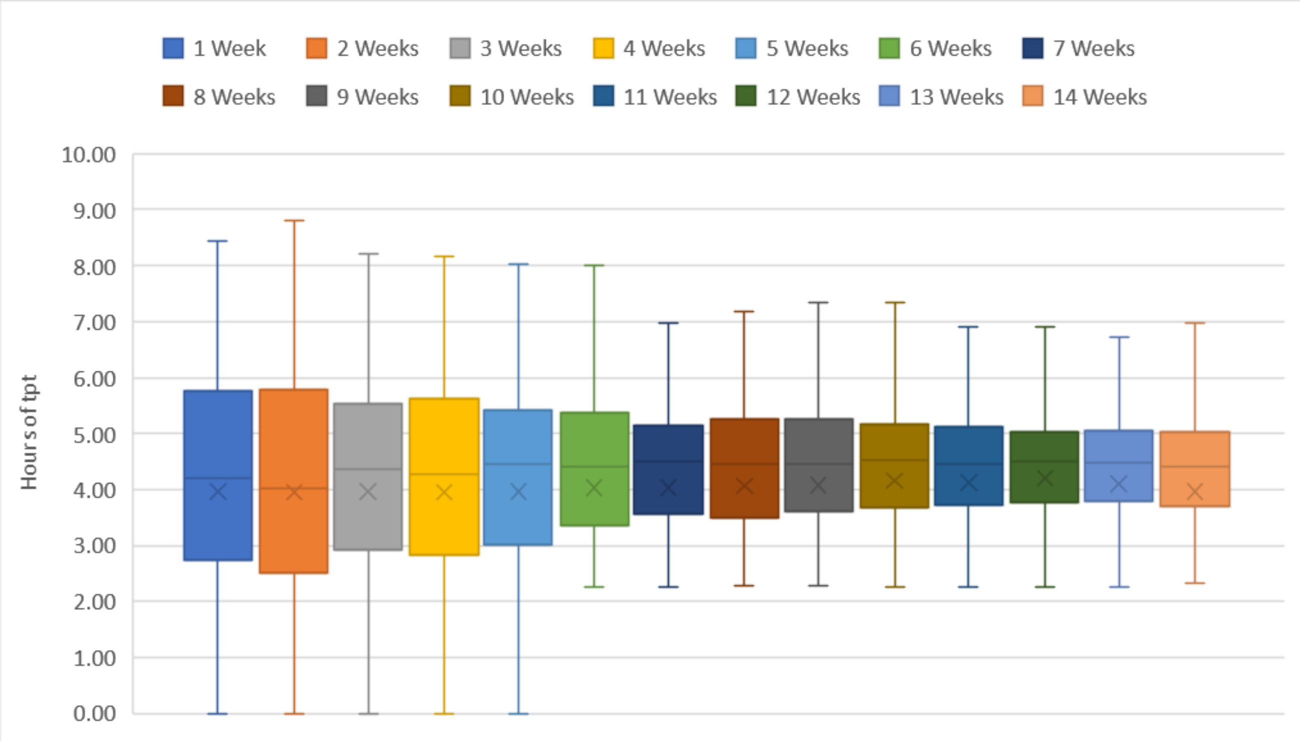
J.5.1 One Day



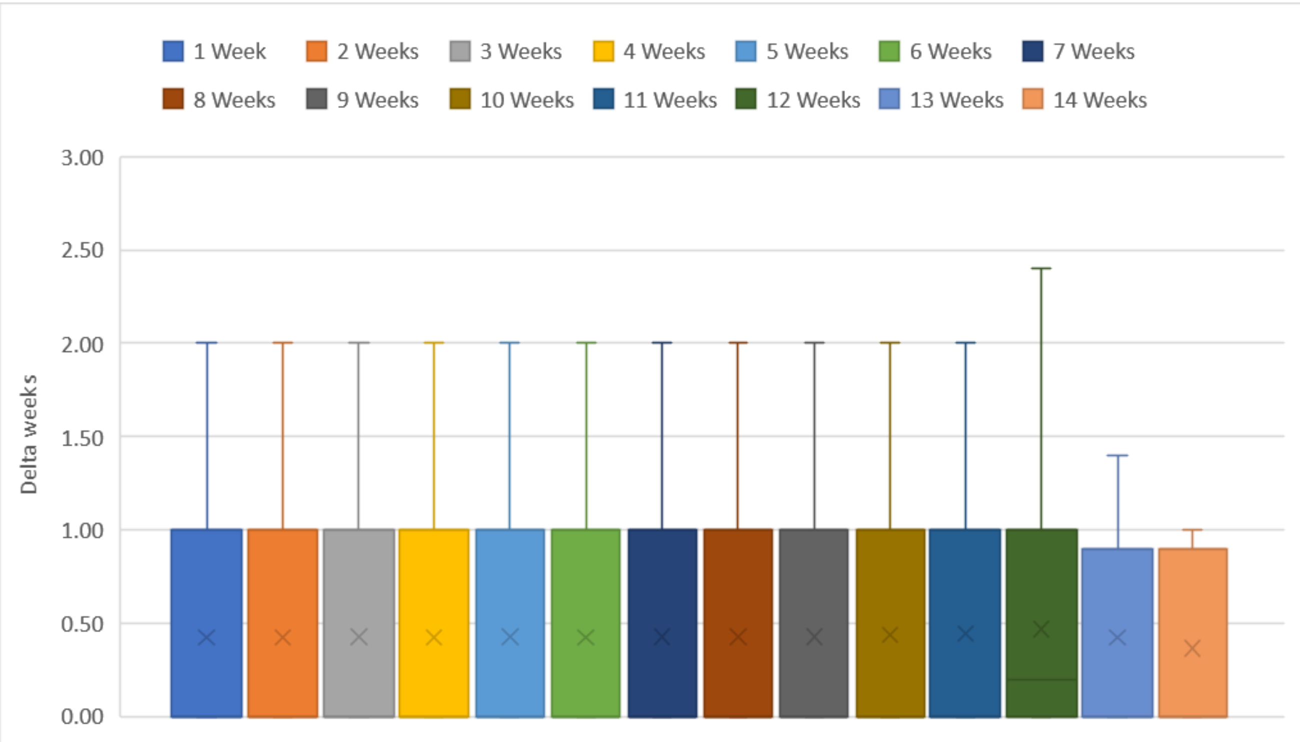
J.5.2 Not Scheduled



J.5.3 Throughput time



J.5.4 Delta weeks



J.6 Fair Workloads

J.6.1 Workload distribution

To determine the distribution of patients based on workload, we first determined the total number of slots every caregiver works in a two-week period. We choose a two-week period, because most caregiver have a different base availability in the even weeks and odd weeks. Based on that we determined the number of patients every caregiver has to help, with the formula:
$\frac{Available\ slot\ caregiver}{Total\ number\ of\ available\ slots\ over\ all\ caregiver} \cdot number\ of\ patients = number\ of\ patients$. Where the nurses and the doctors are calculated separately and the number of patients is 557. This number is rounded down, which results in a total number of patients over all doctors and nurses respectively to be lower than 557. The missing patients are assigned based on the decimal number for every caregiver. A caregiver with a higher decimal number is more likely to end up with an extra patient than a caregiver with a lower decimal number.

After determining the number of patients per caregiver, they are all randomly assigned to patients, to give us a new input list of patients with their preferred doctor and nurse. The expected plan week per patient remained the same.

J.6.2 p values

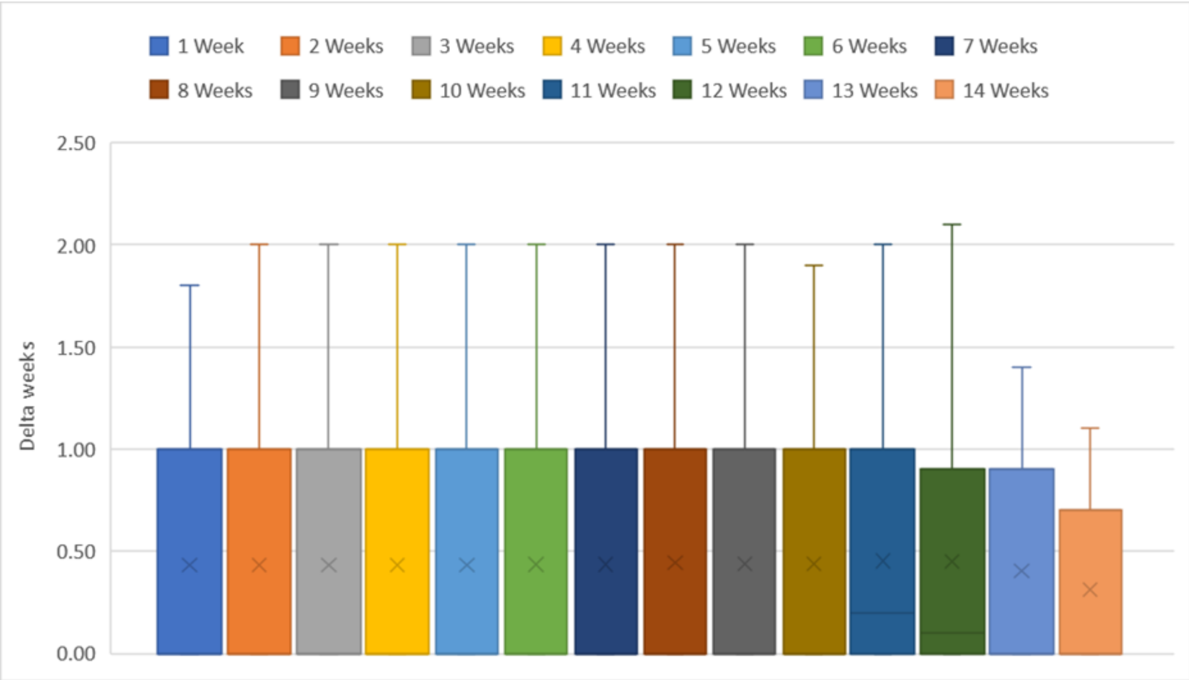
J.7.2.1 One day fraction

Single Day	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 09	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14
Exp 01	0.29	0.122	0.49	0.896	0.083	**0.015**	**0**	**0.002**	**0**	**0**	**0**	**0**	**0**
Exp 02		0.314	0.742	0.128	**0.002**	**0.001**	**0**	**0**	**0**	**0**	**0**	**0**	**0.001**
Exp 03			0.328	**0.021**	**0.001**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.001**
Exp 04				0.437	**0.01**	**0.002**	**0**	**0.001**	**0**	**0**	**0**	**0**	**0**
Exp 05					**0.02**	**0.005**	**0**	**0.001**	**0**	**0**	**0**	**0**	**0**
Exp 06						0.255	**0.003**	**0.029**	**0**	**0**	**0**	**0**	**0**
Exp 07							**0.025**	0.208	**0.001**	**0**	**0**	**0**	**0**
Exp 08								0.298	0.282	**0**	**0**	**0**	**0**
Exp 09									**0.035**	**0**	**0**	**0**	**0**
Exp 10										**0**	**0**	**0**	**0**
Exp 11											**0.02**	0.658	**0**
Exp 12												0.069	**0**
Exp 13													**0**

J.7.2.2 Not scheduled fraction

Not Scheduled	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 09	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14
Exp 01	0.091	**0.019**	**0.005**	**0.017**	**0.019**	**0.006**	**0.005**	**0.005**	**0.004**	**0.006**	**0.025**	0.156	0.346
Exp 02		0.225	**0.016**	0.186	0.237	**0.024**	**0.016**	**0.016**	**0.011**	**0.03**	0.314	0.41	**0**
Exp 03			0.124	1	1	0.194	0.119	0.124	0.073	0.254	0.618	**0.013**	**0**
Exp 04				**0.047**	0.146	0.526	1	1	0.412	0.433	**0.002**	**0**	**0**
Exp 05					1	0.092	**0.043**	**0.047**	**0.021**	0.146	0.532	**0.002**	**0**
Exp 06						0.22	0.141	0.146	0.09	0.28	0.636	**0.018**	**0**
Exp 07							0.471	0.526	0.127	0.795	**0.006**	**0**	**0**
Exp 08								1	0.29	0.395	**0.002**	**0**	**0**
Exp 09									0.412	0.433	**0.002**	**0**	**0**
Exp 10										0.148	**0.001**	**0**	**0**
Exp 11											**0.016**	**0**	**0**
Exp 12												**0.002**	**0**
Exp 13													**0**

J.6.3 Delta weeks



J.7 Smart Pairing of Caregivers

J.7.1 Smart pairing logic

To determine which caregivers are a good pair, a matrix is made based on the number of available slots. To first explain this matrix, we calculated the number of slots a nurse and a doctor have in common over a two weeks period (ten days in total). When both the nurse and the doctor have at least one available slot on the same day, the number of slots the nurse and the doctor have available on that specific day are summed. When only one of the caregivers is available at any given day, this count is set to zero, as they must both have at least one available slot.

By summing all numbers in this matrix, we got a total overall score of 20092. Based on this total score we can calculate the minimum score needed per patients, which is $\frac{20092}{557} = 36.1$. Thereafter we divided every score in the first matrix by 36.1 to create a second matrix that gives us the number of patients that get treated by any given combination of caregivers. This resulted in the following matrix:

Patients per caregiver	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N27	N15	N16
Doc1	0.9	2.2	4.4	2.2	1.7	4.0	2.2	1.7	1.1	1.7	0.0	0.0	2.3	2.9	2.8	0.9
Doc2	3.4	4.3	1.1	4.3	2.8	3.0	3.2	2.8	2.1	2.3	3.0	1.2	4.2	1.0	2.0	3.3
Doc3	3.1	3.6	2.6	3.6	4.2	2.7	3.9	4.2	3.1	1.6	2.5	0.8	3.5	2.4	3.1	4.0
Doc4	2.0	2.2	2.0	2.2	2.6	3.9	1.2	2.7	0.0	3.0	1.2	1.2	2.2	1.8	1.7	2.2
Doc5	2.3	2.7	2.1	2.7	1.9	1.3	4.4	1.9	3.2	2.6	2.6	1.3	2.6	2.0	1.4	4.5
Doc6	1.9	4.5	4.1	4.5	2.5	3.5	5.5	2.5	3.7	1.9	2.6	0.9	4.5	2.9	3.0	3.8
Doc7	3.9	3.5	4.1	3.5	5.4	4.0	3.8	5.4	3.0	3.0	2.5	0.8	3.4	3.7	3.7	4.7
Doc8	3.4	2.9	5.9	2.9	4.4	4.0	5.1	4.4	4.2	4.0	1.9	0.9	2.9	4.5	3.9	5.4
Doc9	1.8	3.3	2.0	3.3	3.0	2.2	3.6	3.0	2.7	1.9	3.1	0.9	3.2	1.8	2.2	3.7
Doc10	3.6	4.9	3.8	4.9	4.4	6.3	2.8	4.5	0.9	4.4	2.6	0.9	4.8	3.5	3.9	3.2
Doc11	4.0	3.8	2.3	3.8	3.9	3.7	3.0	3.9	2.1	2.8	3.0	0.9	3.7	2.2	2.7	3.1
Doc12	1.4	2.5	5.5	2.5	2.5	5.1	2.5	2.6	1.2	2.6	0.0	0.0	2.6	3.8	3.9	1.3

Just like when determining the number of patients per caregiver with the fair workload experiments, we rounded these numbers down to get a first input of all patients and their caregiver combination. Afterwards we assigned caregiver combinations to the remaining patients, based on the decimal numbers. Where a larger decimal number is more likely to have the patient be treated by that specific combination of caregivers. So, for example number of patients treated by the combination of doc1 and n1 is increased from zero to one, before the combination of doc1 and n2 would be increased from two to three. Because 0.9 has a larger decimal number (9) than 2.2 does (2).

J.7.2 p values

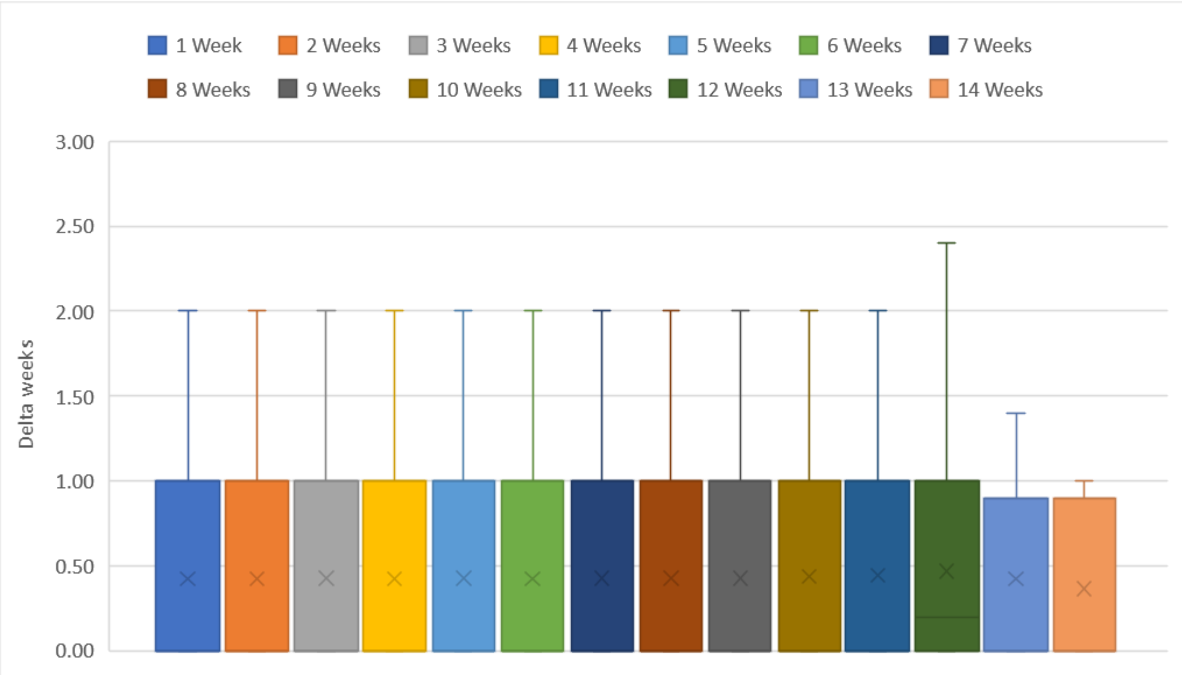
J.8.2.1 One day fraction

Single Day	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 09	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14
Exp 01	0.628	0.471	0.471	**0.039**	0.14	**0.039**	**0.005**	**0**	**0**	**0**	**0**	**0**	0.087
Exp 02		0.268	0.268	**0.024**	0.086	**0.031**	**0.004**	**0**	**0**	**0**	**0**	**0**	0.079
Exp 03			1	0.119	0.349	0.066	**0.008**	**0**	**0**	**0**	**0**	**0**	0.104
Exp 04				0.119	0.349	0.066	**0.008**	**0**	**0**	**0**	**0**	**0**	0.104
Exp 05					0.556	0.327	0.07	**0.003**	**0**	**0**	**0**	**0**	0.192
Exp 06						0.182	**0.031**	**0.001**	**0**	**0**	**0**	**0**	0.149
Exp 07							0.529	0.085	**0.001**	**0**	**0**	**0**	0.374
Exp 08								0.223	**0.002**	**0**	**0**	**0**	0.545
Exp 09									**0.014**	**0**	**0**	**0**	0.959
Exp 10										0.056	**0**	**0**	0.188
Exp 11											**0**	**0**	**0.021**
Exp 12												0.873	**0**
Exp 13													**0**

J.8.2.2 Not planned fraction

Not Scheduled	Exp 02	Exp 03	Exp 04	Exp 05	Exp 06	Exp 07	Exp 08	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14
Exp 01	**0.014**	**0.006**	**0.004**	**0.002**	**0.008**	**0.001**	**0.001**	**0.002**	**0.001**	**0.003**	0.136	**0.005**
Exp 02		0.414	0.255	0.095	0.535	**0.016**	**0.007**	0.068	**0.034**	0.196	0.268	**0**
Exp 03			1	0.668	0.861	0.363	0.253	0.652	0.497	0.838	0.115	**0**
Exp 04				0.53	0.829	0.142	0.061	0.477	0.281	0.777	0.068	**0**
Exp 05					0.519	0.451	0.239	1	0.715	0.777	**0.033**	**0**
Exp 06						0.256	0.172	0.497	0.365	0.682	0.152	**0**
Exp 07							0.557	0.356	0.628	0.335	**0.013**	**0**
Exp 08								0.138	0.29	0.19	**0.009**	**0**
Exp 10									0.66	0.755	**0.029**	**0**
Exp 11										0.528	**0.02**	**0**
Exp 12											0.054	**0**
Exp 13												**0.001**

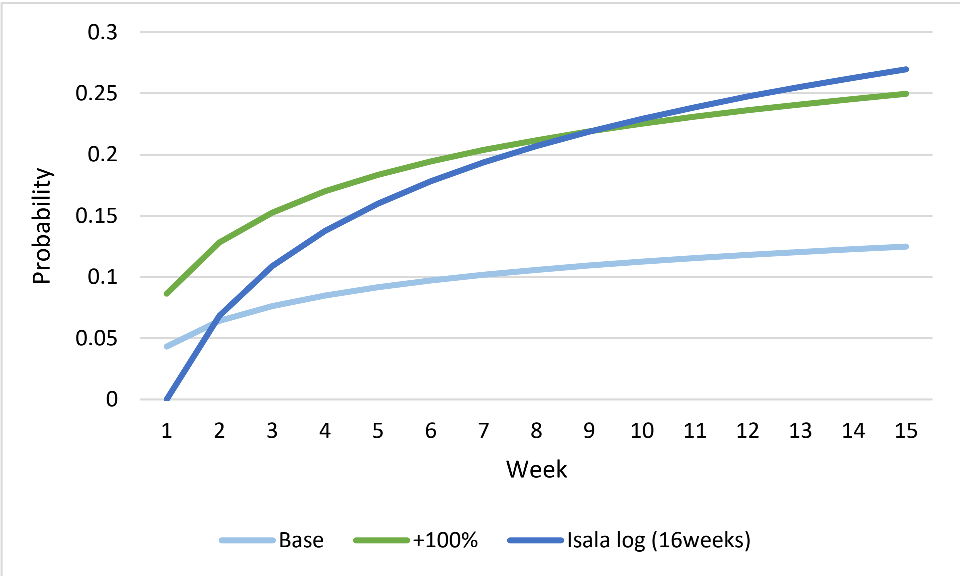
J.7.3 Delta weeks



Appendix K: Isala cancellation data analysis

After finishing the experimental phase of this thesis, the Isala data about cancellations in the diabetes department was uncovered. A set of $211{,}755$ appointments, carried out since 2016 was provided. For every appointment the initial plan date, the initial appointment date, the mutation date and the new appointment date are known. This data set can provide several insights in the cancellation rates over the booking horizon, specifically for the diabetes department in Isala.

By analyzing the data we found a trendline following the logarithmic equation $Y = 0.0999ln(x) - 0.0009$, with $R^2 = 0.9041$. In general an R^2 of above 0.7 is considered a high level of correlation. So, we can conclude that the R^2 shows us that this equation has a high correlation to the data. To visualize the probabilities resulting from this equation, compared to equations used in this research, we provided the following graph. Note, we took $\max(equation; 0)$ for the equation from the data, because a negative probability is impossible. This only changes the probability for week one (from -0.0009 to 0).



From this graph we derive that the experimented +100%-case is closer to the actual cancellation rate than the equation from the base case. Therefore we can conclude that the results from the doubled cancellation rate experiments are a more valid representation of the situation in Isala. As we described in Chapter 5 Results and analysis, the difference in single day fraction between doubled cancellation rate and the base case cancellation rate is extremely small (88.6% and 88.5% respectively). By finding these numbers, we strengthen the validity of the conclusion that the cancellation rate in the diabetes department has a negligible impact on the plannability of the IDEAAL checkups. As the cancellation rates are so close, there is no need for extra experimentation to analyze changes in results.