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DESIGNING A BLUEPRINT SCHEDULE TO MEET ACCESS TIME CRITERIA OF PRIORITY GROUPS IN A PREOPERATIVE ASSESSMENT CLINIC

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UNIVERSITY OF TWENTE.

ST ANTONIUS
een santeon ziekenhuis

Designing a Blueprint Schedule to meet Access Time Criteria of Priority Groups in a Preoperative Assessment Clinic

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Management summary

Background

In 2019, more than three million surgeries were done in the Netherlands. Before a patient is allowed to have surgery, a preoperative screening is performed to determine whether the patient is in good condition to have surgery. Traditionally, preoperative assessment took place the evening before or on the day of surgery. However, currently, patients are assessed several weeks or days before surgery in the preoperative assessment clinic (PAC). A patient should have timely access to the PAC such that the surgery will not be delayed. The access time is defined as the time between the surgery request and the PAC appointment. Whether a patient has timely access to the PAC depends on the access time criteria, which depend on the surgery priority of the patient. The higher the priority, the more restrictive the access time. Thus, a successful PAC should enable the screening of patients within the access time criteria and thereby allows the operating room (OR) department for a more efficient functioning.

In the St. Antonius Hospital, the PAC is located in Nieuwegein and Utrecht. Each location has one or multiple screeners (anaesthetists/PAC employees), nurses, and pharmacists working there. Patients arriving in the PAC can fall under multiple specialties, appointment types, complexities and priorities. As a result of the coronavirus disease 2019 (COVID-19), the situation in the PAC changed. Before COVID-19, all appointments took place physically, while 80% of the patients are currently screened via phone. Next, surgeries are scheduled in the short term as a result of COVID-19. These changes ask for a new design of the PAC.

Objective

Currently, the PAC of the St. Antonius Hospital screens less than 70% of the patients within the access time criteria. The three main reasons for this are: (1) a decrease in capacity as a consequence of the increase in phone consultations, (2) the current blueprint schedule which does not support the PAC planners which priority groups should be scheduled, and (3) the difference in the way of planning between the PAC planners and the OR planners. This study aims to increase the percentage of patients screened within the access time criteria by designing a blueprint schedule.

Solution approach

To improve the access time to the PAC, three interventions are tested. During intervention 1, the screening capacity is increased from seven to eight screeners. Intervention 2 is about designing a blueprint schedule, in which capacity is allocated to priority groups. Allocated appointment slots can only be used by the allocated priority group, while flexible appointment slots can be used by all patients. The allocation is based on a method that takes the mean and standard deviation of the daily number of surgery requests per priority group i into account. Multiple blueprint schedules, which differ in flexibility and number of priority groups, are tested. Figure 1 gives the capacity allocation method. Intervention 3 investigates the offline planning approach, in which high priority patients are scheduled immediately upon request and low priority patients are scheduled when the date of surgery comes close. Then, the best performing blueprint schedule from intervention 2 is combined with intervention 3.

$\mathrm{C_i} = \lfloor \%\ \text{priority group } i * \text{capacity} \rfloor$ $\mathrm{F_i} = \left\lfloor \dfrac{\mathrm{C_i} * \text{flexibility} * \sigma_\mathrm{i}}{\mu_\mathrm{i}} \right\rfloor$ $\mathrm{A_i} = \mathrm{C_i} - \mathrm{F_i}$	μ_i = mean daily number of surgery requests of priority group i σ_i = standard deviation of the daily number of surgery requests of priority group i capacity = the daily number of appointment slots in the PAC schedule $\mathrm{C_i}$ = total daily number of appointment slots for priority group i flexibility = experimental ratio which influences the degree of flexiblity $\mathrm{F_i}$ = daily number of flexible appointment slots contributed by priority group i $\mathrm{A_i}$ = daily number of appointment slots allocated to priority group i

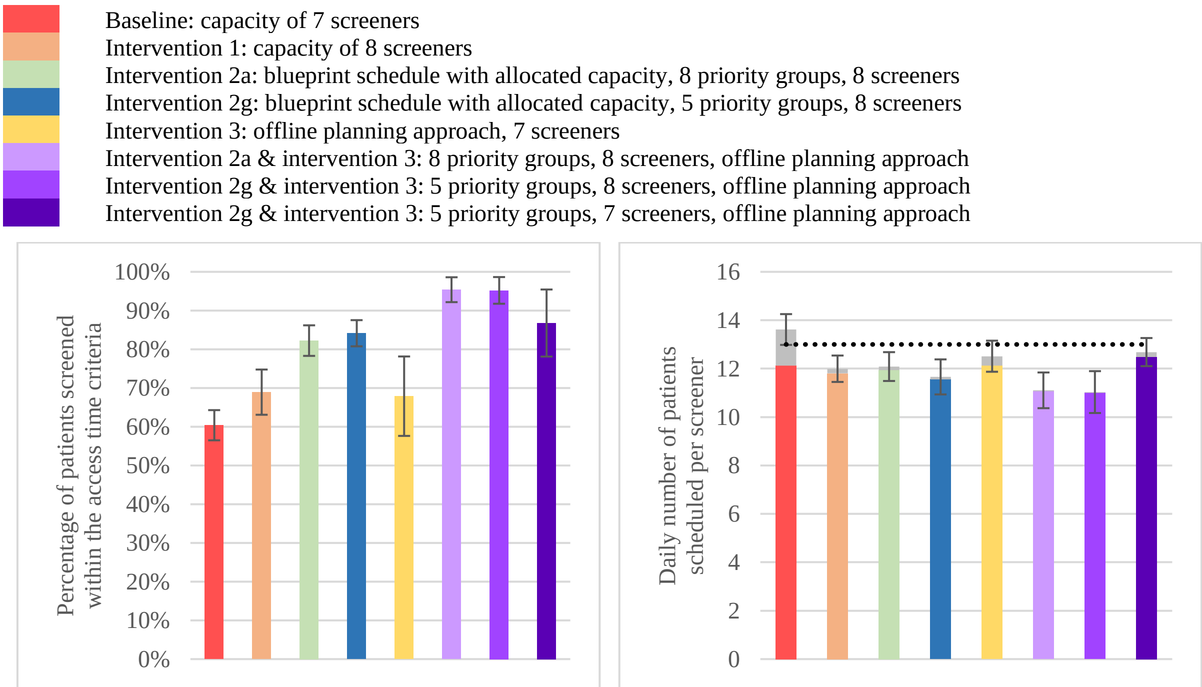
Figure 1. Capacity allocation method to determine the number of flexible and allocated slots per priority group i

The performances of the interventions are determined using a discrete event simulation (DES). The performances are based on four key performance indicators (KPIs). These are: (1) the percentage of patients screened within the access time criteria, (2) the daily number of patients overbooked, (3) the mean utilization per screener, and (4) the variation in workload during the week for screeners and for nurses. The focus is on the first three KPIs because these are in agreement with the goal of this study. Next, a sensitivity analysis is used to determine how sensitive the output of the blueprint schedule is for a change in input. Moreover, the capacity allocation method is used to adapt the blueprint schedule to future scenarios to determine whether the method is able to allocate the capacity correctly in a new situation.

Results

Figure 2 shows the performances of the current situation (baseline), intervention 1, the best performing experiments within intervention 2, and intervention 3. Next, Figure 2 shows in purple the performances of the combined interventions. Figure 2a shows that the percentage of patients screened within the access time criteria significantly increases during each intervention compared to the baseline. Figure 2b shows that the number of patients scheduled per screener decreases to below the capacity restriction. Additionally, the daily number of patients overbooked significantly decreases during each intervention.

The combination of interventions 2 and 3, in which capacity allocation is combined with the offline planning approach, with a capacity of eight screeners results in the most promising results regarding access times and number of patients overbooked. When the capacity is allocated to eight priority groups (intervention 2a & 3), the percentage of patients screened within the access time criteria increases from 60.4% to 95.4%, and the number of patients overbooked decreases from 10.4 to 0.4 patients daily. When the capacity is allocated to five priority groups (intervention 2g & 3), the percentage of patients screened within the access time criteria increases from 60.4% to 95.2%, and the number of patients overbooked decreases from 10.4 to 0.4 patients daily. However, the number of patients scheduled per screener equals 11.1 and 11 patients for these combinational interventions respectively, which is both below the capacity of 13. Meanwhile, the combination of intervention 2g & 3 with seven screeners shows more promising results regarding the number of patients scheduled per screener. On average 12.7 patients are scheduled per screener and the daily number of patients overbooked equals 1.7.



(a) (b)

Figure 2. Results of the DES for the performance of the current situation (red), combined interventions (purple) and individual interventions (other colours). a) shows the percentage of patients screened within the access time criteria and b) shows the daily number of patients scheduled per screener with the number of patients overbooked in grey. The error bar indicates the standard deviation

Future scenarios are tested to investigate if the capacity allocation method is able to allocate the capacity correctly, even when the patient mix changes. A possible future scenario is an increase in the number of high priority patients due to the delayed care resulting from COVID-19. Currently, around 30% of the patients have surgery within 10 days. We compare this current situation with a future scenario, in which 50% of the patients have surgery within 10 days. A new blueprint schedule is designed with the use of the capacity allocation method. A blueprint schedule with a capacity of eight screeners results in 94% of the patients screened within the access time criteria. And, a blueprint schedule with a capacity of seven screeners results in 87% of the patients screened within the access time criteria. Moreover, both blueprint schedules result in a small increase in the number of patients overbooked. A possible reason is that high priority patients have strict restrictions regarding the access time. Consequently, it is more difficult to deal with the fluctuations in demand.

Conclusion and discussion

The analyses show that allocating capacity to priority groups in combination with the offline planning approach contributes to an increase in the percentage of patients that are screened within the access time criteria. Moreover, the new blueprint schedule results in a decrease in the daily number of patients overbooked. When the patient mix changes, the blueprint schedule can be adapted using the capacity allocation method.

A limitation of this study is that we investigated the access time to the PAC, without improving physician idle time and patient waiting time. The main reason for this is the missing data. It is already known that as a consequence of the increase in phone consultations, physician idle time increases because patients do not always answer the phone. We expect that the new blueprint schedule will not change this observation. Next, we expect that, as a consequence of the increase in phone consultations, patient waiting time does not play an important role in patient satisfaction. However, investigating the effect of the new blueprint schedule on patient waiting time and physician idle time is advised.

A recommendation for further research is to investigate the relationship between the developed capacity allocation method and the PAC capacity. In this study, we determined the number of flexible and allocated slots based on the coefficient of variation of the priority groups and tested the degree of flexibility. These calculations are based on a given PAC capacity. The capacity allocation method can be improved when capacity calculations and the relation between capacity, demand and the degree of flexibility are added.

Recommendations

We recommend the St. Antonius Hospital to implement the designed blueprint schedule, in which the capacity is allocated to priority groups. In the current situation, the already designed blueprint schedule can be used. When the situation changes, for example as a consequence of COVID-19, the blueprint schedule can be adapted using the capacity allocation method. Next, we recommend implementing the offline planning approach, in which high priority patients (with a surgery priority of 6 weeks) are scheduled immediately upon request, while low priority patients (with a surgery priority of 6 months) are added to a patient list and scheduled when the date of surgery comes close.

Management samenvatting

Achtergrond

In 2019 werden in Nederland meer dan 3 miljoen operaties uitgevoerd. Voordat een patiënt geopereerd kan worden, moet de patiënt een screening ondergaan, waarbij bepaald wordt of de patiënt in goede gezondheid verkeert om de operatie aan te kunnen. Waar vroeger de screening uitgevoerd werd op de avond voor of de dag van de operatie, moet de patiënt tegenwoordig vooraf langs de preoperatie screening (POS). Een patiënt moet tijdig toegang hebben tot de POS, zodat de operatie geen vertraging oploopt. De toegangstijd is de tijd tussen de aanvraag van de operatie en de POS afspraak. Of een patiënt tijdig toegang heeft tot de POS, hangt af van de toegangstijdcriteria, die op zijn beurt afhangen van de urgentie van de operatie. Des te hoger de urgentie, des te meer restricties op de toegangstijd. Kortom, een succesvolle POS zorgt ervoor dat de screening binnen de toegangstijdcriteria uitgevoerd wordt en waardoor de operatieafdeling effectief kan functioneren.

Het St. Antonius ziekenhuis heeft de POS gelokaliseerd op twee locaties, namelijk Nieuwegein en Utrecht. Op iedere locatie zijn één of meerdere screeners (anesthesisten/POS-medewerkers), verpleegkundigen en apothekers werkzaam. Patiënten met verschillende specialismen, afspraak types, complexiteiten en urgenties arriveren op de POS. Als gevolg van COVID-19 is de situatie op de POS veranderd. Waar vroeger alle afspraken fysiek uitgevoerd werden, wordt tegenwoordig 80% van de patiënten telefonisch gescreend. Daarnaast worden operaties op steeds kortere termijn gepland. Deze veranderingen vragen om een nieuwe inrichting van de POS.

Doel

Momenteel wordt minder dan 70% procent van de patiënten binnen de toegangstijdcriteria gescreend op de POS in het St. Antonius ziekenhuis. De drie voornaamste redenen zijn: (1) de afname in capaciteit als gevolg van de toename in telefonische consulten (2) het huidige agendasjabloon die geen richtlijnen geeft welke urgentiegroepen gepland moeten worden en (3) het verschil in de manier van plannen tussen POS en OK planners. Het doel van dit onderzoek is om het percentage patiënten dat binnen de toegangstijdcriteria gescreend wordt te verhogen door een agendasjabloon te ontwikkelen.

Aanpak

Om de toegangstijd tot de POS te verbeteren, zullen drie interventies getest worden. Tijdens interventie 1 verhogen we het aantal screeners van zeven naar acht. Interventie 2 richt zich op het maken van een nieuw agendasjabloon, waarbij capaciteit toegewezen wordt aan urgentiegroepen. Gealloceerde afspraaksloten mogen alleen gebruikt worden voor de gealloceerde urgentiegroep, terwijl flexibele afspraaksloten gebruikt mogen worden voor alle patiënten. Deze allocatie is gebaseerd op een methode die rekening houdt met het gemiddelde en de standaarddeviatie van het dagelijks aantal operatie aanvragen per urgentiegroep i . Meerdere agendasjablonen, die variëren in flexibiliteit en het aantal urgentiegroepen, worden getest. Figuur 1 geeft de capaciteit allocatie methode. Interventie 3 test het actief inplannen van patiënten waarbij urgente patiënten direct ingepland worden voor de screening en waarbij niet urgente patiënten gepland worden wanneer de operatie nadert. Vervolgens zal het beste agendasjabloon uit interventie 2 gecombineerd worden met interventie 3.

$\mathrm{C_i} = \lfloor \%\ \text{urgentiegroep } i * \text{capaciteit} \rfloor$ $\mathrm{F_i} = \left\lfloor \frac{\mathrm{C_i} * \text{ flexibiliteit} * \sigma_i}{\mu_i} \right\rfloor$ $\mathrm{A_i} = \mathrm{C_i} - \mathrm{F_i}$	μ_i = gemiddeld dagelijks aantal operatie aanvragen van urgentiegroep i σ_i = standaard deviatie van het dagelijks aantal operatie aanvragen van urgentiegroep i capaciteit = dagelijks aantal afspraaksloten in de POS agenda $\mathrm{C_i}$ = totaal dagelijks aantal afspraaksloten voor urgentiegroep i flexibiliteit = experimenteel ratio die de mate van flexibiliteit beïnvloedt $\mathrm{F_i}$ = dagelijks aantal flexibele afspraaksloten bijgedragen door urgentiegroep i $\mathrm{A_i}$ = dagelijks aantal afspraak sloten gealloceerd aan urgentiegroep i

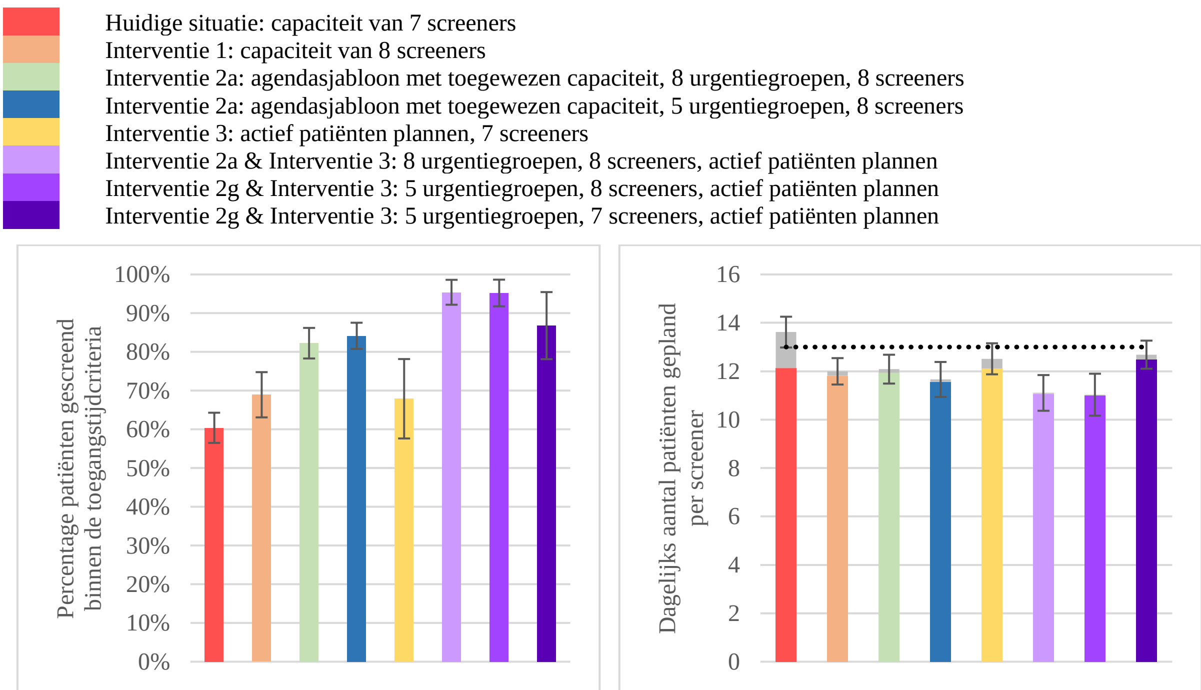
Figuur 1. Capaciteit allocatie methode om de flexibele en gealloceerde afspraaksloten per urgentiegroep i te bepalen

De interventies worden getest met behulp van een simulatie. De simulatie beoordeelt de interventie op basis van vier key performance indicators (KPIs). Deze zijn: (1) het percentage patiënten gescreend binnen de toegangstijdcriteria, (2) het dagelijks aantal patiënten overboekt, (3) de gemiddelde bezettingsgraad per screener en (4) de variatie in werkdruk gedurende de week voor screeners en verpleegkundigen. Hierbij ligt de focus op de eerste drie KPIs omdat deze aansluiten bij het doel van het onderzoek. Vervolgens wordt door middel van een gevoeligheidsanalyse gekeken hoe gevoelig de uitkomst is voor een verandering in input en zal de capaciteit allocatie methode getest worden op nieuwe situaties om te testen of de methode in staat is om in de toekomst de capaciteit juist te alloceren.

Resultaten

Figuur 2 laat de resultaten zien van de huidige situatie, Interventie 1, de best presterende experimenten binnen Interventie 2 en Interventie 3. Daarnaast laat Figuur 2 in paars de resultaten zien van de gecombineerde interventies. Figuur 2a laat zien dat het percentage patiënten dat gescreend is binnen de toegangstijdcriteria significant toeneemt gedurende elke interventie. Figuur 2b laat zien dat het aantal patiënten gepland per screener afneemt tot een aantal binnen de capaciteitsrestricties. Bovendien neemt het aantal patiënten dat dagelijks overboekt wordt significant af gedurende elke interventie.

De combinatie van Interventies 2 en 3, waarbij de capaciteit toegewezen is en patiënten actief ingepland worden, met een capaciteit van acht screeners, laat de meest veelbelovende resultaten zien met betrekking tot de toegangstijden en de overboekingen. Als de capaciteit gealloceerd is aan acht urgentiegroepen (Interventie 2a & 3), neemt het percentage patiënten dat gescreend wordt binnen de toegangstijdcriteria toe van 60,4% naar 95,4% en neemt het aantal overboekingen af van 10,4 naar 0,4 patiënten per dag. Als de capaciteit gealloceerd is aan vijf urgentiegroepen (Interventie 2g & 3), neemt het percentage patiënten dat gescreend wordt binnen de toegangstijdcriteria toe van 60,4% naar 95,2% en neemt het aantal overboekingen af van 10,4 naar 0,4 patiënten per dag. Het aantal geplande patiënten per screener is gelijk aan respectievelijk 11,1 en 11 patiënten voor deze combinatorische interventies, beide onder de capaciteit van 13. Echter, de combinatie van Interventie 2g & 3 met zeven screeners laat betere resultaten zien met betrekking tot het aantal geplande patiënten per screener. Per screener worden gemiddeld 12,7 patiënten ingepland en het dagelijkse aantal overboekingen is gelijk aan 1,7.



(a) (b)

Figuur 2. Resultaten van de simulatie voor de prestatie van de huidige situatie (rood), de gecombineerde interventies (paars) en de individuele interventies (overige kleuren). a) geeft het percentage patiënten dat gescreend is binnen de toegangstijdcriteria en b) geeft het aantal patiënten gepland per screener met in grijs het aantal dat overboekt is. De foutbalk geeft de standaarddeviatie weer

We hebben toekomstige scenario's getest om te onderzoeken of de capaciteit allocatie methode in staat is om de capaciteit juist te alloceren, ook wanneer de patiëntsamenstelling verandert. Verwacht wordt dat er, als gevolg van de uitgestelde zorg, een toename zal ontstaan in het percentage patiënten dat met hoge urgentie geopereerd moet worden. In de huidige situatie moet 30% van de patiënten geopereerd worden binnen 10 dagen. We vergelijken deze huidige situatie met een toekomstig scenario, waarin 50% van de patiënten binnen 10 dagen geopereerd moet worden. Een agendasjabloon met een capaciteit van acht screeners resulteert in 94% van de patiënten die gescreend is binnen de toegangstijdcriteria. En een agendasjabloon met een capaciteit van zeven screeners resulteert in 87% van de patiënten die gescreend is binnen de toegangstijdcriteria. Beide agendasjablonen resulteren in een kleine toename in het aantal patiënten dat overboekt is. Een mogelijke reden hiervoor is dat patiënten met een hoge urgentie strenge restricties hebben met betrekking tot de toegangstijd. Hierdoor is het moeilijker om fluctuaties in de vraag op te vangen.

Conclusie en discussie

De analyses laten zien dat het alloceren van capaciteit aan patiëntgroepen en het actief inplannen van urgentiegroepen bijdraagt aan een toename in het percentage patiënten dat gescreend is binnen de toegangstijdcriteria. Bovendien resulteert dit in een afname van het dagelijks aantal patiënten dat overboekt moet worden. Wanneer de patiëntsamenstelling verandert, kan het agendasjabloon aangepast worden met behulp van de capaciteit allocatie methode.

Een limitatie van deze studie is dat de toegangstijd tot de POS onderzocht is, zonder de onbenutte tijd van de screeners en de wachttijd van de patiënt mee te nemen. De belangrijkste reden is dat hiervan geen data beschikbaar was. Er is al bekend dat als een gevolg van de toename in telefonische consulten, de onbenutte tijd van de arts toeneemt omdat patiënten niet altijd de telefoon opnemen. We verwachten dat een nieuw agendasjabloon deze observatie niet zal veranderen. Daarnaast verwachten we, als gevolg van de toename in telefonische consulten, dat de wachttijd van de patiënt een minder grote rol speelt in de patiënttevredenheid. Verder onderzoek moet uitwijzen wat het effect van het alloceren van capaciteit is op de wachttijd van de patiënt en de onbenutte tijd van de screener.

Een aanbeveling voor verder onderzoek is om de relatie tussen de ontwikkelde capaciteit allocatie methode en de POS capaciteit te onderzoeken. In dit onderzoek hebben we het aantal flexibele en gealloceerde afspraaksloten gebaseerd op de variatiecoëfficiënt van de urgentiegroepen en verschillende mate van flexibiliteit getest. Deze berekeningen zijn gebaseerd op een gegeven POS capaciteit. De capaciteit allocatie methode kan verbeterd worden wanneer capaciteitsberekeningen en de relatie tussen capaciteit, vraag en de mate van flexibiliteit toegevoegd worden.

Aanbevelingen

We raden het St. Antonius ziekenhuis aan om het agendasjabloon aan te passen naar een nieuw sjabloon waarin de capaciteit toegewezen is aan urgentiegroepen. In de huidige situatie kan het gecreëerde agendasjabloon van deze studie gebruikt worden. We raden aan dat als de situatie verandert, bijvoorbeeld als gevolg van COVID-19, om de allocatie te herzien met de beschreven capaciteit allocatie methode. Daarnaast adviseren we om patiënten actief te gaan plannen, waarbij urgente patiënten (operatie < 6 weken) direct gepland worden voor de screening en niet urgente patiënten (operatie < 6 maanden) op een wachtlijst komen en gepland worden wanneer de operatie nadert.

Preface

Hereby, I present you my Master Thesis ‘Designing a Blueprint Schedule to meet Access Time Criteria of Priority Groups in a Preoperative Assessment Clinic’. This thesis is the result of a nine-month research at the St. Antonius Hospital and is the final step towards finishing my Master of Industrial Engineering and Management at the University of Twente. During this Master's degree, I improved my analytical and academic skills and I realise that I enjoyed the Master's degree even more than I expected before. I am looking forward to what the future will bring and I am open to a new challenge.

I am very grateful to everyone at the St. Antonius Hospital who was involved in this project. I thank Marjolein van Swinderen, who supported me during the entire period, guided me in the St. Antonius Hospital and helped me a lot by finding the objective and practical contribution of this Master Thesis. I also thank Mat van Iterson, who encouraged me to think outside the box and asked critical questions to make me think. Moreover, I thank everyone working in the preoperative assessment clinic, and in particular Desiree Wolf, who answered all my questions related to the preoperative assessment clinic such that I got to know the preoperative process in detail.

I am very grateful to my supervisors at the University of Twente. I thank Erwin Hans, who made me feel more confident, supported me to trust my abilities and choices, and provided me with valuable feedback. And, I thank Patricia Rogetzer, who joined towards the end of this Master Thesis but still made time to get fully involved in the project and provided me with useful feedback.

I am very grateful to my parents, friends and loved ones who supported me during this project. I thank my parents, who continuously supported me and offered me a great place to work during COVID-19 times. I also thank my friends and loved ones with whom I could discuss all my thoughts, and in particular Stan, who gave me his endless support. I realise that, especially in COVID-19 times, the support of family and friends is extremely important.

I hope you enjoy reading my Master Thesis.

Remi van Doremalen

Utrecht, February 2022

Contents

List of abbreviations

Abbreviation	Definition
ASA	American Society of Anaesthesiologists
COVID-19	Coronavirus disease 2019
CV	Coefficient of variation
DES	Discrete event simulation
ENT	Ear nose throat
FCFS	First come first served
GE	Gastroenterology
GP	General practitioner
KPI	Key performance indicator
NWG	Nieuwegein
OR	Operating room
PAC	Preoperative assessment clinic
UTR	Utrecht

1 Introduction

Chapter 1 describes the introduction to this study. Section 1.1 gives the context description, including the company description and the research motivation. Then, Section 1.2 discusses the problem description and explains the core problems. Finally, Section 1.3 discusses the research design, including the problem approach and relevant research questions.

1.1 Context description

In 2019, more than three million surgeries were done in the Netherlands (Schrijvers, n.d.) and on average one third of the healthcare expenses are spent on surgical care (Lee et al., 2019). This makes that operating rooms (ORs) play a crucial role in the cost efficiency of hospitals. Preoperative assessment is an essential step in the pathway to surgery (Hawes et al., 2016). Traditionally, preoperative assessment took place the evening before or on the day of surgery (Edward et al., 2008a). However, assessing patients several weeks or days before surgery has led to increased cost-efficiency (Edward et al., 2008c). Because of this reason, a preoperative assessment clinic (PAC) is now implemented in most hospitals.

The PAC has the goal to check whether the patient is in a good condition to undergo anaesthesia and to fully prepare the patient for surgery (Tariq et al., 2016). Hereby, it reduces the risk of cancellation on the day of surgery and the risk of OR delays (Zonderland et al., 2009). Additionally, the rate of same-day admissions increases and perioperative morbidity reduces (Bader, 1999; Edward et al., 2008a; Zonderland et al., 2009). With the advent of the PAC, the OR department allows for a more efficient functioning, which results in decreased costs and improved quality of care.

Since the PAC and the OR department are closely related, the timing of the preoperative screening is important. A patient should have timely access to the PAC such that the surgery will not be delayed. The access time is defined as the time between the surgery request and the PAC appointment. Whether a patient has timely access to the PAC depends on the access time criteria, which differ per surgery priority. The higher the surgery priority, the more restrictive the access time criteria of the PAC. Thus, a successful PAC should enable the screening of patients within the access time criteria and thereby allows the operating room (OR) department for a more efficient functioning.

At a tactical level, access times can be regulated by correctly dividing capacity to patient groups, which is called capacity allocation. A blueprint schedule is a way to allocate capacity and gives an idea of how many appointment slots in a block schedule are assigned to each patient class each day (Hulshof et al., 2012; Leeftink et al., 2020). This study designs a blueprint schedule with capacity allocated to priority groups, such that patients arrive in the PAC within the access time criteria.

Company description

This study is carried out for the St. Antonius Hospital. St. Antonius Hospital was founded in 1910 by five ambitious doctors, who had the mission to work together to enhance the quality of life (*St. Antonius Ziekenhuis*, 2021). In 2020, this hospital provided care for more than 32,000 inpatient patients and performed more than 360,000 appointments in outpatient clinics. Moreover, St. Antonius Hospital has 35 medical specialties, whereby the hospital excels in cardiology, pulmonology, and oncology. The hospital is located in eight locations in the Netherlands, of which Nieuwegein (NWG) and Utrecht (UTR) are the main locations. This study will be carried out for the PAC in the St. Antonius Hospital Nieuwegein and Utrecht.

Research motivation
The PAC in the St. Antonius Hospital strikes to be a supportive outpatient clinic and to smoothen the patient pathway to surgery. The process from the outpatient clinic to the PAC up to the OR department is called the **preoperative process.** Currently, the preoperative process is not performing as desired. On the one hand, there are not enough patients with a PAC agreement to fill the available ORs. This means that patients are not served within their access time criteria. On the other hand, patients have expired PAC agreements. In this way, the PAC is a bottleneck for patients in their pathway from outpatient clinic to surgery. Moreover, PAC employees experience high fluctuating workloads and many patients are overbooked. This problem is frustrating for the PAC planners and OR planners, as well as the surgeons and PAC staff members. Therefore, St. Antonius Hospital would like to know how to organize the PAC, such that the preoperative process is functioning well.

1.2 Problem description

With the arrival of the coronavirus disease 2019 (COVID-19), the preoperative process in the St. Antonius Hospital is not performing well because patients are not screened within the right access time. In more detail, the time between the PAC appointment and surgery is either too long, which renders in an expired PAC agreement. Or, the time between the appointments is too short, with the risk that the patient will not receive an agreement and that the surgery is delayed. This problem results in reduced employee and management satisfaction. For this reason, it is important that the percentage of patients that are screened within the access time criteria increases.

This problem is further analysed from practice and information is gathered from interviews with PAC employees. In this way, the problem is identified and a problem cluster is created. Appendix A includes the problem cluster. The problem cluster includes seven core problems. Section 1.2.1 discusses the three unsolvable core problems. Next, Section 1.2.2 discusses three solvable core problems. Additionally, the focus of this study is on the fourth solvable core problem “No capacity allocation method”. Therefore, Section 1.2.3 discusses the research objective by explaining the fourth solvable core problem.

1.2.1 Unsolvable core problems

This section discusses the three unsolvable core problems.

Planning horizon ORs too short
As a consequence of COVID-19, the planning horizon of the ORs is short. Where before COVID-19 the OR planning was made eight weeks in advance, currently the OR planning is sometimes made a week in advance. As a result, the PAC should arrange a PAC appointment in the short term for patients on the waiting list who forgot to make a PAC appointment. This problem is unsolvable since this problem is a result of the still ongoing consequences of COVID-19. Moreover, this problem is out of scope as well, since this study focuses on the preoperative process rather than the OR scheduling process.

Surgery waiting times are unpredictable
As a consequence of COVID-19, surgery waiting times are unpredictable. Surgery waiting times depend on the patient specialty, the availability of the doctors, OR capacity and bed capacity. Mainly OR capacity and bed capacity fluctuate a lot as a result of COVID-19. The resulting unpredictable waiting times, make it difficult for PAC planners to schedule the patient within the right access time criteria. This problem is unsolvable since too many unpredictable variables influence the surgery waiting time. Thus, this study will not focus on the prediction of the surgery waiting times.

Homogeneous schedule while patients are heterogeneous

Patients arriving in the PAC are very heterogeneous concerning complexity, specialty, priority and routing. Research is done in the field of heterogeneous scheduling in the PAC and showed already promising results with respect to patient waiting time, patient satisfaction, the total length of stay and system robustness (Edward et al., 2010; Edward et al., 2008b; Odijk, 2012; Schoenmakers, 2008). However, as a consequence of COVID-19, the number of consultations performed via phone increased from 0% to 80%. Since patient waiting time plays a minor role in patient satisfaction on the day of the phone consultation and because no data is available regarding the current waiting and consultation times, this problem is unsolvable and out of scope for this study.

1.2.2 Solvable core problems

This section discusses three of the four solvable core problems. The fourth solvable core problem is the focus of this study and will be discussed in the next section.

No method to determine which patients are lost and on top of the surgery waiting list

As a consequence of COVID-19, patients leave the hospital after their visit to the outpatient clinic and have to call the PAC planners to make an appointment. Patients who forget to call, are lost in the system. These patients come into view when they are on top of the surgery waiting list. Then, the PAC planners have to arrange an appointment in the short term. The hospital aims to have an overview of patients who request surgery such that no patients are "lost" anymore. Therefore, this study aims to find a method to create an overview of which patients need a PAC appointment.

Mismatch time planned and time needed for phone consultations

As a consequence of COVID-19, the number of consultations performed via phone increased from 0% to 80%. From practice, it turned out that phone consultations require more time, because the screening is more extensive when the patient is not examined physically and because the patient could not answer the phone. Consequently, half of the available appointment slots are blocked. However, there is a mismatch in the time planned and time needed for a phone consultation, which makes that the resources are not used efficiently. The blueprint schedule does not indicate the right amount of available appointment slots. This makes it hard for PAC planners to make a good schedule. Moreover, the schedule is quickly 'overloaded' and many patients are overbooked. This problem has not the main focus of this study, but when designing a new blueprint schedule, the number of available appointment slots will be taken into account.

Unknown whether the PAC capacity matches the OR capacity

Many patients are overbooked in the short term and it is unknown whether this is because of the PAC capacity or because of the way the capacity is used. Therefore, it is important to know if the PAC capacity is sufficient. When it is not sufficient, this study aims to find out which capacity is needed to meet the capacity of the ORs.

1.2.3 Research objective

Currently, the capacity is not allocated to patient groups in the blueprint schedule. The main reason for this is that there is no method to allocate the capacity. A blueprint schedule without allocated capacity makes it hard for PAC planners to schedule the right mix of patients and to reserve enough slots for high priority patients. This makes that access time criteria of priority groups are not met and that the patient is not screened at the right moment in the preoperative process.

Therefore, the goal of this study is as follows:

> *The goal of this study is to design a blueprint schedule with allocated capacity to priority groups to improve the access time to the PAC*

1.3 Research design

This section gives the problem approach (Section 1.3.1) and the relevant research questions (Section 1.3.2).

1.3.1 Problem approach

The Managerial Problem-Solving Method has been proven to be a successful method for solving business problems systematically (Heerkens & Van Winden, 2017). Therefore, Figure 1.1 shows the seven steps of this Managerial Problem-Solving Method, which are used to solve the core problem.

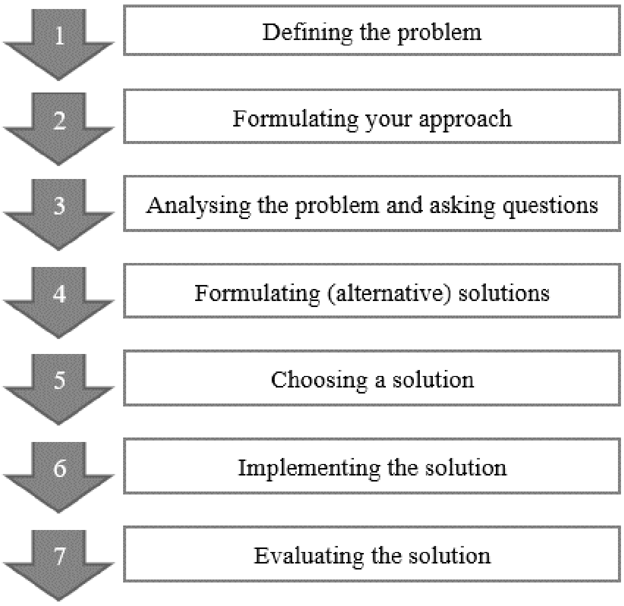


Figure 1.1. Managerial Problem-Solving Method

1.3.2 Research questions

This section discusses the research questions to solve the problem and fulfil the objective of this study.

1. How is the PAC currently organised and what are the performances of the PAC?
Chapter 2 deals with the characteristics, planning processes and performances of the PAC. This includes the preoperative process, PAC employees, and patient types. And, the current blueprint schedule and the PAC planning process, even as the problems faced by PAC planners are discussed. Next, this chapter describes the OR planning process and problems faced by the OR planners. The final part of Chapter 2 shows the performance of the preoperative process, based on important key performance indicators (KPIs), which are for example the number of patients overbooked, the number of patients screened and the performances regarding the access time.

2. What methods are commonly used to allocate capacity and design a blueprint schedule and which methods are used to test the performances of a newly designed blueprint schedule?
Chapter 3 gathers all relevant literature. This includes an introduction to capacity allocation, which is a method to regulate access time requirements. Then, previously performed studies in the PAC are discussed concerning tactical resource capacity planning. No research is performed in the field of designing a blueprint schedule using a capacity allocation method with the goal to improve access times. Therefore, the next part discusses the tactical decisions to design a blueprint schedule, followed by capacity allocation methods applied to other healthcare settings. And, this chapter describes methods to test the performances of a blueprint schedule. Chapter 3 ends with a solution approach.

3. How is the current situation modelled and which interventions are tested?

Chapter 4 includes the conceptual model description, including an overview of the discrete event simulation (DES) and the modelling assumptions. Next, the chapters describe the simulation settings and the verification and validation phase. This chapter ends with an extensive description of the interventions created to improve the percentage of patients screened within the access time criteria. The focus of this study is on the design of the blueprint schedule, however, this chapter also describes two other interventions of which is expected that they will improve the access time to the PAC.

4. Which input and output parameters have to be defined?

Chapter 5 describes the modelling inputs of the DES. This includes the current waiting list and blueprint schedule, patient arrival data, distributions to determine patient characteristics and the planning process. Next, Chapter 5 describes the KPIs to measure the performances of the PAC and gives the corresponding formulas.

5. What are the effects of the interventions on the performances of the PAC?

Chapter 6 includes the results of the DES, based on the KPIs described in Chapter 5. Based on these performances, combinational interventions are tested. Next, a sensitivity analysis of several input parameters on different interventions is discussed. Finally, future scenarios are tested to study whether the method is able to create valuable blueprint schedules in future.

6. How can the interventions be implemented?

The goal of the study is to design an easy-to-implement capacity allocation method, which is used to design a blueprint schedule. Therefore, Chapter 7 explains how to use the method and how to implement the blueprint schedule. When the capacity allocation method is able to generate valuable blueprint schedules, the schedule as well as the method can be used by St. Antonius Hospital using the steps described in Chapter 7.

2 Context analysis

Chapter 2 discusses the context analysis and the problem formulated in Chapter 1 is explained in more detail. Section 2.1 describes the characteristic of the PAC, including the employees working in the PAC and the patient mix. Subsequently, Section 2.2 discusses the PAC planning process, followed by Section 2.3, which discusses the OR planning process. Then, Section 2.4 is about the current performances of the PAC, analysed from a patient, employee and management perspective. And, this section discusses the performances regarding the access time related to the PAC. In the end, a conclusion is drawn about the performances of the PAC (Section 2.5).

2.1 Characteristics of the PAC

This section first discusses the patient flow in which the PAC is involved, followed by the employees working in the PAC and the patients visiting the PAC.

In the St. Antonius Hospital, the PAC is located in Nieuwegein and Utrecht and has the goal to check whether the patient is in a good condition to undergo anaesthesia and to fully prepare the patient for surgery. Patients visiting the PAC require multiple resources, which are anaesthetists or PAC employees, and in some cases pharmacists and/or nurses. Visiting the PAC is an unavoidable step in the way to surgery since a PAC agreement is needed before surgery can start. A PAC agreement is valid for a maximum of six months. From discussions with the management, we concluded that it is most preferable to receive the PAC agreement one to three months before surgery.

The PAC is an outpatient clinic and is involved in the pathway to surgery. In the Dutch healthcare system, a patient first visits the general practitioner (GP) and when necessary, the GP sends the patient to the corresponding outpatient clinic. When the doctor in the outpatient clinic decides that the patient needs to have surgery, this patient is added to the surgery waiting list. In the meanwhile, the patient has to visit the PAC for the preoperative screening. It is not possible to visit the PAC via a referral of the GP. When the patient visits the PAC and it turns out that the patient is in good condition to undergo the anaesthesia, the patient receives a PAC agreement. Some patients need additional examinations before a PAC agreement is given. When the patient has received the PAC agreement and is on top of the surgery waiting list, the OR planner working in the PAC calls the patient to schedule a surgery appointment. On the day of surgery, the patient visits the OR department. After surgery, the patient has to recover in a recovery bed and in the end, is released. Figure 2.1 gives an overview of the patient flow related to the PAC.

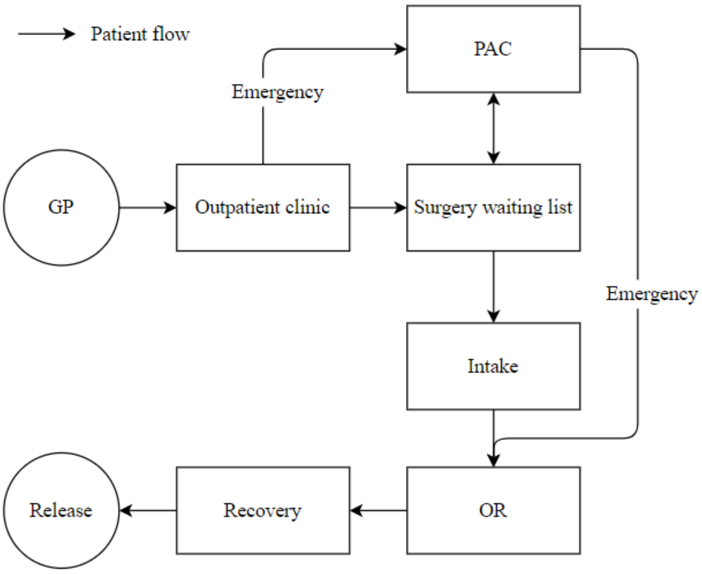


Figure 2.1. Patient flow in which the PAC is involved, based on Schoenmakers (2008)

2.1.1 Employees working in the PAC

Multiple kinds of employees are working in the PAC, subdivided into medical employees and planners.

Medical employees

Three different kinds of medical employees are working in the PAC, which are anaesthetists/PAC employees, nurses, and pharmacists. Anaesthetists and PAC employees perform the same job but are differently educated. Anaesthetists have a higher education than PAC employees and consequently, PAC employees have to discuss complex patients with a supervisor. In this study, anaesthetists and PAC employees are named **screeners**. Figure 2.2 shows the sequence in which patients visit the medical employees in the PAC. Every patient visits the screener. Whether the patient should also visit the pharmacist before that and/or the nurse afterwards, depends on the type of patient. Section 2.1.2 goes deeper into patient routing.

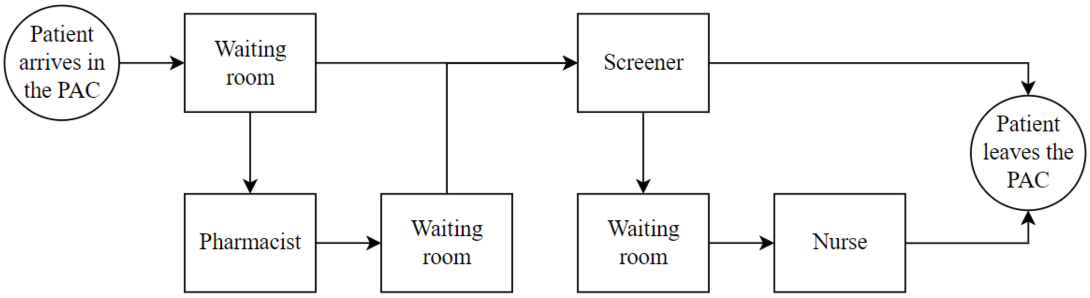


Figure 2.2. The sequence in which patients visit the medical employees in the PAC

Currently, seven screeners, four nurses, and three pharmacists work daily in the rooms given in Table 2.1. Each treatment room has one employee working there. Moreover, complex patients, who need an extensive screening with additional tests, are screened by a screener trained to do these so-called "AGE screenings". On average 1.7 days a week, an additional screener is working in the room "AGE screening" to screen these complex patients. Table 2.1 also gives the location where the screener is located most of the time. The screeners working in the rooms "Anaesthesia 4 NWG" and "Anaesthesia 7 UTR" are located in the inpatient clinics most of the time. The reason for this is that they examine the patients who are already staying in the hospital and are not physically able to visit the PAC. Consequently, these screeners are working in the inpatient clinics, instead of working in their room in the PAC.

Table 2.1. Treatment rooms in the PAC in Nieuwegein and Utrecht

Screening	**Location of the screener**	**Nursing**	**Pharmacy**
Anaesthesia 1 NWG	PAC	Nursing 1 NWG	Pharmacy 1 NWG
Anaesthesia 4 NWG	Inpatient clinic	Nursing 2 NWG	Pharmacy 2 NWG
Anaesthesia 5 NWG	PAC	Nursing 3 UTR	Pharmacy 1 UTR
Anaesthesia 8 NWG	PAC	Nursing 4 UTR	
Anaesthesia 1 UTR	PAC		
Anaesthesia 3 UTR	PAC		
Anaesthesia 7 UTR	Inpatient clinic		
AGE screening	PAC		

Planners

Two kinds of planners are working in the PAC, which are PAC planners and OR planners. PAC planners are the secretary working in the PAC. They are the first point of contact when a patient visits the PAC or calls the PAC to schedule an appointment. These PAC planners schedule the PAC appointments with the screener and when necessary, the pharmacist and/or nurse. OR planners are the planners who schedule the surgery appointment. They call the patient when he or she is on top of the surgery waiting list to arrange an appointment. Section 2.2 detailly describes the PAC planning process and Section 2.3 the OR planning process.

2.1.2 Patient characteristics

The PAC faces many different types of patients. Patients vary with respect to specialty, routing, complexity, and priority. The patient characteristics of patients visiting the PAC are explained in this section. Data from January 2019 is included, except for the first Dutch COVID-19 lockdown period (March, April and May 2020), because the patient mix during this period is not representative.

Since surgery is performed for multiple specialties, the PAC faces patients with multiple diseases. Figure 2.3 shows the distribution of the patient specialties. Ear nose throat (ENT), general surgery, orthopedy, and optometry are the most common specialties and comprise almost 50% of the patients.

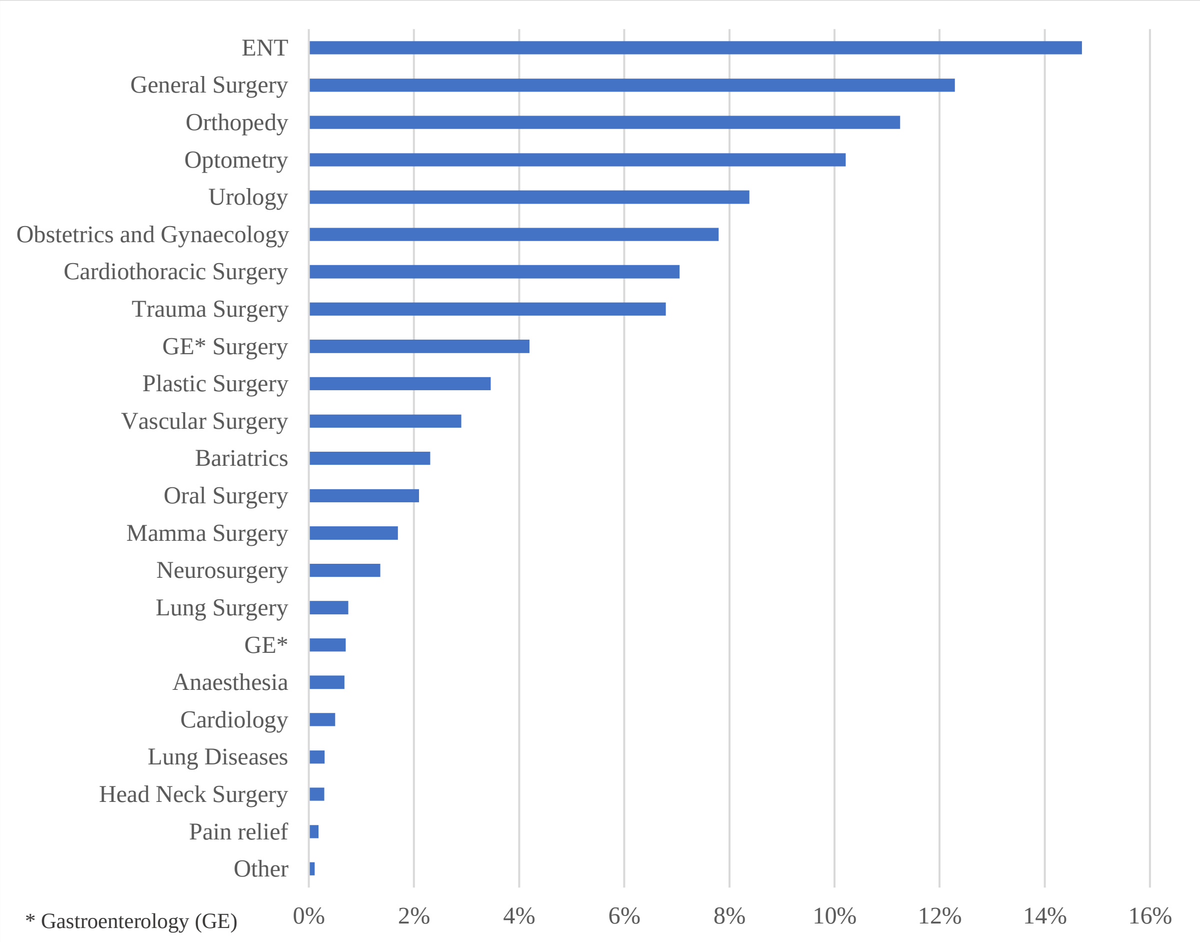


Figure 2.3. PAC demand distribution of the specialties (n=55,831; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

Patient routing implies whether the patient sees the screener only, or also has to visit the pharmacist and/or nurse and depends on the type of patient. From a PAC planning point of view, the St. Antonius Hospital distinguishes five types of patients, which are type 1 and type 2 patients with an appointment, walk-in patients, emergency patients, and inpatient patients. See Table 2.2 for a description of the patient types.

Table 2.2. Patient types faced by the PAC in the St. Antonius Hospital

Patient type	**Description**
Type 1 patient	Patient with an appointment scheduled by a PAC planner
Type 2 patient	Patient with an appointment scheduled by another outpatient clinic
Walk-in patient	A patient who visits the PAC without an appointment
Emergency patient	Inpatient patient who is able to visit the PAC physically
Inpatient patient	Inpatient patient who is not able to visit the PAC physically

Figure 2.4 gives the distribution of the patient routing in the PAC, depending on the type of patient. Inpatient patients and emergency patients always visit the screener only. Moreover, there is a chance of 21% that a type 2 patient visits the screener only and 79% chance that the type 2 patient is treated by the screener and the pharmacist. Next, type 1 patients and walk-in patients share the same patient characteristics and are represented by type 1 patients in Figure 2.4. Whether a type 1 patient has to visit the pharmacist and/or nurse, depends on the patient specialty. Figure 2.4 gives the averages for all specialties.

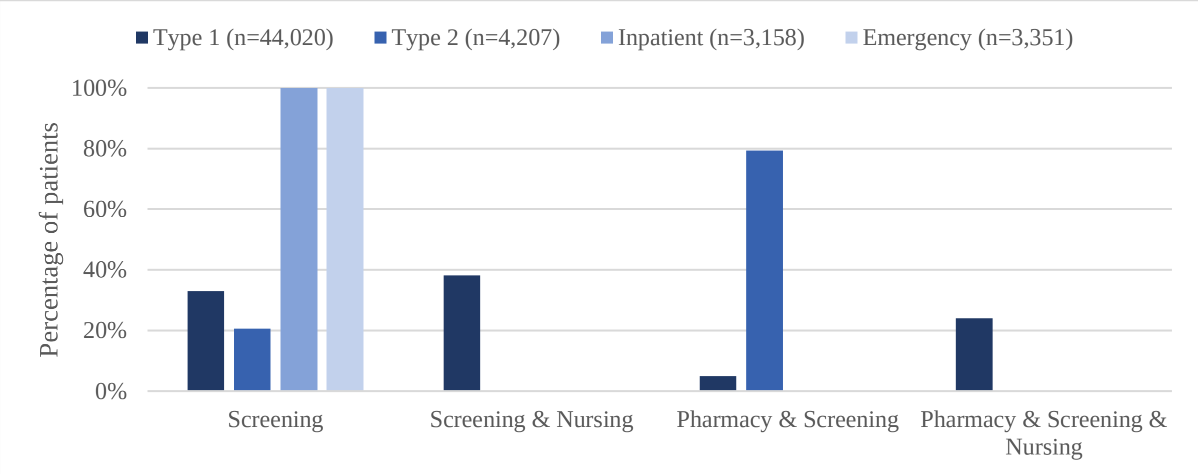


Figure 2.4. Distribution of the patient routing depending on the type of patient (n=54,736; January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

Patients visiting the PAC have a different level of complexity. Complexity is indicated with the American Society of Anaesthesiologists (ASA) classification. The ASA classification includes six categories and is used to indicate the health status of a patient before surgery (Committee on Economics, 2020). The ASA classification ranges from ASA I to ASA VI, where ASA I is used for a normal healthy patient and ASA VI for a declared brain-dead patient. Figure 2.5 gives the patient distribution of the ASA classification. The second indicator of patient complexity is whether a patient has a surgery request for a day treatment or not. Patients with a day treatment are released on the day of surgery. Some of these patients need a bed to recover, while others do not need a recovery bed (fast-track patients). Figure 2.6 shows the percentage of patients with a day treatment, in which fast-track patients are included. This figure shows that on average 49% of the patients have a day treatment. Patients with a day treatment are often associated with a low ASA classification.

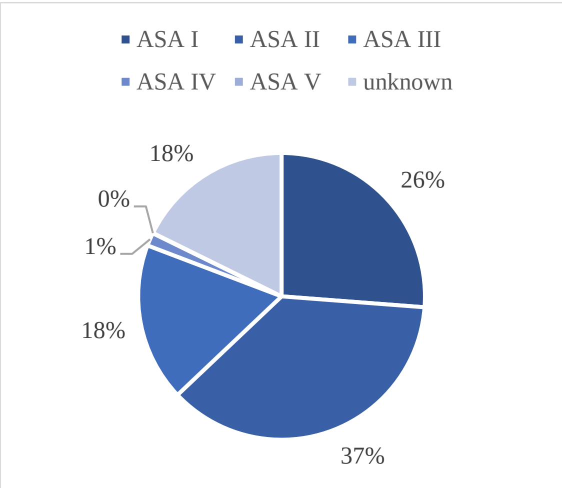


Figure 2.5. Patient distribution for ASA classification (n=55,831; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

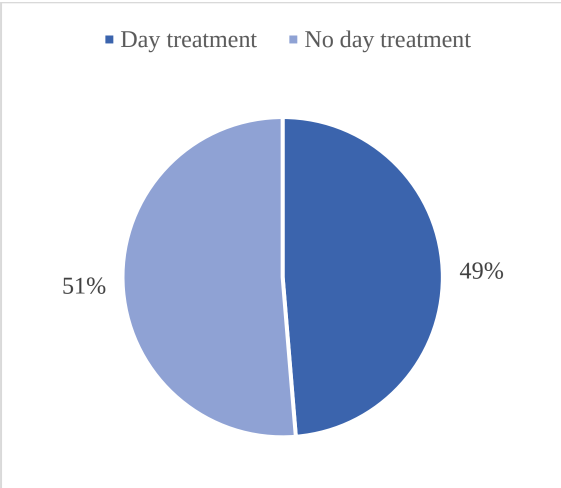


Figure 2.6. Percentage of patients with a day treatment (n=55,831; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

The fourth patient characteristic is the surgery priority. Patients arriving in the PAC have different priority levels. The priority level indicates in which time window the patient should have the surgery. Thus, the expected surgery date of the patient depends on the given priority level. The PAC has the goal to screen the patient before the expected surgery of the patient. Figure 2.7 gives the distribution of patients per priority level. The priorities are categorized into eight groups, ranging from the highest priority of "< 72 hours" to the lowest priority level of "< 6 months".

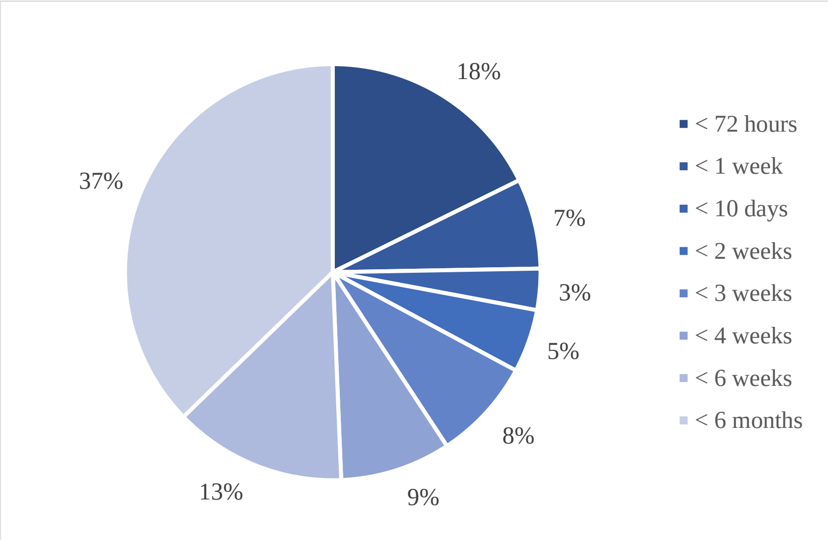


Figure 2.7. Patient distribution for surgery priority (n=55,831; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

2.2 Planning process in the PAC

The PAC planning process plays a role in the performance of the preoperative process. PAC planners schedule the PAC appointments with the pharmacist, screener, and nurse. Section 2.2.1 describes the blueprint schedules which are currently used by the PAC planners to schedule the patients. Next, Section 2.2.2 describes the planning process, which depends on the type of patient. Finally, Section 2.2.3 describes the problems faced by the PAC planners.

2.2.1 Blueprint schedules

Different blueprint schedules are used in the PAC in Utrecht and Nieuwegein, and appointment slots are reserved for the patient types described in Table 2.2. Figure 2.8 shows two example blueprint schedules used in Nieuwegein. The PAC is open from Monday to Friday, from 8:00 AM to 5:00 PM. A patient cannot be screened in the PAC during weekend days. The blueprint schedule in Figure 2.8a is used on Mondays during even weeks and the one in Figure 2.8b on Tuesdays during odd weeks. The blueprint schedule for location Nieuwegein differs daily and differs between even and odd weeks because the distribution of the type 2 slots depends on the blueprint schedules used in other outpatient clinics. Figure 2.8 shows the appointment slots for type 2 in yellow, and these appointment slots are split across the patient specialties, such as "CTC" and "LUNG". Next, green slots indicate an appointment slot for type 1 patients. "TC" indicates a phone consultation. Furthermore, the orange slots are reserved for urgent patients, which are type 1 patients who need an appointment in the short term. And, the pink slots are appointment slots that are blocked as a consequence of the increased consultation time for phone consultations, resulting from COVID-19. Moreover, the slots in grey are used to treat inpatient patients and emergency patients. Recall from Section 2.1.1 that screeners working in the rooms "Anaesthesia 4 NWG" and "Anaesthesia 7 UTR" are screening inpatient patients and are often working in the inpatient clinics. The other screeners who are working in the PAC have their own schedule, with patients to screen. However, when these screeners assessed all the patients on their schedule, they take over patients from each other.

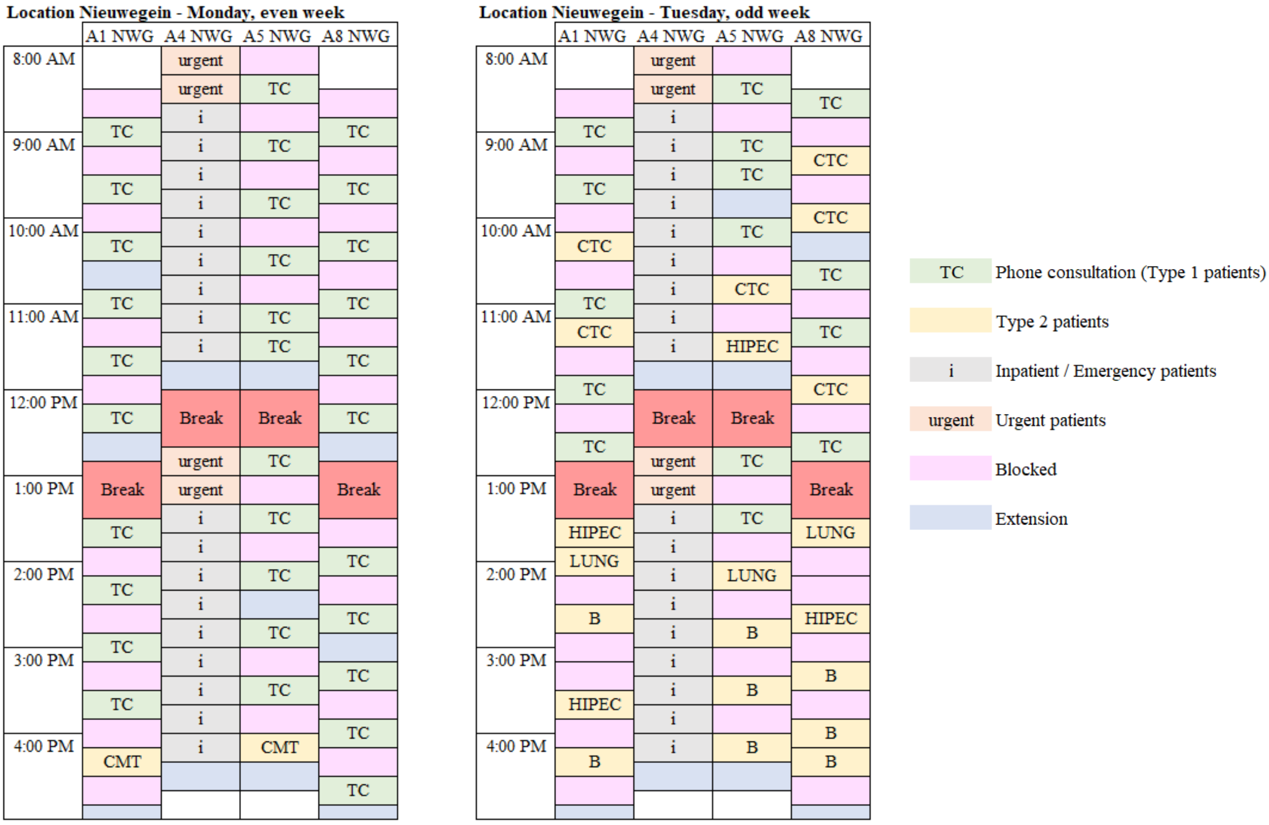


Figure 2.8. Two examples of PAC blueprint schedules at location NWG. a) is used on Mondays in an even week and b) is used on Tuesdays in an odd week

2.2.2 Planning process PAC planners

PAC planners face different types of patients for which different planning rules apply. As discussed in Section 2.1, PAC planners in the St. Antonius Hospital face type 1 or type 2 patients with an appointment, walk-in patients, emergency patients, and inpatient patients. The focus of the planning process is on type 1, emergency, and inpatients patients because walk-in is currently not allowed and because type 2 patients are not scheduled by the PAC planner. Figure 2.9 gives the planning process of type 1, inpatient, and emergency patients and this planning process is explained in this section.

Type 1 patients are regular patients scheduled by the PAC planner. Because during COVID-19 walk-in is not allowed, walk-in patients are currently scheduled as type 1 patients. When a type 1 patient asks for a PAC appointment, the PAC planner searches for the first available appointment with a screener working in the PAC. The PAC planner uses the auto planner to find this first available appointment. The PAC planner uses the priority of the patient to determine whether this first available appointment will probably be before or after the expected surgery date. If this first available appointment is before the expected surgery date, an appointment slot is found and the PAC appointment is scheduled. If the first available appointment slot is after the expected surgery date, no regular appointment that fits the priority of the patient is found. Then, the PAC planner looks for an available type 2 appointment slot on the calling day or one day after the calling day. If a type 2 slot is available, the PAC appointment slot is scheduled. If no type 2 slot is available, the PAC planner searches for an urgent appointment with a screener working inpatient. If an urgent appointment slot is available, the PAC planner schedules the PAC appointment. If no urgent appointment slot is available, the patient is overbooked on an appointment with a screener working in the PAC.

Emergency patients are inpatient patients who are physically able to visit the PAC. When an emergency patient asks for an appointment, the PAC planner is going to search for the first available appointment with one of the screeners working inpatient. The PAC planners use the priority of the patient to determine whether this first available appointment will probably be before or after the expected surgery date. If this first available appointment is before the expected surgery date, an appointment slot is found and the PAC appointment is scheduled. If the first available appointment slot is after the expected surgery date, no inpatient appointment that fits the priority of the patient is found. Then, because an emergency patient is able to visit the PAC physically, the planning process of a type 1 patient is followed to find an appointment with a screener working in the PAC.

Inpatient patients are patients who are staying in an inpatient clinic in the St. Antonius Hospital and who are not able to physically visit the PAC. In this case, the screeners working inpatient visit the patient in the inpatient clinic to screen the patient. When an inpatient patient asks for an appointment, the PAC planner is going to search for the first available appointment with one of the screeners working inpatient. The PAC planners use the priority of the patient to determine whether this first available appointment will probably be before or after the expected surgery date. If this first available appointment is before the expected surgery date, an appointment slot is found and the PAC appointment is scheduled. If no appointment slot is available, the patient is overbooked on an appointment with a screener working inpatient.

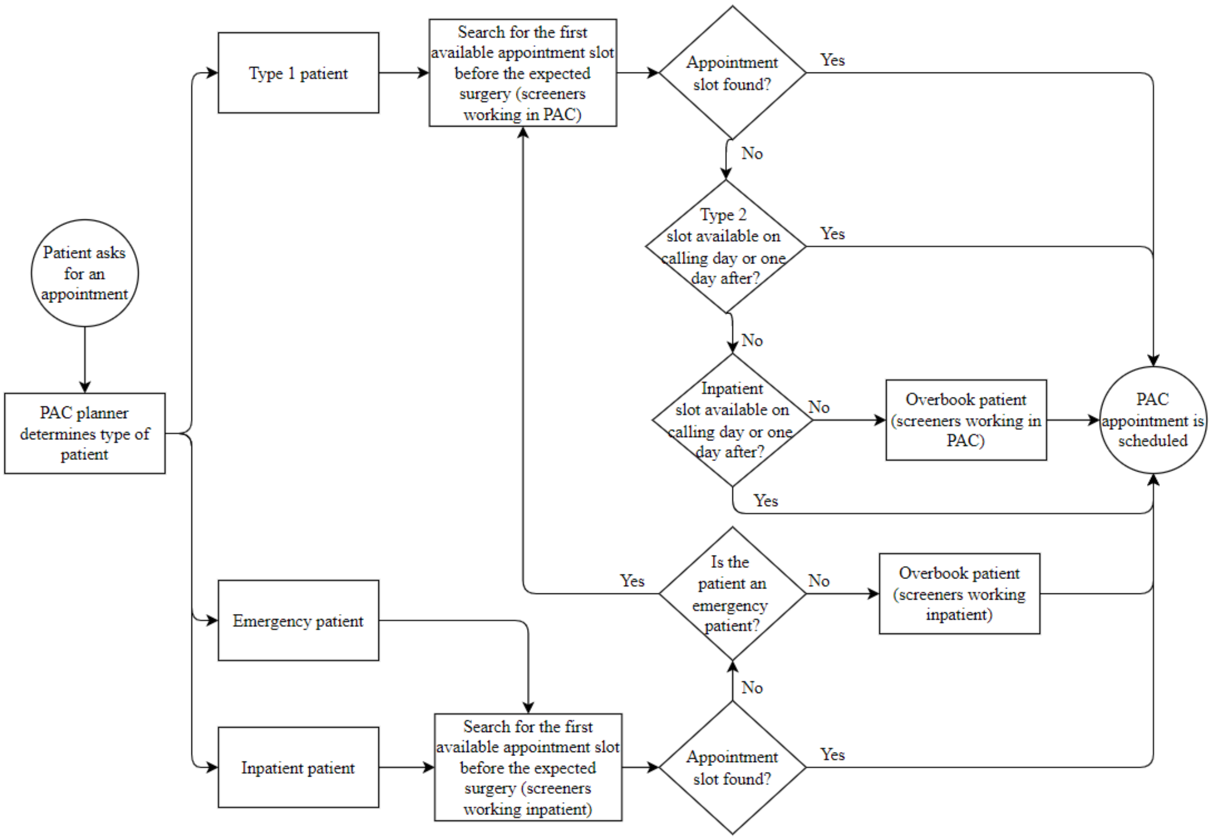


Figure 2.9. PAC planning process depending on the type of patient

2.2.3 Problems faced by PAC planners

PAC planners face problems regarding the current planning process in the PAC. These problems are explained in this section.

The first problem faced by the PAC planners is that the blueprint schedule does not support the scheduling of type 1 patients. These patients are very diverse with respect to specialty, routing, complexity, and priority, as explained in the first section of this chapter. The routing of the patient affects the workload of the nurses. Next, the complexity of the patient affects the workload of the screeners. And, the priority of the patient indicates the time window in which the patient should have surgery. The blueprint schedule does not support the scheduling of type 1 patients, and consequently, PAC planners face difficulties with scheduling these patients correctly.

Second, PAC planners face many patients who need an appointment in the short term, while the blueprint schedule is already fully booked. The OR planners face patients who are on top of the surgery waiting list, but who do not have a PAC agreement yet. Then, OR planners try to arrange a PAC appointment in the short term. PAC planners receive post-its from the OR planners daily, with patient identities of patients who need a PAC appointment immediately. The PAC planner faces difficulties with scheduling these urgent patients because the blueprint schedule is already fully booked.

Third, the number of appointments in the blueprint schedule does not match the capacity of the screener. Consequently, PAC planners have to overbook on average eight patients per day. They experience difficulties with determining which screeners have time to see these patients and at what time the patient should be scheduled.

Fourth, before COVID-19 walk-in patients were allowed and PAC planners had to decide whether to accept walk-in patients. When a walk-in patient enters the front desk, the PAC planner should decide if the walk-in patient can enter the waiting room or if an appointment should be made. For PAC planners, it is difficult to determine whether a patient can be accepted. The PAC planner has to estimate the average waiting time and if this waiting time is less than 20 minutes, the patient can enter the waiting room. Otherwise, an appointment should be scheduled. However, this decision is mainly based on experience and has multiple exceptions, which make it difficult to make the right decisions.

2.3 Planning process in the OR department

Besides the PAC planning process, the OR planning process plays a role in the preoperative process as well. OR planners are the ones who schedule a surgery appointment with the patient. Section 2.2.1 describes the clusters among which the OR planners are divided. Next, Section 2.2.2 describes the OR planning process, which depends on the priority of the patient. Finally, Section 2.2.3 describes the problems faced by the OR planners.

2.3.1 OR clusters

The OR planners are divided among three clusters and each cluster includes multiple specialties, see Table 2.3. OR planners in a certain cluster schedule the surgery appointments for these specialties. Waiting times differ per specialty and per doctor, thus the corresponding OR planner is best able to estimate these waiting times. Table 2.3 also gives the specialties which have a decentral planning. For these specialties, the OR schedule is made by the corresponding outpatient clinic.

Table 2.3. OR planners and clusters ** Gastroenterology (GE)*

Cluster 53126	Cluster 53127	Cluster 53128	Decentral planning
Urology	ENT-children	Orthopaedics	Oral surgery
Gynaecology	ENT-adults	Trauma	Eye surgery
GE* laparoscopic	GE* intern	General surgery	Neurosurgery
cholecystectomy	Neurology	Plastic surgery	Bariatrics
Hernia	Paediatrics	Mamma	GE* oncology
Head / Neck	Lung		Vascular surgery
			Pain relief
			Cardio-Thoracic Surgery

2.3.2 Planning process OR planners

The OR department in the St. Antonius Hospital faces patients with multiple specialties and priorities. In general, OR planners schedule the patient based on the priority of the patient. The priority of the patient is given by the doctor in the outpatient clinic who decided that the patient needs to have surgery. From the OR planner point of view, the patients are divided into three main groups, which differs from the PAC planner perspective. The three main groups from the OR planner perspective are emergency patients scheduled by the emergency coordinator (Dutch: "Spoedcoördinator"), high priority patients scheduled by the OR planners, and low priority patients scheduled by the OR planner. A patient cannot have surgery during weekend days, except for emergency patients.

Emergency patients who need to have surgery within 48 hours are planned by the emergency coordinator. The emergency coordinator arranges a surgery appointment in the OR department and ensures that a bed is available for recovery.

High priority patients are patients with a surgery priority of for example 10 days or a few weeks. Every day OR planners view the patient waiting list with the surgery requests and they schedule the high priority patients. No appointment slots are reserved for high priority patients, thus OR planners have to keep time available for these patients. In the worst case, a low priority patient is cancelled such that the high priority patient is planned within the surgery deadline. When the OR planner has a surgery appointment available, the OR planner first calls the patient to determine whether this surgery appointment fits the availability of the patient. When the surgery appointment is accepted by the patient, the OR planner schedules the appointment.

Low priority patients are patients with a priority of six months and are scheduled following first come first served (FCFS). Low priority patients are on the same patient waiting list as high priority patients. This waiting list can be sorted on priority and can be sorted on the surgery request date. When the high priority patients are scheduled, the OR planner continues with scheduling these low priority patients. To schedule a low priority patient, it is important to check the availability of the doctor, since different doctors perform different surgical interventions. In principle, low priority patients are only scheduled when they received a PAC agreement. However, in practice, OR planners schedule low priority patients following FCFS. Consequently, patients without a PAC agreement are scheduled as well.

2.3.3 Problems faced by OR planners

OR planners face problems regarding the current planning process in the PAC. These planning problems are discussed in this section.

The first problem faced by OR planners is that many type 1 patients are on top of the surgery waiting list, but do not have a PAC agreement yet. Consequently, OR planners try to arrange a PAC appointment for this patient in the short term. They visit the front desk of the PAC and instruct a PAC planner to arrange an appointment for this patient before the surgery appointment. OR planners have the opinion that the PAC planning process could be improved such that low priority patients have a PAC agreement on time.

Second, OR planners do not know when the patient is available to have surgery. As explained in the previous section, the OR planner calls the patient to determine whether the surgery appointment fits the availability of the patient. The patient could not answer the phone or could prefer another surgery date. This makes the planning process time-consuming process. When the availability of the patient is known, the patient can be scheduled immediately.

2.4 Performance of the PAC

This section discusses the performance of the PAC. The performance measures are determined in collaboration with three stakeholders: patients, employees, and the organization of the St. Antonius Hospital. Patient satisfaction is often expressed in patients waiting time. Therefore, Section 2.4.1 describes patient waiting times. Then, Section 2.4.2 discusses employee satisfaction, expressed in the daily number of patients overbooked and the variation in workload. Next, Section 2.4.3 describes the performance from a management point of view, in which the number of patients screened daily, the surgery demand and PAC appointments, and cancellations and no-shows are discussed. Finally, access time is indicated as the most important KPI for all stakeholders to measure the performance, therefore, Section 2.4.4 goes into the performances regarding the access time.

2.4.1 Patient perspective

Waiting time is an important KPI to measure patient satisfaction. The waiting time is the time between the patient arrival and the time the consultation starts. Unfortunately, no information is available regarding the waiting time of patients. Moreover, no data is available regarding the mean consultation time and therefore patient waiting time cannot be calculated. However, because the percentage of phone consultations increased from 0% to 80%, patient waiting time will less affect patient satisfaction. Therefore, patient satisfaction is determined based on the access time to the PAC, which is further discussed in Section 2.4.4.

2.4.2 Employee perspective

From the perspective of the PAC planners, the PAC performance is measured in the daily number of patients overbooked. Next, from the perspective of the nurses and screeners, the PAC performance is measured by the variation in the workload during the week. To measure the workload, data from January 2019 is included, except for the first Dutch COVID-19 lockdown period (March, April and May 2020), because the workload during this period is not representative.

Number of patients overbooked

An overbooking means that two patients are scheduled in one appointment slot. Figure 2.10 shows the average daily number of patients that is overbooked. Overbooking is a way to solve the negative effects of no-shows (Faridimehr et al., 2021). However, Figure 2.10 shows that currently in the screening schedule on average eight patients are overbooked daily, while on average one patient per day does not show up (see Figure 2.16 for the no-show rates). Thus, the number of overbookings is high, which is frustrating for PAC planners, medical employees working in the PAC, and patients.

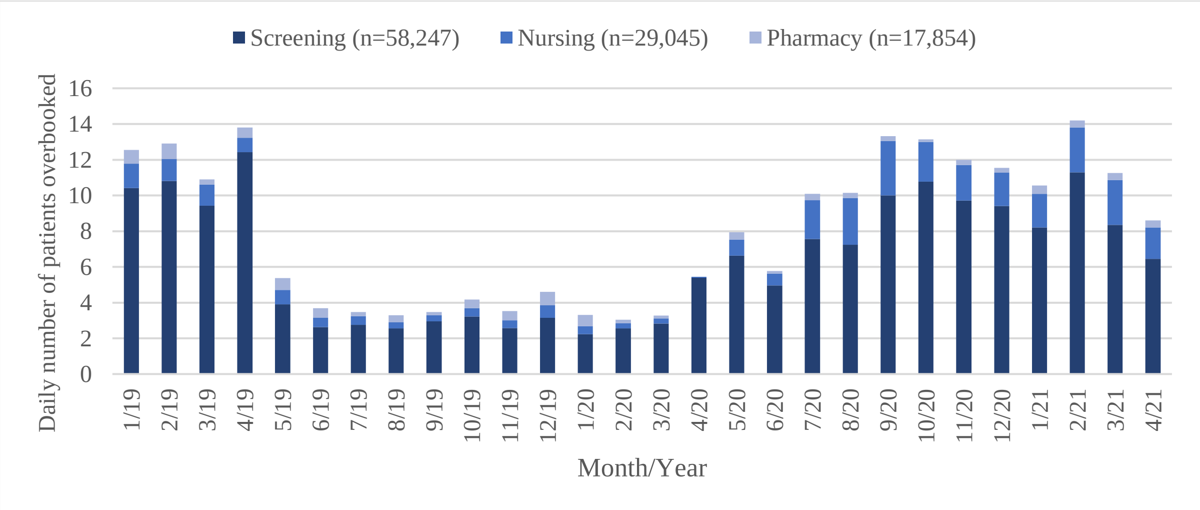


Figure 2.10. Average number of patients overbooked daily (n=58,247; January 2019 – April 2021; St. Antonius Hospital)

Variation in workload for nurses

The variation in workload for nurses indicates how equally the nurse appointments are distributed over the week. Four nurses are working in the PAC every day, which would imply that the number of nurse appointments each day is approximately the same and that only a small variation occurs. However, Figure 2.11 shows that the variation in the number of nurse appointments during the week is high. On Mondays, four nurses have to screen on average 63 patients, which equals 15.7 patients per nurse. On the other hand, on Thursdays, four nurses have to screen on average 45 patients, which equals 11.4 patients per nurse. The main reason for this is that the screening schedule is leading and that the nursing capacity is not adapted to this screening schedule. On Wednesday and Thursday, many type 2 patients visit the PAC and type 2 patients do not visit the nurse, which explains the variation in workload.

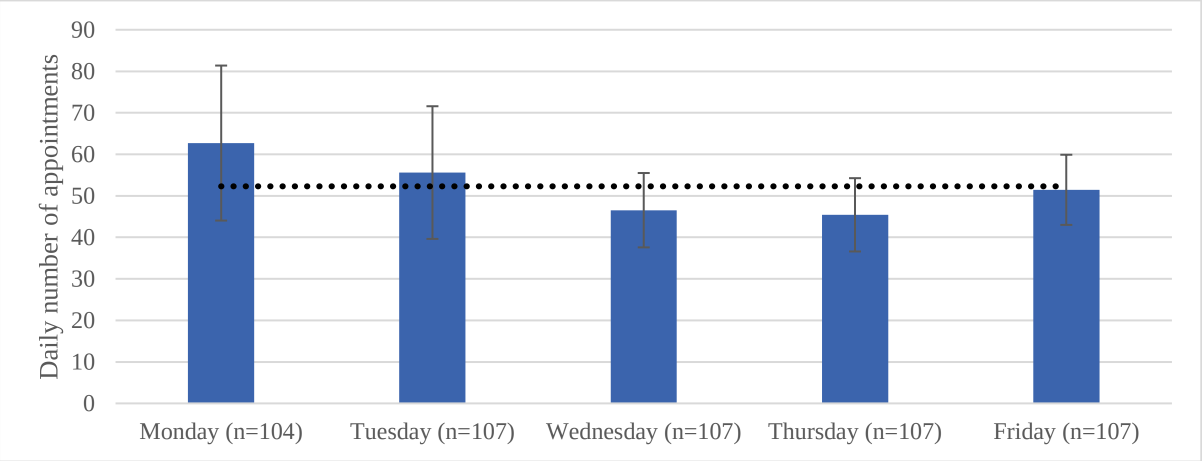


Figure 2.11. Number of appointments per day in the week, with the black dotted line representing the average (n in days; January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

Variation in workload for screeners

The variation in workload for screeners indicates how equally the patients with a day treatment are distributed over the week. Patients with a day treatment often have a low ASA classification, which means that they on average need less consultation time. Around 49% of the patients have a surgery day treatment, which would imply that each day approximately 49% of the patients have a request for a day treatment. Figure 2.12 shows that on Mondays on average 56.5% of the patients have a day treatment, whereas on Tuesdays on average 45.7% of patients have a surgery request for a day treatment. This has probably a relationship with the number of type 2 patients visiting the PAC. Most type 2 patients are associated with a high complexity. Since on Mondays less type 2 patients visit the PAC, the average percentage of patients with a day treatment is relatively high.

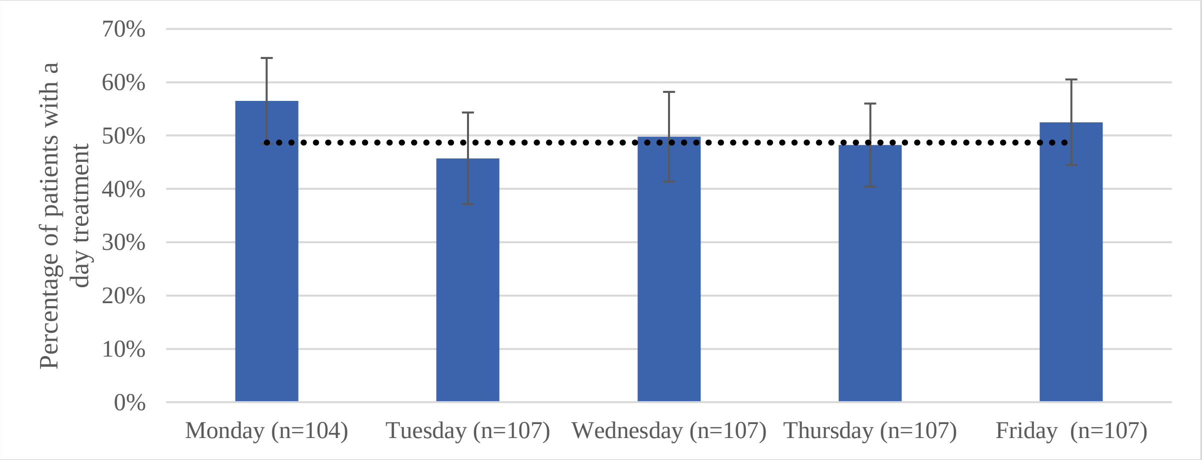


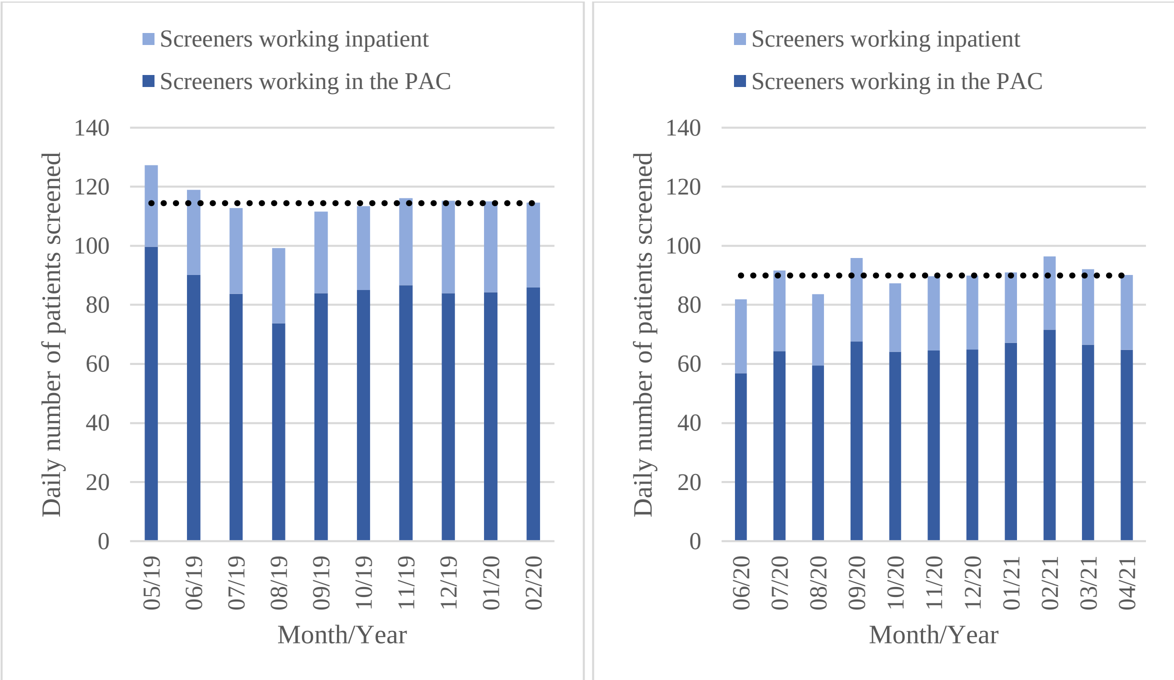
Figure 2.12. Percentage of patients with a day treatment per day in the week, with the black dotted line representing the average (n in days; January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

2.4.3 Management perspective

From a management perspective, the performances of the PAC are represented by the daily number of patients screened, the PAC appointments compared to the surgery demand, utilization, and cancellations and no-shows.

Daily number of patients screened

The number of patients screened represents the number of PAC agreements and the number of PAC appointments. When initially no PAC agreement is given, the patient has examinations and the PAC planners monitor the results. When all results are gathered, the PAC planners sent the information to the supervisor. The supervisor assesses the patient and provides a PAC agreement, without seeing the patient. In this way, the number of PAC appointments equals the number of PAC agreements. Figure 2.13 shows the daily number of PAC patients screened. Figure 2.13a shows the daily number of patients screened before COVID-19, whereas Figure 2.13b shows the daily number of patients screened during COVID-19. Note that the average number of patients screened before COVID-19 equalled 114.4, whereas during COVID-19 on average 89.9 patients are screened daily.



(a) (b)

Figure 2.13. Daily number of patients screened, with the black dotted line indicating the average. a) shows the time before COVID-19 (n = 23,976; May 2019 – February 2020; St. Antonius Hospital) and b) shows the time during COVID-19 (n = 21,140; June 2020 – April 2021; St. Antonius Hospital)

Finished PAC appointments and surgery demand

This part investigates whether the PAC finishes enough appointments to fulfil the surgery demand. In agreement with the management of the PAC, it was decided that the number of surgery requests represents the number of requests for a PAC appointment. However, in reality, it is difficult to predict this number of requests for a PAC appointment. The arrival process in the PAC consists of patients who have surgery as well as patients who undergo anaesthesia without having surgery. Next, some patients have surgery twice but can use one PAC agreement for both surgeries. This makes it difficult to predict the needed PAC capacity. We assume that the number of patients that needs a PAC appointment without having surgery approximately equals the number of patients that does not need a PAC appointment but have surgery. In this way, the number of surgery requests represents the number of requests for a PAC appointment.

Currently, it is unknown whether the PAC carries out enough appointments to fulfil the surgery demand. To find this out, the number of PAC appointments, surgery requests, and surgeries are compared. Figure 2.14 represents the monthly number of surgery requests, PAC appointments, and surgeries. The figure shows that the number of PAC appointments is lower than the number of surgery requests and the number of patients that has surgery, mainly before COVID-19.

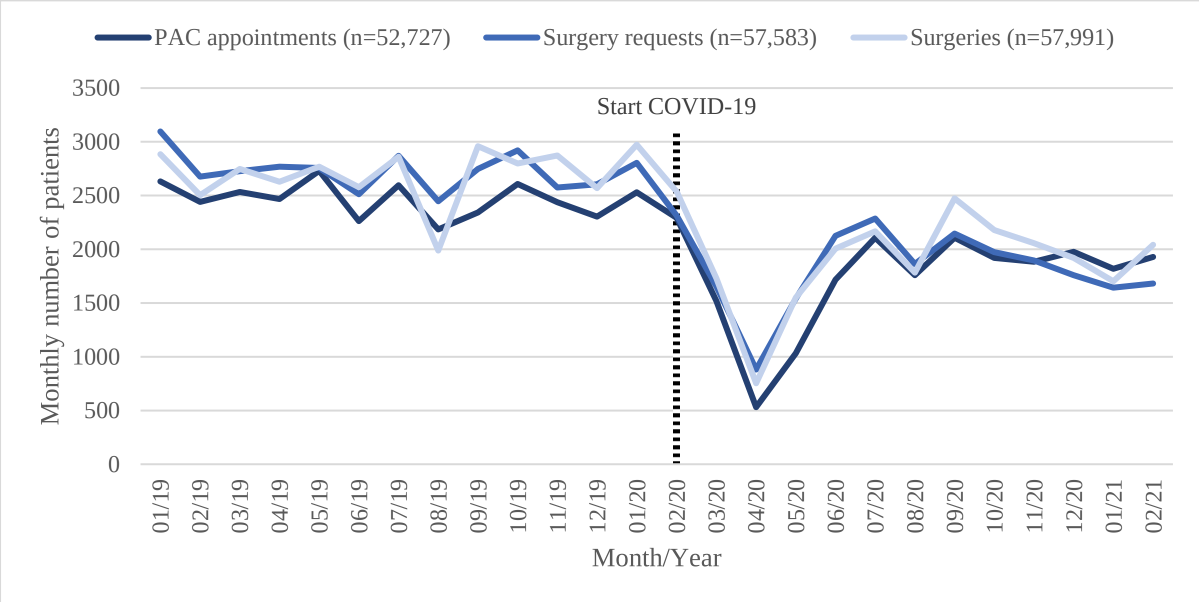


Figure 2.14. Monthly number of PAC appointments, surgery requests and surgeries (January 2019 – February 2021; St. Antonius Hospital)

Utilization

The utilization of a resource represents the degree of occupation of the resource. In the PAC of the St. Antonius Hospital, utilization is difficult to measure because the number of appointment slots in the blueprint schedule does not match the capacity of the screener. Before COVID-19, on average 22 appointment slots were available per screener working in the PAC, while 15 patients on average were scheduled per screener. Next, during COVID-19, on average 12 appointment slots were available per screener working in the PAC, while a screener was able to see 13 patients daily. Thus, the capacity in the blueprint schedule does not match the capacity of the screener.

Figure 2.15 shows the average number of patients scheduled per screener, split across screeners working in the PAC and screeners working inpatient. Data from January 2019 is included, except for the first Dutch COVID-19 lockdown period (March, April and May 2020), because the utilization during this period is not representative. Figure 2.15 shows the situation before COVID-19 in dark blue and the situation during COVID-19 in light blue. Based on interviews, we conclude that phone consultations take more time than physical consultations. Consequently, even though currently fewer patients are treated per screener, screeners indicate that they experience the same workload as before COVID-19. Moreover, from these interviews, we conclude that the current workload equals approximately 87%. Given that the average utilization of 87% equals 13 patients per screener, we conclude that during COVID-19, utilization of 100% equals 15 appointment slots. Thus, we assume a capacity of 13 appointment slots for regular patients and 2 appointment slots for overbookings.

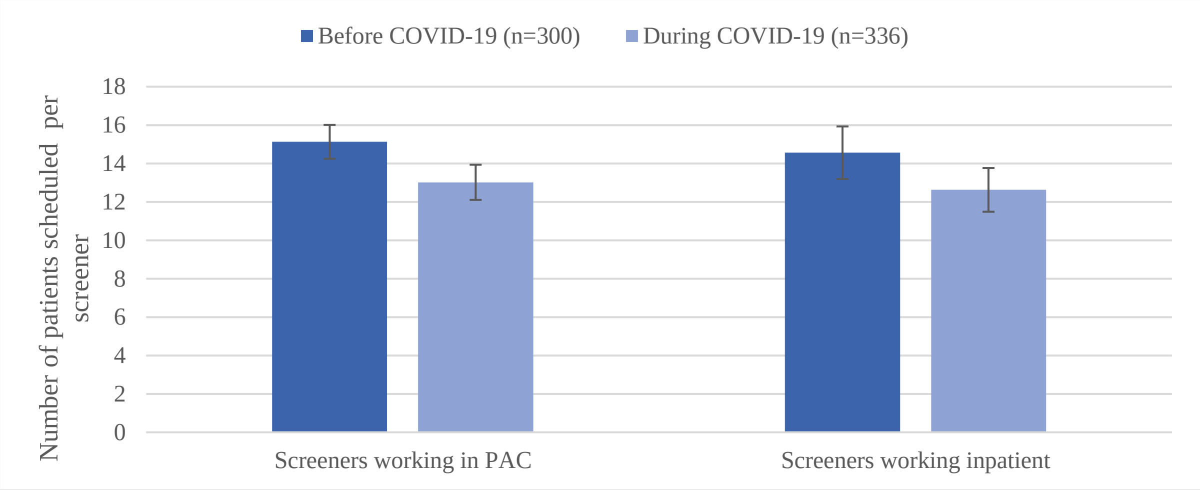


Figure 2.15. Average number of patients scheduled per screener, before versus during COVID-19 and split across screeners working in the PAC and screeners working inpatient (n equals the number of screeners; January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

Cancellations and no-shows

The percentage of consultations that are cancelled reflects the percentage that is cancelled by the patient or by the hospital. The patient should cancel the appointment at least 24h before the consultation starts, otherwise, this patient is called a no-show. The St. Antonius Hospital cancels and reschedules an appointment when the overtime increases to an unacceptable level. The reason for this is often the unexpected amount of emergency patients that need a PAC appointment that day. Figure 2.16 shows the percentage of appointments that are cancelled. On average, without taking the first Dutch COVID-19 lockdown into account (February 2020 – May 2020), 11.9% of appointments are cancelled.

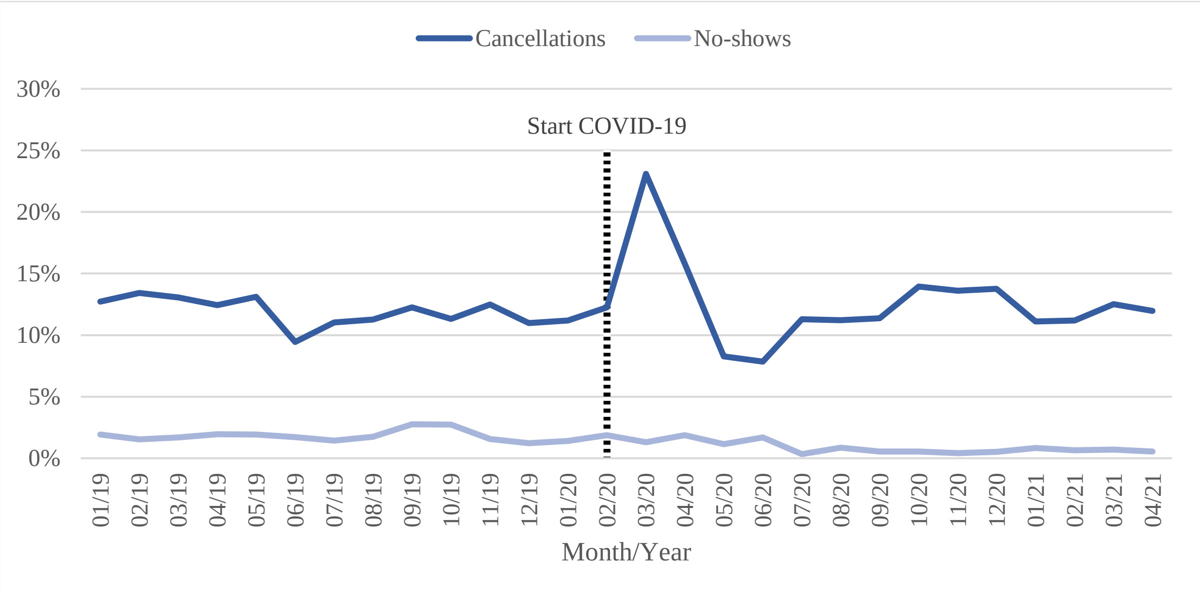


Figure 2.16. Percentage of appointments that are cancelled and percentage of patients that do not show up (n = 67,803; January 2019 – April 2021; St. Antonius Hospital)

Moreover, when a patient does not visit the PAC while having an appointment, this patient is called a no-show. There can be concluded that the percentage of patients that do not show up decreased as a consequence of COVID-19, which is probably a consequence of the increase in phone consultations. Figure 2.16 gives the percentage of no-shows. Currently, 1.3% of the patients do not show up.

2.4.4 Access times related to the PAC

Access time is the time between the request of an appointment and the appointment date itself. The PAC relates to two types of access time. The first one is the time between the appointment in the outpatient clinic where surgery is requested and the PAC appointment, which is the focus of this study. The second one is the time between the PAC appointment and the surgery. Figure 2.17 visualizes the access times related to the PAC. In this section, the performances of the PAC regarding both access times are given. Data from January 2019 is included, except for the first Dutch COVID-19 lockdown period (March, April and May 2020), because the access time during this period is not representative.

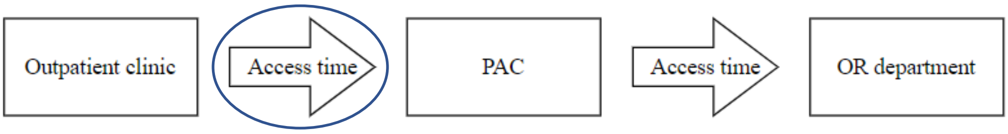


Figure 2.17. Access times related to the PAC

Access time between surgery request and PAC appointment

The allowable access time between the surgery request and PAC appointment depends on the priority of the patient. Thus, the access time criteria differ per priority group, and Table 2.4 gives these access time criteria per priority group. For example, the PAC aims to screen a patient with a surgery priority of 1 week at least two days after the surgery request. Given the access time criteria per priority group, the percentage of patients screened within the access time criteria can be calculated.

Table 2.4. Access time criteria per priority group

Priority group	Access time criteria
< 72 hours	0 days
< 1 week	2 days
< 10 days	5 days
< 2 weeks	7 days
< 3 weeks	10 days
< 4 weeks	14 days
< 6 weeks	21 days

Figure 2.18 gives the percentage of patients that are screened within the access time criteria, per priority group. From Figure 2.18 we conclude that the percentage of patients that are screened on time decreased as a consequence of COVID-19. This decrease holds for each priority group. Taking together, the percentage of patients screened within the access time criteria decreased from 82% before COVID-19 to 67% during COVID-19. As a consequent of this decrease, surgeries are delayed or patients are overbooked just before the surgery date.

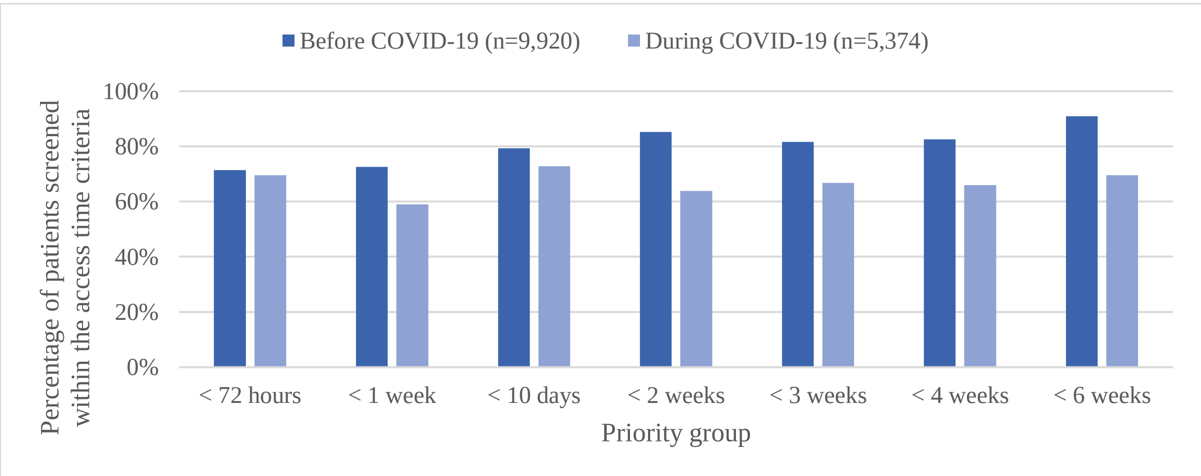


Figure 2.18. Percentage of patients screened within the access time criteria, per priority group (January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

Access time between PAC appointment and surgery

The access time between the PAC appointment and the surgery should not be too long but also not too short. On the one hand, a PAC agreement can expire when the screening took place more than six months before surgery since the patients' health status can change in the meantime. On the other hand, there should be enough time left for additional examinations when necessary, without delaying the surgery. Figure 2.19 shows the time in months between the PAC appointment and surgery. Dark blue indicates the time before COVID-19, while light blue indicates the time during COVID-19. We observe that the percentage of patients that are screened less than a month before surgery increased as a consequence of COVID-19. Moreover, a favourable timing is one till three months before surgery, as described in Section 2.1. Figure 2.19 shows that the percentage of patients screened one to three months before surgery decreased as a consequence of COVID-19.

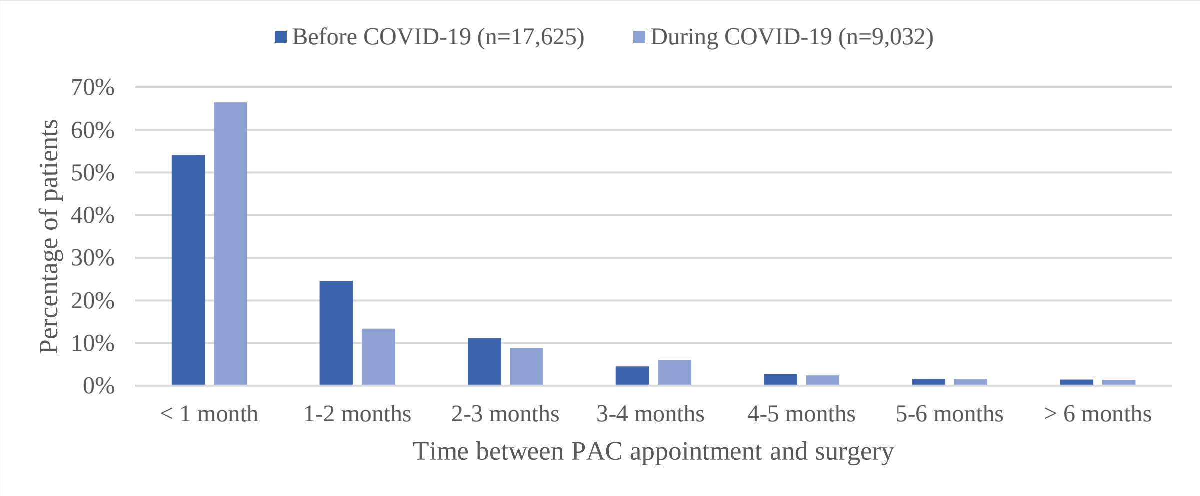


Figure 2.19. Time in months between the PAC appointment and surgery (January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

Next, we are interested in the patients who are screened within one month before surgery. Figure 2.20 shows the number of days between the PAC appointment and surgery for these patients. From Figure 2.20 we conclude that the percentage of patients that are screened one week before surgery increased as a consequence of COVID-19. To conclude, COVID-19 had a negative effect on the time between the PAC appointment and the surgery because the number of patients screened just before the surgery increased.

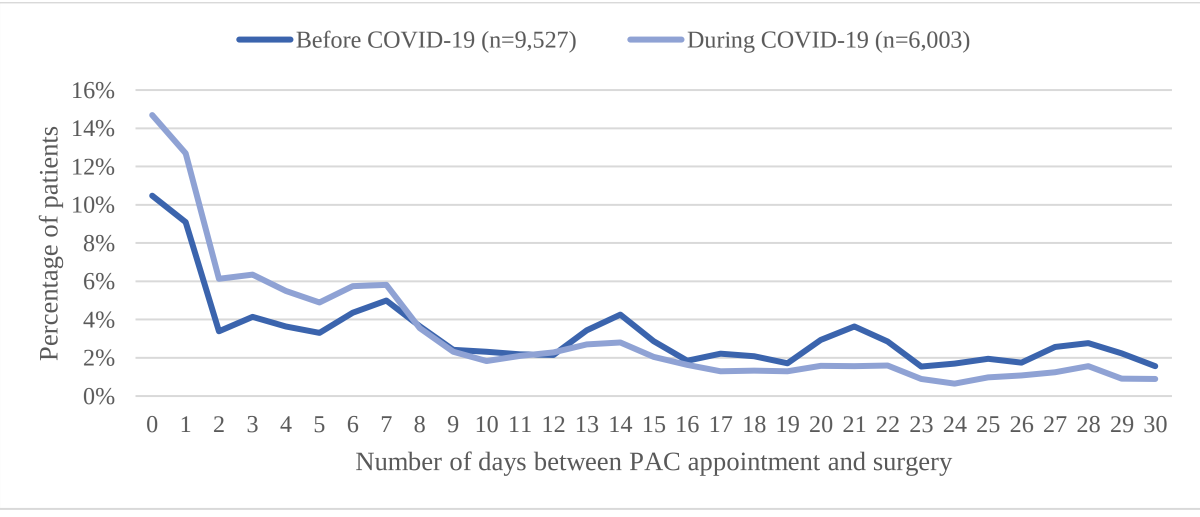


Figure 2.20. Number of days between the PAC appointment and surgery, for patients with a PAC appointment within one month before surgery (January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

2.5 Conclusion

Chapter 2 discussed characteristics and processes regarding the preoperative process. It turned out that patients visiting the PAC are very diverse with respect to specialty, routing, complexity and priority. From a PAC planning point of view, patients are classified into three patient groups: type 1, emergency and inpatient patients and different planning rules apply for these patient groups. PAC planners face problems regarding the blueprint schedule which does not support the scheduling of type 1 patients and regarding the number of patients that needs an appointment in the short term. Moreover, OR planners are divided among clusters, and each cluster includes multiple specialties. OR planners schedule patients based on priority and based on FCFS. OR planners face problems because many type 1 patients are on top of the surgery waiting list, but do not have a PAC agreement yet.

Next, the performances from an employee and management perspective were discussed. From an employee perspective, we conclude that many patients are overbooked. Additionally, the workload varies a lot during the week, for nurses as well as for screeners. From a management perspective, we conclude that as a consequence of COVID-19, the daily number of patients screened decreased. Next, it turned out that the number of PAC appointments is lower than the surgery demand. Moreover, as a consequence of the increase in phone consultations, the capacity of a screener decreased.

In the end, the access times related to the PAC are discussed. These include the access time between the surgery request in the outpatient clinic and the PAC appointment and the time between the PAC appointment and the surgery. Regarding the access time between the outpatient clinic and PAC appointment, we concluded that the number of patients screened within the access time criteria decreased from 82% to 67% as a consequence of COVID-19. Moreover, regarding the access time between the PAC appointment and surgery, we concluded that the percentage of patients screened one week before surgery increased.

Concluding, the access time between the surgery request in the outpatient clinic could be improved and the blueprint schedule could be optimized.

3 Literature review

Chapter 3 presents answers to the knowledge questions discussed in Chapter 1 and discusses possible solutions for the problems mentioned in Chapter 1. Section 3.1 discusses capacity allocation, which is a widely known method to improve or regulate access times. Then, Section 3.2 describes queueing systems and the advantages and disadvantages of pooling for different queueing systems. Section 3.3 describes the literature regarding tactical capacity planning in the PAC to investigate whether earlier studies aimed to improve access times in the PAC. Then, because capacity allocation can be applied via a blueprint schedule, Section 3.4 describes tactical decisions to design a blueprint schedule. Moreover, Section 3.5 discusses the optimization methods as well as the key factors to generate an easy-to-implement capacity allocation. In the end, the blueprint schedule should be tested on its performances, therefore Section 3.6 describes methods with which the performances of a blueprint schedule can be tested. Finally, Section 3.7 summarizes this chapter and discusses the solution approach.

3.1 Capacity allocation to regulate access times

Access time requirements can differ between patient groups (Zonderland et al., 2021). To what extent the capacity matches patient demand influences the access time of patient groups. Moreover, the ability to deal with fluctuations in capacity and demand affects the access time of patient groups as well. A method to regulate access time requirements for multiple priority groups is capacity allocation. When the resource requirements of patient groups are known, capacity can be allocated to these patient groups to improve healthcare performances (Hulshof et al., 2012). Thus, capacity allocation divides the available resource capacity among patient groups (Ahmadi-Javid et al., 2017).

Capacity allocation has multiple goals, with respect to improving appointment scheduling. First, capacity allocation has the goal to find equitable access times for multiple patient classes (Aslani et al., 2021; Deglise-Hawkinson et al., 2018; Ma et al., 2016). Access time is a typical performance indicator in outpatient clinics (Aslani et al., 2021). Access time is the time between the request of an appointment and the scheduled appointment time. Short access times contribute to achieving service levels for all patient classes. Second, with capacity allocation, a company or hospital tries to maximize resource utilization or use resources efficiently (Batista et al., 2020; Hulshof et al., 2013; Vissers, 1998). Moreover, Nguyen et al. (2015) performed a study with the goal to minimize the maximum required capacity and Aslani et al. (2021) extended this to minimize the maximum required capacity in the worst-case scenario. Third, capacity allocation can be used to balance workload (Deglise-Hawkinson et al., 2018; Hulshof et al., 2013). Fourth, some studies use capacity allocation to increase hospital revenue or decrease the cost of service (Li et al., 2021; Zhu et al., 2020). Finally, capacity allocation has the objective to serve the number of patients that was strategically determined (Hulshof et al., 2013) and to minimize overtime (Deglise-Hawkinson et al., 2018).

Ways to allocate capacity

Capacity allocation can be applied in healthcare settings in multiple ways:

- One way is to design an **admission plan** or **blueprint schedule**, which gives how many appointment slots in a block schedule are assigned to each patient class each day (Hulshof et al., 2012; Leeftink et al., 2020).
- The second way is **admission planning** or **admission control**, which involves the rules about how many and which patients to select from the waiting list (Hulshof et al., 2012; Leeftink et al., 2020).
- The third way is **temporary resource capacity changes**, which are changes in the capacity allocation within a specific time frame, to deal with demand fluctuations (Leeftink et al., 2020).

3.2 The relation between queueing theory and capacity allocation

Whether capacity allocation will show promising results depends on the queueing system. This section introduces queueing theory in healthcare (Section 3.2.1), followed by the consideration of whether to pool or not (Section 3.2.2).

3.2.1 Queueing theory in healthcare

A healthcare system can be seen as a complex queueing network (Creemers & Lambrecht, 2008). The patient flow through the healthcare system influences the outcomes of a blueprint schedule (Srinivas & Ravindran, 2020). This patient flow can be described using queueing theory. Servers are in parallel if a patient needs to pass through only one server to complete the service (Winston & Goldberg, 2004). Serial servers provide a different type of service and patients need to pass them all before completing the service. When a patient waits multiple times for multiple servers, the same blueprint schedule results in different waiting times compared with a system in which a patient queues for a single server (Srinivas & Ravindran, 2020). Thus, the queueing system description of the patient flow through multiple stages influences the outcome of the blueprint schedule. Figure 3.1 shows the four different queueing systems.

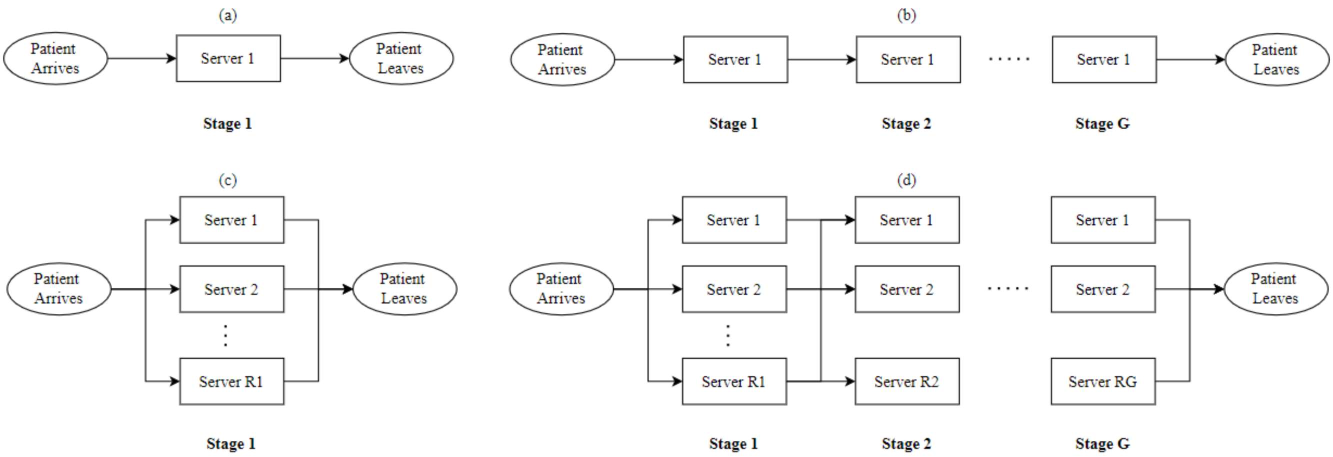


Figure 3.1. Queueing systems: (a) Single-Stage Single-Server (b) Multi-Stage Single-Server (c) Single-Stage Multi-Server (d) Multi-Stage Multi-Server (Srinivas & Ravindran, 2020)

Queueing disciplines

"The queue discipline describes the method used to determine the order in which customers are served" (Winston & Goldberg, 2004, p. 1052). When patients are served following FCFS, they are served in the order of their arrival (Winston & Goldberg, 2004). And, when the most recent arrival is served first, the last come first served discipline is applied. Moreover, when the arrival does not influence the order of service, patients get service in random order. There are also some queueing disciplines that take the priority of the patient into account, which are called priority queueing disciplines. Then, patients are classified in categories and each category has a priority level. Within each category, patients are served following FCFS. Two commonly used queuing disciplines in healthcare are FCFS and priority queueing (Tao & Liu, 2019). Figure 3.2 shows an example of a priority queueing discipline in healthcare.

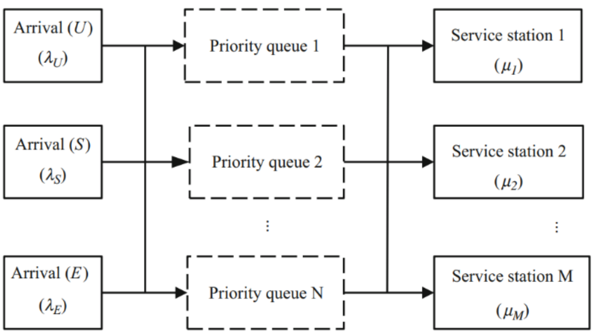


Figure 0.2 Priority queueing discipline in healthcare (Tao & Liu, 2019)

3.2.2 To pool or not to pool

Pooling and capacity allocation have a strong relationship. A situation with allocated capacity implies a non-pooled situation. “In general, pooling refers to the phenomenon that available inventory or capacity is shared among various sources of demand” (Creemers & Lambrecht, 2008, p. 5). In a non-pooled situation, patients queue for a single specialist, which means that each specialist fulfils its own demand (Creemers & Lambrecht, 2008). In a pooled situation, patients are aggregated and treated by the first available specialist. Whether pooling is beneficial depends on the situation.

Situations in which pooling is beneficial

Pooling showed already promising results (Creemers & Lambrecht, 2008). Pooling avoids that servers are idle because an empty queue is less likely to occur. And, pooling minimizes variability, such that less capacity is needed to maintain a certain service level. In call centres, pooling showed already good results with respect to waiting times and capacity (van Dijk & van der Sluis, 2009). Single-Stage Multi-Server queueing systems where the pooling principle was applied, result in a mean delay reduction (van Dijk & van der Sluis, 2008). In a situation with a single type of arrival, which implies no variation in the characteristics of the arrival, pooling is beneficial.

Situations in which pooling is <u>not</u> beneficial

Pooling in healthcare has also a number of limitations (Creemers & Lambrecht, 2008). First, patients often want to see their own doctor. Second, doctors have their own specialization and cannot divide some tasks. Third, doctors have different time instances or schedules. In call centres, a Single-Server queueing system shows a negative effect of pooling when multiple different servers were mixed (van Dijk & van der Sluis, 2008). More specifically, the average waiting time increased. Next, in a call centre environment, pooling with high variable customer classes could result in a negative effect. Moreover, also in a Multi-Stage Multi-Server queueing system, it is questioned whether pooling will show advantageous results (van Dijk & van der Sluis, 2009). Concluding, high mix variability by pooling should be avoided.

3.3 Tactical capacity planning in the PAC

This section summarizes what is done in the field of resource capacity planning in the PAC. Appendix B describes the details of this literature search. Some studies investigated the design of the PAC, for example, appointment-based, walk-in based, or a combination of these two. Others tested heterogenic scheduling based on the ASA classification. Only one study considered access times in the PAC and investigated the relationship between the amount of capacity and access times. This section discusses these studies in more detail.

Some studies investigated the performances of an appointment-based PAC. Currently, there is no consensus on the performance of an appointment-based PAC. On the one hand, Dexter (1999) concludes that a PAC with consultations by appointments provides better service than one that serves on a walk-in base. Moreover, an appointment-based PAC has less variability in arrival times, which leads to a shorter average patient waiting time (Edward et al., 2008a). On the other hand, Zonderland et al. (2009) tested a design with consultations based on appointments only, which did not result in a better performance. This was mainly because patients had an increased waiting time for the secretary and an appointment-based system was not seen as patient-friendly. Thus, currently, no conclusions can be drawn about a PAC which serves patients using an appointment-based system.

Next, research is performed to investigate the performances of a PAC on a walk-in basis. A PAC on a walk-in basis was initially thought to have a longer average waiting time compared to a PAC based on appointments only (Dexter, 1999). However, current research shows that a PAC on a walk-in basis has some advantages. First, patients do not have to visit the hospital again for the preoperative assessment but can do the assessment directly after the consultation with the specialist, which is also called one-stop-shop (Edward et al., 2008a). Secondly, a mixture between walk-in and appointment results in a reduced access time and waiting time (Odijk, 2012). Scheduling appointments complementary to walk-in arrivals results in a more homogeneous patient arrival pattern (Zonderland et al., 2009). Multiple authors suggest to see ASA I and ASA II patients on a walk-in base and ASA III and ASA IV patients appointment-based (Schoenmakers, 2008; Zonderland et al., 2009).

Some studies research the relation between consultation times and patient ASA classification. Consultation times of patients are highly variable and depend on patient ASA class (Edward et al., 2008a; Schoenmakers, 2008). When the patient ASA class is known, the management of the hospital can allocate consultation times more accurately (Hawes et al., 2016). In recent years, research is performed to test adapted consultation times to the patients' ASA classification. Waiting time reduced and patient satisfaction increased (Edward et al., 2010; Edward et al., 2008b; Odijk, 2012). The total length of stay of the patient and the system robustness showed better results in a heterogenic appointment system based on ASA classification (Schoenmakers, 2008).

Only one study investigated the PAC capacity in relation to access times. Edward et al. (2008b) developed a simulation model which determines the required capacity of the PAC. The goal of this study was to reduce the access time. It turned out that the model was able to calculate the number of appointments needed to reduce the access time. Moreover, they also studied the effect of grouping patient classes, since they expected that grouping would result in less fluctuation in demand and consequently in reduced required capacity. However, grouping regular and semi-urgent patients did not reduce the fluctuation in demand, but the patient classes were still grouped because it simplifies the planning.

3.4 Tactical decisions to design a blueprint schedule

This section explains which tactical decisions are considered when designing a blueprint schedule. Eight tactical decisions are considered when designing a blueprint schedule (Hulshof et al., 2012; Zonderland et al., 2021):

Capacity allocation

Capacity allocation is about how capacity should be divided among multiple patient classes (Ahmadi-Javid et al., 2017). Capacity allocation affects access times of patient groups and the utilization of resources (Hulshof et al., 2012).

Number of patients per consultation session

The number of patients per consultation session affects patient access time and patient waiting time (Hulshof et al., 2012). An increase in the number of patients per consultation session will result in a decrease in patient access times. However, patient waiting times and staff overtime will increase.

Patient overbooking

The decision whether or not it is allowed to overbook patients affects staff productivity (Hulshof et al., 2012). Patient overbooking compensates for no-shows and no-shows have a negative effect on the staff idle time. Moreover, patient overbooking improves patient access times and decreases staff idle time. However, patient waiting times and staff overtime can increase.

Length of the appointment slot
The length of an appointment slot affects resource utilization and patient waiting times (Hulshof et al., 2012). An increased length of an appointment slot will result in an increase in staff idle time and a decrease in patient waiting time. Moreover, the slot length can be equal for each patient group, however heterogenic scheduling, with different appropriate slot lengths, may decrease patient waiting time and staff idle time. This scheduling method is mainly applied in situations where the consultation times differ between patient groups. Ahmadi-Javid et al. (2017) summarize the literature regarding the performance of multiple patterns for the appointment slot length, such as the dome-shaped pattern, a plateau-dome structure, an increasing structure or a uniform pattern.

Number of patients per appointment slot
The number of patients per appointment slot affects staff idle time and patient waiting time (Hulshof et al., 2012). “Block size is the number of patients in a block or the number of patients scheduled at the beginning of a slot” (Ahmadi-Javid et al., 2017, p. 9). Four rules are used to determine the bock size (Ahmadi-Javid et al., 2017). Bailey’s rule suggests to schedule two patients in the initial slot, one patient in all other slots and no patient in the last slot The individual block rule suggests to schedule one patient in all slots and the multiple block rule suggest to schedule a fixed batch of patients in all slots. Finally, the variable block rule suggests that a varying number of patients can be scheduled in a slot. The decision about the number of patients per appointment slot is mainly interesting when patients are homogenous

Sequence of appointments
The sequence of appointments affects patient waiting times and staff utilization (Hulshof et al., 2012). Sequencing rules are for example based on patient groups or patients with the lowest variation of consultation duration first. This second rule showed the most promising result with respect to patient waiting time and resource idle time.

Queue discipline in the waiting room
The queue discipline affects patient waiting time (Hulshof et al., 2012). A common queue discipline is FCFS. However, a distinction could be made between high priority patients, for example, emergency patients, and low priority patients, which could be walk-in patients. Then, high priority patients are served first and have a lower waiting time compared to low priority patients.

Anticipation for unscheduled patients
The anticipation for unscheduled patients, such as walk-in or emergency patients, implies the approach that is used to reserve slack capacity (Hulshof et al., 2012). Leaving appointment slots open or increasing the length of the appointment slots are examples of approaches. Reserving capacity affects resource idle time. When too much capacity is reserved, resource idle time increases and vice versa. Reserving appointment slots at the right moment will result in a decrease in patient waiting time and an increase in resource utilization.

3.5 Capacity allocation methods
Capacity allocation methods are used to solve capacity allocation problems. Adan & Vissers (2002) considered a capacity allocation problem using the question: “How can a hospital generate an admission profile for a specialty, given a target patient throughput and utilization of resources, while satisfying given restrictions?” (p. 446). This capacity allocation problem can be solved using a capacity allocation method (Adan & Vissers, 2002). In a capacity allocation method, the goal is to determine the number and mix of patients that can be scheduled each day, which is based on the availability of capacity for patient groups. Section 3.5.1 describes optimization models to solve the capacity allocation problem. However, simulation models can result in an optimal but complex template, which can be challenging to follow (Hribar et al., 2018). Therefore, Section 3.5.2 describes methods to identify patient groups and deal with flexibility, which can be used to make an easy-to-implement blueprint schedule.

3.5.1 Optimization models to solve a capacity allocation problem

This section discusses optimization models that are widely applied in solving the capacity allocation problem in healthcare settings with the goal to reduce access times of multiple patient groups.

Ayvaz & Huh (2010) developed a dynamic programming model to dynamically allocate capacity among emergency and elective patients. Emergency patients need to be served immediately upon arrival, whereas elective patients wait to be served because they do not have a high urgency. The number of emergency patients that arrives during the day is unknown. Therefore, it is a challenging task to reserve the right amount of capacity for these patient groups. Moreover, emergency and elective patients have different access time requirements. More detailed, elective patients can be fully backlogged whereas emergency patients will be lost if they are not immediately served. Stochasticity in patient arrival was taken into account.

Furthermore, Huh et al. (2013) considered an allocation problem taking multiple resources into account. They formulated the problem as a Markov decision process. Demand and resource uncertainties were taken into account. Capacity should be allocated to elective and emergency patients. The formulation was proved to be convex, which means that the capacity reserved for emergency patients reduces when the number of elective patients on the waiting list increases.

Moreover, Hulshof et al. (2013) developed a method to create a tactical resource allocation plan, where available resources are allocated to care processes. Next, a patient admission plan was developed to select which elective patients with various treatment paths to be served. Mixed Integer Linear Programming is used to develop the method. The method can create multiple tactical plans, whereby it integrates the decision making for multiple resources. Hereby, access times, the duration of the care process and the number of patients served improved.

With their model, Ma et al. (2016) improved access times for oncology patients. Simulation was used to determine the available number of appointment slots, to test multiple appointment scheduling policies and to test physician specialization templates. A Mixed Integer Programming model was used to determine the patient mix. They concluded that systems with capacity below or close to demand will run more efficiently when also request and resource type are matched.

And, Deglise-Hawkinson et al. (2018) used a queueing model to simulate the healthcare processes and solved the model by deterministic linear optimization. Patients were classified as new, urgent patients who require rapid diagnosis and as non-urgent patients who require a follow-up appointment. Appointment slots are reserved based on urgency, which resulted in reduced access time delays and increased throughput.

Moreover, Aslani et al. (2021) considered access time targets for first-visit and re-visit patients. They developed a robust optimization model with which a tactical capacity plan is created. With the tactical plan, money was saved and demand uncertainties were met. And, patients were seen within the subsequent planning horizon.

3.5.2 Methods to identify patient groups and deal with demand fluctuations

This section first describes the inputs which are required by a capacity allocation method. A capacity allocation model requires several inputs (Adan & Vissers, 2002; Ahmadi-Javid et al., 2017). One of these inputs are the patient categories, including the demand distribution, priority level, no-show probability and revenue of each patient category (Ahmadi-Javid et al., 2017). Next, the resources and their available capacity, planning cycle, admission profile and restrictions on admission profiles, target patient throughput and target utilization of resources are required as input for a capacity allocation method (Adan & Vissers, 2002).

Huang & Verduzco (2015) showed that with the use of the demand distribution of priority groups, the number of slots needed for each patient group can be determined. Using the number of appointment slots available and the percentage of patients per patient group, the number of appointment slots per patient group was calculated. Next, the appointment slots for each patient group were distributed evenly throughout the day. Thus, by identifying patient groups and using their demand distributions, capacity can be allocated. Therefore, this section discusses the identification of patient groups and methods to deal with demand uncertainties when designing a blueprint schedule.

Identify patient groups

To allocate capacity over patient groups, first patients need to be identified (Hulshof et al., 2012). Multiple patient groups with different properties make use of hospital resources (Vermeulen et al., 2009). Patients can be divided into groups based on for example the referring department, specialty, capacity requirements, medical constraints or level of urgency. Moreover, a patient group should have a minimal variation to make the blueprint schedule cost-effective (Huang & Verduzco, 2015). Therefore, patient groups that share the same properties can be reclassified to minimize the coefficient of variation (CV) of this group.

Uncertainty in demand

Blueprint schedules have to serve multiple patient groups with demand uncertainties. There are two ways to deal with this demand uncertainty, which are dynamic blueprint schedules and the use of flexible capacity.

Dynamic schedules are blueprint schedules that are able to respond to variability in demand and supply (Hulshof et al., 2012, 2013), and have already shown good performances (Nguyen et al., 2015; Vermeulen et al., 2009). By implementing dynamic schedules, patient access times decrease (Hulshof et al., 2012, 2013), resource utilization increases (Hulshof et al., 2013), flexibility increases and staffing costs decrease (Hulshof et al., 2012).

Static blueprint schedules are long-term cyclic plans (Hulshof et al., 2013). In these static blueprint schedules, flexible capacity can be used to cope with fluctuating patient arrivals during the week (Vermeulen et al., 2009; Wiesche et al., 2017). It is a challenging task to determine the fixed and flexible capacity needed in an outpatient clinic (Zonderland et al., 2021). Typically 20-40% of the capacity should be used flexibly, such that variation in patient demand can be handled.

3.6 The performances of a blueprint schedule

The performances of a blueprint schedule can be tested using numerical examples or using simulation models. This section compares these methods.

Numerical examples

Ayvaz & Huh (2010), Huh et al., (2013), Nguyen et al. (2015), Srinivas & Ravindran (2020) and Aslani et al. (2021) use numerical examples to test the performances of the capacity allocation method. An advantage of using numerical examples is that it requires a reasonable computation effort (Huh et al., 2013). Moreover, Srinivas & Ravindran (2020) demonstrated the capacity allocation method by applying the method to the data of a specific outpatient clinic. The biggest advantage of numerical examples is that it uses less computational time than a DES.

Discrete event simulation

Gocgun & Puterman (2014), Bikker et al. (2015), Huang & Marcak (2015), Huang & Verduzco (2015), Ma et al. (2016) and Hribar et al. (2018) use a simulation to show the effects of the capacity allocation method or generated template. A simulation model is able to show the performances in a stochastic environment (Bikker et al., 2015). Moreover, queueing effects and variability are taken into account when using a simulation. Next, a simulation model is able to reflect the patient flow in a detailed way (Huang & Verduzco, 2015). Thus, the biggest advantage of a DES is that it can take stochasticity into account and that it reflects the patient flow and queueing effects.

3.7 Solution approach

Chapter 3 presented answers to the research questions in Chapter 1 which are related to the literature review. Access times can be improved or regulated via capacity allocation, which divides the available resource capacity among patient groups. A way to apply capacity allocation in healthcare settings is to design a blueprint schedule. A blueprint schedule gives how many appointment slots are assigned to each patient class each day. The way from the outpatient clinic to the PAC to the OR department can be seen as a Multi-Stage Multi-Server queueing system. In a Multi-Stage Multi-Server queueing system, it is questionable whether pooling will show advantageous results. Moreover, as discussed in Chapter 2, the PAC faces a high variable patient mix. Research proved that a high mix variability by pooling should be avoided. Therefore, allocating capacity in a system such as the PAC will probably improve the performance.

Previous literature showed that research is done to test the performances of a PAC on an appointment and a walk-in basis. Next, the relationship between consultation times and ASA classification is studied. One study investigated the relationship between the amount of capacity and access time. No research is performed in the field of improving access times by allocating capacity using a blueprint schedule.

A tactical decision that is considered when designing a blueprint schedule is capacity allocation. However, next to capacity allocation, the number of patients per consultation session, patient overbookings, length of an appointment slot, number of patients per appointment slot, sequence of appointments, queue discipline in the waiting room and anticipation for unscheduled patients should be considered as well.

The focus of this study is to allocate capacity to multiple priority groups and to design an easy-to-implement capacity allocation method that can be used in the design of the blueprint schedule. Multiple optimization models show promising results regarding the improvement of access times. However, simulation models can result in an optimal but complex template, which can be challenging to follow. Huang & Verduzco (2015) showed that using the demand distribution of patient groups, capacity can be allocated. Thereby, it is important to group patients such that the CV in the group is minimized. This study allocates capacity to priority groups and performs experiments to subdivide the priority groups. Next, a static blueprint schedule should be able to cope with variability in demand and therefore flexible capacity should be implemented. We are going to determine the number of flexible slots based on the CV of the priority group, taking in mind that typically 20-40% of the capacity should be used flexibly (Zonderland et al., 2021), such that variation in patient demand can be handled. When the blueprint schedule is designed, its performances are tested using DES. Even though DES uses more computational time than numerical examples, DES can model stochasticity and patient flow.

4 Conceptual model

Chapter 4 describes the conceptual model of the DES and discusses the interventions. As discussed in Chapter 3, a DES is a valuable way of analysing the performances of a system, taking patient flows and stochasticity into account. Therefore, this study uses DES to test the impact of multiple interventions on the performances of the PAC. Section 4.1 describes the steps of the simulation process, followed by Section 4.2, which discusses the model assumptions. Then, Section 4.3 describes the simulation settings and Section 4.4 discusses the verification and validation of the model. Furthermore, Section 4.5 describes the interventions which are tested in this study using DES. This chapter ends with a conclusion.

4.1 DES in seven steps

The DES is modelled in seven steps to correctly represent the patient and information flow in the PAC. Figure 4.1 shows these seven steps. Every step requires input to be able to model the step correctly. The required input is discussed in Chapter 5.

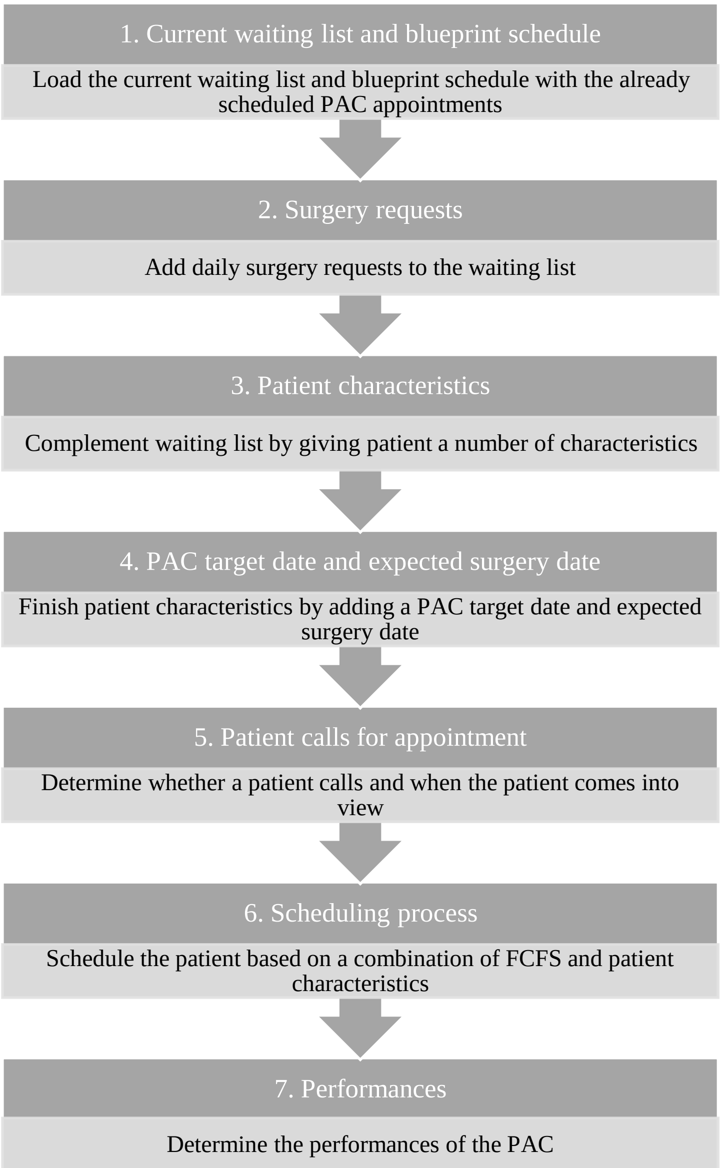


Figure 4.1. The simulation of the PAC represented in seven steps

As shown in Figure 4.1, the first step of the DES is the implementation of the current waiting list and the blueprint schedule with the already scheduled PAC appointments. Thus, the model starts with an initial situation. The reason for this is that the PAC system is never empty because there is always a waiting list with patients waiting to be screened and a schedule that is partly filled. When the system starts empty, it would take a while to reach a steady state situation that represents reality. Therefore, we decided to start the simulation with the current waiting list and PAC appointments.

The second step of the DES is the generation of a number of surgery requests per day, which are added to the initial waiting list from step one. The number of surgery requests during weekdays is determined using an empirical distribution whereas for the surgery requests during a weekend day a Poisson distribution is used. This will be further discussed in Chapter 5.

Third, the waiting list is further complemented by giving the generated requests several patient characteristics. These are patientID, specialty, day treatment, priority, type of patient and routing. The type of patient determines whether the patient is treated by a screener working in the PAC or working inpatient. Routing determines whether a patient needs an appointment with the screener only or that appointments with the pharmacist and/or nurse are required as well. These patient characteristics influence the patient flow and are therefore a step in the process, see Table 4.1 for two example patients.

In the fourth step, the patient characteristics are completed by adding a PAC target date and the expected surgery date. The PAC target date indicates the latest screening date to screen the patient within the access time criterium. The patient priority is used to determine the PAC target date and the expected surgery date. Table 4.1 shows two example patients with the patient characteristics, surgery request date, PAC target date and expected surgery date. Moreover, the patients have a call date and after calling, the patient receives an appointment (PAC date).

Fifth, patients call for an appointment. Patients can call on the surgery request date or during one of the following days. Though, it is also possible that patients forget to call. The call date is important since PAC planners schedule patients partly based on FCFS and partly based on patient characteristics, which will be further explained in Chapter 5.

Sixth, when a patient calls for an appointment, a PAC planner immediately schedules an appointment. Patient characteristics, such as priority, type of patient and routing influence the planning process. Patients are scheduled in the first available appointment slot, but the appointment has to be scheduled before the expected surgery date. Therefore, overbooking is allowed to ensure that patients are screened before the expected surgery date.

Finally, the performances of the PAC are gathered. This includes the time between the surgery request and PAC appointment (access time), number of patients overbooked, utilization and the variation in workload for nurses and for screeners.

Table 4.1. Example of two patients generated and scheduled by the model

Patient characteristics		
PatientID	4313	5470
Specialty	Trauma Surgery	Optometry
Day treatment	NO	YES
Priority	< 72 hours	< 4 weeks
Type of patient	Emergency	Type 1
Routing	Screening only	Screening only
Surgery request date	2021-11-17	2021-12-01
PAC target date	2021-11-17	2021-12-15
Expected surgery date	2021-11-18	2021-12-29
Call date	2021-11-17	2021-12-15
PAC date	2021-11-17	2021-12-22

4.2 Assumptions

During the development of the model, assumptions are made. These assumptions are as follows:

1. Patients have no preference for appointment date and time. Patients are scheduled on the appointment date given by the PAC planners. We assume that patients are available on the scheduled appointment date.

2. Holidays and seasonal effects are not taken into account. This implies that each weekday has the same capacity and no holidays are included. Moreover, seasonal effects, such as differences between the number of summer and winter requests, are not taken into account. However, daily seasonal effects, such as differences between days in the week and the differences between weekdays and weekend days, are included.

3. Screening capacity is assumed to be constant during the week. In reality, the screening capacity varies between seven and eight screeners. However, this variation has no pattern and is based on the feeling of whether the PAC capacity matches the OR capacity or not and on the availability of screeners. This variation is not taken into account, thus, the same capacity is available to screen patients every day.

4. No shows are neglected. Before COVID-19, 100% of the consultations physically took place, whereas, during COVID-19, 80% of the consultations is via phone. As a result, the number of no-shows decreased. During COVID-19, the no-show rate is mainly influenced by somebody not picking up the phone, and equals 0.7%, which is less than one patient per day. Therefore, no shows are negligible.

5. Cancellations are neglected. Appointments are cancelled by the patient or by the hospital and it is unknown by whom the appointment is cancelled. Appointments cancelled by the hospital are often a consequence of a schedule that is overloaded. We assume that this will not occur when the schedule matches the demand and therefore these cancellations are neglected. Next, appointments cancelled by the patients are cancelled at least 24 hours before the appointment would take place. Then, we assume that PAC planners can schedule a new patient and that it does not affect the performances much. Therefore, cancellations are not taken into account.

6. Patient waiting time is out of scope. The distribution of the consultation time, as well as the punctuality of the medical employees, were not available. Since currently 80% of the appointments take place via phone, we expect that patient satisfaction is less affected by waiting time, because the patient does not physically wait in the waiting room. Therefore, it is not necessary to measure consultation time and punctuality in practice. The model includes a mean consultation time, based on the capacity of the screener, to be able to generate a blueprint schedule.

7. No distinction is made between PAC employees and anaesthetists. In reality, PAC employees have to discuss complex patients with a supervisor. Consequently, an anaesthetist needs less time to screen a patient. In practice, when an anaesthetist is finished, the anaesthetist can treat a patient from the PAC employee instead of being idle. In this way, the total number of consultations daily remains the same. Thus, we do not study the differences between anaesthetists and PAC employees.

4.3 Simulation settings

This section discusses the simulation settings. In this study, the batch means of methods is applied. This method is able to determine the warmup period and the number of batches. The batch means of methods implies that the model runs once with several batches and one warmup period is deleted from the output (Law, 2015). Section 4.3.1 discusses the Marginal Standard Error Rule (MSER), which is a procedure to determine a warmup period. The warmup period is determined in two experimental settings, which are the current situation and an expected situation after COVID-19. Section 4.3.2 and Section 4.3.3 give the results of these settings respectively.

4.3.1 Marginal Standard Error Rule

The warmup period is the period in which the observations depend on the initial conditions (Law, 2015). These observations are not representative of the steady state behaviour of the simulation. Recall from Section 4.1 that the model starts with an initial situation, which means that the current waiting list and PAC appointments are implemented. Thus, in this study, the warmup period is the period in which the observations depend on the initial waiting list and PAC appointments.

The MSER is a procedure to determine the warmup period, in which the mean-squared error is minimized (Law, 2015). Since it is better to measure the observations over multiple replications, we use the MSER-k, which works with batch averages. We choose to measure the observations over five replications or days. The reason for this is that MSER-5 is frequently considered and because five observations equal one working week. Appendix C1 shows the procedure and accessory formulas of the MSER-k.

The MSER-5 is applied to the observations from the simulation. These observations depend on the experimental setting and the KPI. We choose to select two experimental settings and one KPI to determine the warmup period and the number of batches. The experimental settings are the current situation and the expected situation after COVID-19. The KPI is the daily number of patients overbooked.

4.3.2 Current situation

The MSER-5 is applied to the current situation and the daily number of patients overbooked is used as KPI. Figure 4.2 shows the batch averages of the daily number of patients overbooked. From this figure, we conclude that when the batch number equals four, a steady state situation arises. Therefore, the anticipated warmup period equals four batches.

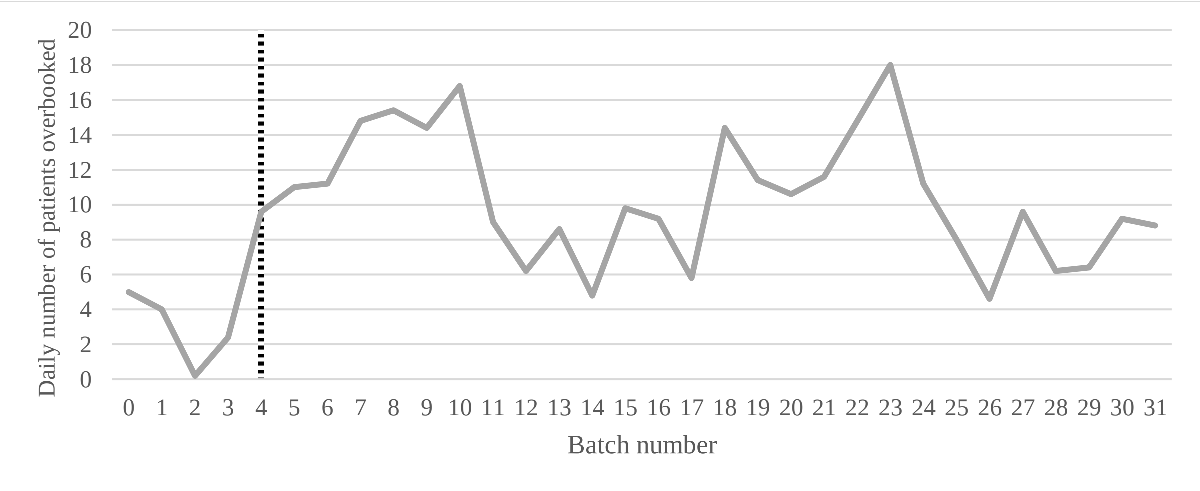


Figure 4.2. Average daily number of patients overbooked, plotted against the batch number where each batch equals one week

The run length should be much larger than the anticipated warmup length (Law, 2015). Therefore, we apply the MSER-5 and run the model for 32 batches. Figure 4.3 shows the MSER-5 statistic as a function of the warmup period. The warmup period which minimizes the MSER-5 statistic equals four. Figure 4.3 shows this minimum MSER-5 statistic with an orange dot.

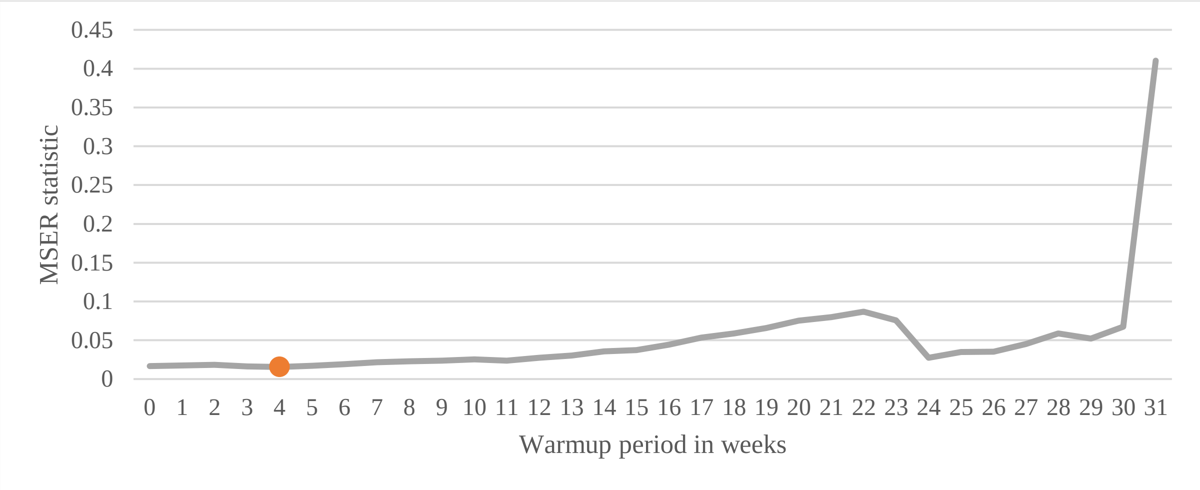


Figure 4.3. The MSER-5 statistic as a function of the warmup period in weeks

4.3.3 Expected situation after COVID-19

The second experimental setting is the expected situation after COVID-19, in which the number of surgery requests is higher than in the current situation. Moreover, the screening capacity is increased by one additional screener. The MSER-5 is applied to the expected situation after COVID-19, with the daily number of patients overbooked as KPI. Figure 4.4 shows the batch averages of the daily number of patients overbooked. From this figure, we conclude that when the batch number equals four, a steady state situation arises. Therefore, the anticipated warmup period equals four batches.

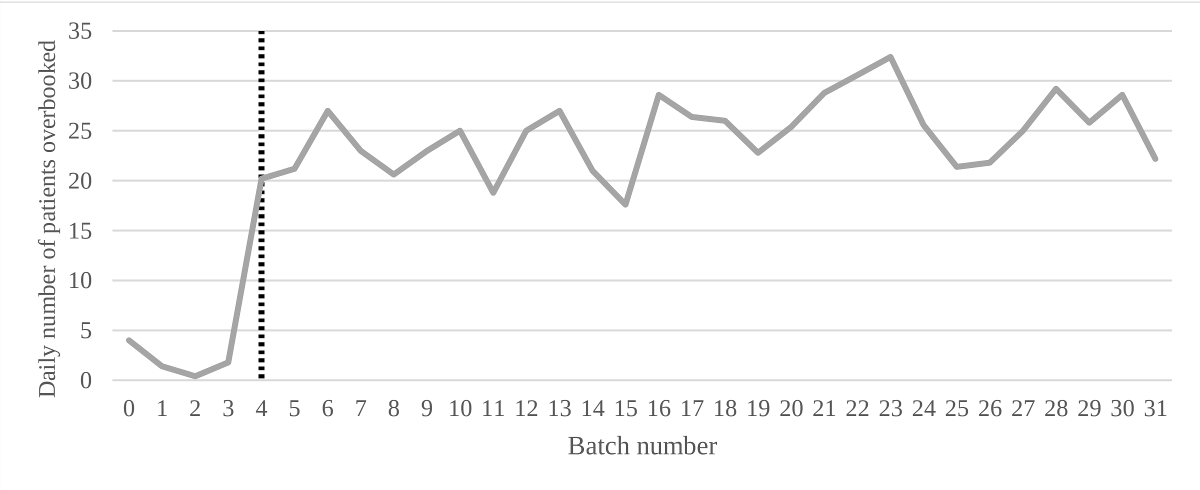


Figure 4.4. Average daily number of patients overbooked, plotted against the batch number where each batch equals one week

We apply the MSER-5 and again run the model for 32 batches. Figure 4.5 shows the MSER-5 statistic as a function of the warmup period. The warmup period which minimizes the MSER-5 statistic equals four. Figure 4.5 shows this minimum MSER-5 statistic with an orange dot.

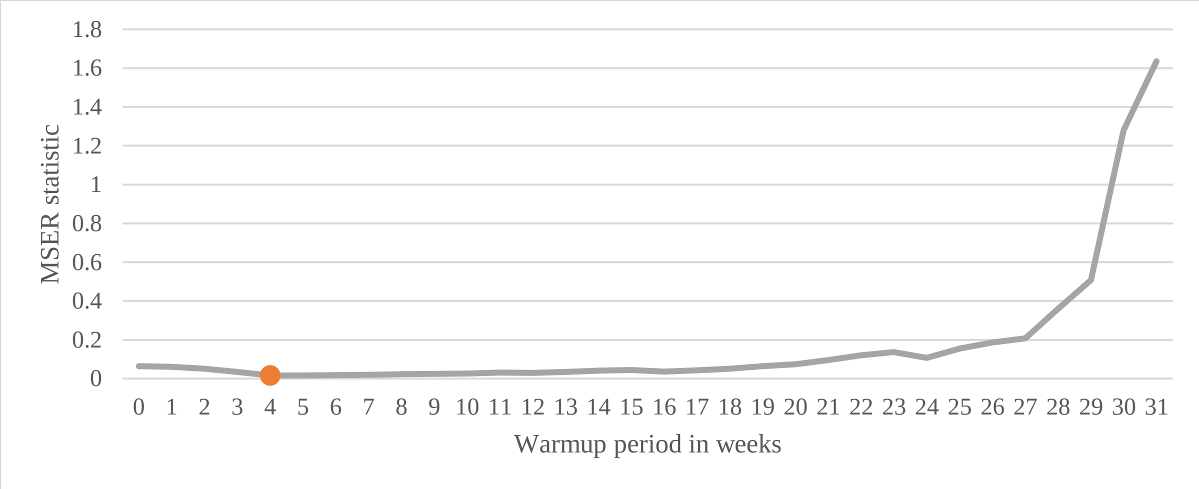


Figure 4.5. The MSER-5 statistic as a function of the warmup period in weeks

Concluding, the MSER-5 is applied to two experimental settings, with the daily number of patients overbooked as KPI. In the current situation as well as in an experimental setting, the warmup period equals four batches. Therefore, we choose to run each intervention with a warmup period of four batches. We run the model for 32 batches, leaving 28 batches for statistical analyses.

4.4 Verification and validation

This section discusses model verification and validation. The current situation in the model should represent reality. Section 4.4.1 describes the verification phase. Next, Section 4.4.2 discusses the validation phase.

4.4.1 Verification

In the verification phase, the goal is to determine whether the assumptions are correctly translated to the simulation computer program (Law, 2015). Law describes eight techniques that can be used to verify the simulation computer program. Two techniques are used to verify the model.

The first technique to verify a model is writing and debugging the simulation computer program in small modules. Thus, debug the small modules first, and when the modules are correct, combine the modules into the final model. We verified the model by writing small functions and testing the function individually using debugging. Then we combined all functions and created the model.

The second technique to verify a model is to calculate the mean and variance of the simulation input and then compare these values with the desired mean and variance. In this way, the input distributions are checked. Appendix C2 gives the verification of multiple simulation input distributions. For the daily number of surgery requests during weekdays and weekend days, the mean and standard deviation are determined. For the other patient characteristics, the percentage is determined. Concluding, the simulation input approaches the historical data.

4.4.2 Validation

In the validation phase, the goal is to determine whether the simulation model accurately represents reality (Law, 2015). In this study, the model is validated as follows:

1. Discuss the model with stakeholders and employees who are close to the processes which take place in the PAC.
2. Compare model outcomes with real data

The first validation step is to discuss the model with stakeholders and employees. The model is validated with the help of Desiree Wolf, department head of the PAC. The model was discussed following the same steps as described in Section 4.1. Moreover, definitions regarding patient types, assumptions and planning decisions were reviewed. Possible mistakes were removed from the model. In the end, the model was rated as valid.

The second validation step is to compare the outcomes of the model with real data. It is questionable whether a statistical test can be applied to compare the results since the model is an approximation of reality (Law, 2015). Despite the result of the statistical test, it is not possible to say that the model and reality are the same. However, we use a Two-Sample t-Test assuming equal variances to test whether the model output approaches the real data. Table 4.2 gives the mean and variance of the data and the p-value of the Two-Sample t-Test. The first test gives a p-value of 0.02, which means that the model significantly differs from the real data. Next, the second test results in p = 0.27, which means that the observations do not significantly differ. Because the daily number of patients scheduled only differs three patients from reality, we conclude that the model is able to approximate reality.

Table 4.2. Statistical analysis of the number of patients scheduled and the daily number of patients overbooked

	Daily number of patients scheduled		**Daily number of patients overbooked**	
	Real data	**Model**	**Real data**	**Model**
Mean	92.3	95.3	9.5	10.4
Variance	22.4	19.8	7.4	13.1
Observations	28	28	28	28
p-value	0.02		0.27	

4.5 Interventions

This section discusses three interventions that are tested using the DES described above. Section 4.5.1 explains the first intervention, in which the screening capacity is increased by one additional screener. Then, Section 4.5.2 goes deeper into the intervention in which capacity is allocated to multiple priority groups. Next, Section 4.5.3 discusses an offline planning approach, in which a group of patients is gathered and scheduled based on their priority. Finally, Section 4.5.4 summarizes the interventions.

4.5.1 Increase the screening capacity by one additional screener

In the first intervention, the screening capacity is increased by one additional screener. This means that the first intervention tests the performances of a PAC with a capacity of eight screeners instead of seven screeners. As described in Chapter 3, increasing the capacity of the PAC is one way to decrease the access time. From Chapter 2 we conclude that the PAC capacity does not match the OR capacity. Moreover, we conclude from Chapter 2 that on average eight patients are overbooked daily. This could imply that the PAC capacity is not sufficient or that the blueprint schedule does not match the capacity of the screeners. Therefore, during the first intervention, the capacity is increased to eight screeners.

4.5.2 Blueprint schedule with capacity allocated to priority groups

Allocating capacity showed already promising results with respect to regulating access times for different priority groups (see Chapter 3). Therefore, in the second intervention, a blueprint schedule with capacity allocated to priority groups is tested. Multiple experiments are performed to find the best configuration, with respect to the number of priority groups and the number of flexible and allocated appointment slots.

Number of priority groups

The doctor who requests surgery for the patient can choose between twelve priority groups made by the St. Antonius Hospital. Recall from Chapter 3 that merging patient classes simplifies the planning and will decrease demand fluctuations. Since the number of priority groups is too large, four new subdivisions of priority groups are tested, see Figure 4.6. In each subdivision, the left column shows the initial twelve priority groups. In the middle, the new priority groups are given and on the right side, the access time criteria are given. When priority groups are merged, they get the requirements of the most restrictive priority group. For example, in Figure 4.6b, "< 3 weeks" and "< 4 weeks" are merged and called "< 4 weeks". However, all patients in this priority group should meet the requirements of the patients that have surgery within 3 weeks. Therefore, their access time criterium equals 10 days instead of 14 days. An exception holds for the priority group "< 6 months", which includes all patients that need to have surgery within 2 months, 3 months or 6 months. The reason for this exception is that doctors use these priority groups with the same goal: the patient has a low priority and is added to the waiting list. Since the current waiting times are longer than 6 months for most specialties, the access time criterium equals 91 days.

Figure 4.6a shows the first subdivision of priority groups, which is based on the access time criteria of the priority groups. The twelve priority groups are reduced to eight priority groups. The priority group "< 72 hours" includes all patients that need to have surgery within 72 hours. The three priority groups within this priority group share the same requirements regarding their access time, therefore these priority groups can be merged into one priority group. The priority group "< 6 months" includes all patients that need to have surgery within 2 months, 3 months or 6 months.

Figure 4.6b shows the second subdivision of priority groups, which minimizes the CV and takes the access time criteria of the priority groups into account. The CV is calculated by the standard deviation divided by the mean. Table 4.3a gives the CV when the number of priority groups equals eight. Table 4.3b gives the CV when capacity is allocated to five priority groups. We conclude that grouping priority groups reduces the CV.

Group	**Mean daily number of requests**	**Standard deviation**	**CV**
< 72 hours	19.3	5.0	0.26
< 1 week	7.6	3.7	0.49
< 10 days	3.5	2.9	0.83
< 2 weeks	5.4	2.9	0.54
< 3 weeks	8.6	4.4	0.51
< 4 weeks	9.3	4.8	0.52
< 6 weeks	14.6	7.1	0.49
< 6 months	40.5	13.4	0.33
Total	**108.8**		

(a)

Group	**Mean daily number of requests**	**Standard deviation**	**CV**
< 72 hours	19.3	5.0	0.26
< 2 weeks	16.5	5.8	0.35
< 4 weeks	17.9	7.3	0.41
< 6 weeks	14.6	7.1	0.49
< 6 months	40.5	13.4	0.33
Total	**108.8**		

(b)

Table 4.3. Mean daily number of surgery requests, standard deviation and CV of the priority groups made by this study. a) shows the numbers for eight priority groups and (b) shows the numbers for five priority groups (n=488 weekdays; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

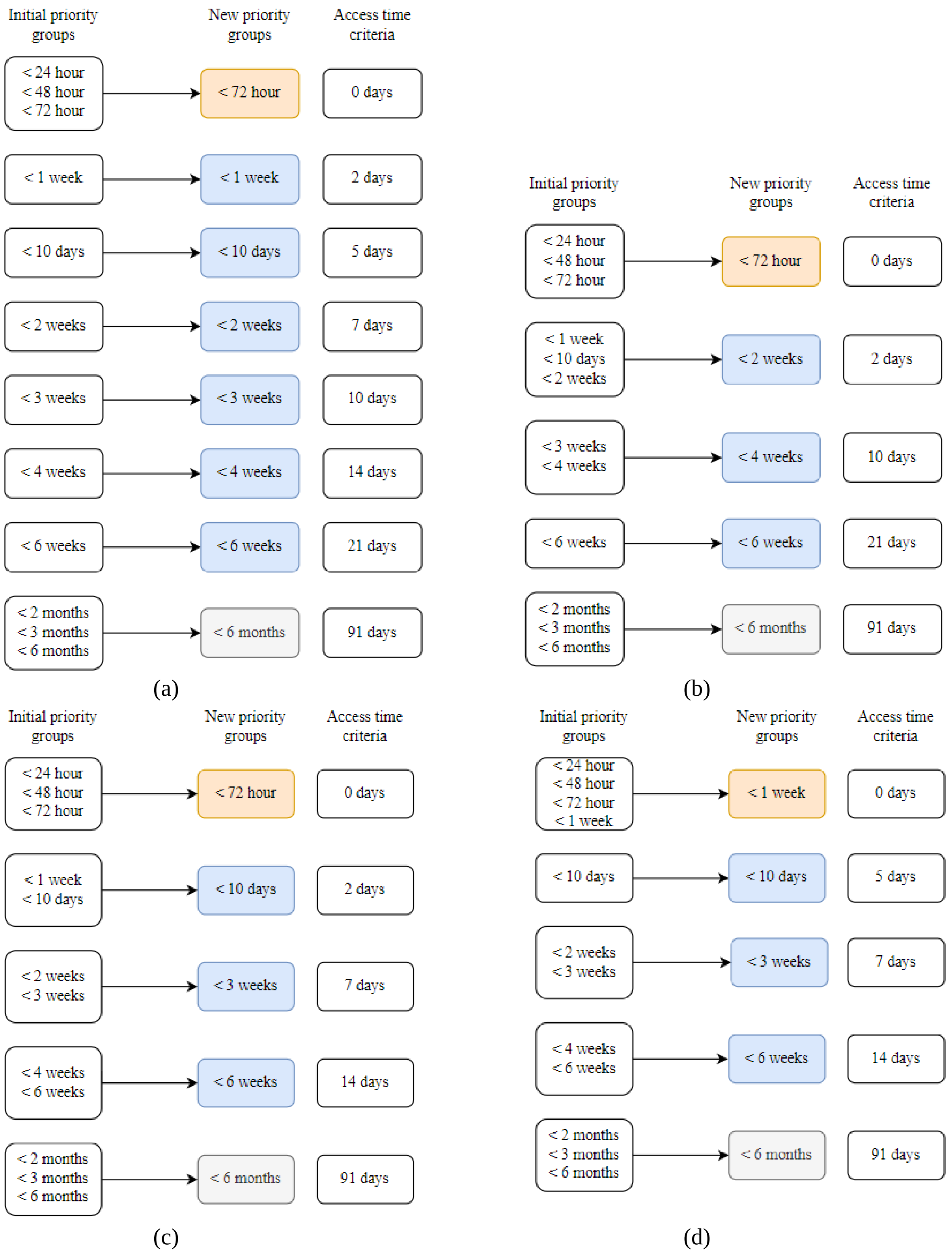


Figure 4.6. Four subdivisions of priority groups, with the initial priority groups in the first column, the grouped priority groups in the middle and the access time criteria in the right column. a) subdivision of eight priority groups made by this study, b) subdivision of five priority groups made by this study, c) subdivision of five priority groups made by OR planners and d) subdivision of five priority groups made by PAC planners

The third and fourth subdivisions are made by OR planners and PAC planners, respectively. OR planners and PAC planners share the same vision that the number of priority groups is too large. These planners have their preferences in how the initial priority groups should be reorganized into new priority groups. When capacity allocation shows improved results, these planners have to deal with the new subdivision. Therefore, their preferences regarding the reorganization of priority groups are tested as well. Figure 4.6c shows a subdivision made by OR planners and Figure 4.6d shows a subdivision made by PAC planners. The difference between the subdivisions is the group in which patients with a priority of "< 1 week" are placed. PAC planners prefer to merge all patients with a priority "< 1 week" with the access time criterium of 0 days. On the other hand, OR planners prefer a group with the priority "< 72 hours" and a group in which patients with the priority "< 1 week" and "< 10 days" are merged.

Number of flexible and allocated appointment slots

A capacity allocation method is used to divide the appointment slots to the priority groups. Recall from Chapter 3 that a blueprint schedule should include flexible capacity to be able to deal with demand fluctuations. Therefore, the capacity allocation method also determines how many appointment slots each priority group should contribute to the flexible appointment slots. Allocated appointment slots can only be used by the allocated priority group, while flexible appointment slots can be used by all patients. The capacity allocation method, which is used to determine the number of flexible and allocated appointment slots, is explained in this part.

A capacity allocation method requires several inputs. Thus, the first step is to determine the mean daily number of surgery requests and standard deviation per priority group i. This mean and standard deviation are based on historical data. Next, the total daily number of surgery requests is calculated and the number of appointment slots in the PAC schedule are counted. Moreover, we introduce the following variables needed to do the calculations of the capacity allocation method:

- μ_i = mean daily number of surgery requests of priority group i
- σ_i = standard deviation of the daily number of surgery requests of priority group i
- capacity = the daily number of appointment slots in the PAC schedule
- C_i = total daily number of appointment slots for priority group i
- flexibility = experimental ratio which influences the flexibility of the blueprint schedule
- F_i = daily number of flexible appointment slots contributed by priority group i
- A_i = daily number of appointment slots allocated to priority group i

Given the mean daily number of surgery requests per priority group i (μ_i) and the total daily number of surgery requests, the percentage of priority group i is calculated. Then, the number of appointment slots per priority group (C_i) is determined with the use of the percentage of priority group i and the available number of appointment slots in the PAC schedule (capacity). Equation 4.1 gives the formula to calculate the number of appointment slots per priority group i (C_i).

$$C_i = \lfloor \text{Percentage of priority group } i * \text{capacity} \rfloor \qquad \text{Equation 4.1}$$

Table 4.4 gives the mean daily number of surgery requests per priority group i (μ_i) and the standard deviation per priority group i (σ_i), using the subdivision of priority groups as given in Figure 4.6a. Next, this table gives the percentages per priority group i. Moreover, Table 4.4 gives an example in which a total of 97 appointment slots are available daily (capacity). Using Equation 4.1, these 97 appointment slots are divided among the priority groups. For example, the priority group "< 72 hours" includes 17.7% of the patients and therefore receives 14.3 appointment slots. This number of total appointment slots is rounded down to 14 appointment slots. Since the number of appointment slots per priority group i is rounded down, a total of 94 appointment slots are divided instead of the capacity of 97. The remaining 3 appointment slots become flexible appointment slots.

Table 4.4. Surgery request data (including mean (μ) and standard deviation (σ)) to calculate the number of appointment slots per priority group (n=488 weekdays; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

Priority group i	μ_i	σ_i	**Percentage of priority group i**	C_i
< 72 hours	19.3	5.0	17.7%	17
< 1 week	7.6	3.7	7.0%	6
< 10 days	3.5	2.9	3.2%	3
< 2 weeks	5.4	2.9	4.9%	4
< 3 weeks	8.6	4.4	7.9%	7
< 4 weeks	9.3	4.8	8.6%	8
< 6 weeks	14.6	7.1	13.4%	13
< 6 months	40.5	13.4	37.2%	36
Total	**108.8**		**100%**	**94**

The next step in the capacity allocation method is to determine how many appointment slots each priority group should contribute to the flexible appointment slots. The number of flexible appointment slots contributed by priority group i (F_i) depends on the CV of priority group i. To calculate the number of flexible slots, the CV is multiplied by the number of appointment slots for that priority group (C_i). Next, we multiply this with an experimental ratio (flexibility) to be able to vary the degree of flexibility. We test a flexibility of 1 and a flexibility of 0.55. Recall from Chapter 3 that typically 20-40% of the capacity should be used flexibly. In this study, a flexibility of 1 results in an average flexibility of approximately 36% and a flexibility of 0.55 results in an average flexibility of approximately 20%. Equation 4.2 shows the formula to calculate the number of flexible appointment slots contributed by priority group i (F_i).

$$F_i = \left\lfloor \frac{C_i * \text{ flexibility} * \sigma_i}{\mu_i} \right\rfloor \qquad \text{Equation 4.2}$$

After determining how many slots priority group i should contribute to the flexible appointment slots, the number of allocated appointment slots for priority group i (A_i) are calculated. The number of allocated appointment slots for priority group i (A_i) equals the total number of appointment slots for that priority group (C_i) minus the number of flexible appointment slots contributed by priority group i (F_i). Equation 4.3 shows the corresponding formula.

$$A_i = C_i - F_i \qquad \text{Equation 4.3}$$

Table 4.5 is a continuation of Table 4.4 and shows the results of the calculation of the number of flexible appointment slots contributed by priority group i (F_i) and the number of allocated appointment slots for priority group i (A_i). In this example, a flexibility of 1 is used.

Table 4.5. An example of the number of flexible appointment slots contributed by priority group i (F_i) and the number of allocated appointment slots per priority group i (A_i), using a flexibility of 1

Priority group i	μ_i	σ_i	**Percentage of priority group i**	C_i	F_i	A_i
< 72 hours	19.3	5.0	17.7%	17	4	13
< 1 week	7.6	3.7	7.0%	6	2	4
< 10 days	3.5	2.9	3.2%	3	2	1
< 2 weeks	5.4	2.9	4.9%	4	2	2
< 3 weeks	8.6	4.4	7.9%	7	3	4
< 4 weeks	9.3	4.8	8.6%	8	3	5
< 6 weeks	14.6	7.1	13.4%	13	6	7
< 6 months	40.5	13.4	37.2%	36	10	26
Total	**108.8**		**100%**	**94**	**32**	**62**

Next to the number of flexible and allocated appointment slots, one experiment is about the effect of restrictions on the use of flexible slots. During this experiment, the flexible appointment slots for priority groups "< 1 week", "< 10 days" and "< 2 weeks" are called "flex1/2" and can only be used by these priority groups. And, the flexible appointment slots for priority groups "< 3 weeks" and "< 4 weeks" are called "flex3/4" and can only be used by these priority groups. The other priority groups make use of the general flexible appointment slots. These flexible appointment slots consist of the number of flexible appointment slots contributed by these priority groups and the flexible appointment slots which arise as a consequence of the rounded down numbers used in the capacity allocation method.

4.5.3 Offline planning approach

In the third intervention, the offline planning approach is tested. Currently, the online planning approach is used, which means that patients are scheduled immediately when they call for an appointment (Ahmadi-Javid et al., 2017). In the offline approach, all requests are gathered and then patients are scheduled. As described in Chapter 2, PAC planners schedule patients using the auto planner, which finds the first available appointment when the patient calls. The combination of an online planning approach and the auto planners results in an appointment date which is greatly influenced by the moment the patient calls for an appointment. In the third intervention, the offline planning approach is applied and patients are scheduled based on their priority. Patients with a priority of six weeks are scheduled immediately when the surgery is requested. PAC planners do not wait for the patient to call but actively call the patient to schedule an appointment. Patients with a priority "< 6 months" are scheduled after two months of their surgery request. In this way, patients are scheduled in the right order and we expect that this improves the access time for each priority group.

4.5.4 Summary of the interventions

This section summarizes the interventions described in Section 4.5. Eight individual interventions, of which one tests the increase in screening capacity by one additional screener, six interventions test a blueprint schedule with allocated capacity to priority groups and the final individual intervention investigates the offline planning approach, in which high priority patients are scheduled immediately upon request and in which low priority patients are scheduled when the date of surgery comes close. See Table 4.6 for the interventions. Next, three combinations of interventions are tested, in which the three interventions are combined. These interventions are tested using DES and the results are described in Chapter 6.

Table 4.6. Summary of the interventions to find the best performing PAC

Inter-vention	Description	Number of screeners	Priority groups	Flexible slots contributed by priority group i (F_i)	Allocated slots for priority group i (A_i)
1	+ 1 screener	8	Figure 4.6a	100%	0%
2a	Allocation (flexibility = 1)	8	Figure 4.6a	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2b	Allocation (flexibility = 0.55)	8	Figure 4.6a	$\left\lfloor \frac{C_i * 0.55 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2c	Allocation (flex restriction)	8	Figure 4.6a	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$ and flex restriction	$C_i - F_i$
2e	Allocation (5 groups)	8	Figure 4.6b	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2f	Allocation (5 groups)	8	Figure 4.6c	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2g	Allocation (5 groups)	8	Figure 4.6d	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$

3	Offline planning approach	7	Figure 4.6a	100%	0%
2a & 3	Combination intervention 2 & 3	8	Figure 4.6a	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2g & 3 – 8 screeners	Combination intervention 2 & 3	8	Figure 4.6d	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2g & 3 – 7 screeners	Combination intervention 2 & 3	7	Figure 4.6d	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$

4.6 Conclusion

Chapter 4 discussed the conceptual model of the DES. The DES is modelled in seven steps. First, the current waiting list and blueprint schedule are loaded, then surgeries are requested and the waiting list is complemented by giving the requests patient characteristics. Next, the PAC target date, expected surgery date and calling date are determined. When the patient calls for an appointment, the appointment is scheduled and in the end, the performances of the PAC are gathered.

Chapter 4 also discussed the model assumptions, simulation settings, verification and validation. Model assumptions are made regarding patient preferences, seasonal effects, screening capacity, no shows, cancellations, patient waiting time and the difference between PAC employees and anaesthetists. Next, using the MSER-5, the warmup period is determined for two experimental settings. The daily number of patients overbooked is used as KPI. It turned out that the warmup period equals four batches, which equals four weeks. Then, the model is verified by writing and debugging the simulation computer program in small modules and by calculating the mean and variance of the simulation input and then compare these values with the desired mean and variance. And, the model is validated by discussing the model with stakeholders and employees and by comparing the model with real data. We concluded that the model was a good approximation of reality.

In the end, Chapter 4 explained three interventions. During intervention 1, the screening capacity is increased by one additional screener. During intervention 2, multiple versions of a blueprint schedule with allocated capacity that vary in the degree of flexibility and the number of priority groups are designed. The versions of the blueprint schedule are created using the capacity allocation method described in Section 4.5.2. During intervention 3, the offline planning approach is represented by scheduling patients with a priority of six weeks immediately and by scheduling patients with a priority "< 6 months" after two months of their surgery request. The DES is used to investigate the performances of eleven interventions.

5 Discrete event simulation: model inputs

Chapter 5 describes the model inputs for the DES, which are required to model the PAC correctly. As described in Chapter 4, the DES is modelled in seven steps. This chapter gives the model inputs, following the same seven steps. Section 5.1 starts with the data preparation of the current waiting list and gives the new blueprint schedule and PAC appointments. Then, Section 5.2 discusses the distributions to determine the daily number of surgery requests, followed by Section 5.3 which is about the distributions to model patient characteristics. Then, Section 5.4 gives the formulas to calculate the PAC target date and expected surgery date. Section 5.5 discusses the moment the patient calls, followed by Section 5.6 which is about the PAC planning process. Finally, Section 5.7 gives the performance indicators and this chapter ends with a conclusion.

5.1 Current waiting list and blueprint schedule

This section describes the data preparation of the current waiting list and the allocation of the newly designed blueprint schedule. The current waiting list and current PAC appointments are gathered on the 15th of November. The first part describes the data preparation of the current waiting list. The second part gives the newly designed blueprint schedule and in the third part, the way the PAC appointments are implemented in the new blueprint schedule is given.

Leaving out patients from the current waiting list

The current waiting list is gathered on the 15th of November and includes all patients that requested surgery in the past who did not have surgery yet. Some of these patients have an expected surgery date in the future. For example, if a patient requested surgery on the 12th of November with a priority of "< 2 weeks", the expected surgery date will be in the future, close to the 26th of November. However, there are also patients on the waiting list with a request date in 2018. For patients with an expected surgery date in the past, thus before the 15th of November, we assume that they do not want to have surgery in the near future. For patients with a surgery request in the past but an expected surgery date in the future, we assume that these patients will have surgery in the near future. Some of these patients have a PAC appointment already, while others still need to make a PAC appointment. Patients with a PAC appointment, are left out because these patients are not scheduled by the model. The patients that still need a PAC appointment will stay on the waiting list and a PAC appointment will be arranged by the model. Table 5.1 shows these assumptions. In this way, the surgery waiting list best represents the patients who are waiting for a PAC appointment and surgery.

Table 5.1 Assumptions regarding the current waiting list

	Request date	**Expected surgery date**	**Assumption**
1	Past *Before 2021-11-15*	Past *Before 2021-11-15*	The patient does not want to have surgery in the near future
2	Past *Before 2021-11-15*	Future *After 2021-11-15*	Patients that still need a PAC appointment stay on the waiting list

Complementation of the missing data in the current waiting list

As described in Chapter 4, patients get assigned multiple characteristics, which are specialty, day treatment, priority, type of patient, and routing. The patient characteristics type of patient, priority and routing are missing for some patients in the current waiting list and need to be complemented.

The distribution used to determine the type of patient for the daily surgery requests cannot be used to generate the type of patient for patients on the waiting list since these types differ. For example, no emergency and inpatient patients are on the waiting list, since these patients are screened immediately. Therefore, we use a new distribution to determine the type of patient. The following decisions are taken into account: if the patient has a day treatment, this patient is always a type 1 patient. Else, if the patient does not have a day treatment, the patient can be a type 1 or type 2 patient. Whether this patient is a type 1 or type 2 patient is based on the patient specialty. This distribution is given in Appendix D1.

The priority distribution of the daily surgery requests differs from the priority distribution of the patients on the waiting list as well. For example, the number of patients with a priority of "< 72 hours" is minimal on the waiting list, while daily, around 20% of the patients receive this priority. Because these high priority patients are immediately screened and operated, these patient priorities hardly occur on the waiting list. Only 69 of the 1,366 patients on the waiting list (5%) had no priority indication. For these patients, we assumed that they have the lowest priority of "< 6 months".

The patient characteristic routing depends on the type of patient and patient specialty. We assume that the routing of patients does not differ for patients on the waiting list compared to the daily surgery requests. Since the waiting list is now complete for these patient characteristics, Routing is based on the same distribution as the daily surgery requests. This is further explained in Section 5.3.

Allocation of the newly designed blueprint schedule
During intervention 2, new blueprint schedules are designed and depend on the intervention. Table 5.2 gives the number of allocated slots per priority group and the total number of flexible appointment slots of intervention 2a, in which capacity is allocated to eight priority groups, screening capacity equals eight and a flexibility of 1 is used. The other allocations are given in Appendix D2.

Table 5.2. Example of the allocation of the appointment slots during intervention 2a

Appointment slot	Number of appointment slots
< 72 hours	13
< 1 week	4
< 10 days	1
< 2 weeks	2
< 3 weeks	4
< 4 weeks	5
< 6 weeks	7
< 6 months	26
Flexible slots	35
Type 2 slots	15
Total	**112**

Data preparation of the current PAC appointments
The current PAC appointments are gathered on the 15th of November and include all patients that have a PAC appointment scheduled in the upcoming six months. How the PAC appointments are translated to the PAC schedule depends on the intervention. During interventions 1 and 3, the PAC schedule is the same as in the current situation. Therefore, the date and time of the PAC appointments can be easily translated to the PAC schedule. During intervention 2, dates and times changed in the PAC blueprint schedule. The PAC blueprint schedule has appointment slots of 30 minutes instead of appointment slots of 20 minutes. Since the time of the appointment does not impact the performance of the PAC, the appointment is placed in an arbitrary appointment slot on the day of the appointment.

5.2 Patient arrival

Patients arriving in the PAC request surgery in one of the outpatient clinics in the hospital. Therefore, patient arrival data was obtained from the OR planning department in the St. Antonius Hospital. Three datasets were created:

- Surgery requests during weekend days. Surgery requests between January 2019 and February 2021 were included, except for the first Dutch lockdown period (March, April and May 2020).
- Surgery requests during weekdays, before COVID-19. Surgery requests between January 2019 and February 2020 were included.
- Surgery requests during weekdays, during COVID-19. Surgery requests between June 2020 and February 2021 were included.

Arrival process during weekend days

The mean daily number of surgery requests during weekend days is 12.6, with a standard deviation of 3.6. Since a Poisson distribution is often used to represent arrival data (Law, 2015), we fit a Poisson distribution to the number of surgery requests with $\lambda = 12.6$. Figure 5.1 shows the probability density function of the data and the fitted Poisson distribution. We use a Pearson's Chi-Squared test with 25 degrees of freedom and $\alpha = 0.05$ to find out whether the Poisson distribution fits the data. The Chi-Squared test shows that the Poisson distribution does not significantly differ from the historical data ($p = 0.74$). Therefore, we use the Poisson distribution to generate the number of surgery requests during a weekend day.

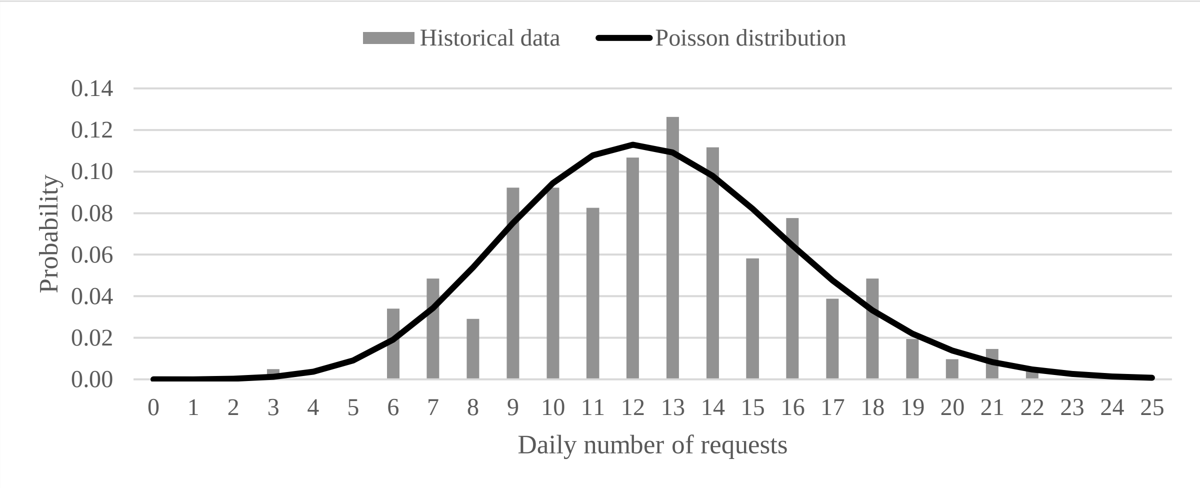


Figure 5.1. Empirical (grey) and theoretical (black) distribution of the daily number of surgery requests during a weekend day (n=206 days; January 2019 – February 2020 & June 2020 – April 2021; St. Antonius Hospital)

Arrival process during weekdays before COVID-19

The mean daily number of surgery requests during weekdays before COVID-19 is 121.9, with a standard deviation of 19.3. We fit a Poisson distribution to the number of surgery requests with $\lambda = 121.9$. Figure 5.2 shows the probability density function of the data and the fitted Poisson distribution. We use a Pearson's Chi-Squared test with 99 degrees of freedom and $\alpha = 0.05$ to find out whether the Poisson distribution fits the data. The Chi-Square test shows that the Poisson distribution significantly differs from the historical data ($p = 0.000$). Concluding, we are not able to use a Poisson distribution, thus the empirical distribution is used to represent the arrival process during weekdays before COVID-19.

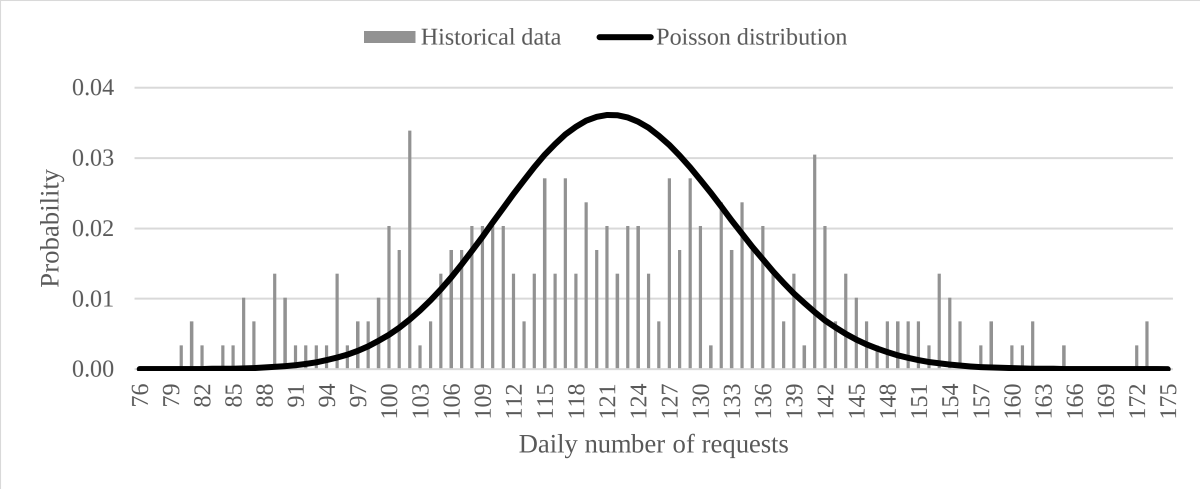


Figure 5.2. Empirical (grey) and theoretical (black) distribution of the daily number of surgery requests during a weekday before COVID-19 (n=295 days; January 2019 – February 2020; St. Antonius Hospital)

Arrival process during weekdays during COVID-19

The mean daily number of surgery requests during weekdays during COVID-19 is 88.5, with a standard deviation of 14.7. We fit a Poisson distribution to the number of surgery requests with $\lambda = 88.5$ Figure 5.3 shows the probability density function of the data and the fitted Poisson distribution. We use a Pearson's Chi-Squared test with 85 degrees of freedom and $\alpha = 0.05$ to find out whether the Poisson distribution fits the data. The Chi-Square test shows that the Poisson distribution significantly differs from the historical data ($p = 0.000$). Concluding, we are not able to use a Poisson distribution, thus the empirical distribution is used to represent the arrival process during weekdays during COVID-19.

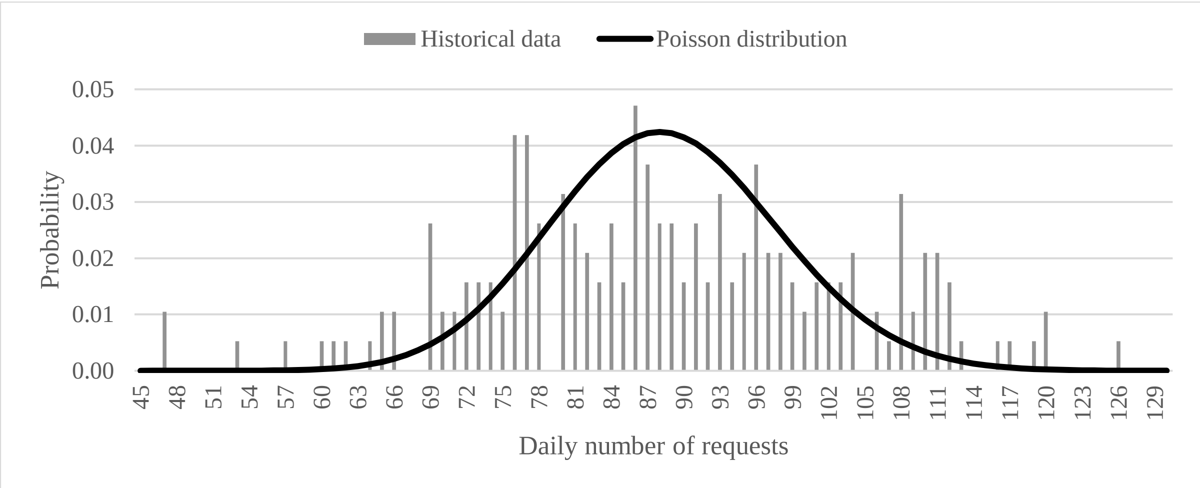


Figure 5.3. Empirical (grey) and theoretical (black) distribution of the daily number of surgery requests during a weekday during COVID-19 (n=191 days; June 2020 – April 2021; St. Antonius Hospital)

To determine the number of surgery requests on a day, a random value is drawn from the distributions described in this section. Every surgery request represents a patient that should visit the PAC. Therefore, each patient receives a unique patientID. In the next section, the patients receive more patient characteristics.

5.3 Patient characteristics

In the third step of the DES, the model assigns patient characteristics to the generated surgery requests. Five patient characteristics are assigned, which are specialty, day treatment, priority, type of patient and routing. Some patient characteristics are dependent and the relations between the patient characteristics are obtained through interviews. Figure 5.4 shows the relations between the patient characteristics.

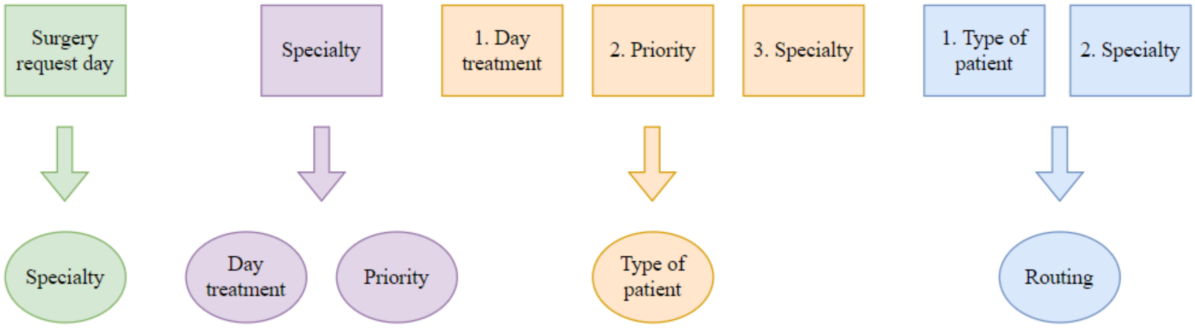


Figure 5.4. Patient characteristics and their relations. The top row represents the variables that serve as an input to determine the patient characteristic in the bottom row.

First, the model assigns the patient a specialty. The probability that the patient will have a certain specialty depends on the surgery request day. For example, during weekend days the chance is high that a patient has the specialty general surgery or trauma surgery, whereas during weekdays the patient has a high chance to request surgery in the ENT outpatient department. Therefore, Appendix D3 gives the distribution of specialties per day in the week.

Then, the model determines whether the patient will have a day treatment and at the same time, the priority of the patient is set. These patient characteristics have a strong relationship and depend on the patient specialty. The data lacks some patient priorities. For these patients, we assumed that the time between the surgery request and the surgery equals the priority of the patient. For example, when the time between the surgery request and the surgery is 3.5 weeks, we assume that the patient had the priority "< 4 weeks". An exception holds for the patients who had a waiting time of more than two months. For these patients, we concluded that it was not possible to assume the priority of the patient, because the length of the waiting list highly affects this waiting time. These patients are therefore gathered in the priority group "< 6 months". Thus, the priority group "< 6 months" represents the low priority patients. The patient characteristic day treatment includes patients who have a day treatment or fast-track. Appendix D4 gives the distribution of day treatment and priority, per specialty.

Third, day treatment, priority and specialty are used to determine the type of patient, which indicates what kind of appointment the patient needs in the PAC. Figure 5.5 shows a flowchart of this process. Patients who have a day treatment are always type 1 patients, see Distribution 3A in Appendix D5. Therefore, when a patient has a day treatment, priority and specialty do not play a role and the patient is indicated as a type 1 patient. Moreover, priority and type of patient have a strong relationship as well. When the patient has the priority "< 72 hours", the patient is always an inpatient patient or an emergency patient, see Distribution 3B in Appendix D5. When the patient has no day treatment and no priority "< 72 hours" the patient specialty determines whether the patient is type 1, type 2 or an emergency, inpatient or AGE patient, see Distribution 3C in Appendix D5.

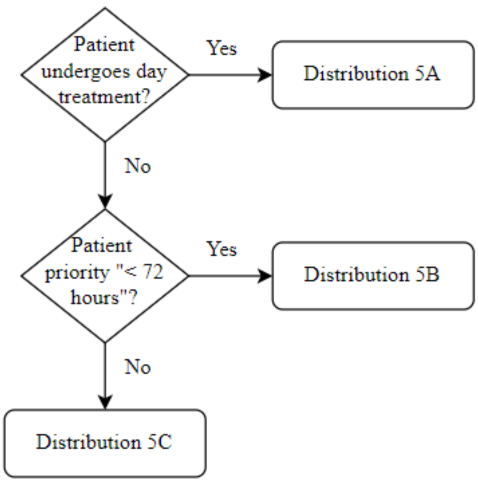


Figure 5.5. Flowchart to choose the distribution to determine type of patient

Finally, the model determines the routing of the patient. Routing depends on the characteristic type of patient. When a patient is an emergency, inpatient, AGE or a type 2 patient, Distribution 6A in Appendix D6 is used to determine the routing. When a patient is a type 1 patient, the routing depends on the patient specialty. Distribution 6B in Appendix D6 gives the distribution of routing based on specialty. Using the distributions described in this section, the patients receive the patient characteristics specialty, day treatment, priority, type of patient and routing.

5.4 PAC target date and expected surgery date

To finish the patient characteristics in the waiting list, the PAC target date and expected surgery date are calculated. These dates depend on the surgery request date and the patient priority. The PAC target date equals the surgery request date plus the access time criteria. Equation 5.1 shows this formula. Table 5.3 gives the access time criteria per priority group, which was already explained in Chapter 2 and Chapter 4.

$$\text{PAC target date} = \text{Request date} + \text{access time criteria} \qquad \text{Equation 5.1}$$

With the patient characteristic priority, we can calculate the number of days till surgery will take place. This number indicates how many days are between the surgery request date and the expected surgery date. Table 5.3 shows the surgery in days for each priority group. The surgery in days is equal to the maximum number of days that is acceptable for the most demanding group within the priority group. For example, in the current situation, patients are divided into eight priority groups. The first priority group consists of patients with a priority "< 24 hours", "< 48 hours", "< 72 hours", as described in Section 4.5.2. This priority group is called "< 72 hours" since all these patients need to have surgery within 72 hours. The most demanding group within this priority group is the group with priority "< 24 hours". Therefore, the surgery (in days) for this priority group equals one, because these patients should have surgery one day after the request date, at the latest. The expected surgery date equals the request date plus the surgery in days. The corresponding formula is given in Equation 5.2.

$$\text{Expected surgery date} = \text{Request date} + \text{surgery day} \qquad \text{Equation 5.2}$$

Table 5.3. Access time criteria and surgery days for the eight priority groups

Priority group	**Access time criteria (days)**	**Surgery (days)**
< 72 hours	0	1
< 1 week	2	7
< 10 days	5	10
< 2 weeks	7	14
< 3 weeks	10	21
< 4 weeks	14	28
< 6 weeks	21	42
< 6 months	91	182

In the end, the target appointment date and expected surgery date are analysed. These dates might be during weekend days, which is not possible as described in Chapter 2. When the model results in weekend days for regular patients, the target appointment and expected surgery dates are adapted. When the target appointment date is on Saturday or Sunday, this date is brought forward, to Friday. When the expected surgery date is Saturday or Sunday, this date is brought to the following Monday.

5.5 Patient calls for an appointment

In step five of the DES, the patient calls for an appointment on time or forgets to call. Unfortunately, no data is available about the moment the patient calls for an appointment. Because of the current COVID-19 situation with scaled-down OR capacity, the process is disrupted and it is not possible to gather the missing data in practice. Therefore, the current waiting list is used to determine whether a patient calls for an appointment or forgets to call.

Together with the management of the PAC, the latest calling day is determined. This latest calling day indicates how many days after the request day the patient has the opportunity to call. When the patient did not call before this latest calling day, we assume that the patient forgets to call or that the patient does not want to have surgery in the (near) future anymore. For patients with priority "< 4 weeks", "< 6 weeks" and "< 6 months", the latest calling day equals 14 days. In other words, when the patient did not call within two weeks, this patient forgot to call or did not want to have surgery in the (near) future anymore. For patients with a higher priority, the latest calling day equals the target day. For patients with a priority "< 72 hours", we assume that the PAC planners are in control of scheduling an appointment. Table 5.4 shows this latest calling day per priority group.

Table 5.4 also shows the percentage of patients that forgot to call. We use the waiting list, which was gathered on the 15th of November. We determined the percentage of patients without a PAC appointment scheduled per priority group. Next, we assume that half of these patients do not want to have surgery in the (near) future and the other half forgot to call. Thus, the percentage of patients without a PAC appointment is divided by two to determine the percentage of patients that forgot to call.

As explained in Chapter 1, when patients forget to call, they are lost in the system and come into view when they are on top of the surgery waiting list. Therefore, we need to know how many days before surgery this patient comes into view since the PAC planners should arrange an appointment in the short term, before the expected surgery date. See Table 5.4 for the number of days that a patient comes into view before the expected surgery date. This number was based on interviews with PAC and OR planners. For example, for a patient who has surgery within two weeks, we assume that they come into view three days before the expected surgery date.

Table 5.4. Latest calling day, percentage of patients that forgot to call and days before surgery the patient comes into view when the patient forgets to call (n=3,984; 15th of November; St. Antonius Hospital)

Priority group	Latest calling day	Percentage of patients that forgot to call	Days before surgery patient comes into view	n
< 72 hours	0	0%	0	-
< 1 week	2	33%	3	42
< 10 days	5	25%	3	12
< 2 weeks	7	16%	3	41
< 3 weeks	10	9%	7	45
< 4 weeks	14	6%	7	136
< 6 weeks	14	10%	11	230
< 6 months	14	14%	11	3478

5.6 PAC planning process

During step six of the DES, patients are scheduled for a PAC appointment. In general, the current planning process is still applied during each intervention. Figure 5.6 shows a flowchart representing how the PAC planning process is modelled in the DES. Type 2 patients are scheduled on an appointment slot for type 2 patients by the outpatient clinic itself and are therefore not taken into account in Figure 5.6.

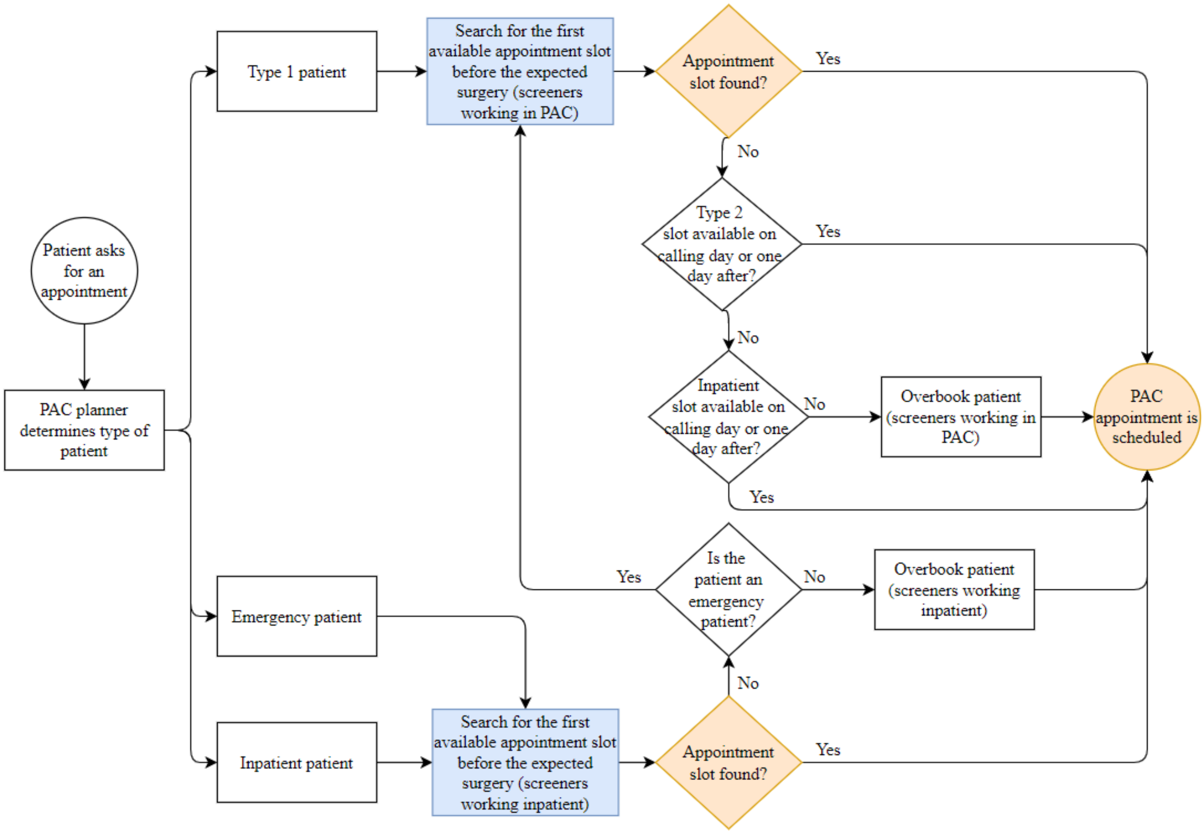
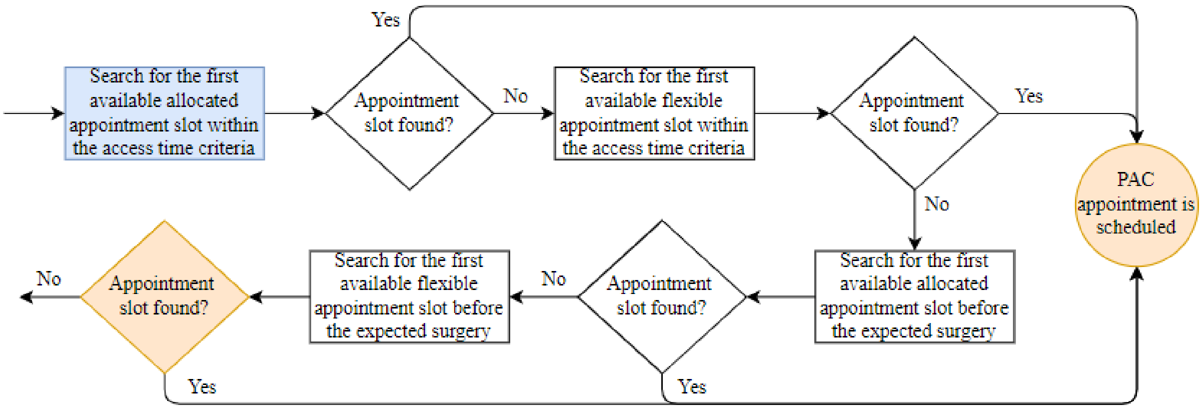
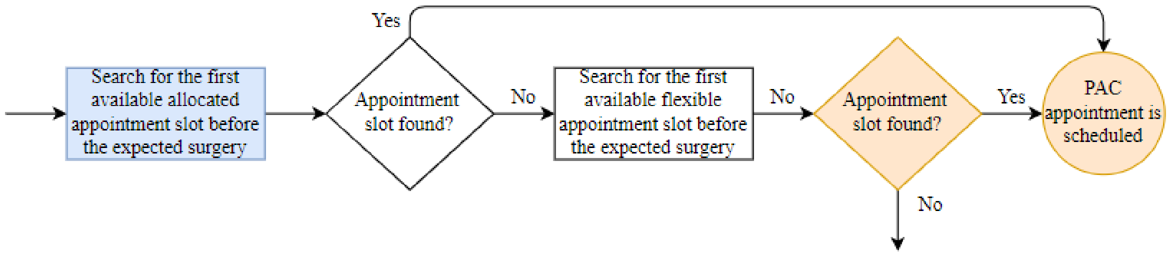


Figure 5.6. Flowchart of how the current PAC planning process is modelled in the DES, with in blue the start where the planning process changes for intervention 2 and in orange the moment intervention 2 follows the same planning process as interventions 1 and 3 again

The planning process as given in Figure 5.6 is followed during interventions 1 and 3. During intervention 2, in which capacity is allocated to multiple priority groups, the same principles hold, however, due to the allocated and flexible appointment slots, some of the auto planner scheduling decisions are extended. Figure 5.6 shows the start of the auto planner with blue and the end with orange. In between blue and orange, planning rules are added. Figure 5.7 shows the extended decision process, with the start in blue, the added planning rules in white and the end in orange. Figure 5.7a shows this process for the screeners working in the PAC and Figure 5.7b shows this process for the screeners working inpatient.



(a)



(b)

Figure 5.7. Flowchart of the extended planning process which is used during intervention 2. a) shows this extension when a PAC planner searches for an appointment slot in the PAC and b) shows this extension when a PAC planner searches for an appointment slot inpatient

5.7 Performance measurement

The final step in the DES is to determine the performance of the system. This step does not require model input, however, equations are used to calculate the KPIs. Therefore, this section explains the KPIs and the corresponding equations.

Percentage of patients screened within access time criteria

The access time is defined as the time between the surgery request and the PAC appointment. The first KPI is the percentage of patients that are screened within the access time criteria. Access time is often measured in days or weeks (Zonderland et al., 2021), in this study, the access time is measured in days. An access time of zero days means that the patient is screened on the day of the request, which is for example the case for walk-in patients or emergency patients. Patients should be screened within the access time criteria such that the surgery will not experience any delay or such that the assessment is up to date and the health status did not change in the meantime.

To calculate this percentage, the time between the surgery request date and the PAC appointment date is determined using Equation 5.3. Then, the number of patients per priority group is counted and the number of patients that are screened within the access time criteria is counted. In this way, the percentage of patients screened within the access time criteria can be calculated. Equation 5.4 shows the formula to calculate the percentage of patients that are screened within the access time.

$$\text{Access time} = \text{PAC appointment date} - \text{surgery request date} \qquad \text{Equation 5.3}$$

$$\text{Percentage of patients within access time criteria} = \frac{\#\text{ patients within access time criteria}}{\text{total }\#\text{ patients}} * 100\% \qquad \text{Equation 5.4}$$

Daily number of patients overbooked

An overbooking means that two patients are scheduled in one available appointment slot. The daily number of patients overbooked indicates to what extent the blueprint schedule matches the patient inflow and whether the patients are scheduled in the right order. A high number of patients overbooked implies that the blueprint schedule does not meet the capacity requirements or that the capacity is not correctly allocated to the multiple priority groups. Therefore, the daily number of patients overbooked should be minimized.

Utilization of screeners

The utilization of a resource indicates to what extent the resource is used. The utilization of a resource should not be maximized, because when the utilization approaches to be 100%, extreme growth of queue lengths and waiting times will arise (Griffiths, 1996). The utilization is calculated by the number of patients scheduled divided by the number of available time slots in the blueprint schedule. Equation 5.5 gives the formula to calculate the utilization.

$$\text{Utilization of screeners} = \frac{\text{\# patients scheduled}}{\text{\# available time slots}} * 100\% \qquad \text{Equation 5.5}$$

Variation in workload for nurses

The variation in workload during the week indicates how equally patients are distributed over the week. Every day, the number of nurses equals four, thus the number of patients treated should be approximately equal every day. The standard deviation of the number of patients treated during a week should therefore be minimized. Equation 5.6 gives the formula to calculate the standard deviation.

$\mathrm{n_d}$ = # patients scheduled for a nurse appointment on day d

$$\text{Standard deviation workload nurses} = \sqrt{\frac{\sum_{d=1}^{5}(n_d - \bar{n})^2}{4}} \qquad \text{Equation 5.6}$$

Variation in workload for screeners

The variation in workload during the week indicates how equally patients with a day treatment are distributed over the week. Because patients with a day treatment mostly require less consultation time, the number of these patients should be equal every day to ensure an equally distributed workload. The standard deviation of the number of patients with a day treatment during the week should therefore be minimized. Equation 5.7 gives the formula to calculate the standard deviation.

$\mathrm{a_d}$ = # patients with a day treatment scheduled on day d

$$\text{Standard deviation workload screeners} = \sqrt{\frac{\sum_{d=1}^{5}(a_d - \bar{a})^2}{4}} \qquad \text{Equation 5.7}$$

5.8 Conclusion

Chapter 5 discussed the model inputs of the DES, following the same seven steps as used in the conceptual model described in Section 4.1. First, assumptions are made regarding the patients on the current waiting list and distributions to complement the missing patient characteristics are given. An example of a newly designed blueprint schedule is given. Then, the patient arrival data during weekend days is represented using a Poisson distribution, and the patient arrival data during weekdays before and during COVID-19 are represented by the empirical distributions.

Patient characteristics turned out to be dependent. The patient specialty depends on the day the surgery is requested. Whether a patient will have a day treatment and the surgery priority of the patient depend on the patient specialty. Next, these patient characteristics are used to determine the type of patient. Moreover, the type of patient and patient specialty are used to determine the routing. Then, given the priority of the patient, formulas are discussed to calculate the access time criteria and expected surgery in days. Moreover, the percentage of patients that forget to call is given. During intervention 2, the planning decisions change and the new planning decisions are explained.

In the end, Chapter 5 explained the KPIs and the corresponding formulas. These are: (1) the percentage of patients screened within the access time criteria, (2) the daily number of patients overbooked, (3) utilization of screeners, (4) variation in workload for nurses and (5) variation in workload for screeners.

6 Results

Chapter 6 discusses the results of the interventions, which are tested using the DES discussed in Chapter 5. Table 6.1 gives a summary of the interventions. See Chapter 4 for an elaboration on the interventions. The remainder of this chapter is organized as follows. Section 6.1 describes the results of the interventions regarding the first KPI, which is the percentage of patients screened within the access time criteria. Then, Section 6.2 describes the results with respect to the daily number of patients overbooked. Additionally, Section 6.3 describes the results regarding the average utilization of the screeners. Section 6.4 discusses the results with respect to the variation in workload, for nurses as well as for screeners. Then, Section 6.5 discusses the results of the combined interventions, measured in the percentage of patients that meet the access time criteria, the daily number of patients overbooked, and the daily number of patients scheduled per screener. Section 6.6 gives the results of the sensitivity analyses, followed by Section 6.7 which describes the performance of the blueprint schedule in three future scenarios. Chapter 6 ends with a conclusion (Section 6.8).

Table 6.1. Interventions to find the best performing PAC

Inter-vention	Description	Number of screeners	Priority groups	Flexible slots contributed by priority group i (F_i)	Allocated slots for priority group i (A_i)
1	+ 1 screener	8	Figure 4.6a	100%	0%
2a	Allocation (flexibility = 1)	8	Figure 4.6a	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2b	Allocation (flexibility = 0.55)	8	Figure 4.6a	$\left\lfloor \frac{C_i * 0.55 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2c	Allocation (flex restriction)	8	Figure 4.6a	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$ and flex restriction	$C_i - F_i$
2e	Allocation (5 groups)	8	Figure 4.6b	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2f	Allocation (5 groups)	8	Figure 4.6c	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2g	Allocation (5 groups)	8	Figure 4.6d	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
3	Offline planning approach	7	Figure 4.6a	100%	0%
2a & 3	Combination intervention 2 & 3	8	Figure 4.6a	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2g & 3 – 8 screeners	Combination intervention 2 & 3	8	Figure 4.6d	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$
2g & 3 – 7 screeners	Combination intervention 2 & 3	7	Figure 4.6d	$\left\lfloor \frac{C_i * 1 * \sigma_i}{\mu_i} \right\rfloor$	$C_i - F_i$

6.1 Access time

The main goal of this study is to ensure that patients are screened within the access time criteria. The access time is defined as the time between the surgery request and the PAC appointment. Patients should be screened within the access time criteria such that there is enough time to do additional examinations when necessary and to give the OR planner time to schedule the patient for surgery.

Table 6.2 indicates the access time criteria per priority group. For example, patients in the priority group "< 10 days" have an access time criteria of five days which means that they should be screened on day five at least. All patients screened on day five or before day five, meet the access time criteria and are screened on time. An access time of zero days means that the patient is screened on the day of the request, which is for example the case for walk-in or emergency patients.

Table 6.2. Access time criteria per priority group

Priority group	Access time criteria (days)
< 72 hours	0
< 1 week	2
< 10 days	5
< 2 weeks	7
< 3 weeks	10
< 4 weeks	14
< 6 weeks	21
< 6 months	91

Figure 6.1 shows the percentage of patients that are screened within the access time criteria, for each intervention. We expect that during intervention 1, in which the screening capacity is increased by one additional screener, the percentage of patients screened within the access time criteria increases compared to the current situation. From Figure 6.1 we conclude that 68.9% of the patients are screened before the access time criteria, while in the current situation with seven screeners (baseline) only 60.4% of the patients are screened on time. This percentage differs significantly when compared using a Two-Sample t-Test, with $p = 0.00$. Thus, increasing the capacity by one additional screener significantly increases the percentage of patients screened within the access time criteria.

Next, intervention 2, in which the capacity is allocated to priority groups, is compared with intervention 1, since both use a capacity of eight screeners. We expect that the allocation of capacity to priority groups increases the percentage of patients screened within the access time criteria. It turns out that all experiments within intervention 2 result in a significant increase in the percentage of patients that are screened within the access time criteria ($p < 0.05$). During intervention 1, 68.9% of the patients are screened before the access time criteria, while during intervention 2 at least 76% of the patients are screened on time. Moreover, within intervention 2, we compare the best performing experiment with the numbers two, three and four, to see whether this best performing experiment is significantly better than the other experiments. From Figure 6.1 we conclude that intervention 2g is the best performing experiment, followed by intervention 2a, intervention 2b and intervention 2e. Intervention 2g did not show a significant difference with intervention 2a ($p = 0.06$). However, there is a significant difference between intervention 2b and intervention 2g ($p = 0.02$), and between intervention 2e and intervention 2g ($p = 0.00$). Appendix E1 gives the results of the statistical analyses. Thus, within intervention 2, intervention 2a and intervention 2g show the most promising results, with 82.2% and 84.1% of the patients screened within the access time criteria respectively.

We compare intervention 3, in which we test the offline planning approach, with the current blueprint schedule with seven screeners (baseline). We expect that intervention 3 results in an increase in the percentage of patients screened within the access time criteria because patients are scheduled in the right order. Intervention 3 results in 67.9% of the patients that are screened before the access time criteria, whereas the current blueprint schedule results in 60.4% of the patients screened on time. This difference is significant, with p = 0.00. Thus, the offline planning approach significantly increases the percentage of patients screened within the access time criteria.

We conclude that each intervention results in a significant increase in the percentage of patients that are screened within the access time criteria compared to the current blueprint schedule.

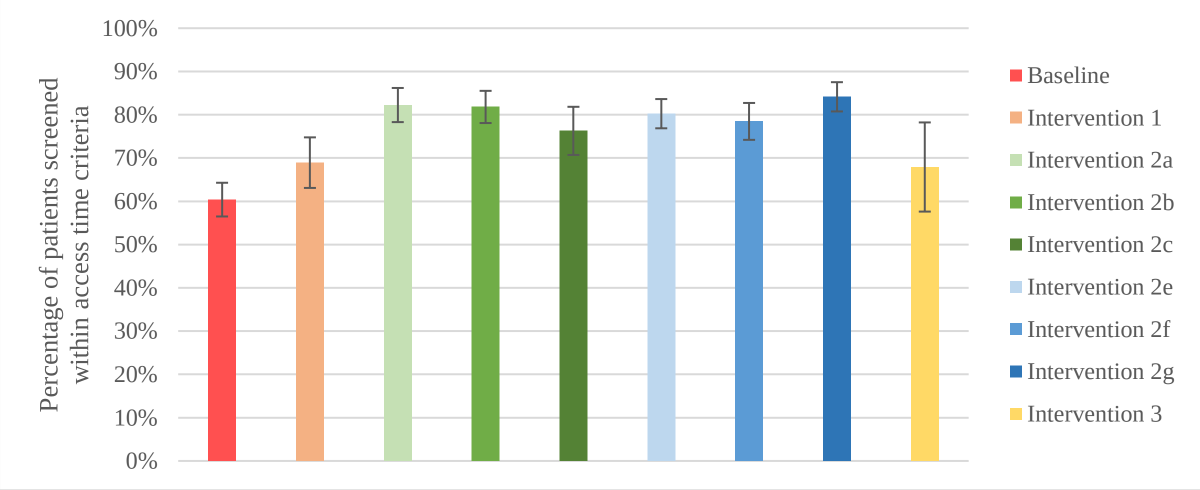
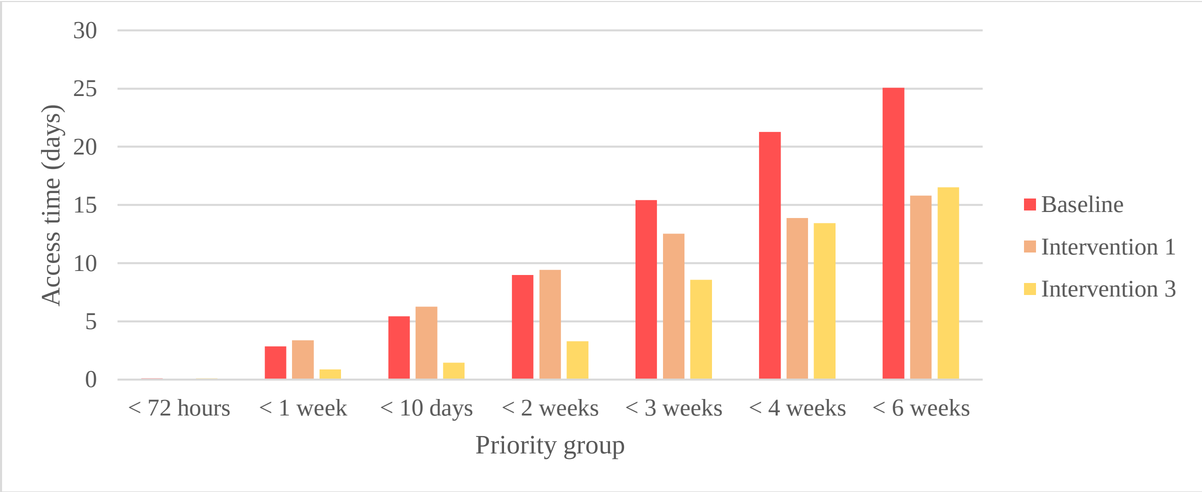


Figure 6.1. Results of the DES for the percentage of patients screened within the access time criteria. The error bar indicates the standard deviation

Access time in days per priority group

In this part, we investigate the access time per priority group, measured in days. Figure 6.2 shows the average access time in days, split across seven priority groups. Figure 6.2a shows the access time for the current blueprint schedule, intervention 1 and intervention 3. From Figure 6.2a we conclude that increasing the capacity by one additional screener (intervention 1) decreases the average access time of patients in the groups "< 72 hours", "< 3 weeks", "< 4 weeks" and "< 6 weeks". The reason why the average access time increases for the other priority groups is probably because the number of patients overbooked in these high priority groups decreases. The PAC planners find an available appointment slot for these patients, just before the expected surgery date, where in the current situation all appointment slots are already filled and the patient needs to be overbooked. Following the planning decisions, the patient is overbooked as early as possible. This declares the small increase in the average access time of high priority patients. Section 6.2 goes deeper into the percentage of patients per priority group that are overbooked. Next, the offline planning approach (intervention 3) improves the performances of the PAC with respect to the average access time in days for each priority group, see Figure 6.2a. Figure 6.2b shows the percentage of patients that are screened within the access time criteria for intervention 1 and for the experiments within intervention 2. We conclude that each experiment decreases the average access time compared with intervention 1, except for the patients in the priority group "< 6 weeks". Recall from Section 4.5.2 that the priority group "< 6 weeks" can only use the general flexible slots, whereas for the patients with a higher priority, flexible appointment slots are reserved. This declares the high access time of patients in the priority group "< 6 weeks".



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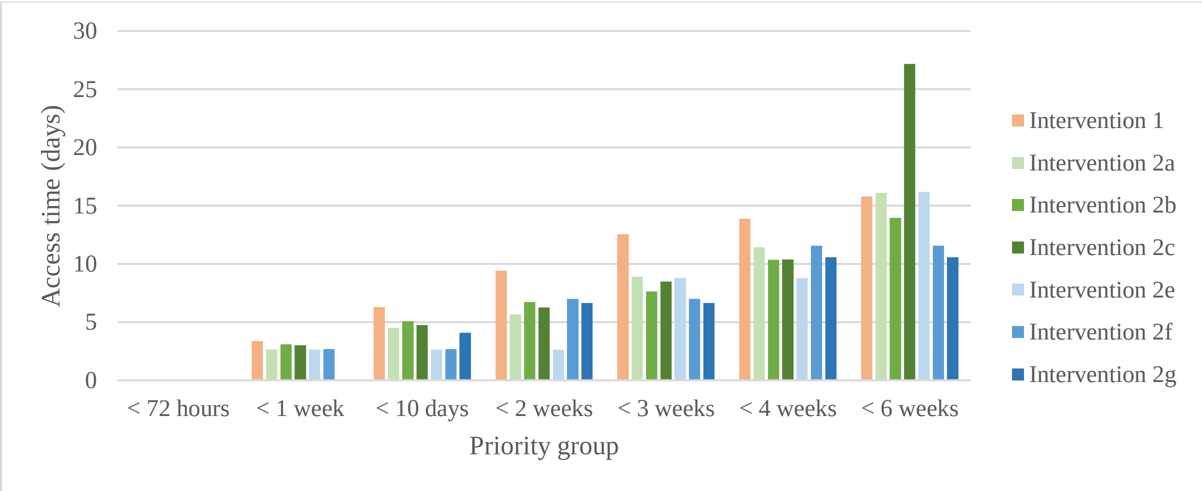


(b)

Figure 6.2. Results of the DES for the average access time in days, split across seven priority groups. a) shows the average access times for the current blueprint schedule, intervention 1 and intervention 3 and b) shows the average access times for intervention 1 and the experiments within intervention 2

6.2 Number of patients overbooked

The second KPI of this study is the daily number of patients overbooked. An overbooking means that two patients are scheduled in one available appointment slot. A high number of patients overbooked implies that the blueprint schedule does not meet the capacity requirements or that the capacity is not correctly allocated to the multiple priority groups.

Figure 6.3 shows the daily number of patients overbooked. We compare the new blueprint schedule, in which the screening capacity is increased by one additional screener (intervention 1), with the baseline. We expect that an increase in screening capacity results in a decrease in the number of patients overbooked. During intervention 1, on average 2.2 patients are overbooked daily, whereas, with the current blueprint schedule (baseline), 10.4 patients are overbooked daily. The increase in screening capacity by one additional screener results in a significant decrease in the daily number of patients overbooked ($p = 0.00$).

Next, intervention 2, in which the capacity is allocated to priority groups, is compared with intervention 1, since both use a capacity of eight screeners. We expect that the daily number of patients overbooked does not change since both use a capacity of eight screeners. During intervention 2, only intervention 2g results in a significant decrease in the daily number of patients overbooked ($p = 0.05$). During intervention 1, on average 2.2 patients are overbooked daily, whereas during intervention 2g only 1.4

patients are overbooked daily. Appendix E2 gives the results of the statistical analyses. Moreover, within intervention 2, we compare the best performing experiment with the numbers two, three and four, to see whether this best performing experiment is significantly better than the other experiments. From Figure 6.3 we conclude that intervention 2g is the best performing experiment, followed by intervention 2a, intervention 2c and intervention 2f. Between these experiments, no significant difference is found regarding the daily number of patients overbooked. However, allocating capacity to priority groups resulted in a significant decrease in the daily number of patients overbooked, compared with the current situation (baseline).

We compare intervention 3, in which the offline planning approach is tested, with the current blueprint schedule (baseline). We expect that the daily number of patients overbooked decreases because patients are scheduled in the right order and fewer patients need to be scheduled last minute. Intervention 3 results in a daily number of 3.6 patients overbooked, whereas the current blueprint schedule results in 10.4 patients overbooked daily. The offline planning approach significantly decreases the daily number of patients overbooked ($p = 0.00$).

Concluding, each intervention results in a decrease in the daily number of patients overbooked compared with the current blueprint schedule (baseline).

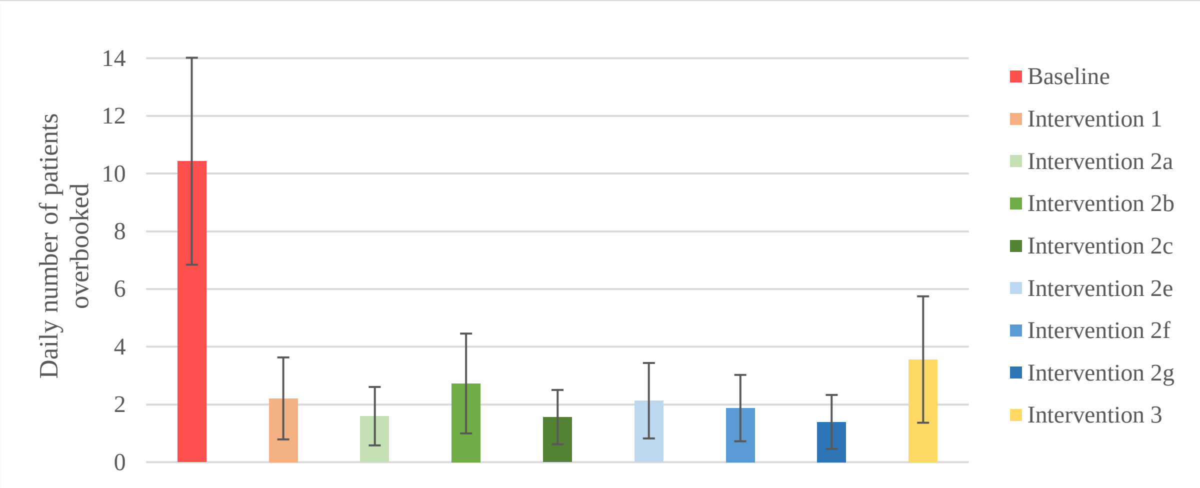
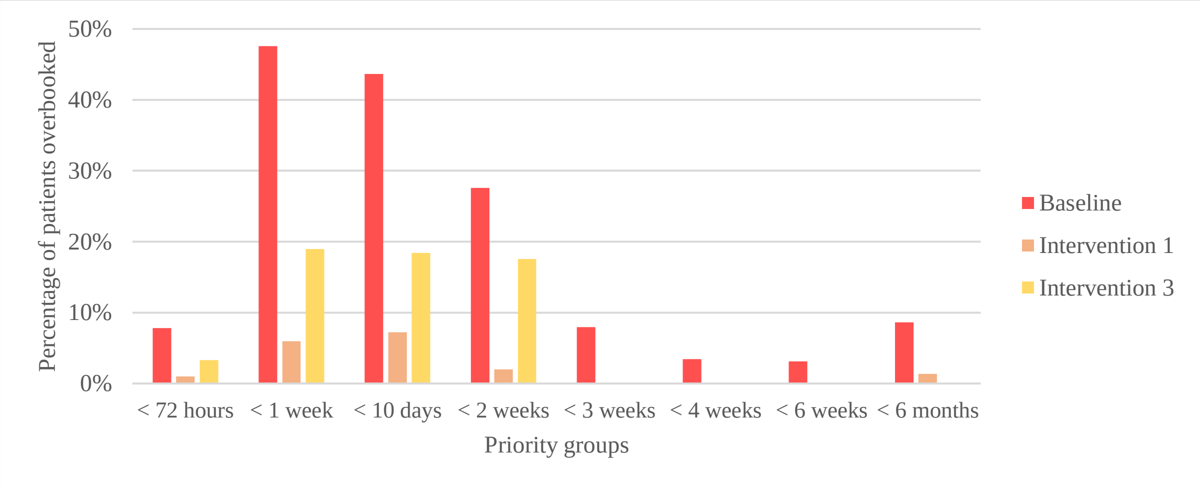


Figure 6.3. Results of the DES for the daily number of patients overbooked. The error bar indicates the standard deviation

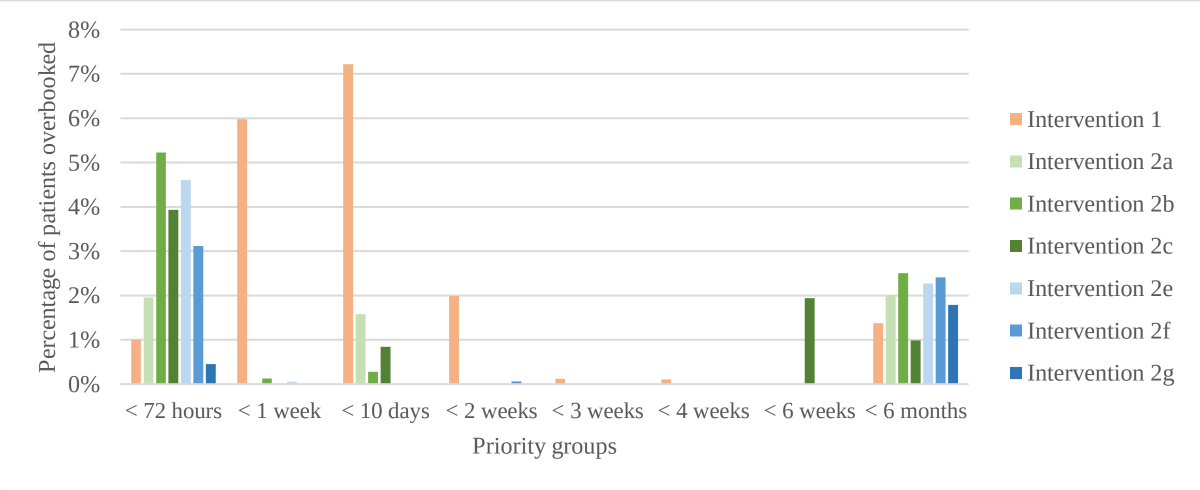
Patients overbooked per priority group

In this part, we investigate the percentage of patients that are overbooked per priority group. Figure 6.4 shows the percentage of patients that are overbooked, split across eight priority groups. Figure 6.4a shows this percentage for the current blueprint schedule, interventions 1 and 3. We expect that the percentage of patients that are overbooked decreases because the daily number of patients overbooked decreases as well, as shown in Figure 6.3. From Figure 6.4a we conclude that with the current blueprint schedule a high percentage of patients are overbooked. On average 50% of the patients with a priority "< 1 week" are currently overbooked. This declares the relatively high percentage of patients screened on time, as discussed in Section 6.1. Next, intervention 1, in which the screening capacity is increased by one additional screener, results in a decrease in the percentage of patients overbooked for each priority group. This also holds for intervention 3, which tests the offline planning approach.

Figure 6.4b shows the percentage of patients that are overbooked for intervention 1 and for the experiments within intervention 2. Note that the y-axis is differently scaled compared to Figure 6.4a. We expect that the percentage of patients that are overbooked is approximately the same for interventions 1 and 2 because the daily number of patients overbooked is also approximately the same, as shown in Figure 6.3. A small increase in the percentage of patients overbooked for the priority groups "< 72 hours" and "< 6 months" is visible for the experiments within intervention 2 compared to intervention 1. On the other hand, for the remaining priority patients, the percentage of patients that are overbooked decreases compared with intervention 1.



(a)



(b)

Figure 6.4. Results of the DES for the percentage of patients overbooked per priority group. a) shows the percentages for the current blueprint schedule, intervention 1 and intervention 3 and b) shows the percentages for intervention 1 and the experiments within intervention 2

6.3 Utilization

The third goal of this study is to decrease the utilization. The utilization is defined as the number of patients scheduled divided by the number of appointment slots in the blueprint schedule. The utilization of a resource should not be maximized, because when the utilization tends to 100%, extreme growth of queue lengths and waiting times will arise. Therefore, the aim is to have a utilization of approximately 85%. We expect that the utilization decreases during interventions 1 and 2 because both interventions use a capacity of eight screeners instead of seven. Figure 6.5 shows the utilization for each intervention. During intervention 1, in which the screening capacity is increased by one additional screener, the average utilization equals 89.0%. Using the current blueprint schedule (baseline) results in an average utilization of 99.8%. Thus, increasing the screening capacity by one additional screener decreases the utilization. Next, we compare intervention 2 with intervention 1, since both use a capacity of eight screeners. Intervention 2 tests multiple blueprint schedules with capacity allocated to priority groups. The average utilization during the experiments of intervention 2 is between 83.3% and 86.3%. During intervention 1, in which the capacity of the screeners equals eight as well, the utilization equals 89.0%. This difference is a consequence of the fact that the current blueprint schedule includes fewer appointment slots than the newly designed blueprint schedule. Consequently, the utilization differs. We compare intervention 3 with the current blueprint schedule, thus with the baseline. Intervention 3 results in an average screening utilization of 90.5%, whereas the current blueprint schedule results in a utilization of 99.8%. A possible explanation for this decrease is that in the current situation all patients are scheduled immediately when they call for an appointment and the patients from the waiting list should be scheduled as well. Intervention 3 uses the offline planning approach and thereby schedules the patients based on priority. Low priority patients are probably scheduled in future and in this way the utilization in the short term is lower. Concluding, each intervention results in a decrease in the average utilization of the screeners compared to the current situation.

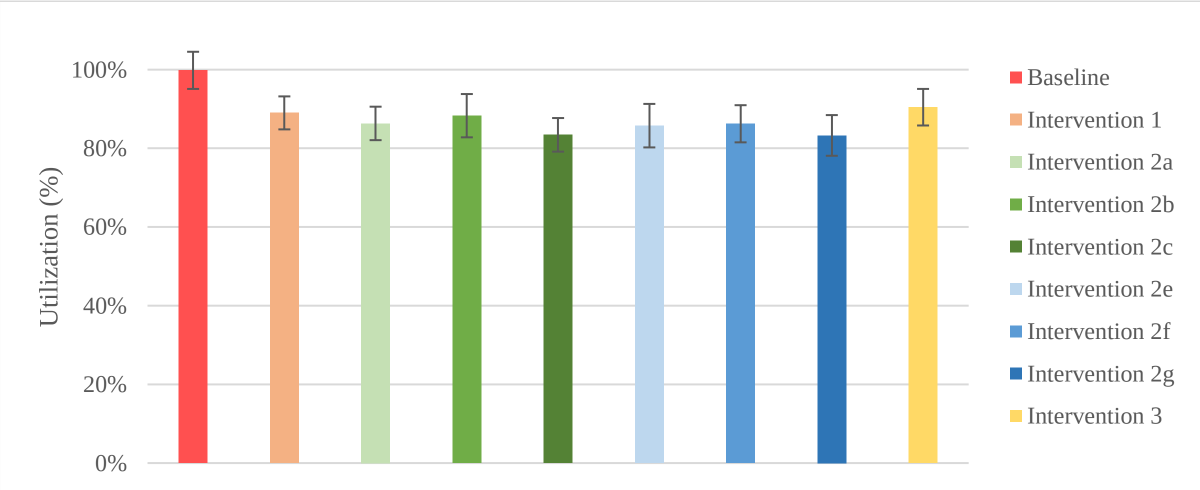


Figure 6.5. Results of the DES for the average utilization of the screeners. The error bar indicates the standard deviation

Since the utilization depends on the number of appointment slots in the blueprint schedule, we are also curious how many patients are scheduled per screener for each intervention. Recall from Section 2.4.3 that 13 patients per screeners equals a utilization of 87% and 15 patients equals a utilization of 100%. Thus, we assume a capacity of 13 appointment slots for regular patients and 2 appointment slots for overbookings. Figure 6.6 shows the daily number of patients scheduled per screener, with the black dotted line indicating the capacity of 13 patients.

In the current situation (baseline) and during intervention 3 a capacity of seven screeners is available. From Figure 6.6 we conclude that it is possible to have a capacity of seven screeners because during intervention 3 on average 12.5 patients are scheduled per screener daily. We note that in the current situation (baseline) the number of patients scheduled per screener is high compared to the offline planning approach with seven screeners (intervention 3), while the number of screeners and surgery requests are the same. A possible reason is that in the current situation the patients on the waiting list are scheduled while also new generated patients who call for an appointment are scheduled immediately. This makes that this intervention tries to schedule more patients in a short period. Intervention 3 uses the offline planning approach and thereby schedules the patients based on priority. Low priority patients are probably scheduled in future and in this way the patients are more equally distributed over time. This probably declares the difference in the average number of patients scheduled per screener.

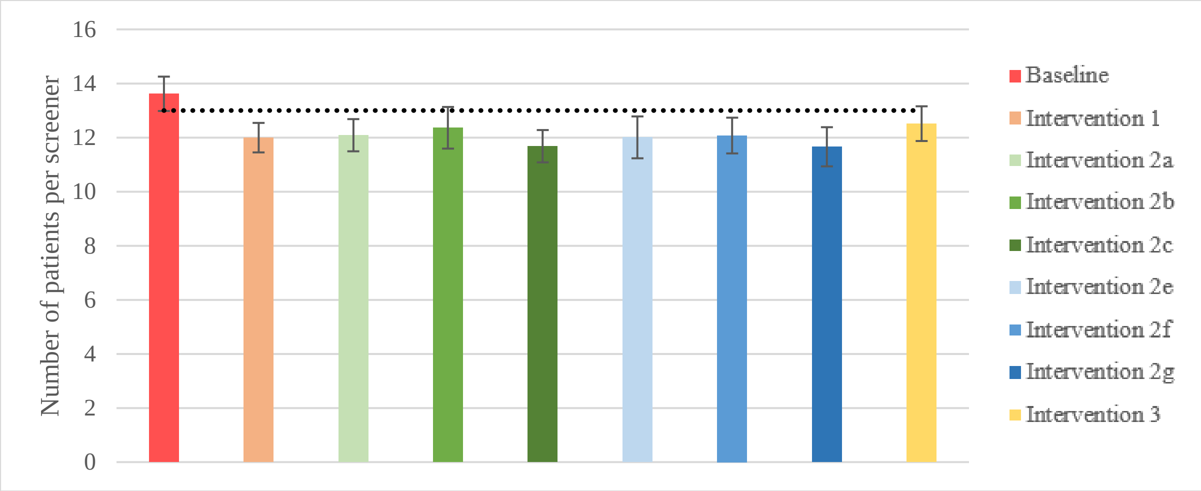


Figure 6.6. Results of the DES for the average number of patients scheduled per screener, with the black dotted line indicating the capacity of a screener. The error bar indicates the standard deviation

6.4 Variation in workload

The fourth KPI of this study is the variation in workload, for nurses as well as for screeners. For nurses, this variation is based on how equally the patients with a nurse appointment are distributed over the week. For screeners, the variation in workload depends on how equally the number of day treatments are distributed over the week. The variation in workload is expressed in the standard deviation of the number of nurse appointments during the week for nurses and the number of day treatments during the week for screeners. We expect that during intervention 1, in which the screening capacity is increased by one additional screener, the standard deviation decreases compared to the current situation. Because the capacity is higher, the blueprint schedule includes more flexibility such that variability can be managed. Moreover, recall from Section 2.4.2 that the high variation in workload is mainly a consequence of the unevenly distributed type 2 appointment slots over the week. Therefore, during intervention 2, in which blueprint schedule with allocated capacity is tested, we expect that the standard deviation decreases because in this intervention the type 2 slots are equally distributed over the week. And, during intervention 3, in which the offline planning approach is tested, we expect that the standard deviation decreases as well. The reason is that the patient mix is more equally distributed over the week when the mix is based on the surgery requests than when it is based on a combination of the surgery requests and calling behaviour of patients.

Figure 6.7 shows the standard deviation of the number of patients with a nurse appointment during the week. Figure 6.7 shows that during intervention 1 the standard deviation of the number of nurse appointments during the week equals 6.6, compared to 9.3 in the current situation (baseline). Increasing the screening capacity by one additional screener significantly decreases the standard deviation of the number of patients with a nurse appointment during the week ($p = 0.00$). Next, we compare intervention 2 with intervention 1, since both use a capacity of eight screeners. During intervention 2, no experiment significantly decreases the standard deviation of the number of patients with a nurse appointment ($p > 0.05$). The reason for this is that the number of type 2 appointment slots available in the schedule is larger than the number of type 2 patients that requests a PAC appointment. This makes that the newly designed blueprint schedule still depends on the distribution of the type 2 patients. Moreover, we compare intervention 3 with the current blueprint schedule (baseline). Intervention 3 results in a standard deviation of 6.3, whereas the current blueprint schedule results in a standard deviation of 9.3. The offline planning approach significantly decreases the standard deviation of the number of nurse appointments during the week ($p = 0.00$). Appendix E3 gives the results of the statistical analyses. To conclude, each intervention results in a decrease in the standard deviation of the number of nurse appointments during the week compared with the current blueprint schedule (baseline).

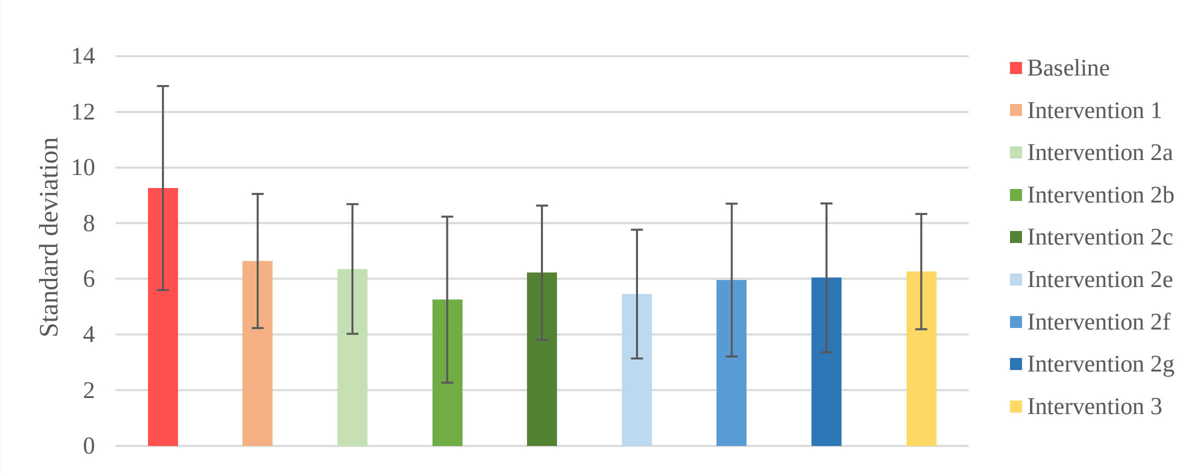


Figure 6.7. Results of the DES for the standard deviation of the number of patients with a nurse appointment during the week. The error bar indicates the standard deviation

Figure 6.8 shows the standard deviation of the number of patients with a day treatment during the week to represent the variation in workload for screeners. During intervention 1, in which the screening capacity is increased by one additional screener, the standard deviation equals 5.6. Using the current blueprint schedule (baseline) results in a standard deviation of 8.2. Increasing the screening capacity by one additional screener significantly decreases the standard deviation of the number of patients with a day treatment during the week ($p=0.00$). Next, we compare intervention 2 with intervention 1, since both use a capacity of eight screeners. During intervention 2, no experiment significantly decreases the standard deviation of the number of patients with a day treatment ($p > 0.05$). The reason for this is the same as in the previous part. The number of type 2 appointment slots available in the schedule is larger than the number of type 2 patients that requests a PAC appointment. This makes that the newly designed blueprint schedule still depends on the distribution of the type 2 patients. Moreover, we compare intervention 3 with the current blueprint schedule, thus with the baseline. Intervention 3 results in a standard deviation of 5.7, whereas the current blueprint schedule results in a standard deviation of 8.2. The offline planning approach significantly decreases the standard deviation of the number of patients with a day treatment during the week ($p = 0.00$). Appendix E4 gives the results of the statistical analyses.

Concluding, each intervention results in a decrease in the standard deviation of the number of nurse appointments during the week and results in a decrease in the standard deviation of the number of patients with a day treatment during the week, compared to the current situation.

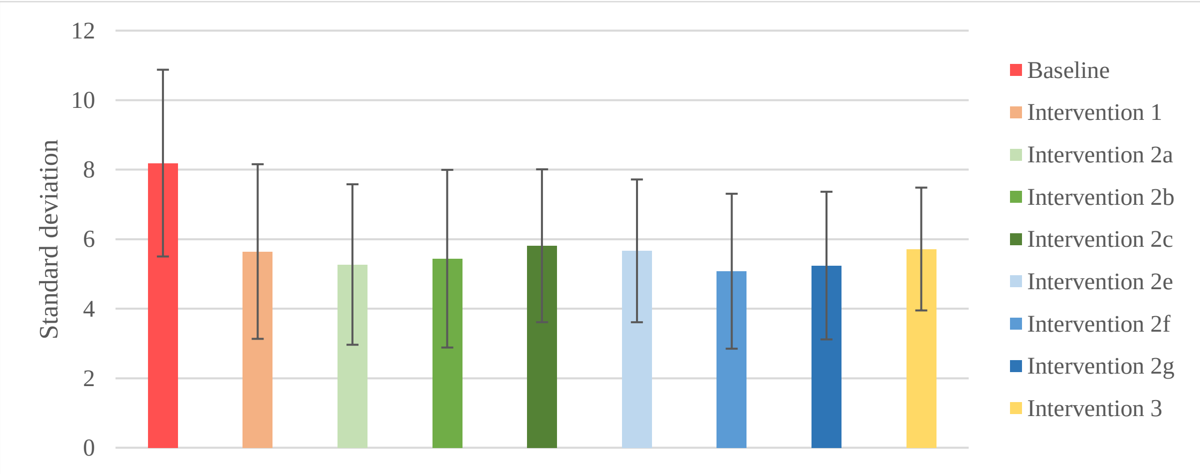


Figure 6.8. Results of the DES for the standard deviation of the number of patients with a day treatment during the week. The error bar indicates the standard deviation

6.5 Results combined interventions

This section discusses the results of the combined interventions. Section 6.5.1 first concludes the results of the individual interventions and defines the combinations of the interventions. Then, Section 6.5.2 presents the results of the combined interventions.

6.5.1 Summary results individual interventions

This section discusses the results of the individual interventions. Increasing the capacity from seven screeners to eight screeners (intervention 1) improves the performances of the PAC with respect to access time, overbookings, utilization and variation in workload for nurses and for screeners. However, the percentage of patients that are screened within the access time criteria decreases for the priority groups "< 1 week", "< 10 days" and "< 2 weeks". The main reason for this is that currently many of the patients in these priority groups are overbooked, which results in a relatively high percentage of patients screened within the access time criteria.

During intervention 2, a new blueprint schedule is created, in which the capacity of eight screeners is allocated to multiple priority groups. Within intervention 2, six experiments are performed. During intervention 2a, intervention 2b and intervention 2c, we varied the ratio of flexibility. During intervention 2e, intervention 2f and intervention 2g, we varied the composition of the priority groups. We compared the experiments with intervention 1 because both include a capacity of eight screeners. We conclude that allocating capacity improves the performance of the PAC with respect to access time. Intervention 2a and intervention 2g showed the most promising results. Only intervention 2g results in a significant decrease in the daily number of patients overbooked compared with intervention 1. No significant difference between intervention 2 and intervention 1 is found with respect to utilization and variation in workload for nurses and for screeners. Moreover, in the current COVID-19 situation, a capacity of eight screeners in combination with the blueprint schedule with allocated capacity results in idle time of the screeners.

The third intervention, in which the offline planning approach is tested, shows improvements regarding the performances of the PAC. This intervention significantly increases the percentage of patients that are screened within the access time criteria. Moreover, it significantly decreases the number of patients overbooked and the variation in workload for nurses and for screeners, and decreases the utilization.

To conclude, all three interventions improve the performances of the PAC. In the next section, we investigate whether the combination of intervention 2 (with seven or eight screeners) and intervention 3 results in improved performance compared with the individual interventions.

6.5.2 Results intervention 2 and intervention 3

This section presents the results of the best performing individual interventions and the combined interventions. The performances are represented using the following three KPIs: (1) percentage of patients screened within the access time criteria, (2) daily number of patients overbooked, and (3) daily number of patients scheduled per screener.

Figure 6.9 shows the percentage of patients that are screened within the access time criteria, for each intervention. The figure gives the results of the combined interventions in purple. We expect that the combination of interventions 2 and 3 increases the percentage of patients screened within the access time criteria. Intervention 2a, in which the screening capacity is allocated to eight priority groups with a capacity of eight screeners, resulted in 82.2% of the patients screened within the access time criteria. Intervention 3, which tested the offline planning approach using seven screeners, resulted in 67.9% of the patients screened on time. When these interventions are combined (intervention 2a & 3), the percentage of patients screened on time increases to 95.4%. We conclude that the combination of interventions 2a and 3 results in an increase in the percentage of patients screened within the access time criteria.

Next, we compare intervention 2g & 3 with their individual interventions. Intervention 2g, in which the screening capacity is allocated to five priority groups with a capacity of eight screeners, resulted in 84.1% of the patients screened within the access time criteria. Intervention 3, which tested the offline planning approach using seven screeners, resulted in 67.9% of the patients screened on time. When these interventions are combined (intervention 2g & 3 eight screeners), the percentage of patients screened on time increases to 95.2%. We are interested in what the results would be when a blueprint schedule with seven screeners is tested. Intervention 2g & 3 with a capacity of seven screeners results in 86.8% of the patients screened within the access time criteria. We conclude that the combination of interventions 2g and 3, with seven or eight screeners, result both in an increase in the percentage of patients screened within the access time criteria.

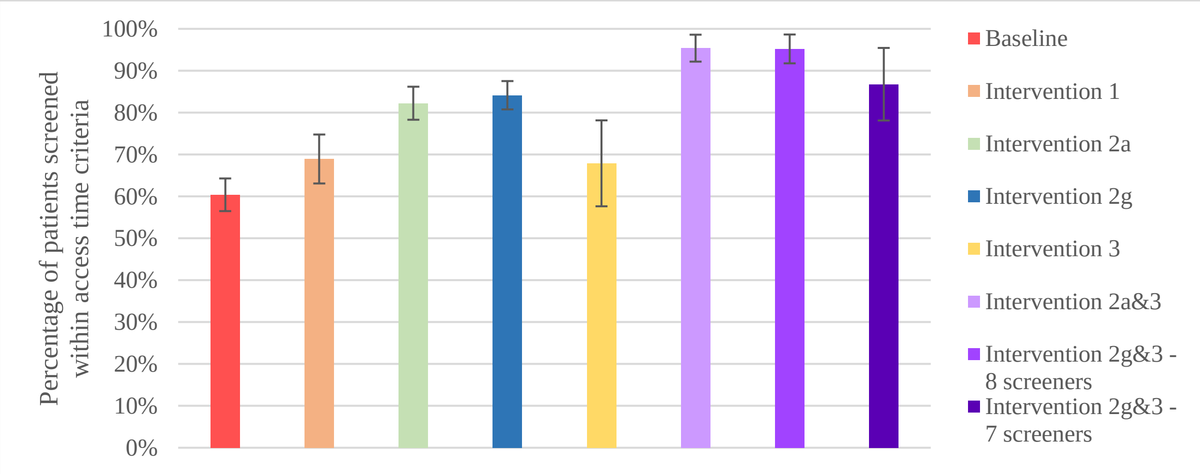


Figure 6.9. Results of the DES for the percentage of patients screened within the access time criteria. The error bar indicates the standard deviation

Figure 6.10 shows the daily number of patients overbooked. The figure gives the results of the combined interventions in purple. We expect that the combination of interventions 2 and 3 decreases the daily number of patients overbooked. Intervention 2a, in which the screening capacity is allocated to eight priority groups with a capacity of eight screeners, resulted in 1.6 patients overbooked daily. Intervention 3, which tested the offline planning approach using seven screeners, resulted in 3.6 patients overbooked daily. When these interventions are combined (intervention 2a & 3), this daily number of patients overbooked decreases to 0.4. Combining intervention 2a and 3 results in a decrease in the daily number of patients overbooked.

Next, we compare intervention 2g & 3 with their individual interventions. Intervention 2g, in which the screening capacity is allocated to five priority groups with a capacity of eight screeners, resulted in 1.4 patients overbooked daily. Intervention 3, which tested the offline planning approach using seven screeners, resulted in 3.6 patients overbooked daily. When these interventions are combined (intervention 2g & 3 eight screeners), this number decreases to 0.4. We are interested in what the results would be when a blueprint schedule with seven screeners is tested. Intervention 2g & 3 with a capacity of seven screeners results in 1.7 patients overbooked daily. We conclude that the combination of interventions 2g and 3 with eight screeners, results in a decrease in the daily number of patients overbooked.

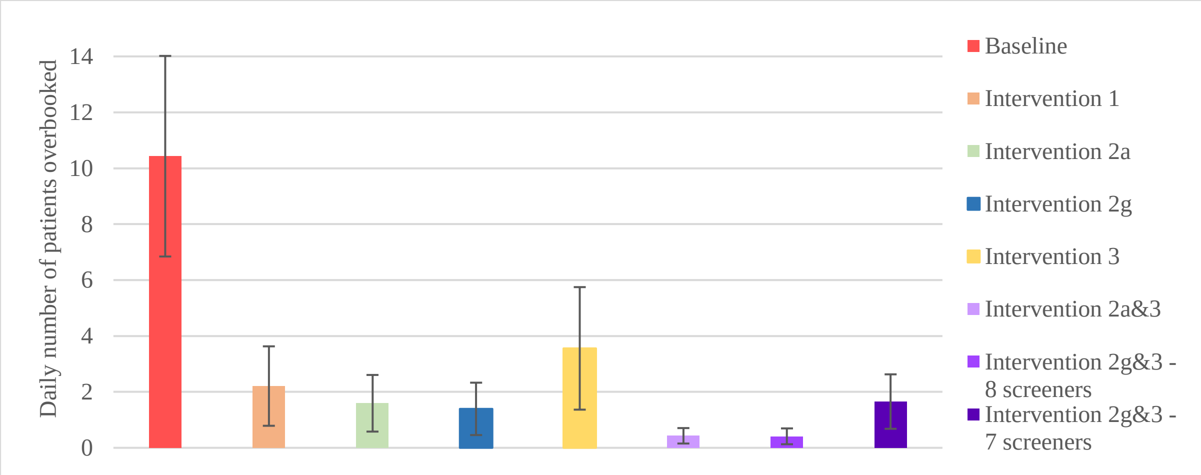


Figure 6.10. Results of the DES for the daily number of patients overbooked. The error bar indicates the standard deviation

Figure 6.11 shows the daily number of patients scheduled per screener. The figure gives the capacity of 13 patients per screener with the black dotted line and the results of the combined interventions in purple. We expect that a capacity of seven screeners is enough to screen patients on time. Intervention 2a, in which the screening capacity is allocated to eight priority groups with a capacity of eight screeners, resulted in on average 12.1 patients scheduled per screener daily. Intervention 3, which tested the offline planning approach using seven screeners, resulted in 12.5 patients scheduled per screener daily. When these interventions are combined (intervention 2a & 3), the number of patients scheduled per screener equals 11.1. We expected that the number of patients scheduled per screener would result in a small decrease compared to intervention 2a since the offline planning approach better distributes the patients over time.

Next, we compare intervention 2g & 3 with their individual interventions. Intervention 2g, in which the screening capacity is allocated to five priority groups with a capacity of eight screeners, resulted in on average 11.7 patients scheduled per screener daily. Intervention 3, which tested the offline planning approach using seven screeners, resulted in 12.5 patients scheduled per screener daily. When these interventions are combined (intervention 2g & 3 eight screeners), the number equals 11.0. We are interested in what the results would be when a blueprint schedule with seven screeners is tested. Intervention 2g & 3 with a capacity of seven screeners results in on average 12.7 patients scheduled per screener daily. Thus, combining intervention 2g and 3 with seven screeners is possible given the capacity of 13 patients per screeners.

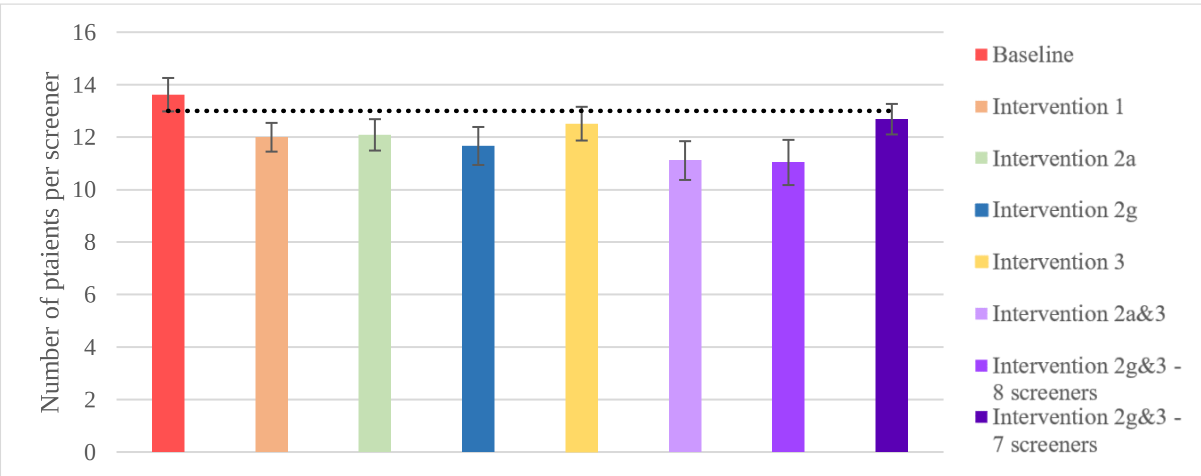


Figure 6.11. Results of the DES for the daily number of patients scheduled per screener, with the black dotted line indicating the capacity of a screener. The error bar indicates the standard deviation

Concluding, the combination of interventions 2 and 3 improves the performances of the PAC for the percentage of patients screened within the access time criteria and the daily number of patients overbooked, compared with their individual interventions and the current situation. Concerning the percentage of patients screened within the access time criteria and the daily number of patients overbooked, capacity allocation with a capacity of eight screeners shows the most promising results. Moreover, when investigating the number of patients scheduled per screener compared to the capacity of a screener, intervention 2g & 3 with seven screeners shows the most promising results.

6.6 Sensitivity analysis

A sensitivity analysis is used to find out which input factors affect the outcome of the model (Law, 2015). With this analysis, we are going to determine how sensitive the best performing intervention is for changes in the input parameters. From the previous section, we conclude that intervention 2g & 3 and intervention 2a & 3 with eight screeners performs best with respect to the access time and number of patients overbooked. And, intervention 2g & 3, with seven screeners, performs best regarding the number of patients scheduled per screener. Therefore, we choose intervention 2g & 3 with eight screeners instead of intervention 2a & 3 with eight screeners because the differences between eight and seven screeners can be better analysed, leaving all other variables the same. Thus, the blueprint schedule with allocated capacity to five priority groups, in combination with the offline planning approach and a capacity of seven or eight screeners are used in the sensitivity analyses.

The input parameters are grouped in three main categories: patient characteristics, the patient's calling behaviour and the maximum access times set by the hospital. The best performing interventions, as described above, include the offline planning approach, which means that these interventions are not sensitive to patient's calling behaviour. Therefore, we perform a sensitivity analysis for the other two categories. Section 6.5.1 describes the sensitivity analysis of a change in the percentage of high priority patients. Then, Section 6.5.2 describes the sensitivity analysis of a change in the access time criteria.

6.6.1 Percentage of high priority patients

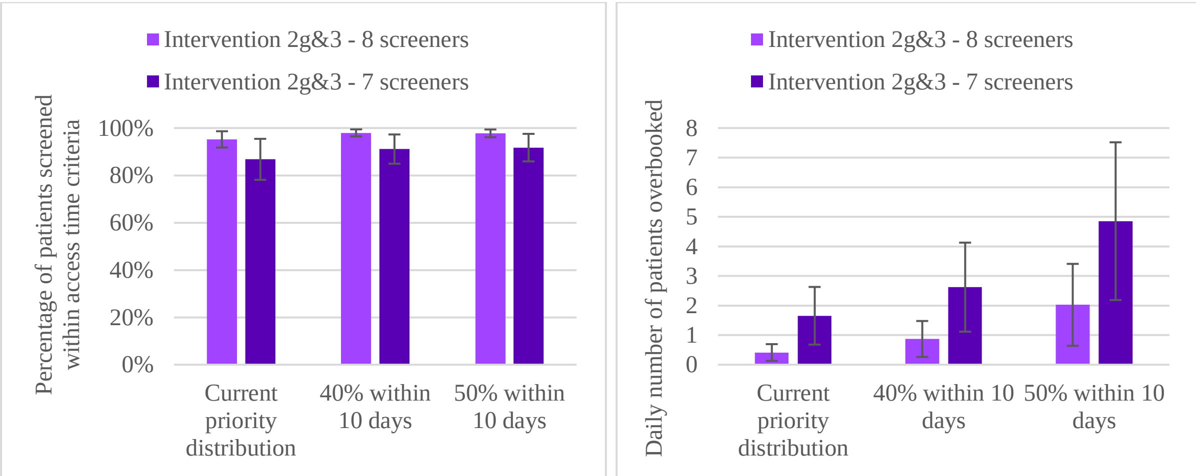
This sensitivity analysis investigates whether a change in the percentage of patients per priority group affects the performances of the already designed blueprint schedule. Thus, the blueprint schedule is not adapted. Adaptations to the blueprint schedule are tested in Section 6.7. The allocation of appointment slots in the blueprint schedule depends on the mean and standard deviation of the priority groups. Currently, around 30% of the patients have a priority of 10 days. Table 6.3 shows the current priority distribution, and two changes in patient characteristics leading to 40% of the patients with a priority of 10 days and 50% of the patients with a priority of 10 days.

Table 6.3. Percentage of patients per priority group for the current situation and two changes in input

Priority group	**Current priority distribution**	**40% of the patients with a priority of 10 days**	**50% of the patients with a priority of 10 days**
< 1 week	24.7%	34.4%	41.7%
< 10 days	3.2%	5.2%	6.3%
< 3 weeks	12.9%	13.3%	13.6%
< 6 weeks	22.0%	17.9%	14.3%
< 6 months	37.2%	29.2%	24.1%
Total	100%	100%	100%

Figure 6.12 shows the performances of the designed blueprint schedules regarding the percentage of patients that are screened within the access time criteria and the daily number of patients overbooked. We expect that the change in patient priorities does not affect the percentage of patients screened within the access time criteria because the main change is made to the patients in the priority group "< 1 week", and this group has the access time criterium that they should be screened on the day of the request. As expected, Figure 6.12a shows that the percentage of patients screened within the access time criteria did not change as a consequence of the change in patient characteristics. However, we expect that the

daily number of patients overbooked increases since the already designed blueprint schedule is not adapted to this change in patient priority. Figure 6.12b shows that the daily number of patients overbooked increases. Intervention 2g&3 with eight screeners results in an increase from 0.4 to 2 patients overbooked daily and intervention 2g&3 with seven screeners results in an increase from 1.7 to 4.9 patients overbooked daily. Thus, the blueprint schedule with seven screeners results in the main increase in the daily number of patients overbooked, which is as expected because this blueprint schedule has less flexibility than the blueprint schedule with eight screeners.



(a) (b)

Figure 6.12. Results of the DES for the performances of the already designed blueprint schedules for different percentages of high priority patients. a) shows the percentage of patients that meets the access time criteria and b) shows the daily number of patients overbooked. The error bar indicates the standard deviation

6.6.2 Access time criteria per priority group

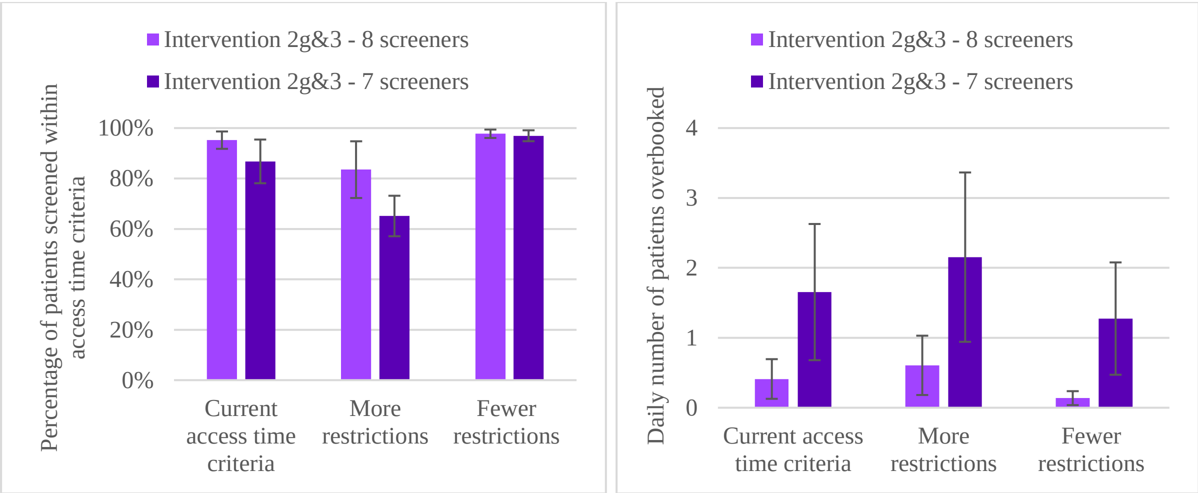
This sensitivity analysis investigates whether a change in the criteria affects the performances of the already designed blueprint schedule. The performances of the blueprint schedule depend on the access time criteria given by St. Antonius Hospital. Table 6.4 shows the access time criteria per priority group for the current situation. Next, the table gives a situation in which the criteria are more restricted and one in which the criteria are less restricted.

Table 6.4. Access time criteria in days per priority group for the current situation and two changes in criteria

Priority group	**Current access time criteria**	**More restrictions on access time**	**Fewer restrictions on access time**	**Surgery day (days)**
< 1 week	0	0	0	1
< 10 days	5	2	8	10
< 3 weeks	7	3	11	14
< 6 weeks	14	7	21	28
< 6 months	91	61	121	182

Figure 6.13 shows the performances of the designed blueprint schedules regarding the percentage of patients that are screened within the access time criteria and the daily number of patients overbooked. We expect that a change in access time criteria affects the percentage of patients screened within the access time criteria. We expect that more restrictions decrease the percentage of patients screened on time, whereas fewer restrictions increase the percentage of patients screened within the access time criteria. As expected, Figure 6.13a shows that the percentage of patients screened within the access time criteria decreases with more restrictions and increases with fewer restrictions. However, the results show that the average access time in days decreases as a consequence of the more restrictions on access time. This is as expected because the PAC planner tries to find an appointment within a smaller time window first. Next, we expect that the daily number of patients overbooked is sensitive for a change in the access time criteria because the planning decisions depend on these criteria. When the access time

criteria are more restrictive, patients are scheduled in the short term, which results in less flexibility in the short term. Figure 6.13b shows that the daily number of patients overbooked increases a little bit when the access time criteria are more restrictive.



(a) (b)

Figure 6.13. Results of the DES for the performances of the already designed blueprint schedules for different restrictions on the access time. a) shows the percentage of patients that meets the access time criteria and b) shows the daily number of patients overbooked. The error bar indicates the standard deviation

6.7 Future scenarios

The capacity allocation method is tested on two future scenarios to investigate whether the method will show promising results in future. During the analyses of the future scenarios, the blueprint schedule is adapted to a new possible future scenario and tested on its performances. From the previous sections, we conclude that the blueprint schedules with capacity allocated to five priority groups (intervention 2g) with seven or eight screeners performed best. Therefore, these blueprint schedules are adapted to a future scenario and tested using the DES.

Before we describe the results of the future scenarios, we discuss the future perspective of the already designed blueprint schedules. Section 6.7.1 discusses this future perspective. Then, a first possible future scenario is that the number of high priority patients will increases due to the delayed care as a result of COVID-19. Section 6.7.2 describes the results of the adapted blueprint schedule to this first future scenario. A second possible future scenario is that the number of surgery requests will increase after COVID-19 and that patients with a day treatment are screened online. Section 6.7.3 describes the results of the adapted blueprint schedule to this second future scenario.

6.7.1 Future perspective

This section describes the future perspective of the already designed blueprint schedule. This future perspective is based on the trend of the percentage of patients per priority group. We expect that if this trend shows a constant pattern, that the already designed blueprint schedule can be used without any adaptation in the near future. Figure 6.14 shows the percentage of patients per priority group, plotted against the time. Note that the time during the first Dutch COVID-19 lockdown is not included in this figure. From Figure 6.14, we conclude that the percentage of patients per priority group shows a constant pattern. A small reduction in the percentage of patients "< 6 months" and a small accession in the percentage of patients "< 72 hours" are visible in 2021. However, a possible reason for this is that the surgery requests in the data are the requests of the patients that already had surgery. The data was gathered in May 2021, thus probably all high priority patients from February 2021 are already operated, while some low priority patients are still on the waiting list and not visible in the data. This explains the pattern in the end, of which we do not expect that it will continue. Therefore, we expect that the already designed blueprint schedule fits the situation in the near future.

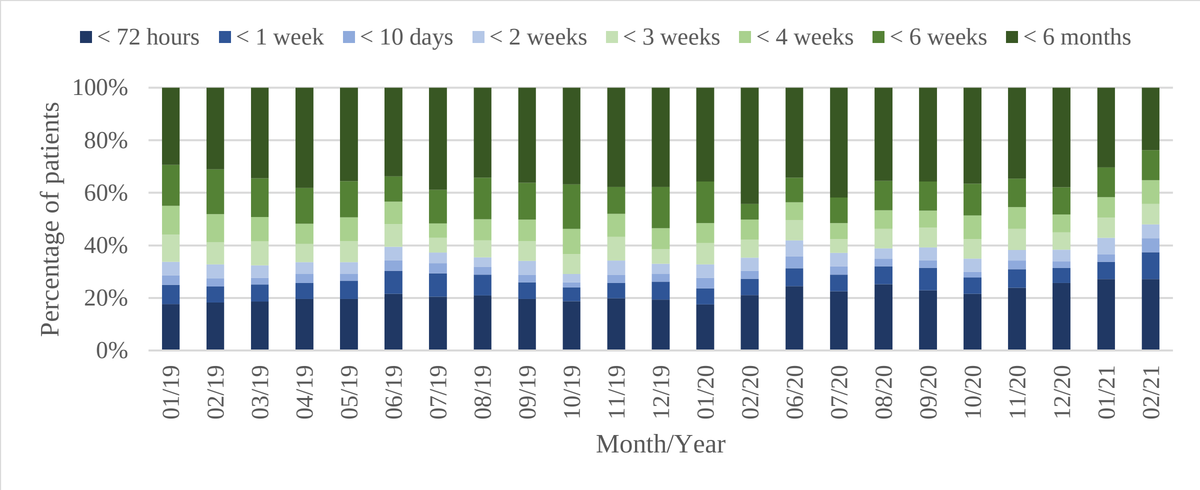


Figure 6.14. Distribution of the percentage of patients per priority group, plotted against the time (n=55,831; January 2019 – February 2020 & June 2020 – February 2021; St. Antonius Hospital)

6.7.2 Increase in the number of high priority patients

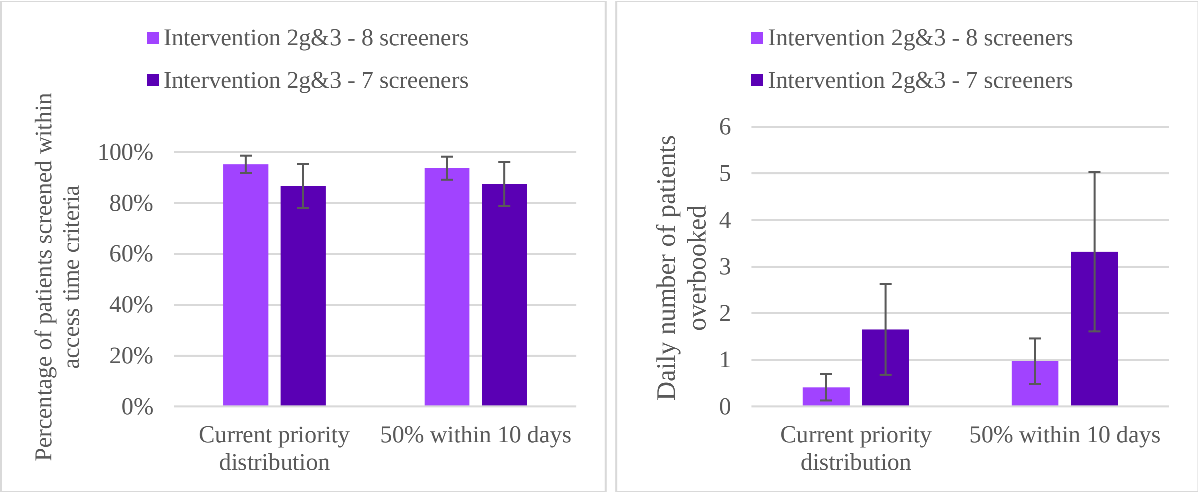
A first possible future scenario is an increase in the number of high priority patients due to the delayed care as a result of COVID-19. When this future scenario becomes reality, the blueprint schedule should be adapted to this new scenario. The capacity allocation method requires the mean and standard deviation of the daily number of surgery requests per priority group. Table 6.5 shows the current priority distribution, with the percentage of patients per priority group and the mean and standard deviation for each priority group. Next, Table 6.5 gives a future scenario in which around 50% of the patients have a priority of 10 days.

Table 6.5. Priority distribution and mean and standard deviation per priority group, for the current situation and an increase in high priority patients

	Current priority distribution			**50% of the patients with a priority of 10 days**		
Priority group	Mean daily number of requests	Standard deviation	Percentage	Mean daily number of requests	Standard deviation	Percentage
< 1 week	26.9	6.3	24.7%	43.0	9.6	41.7%
< 10 days	3.5	2.9	3.2%	6.5	3.8	6.3%
< 3 weeks	14.0	5.6	12.9%	14.1	4.7	13.6%
< 6 weeks	23.9	9.9	22.0%	14.7	5.3	14.3%
< 6 months	40.5	12.2	37.2%	24.9	8.1	24.1%
Total	108.8		100%	103.2		100%

Figure 6.15 shows the performances of the adapted blueprint schedules regarding the percentage of patients that are screened within the access time criteria and the daily number of patients overbooked. We expect that the change in patient priorities does not affect the percentage of patients screened within the access time criteria because the blueprint schedule is adapted to this change. Figure 6.15a shows that the blueprint schedule with eight screeners results in 93.7% of the patients screened on time and the blueprint schedule with seven screeners in 87.5% screened within the access time criteria.

Next, we expect that the daily number of patients overbooked does not change, because the blueprint schedule is adapted to this new patient priority distribution. However, Figure 6.15b shows that the daily number of patients overbooked increases with 0.6 for the blueprint schedule with eight screeners and with 1.7 for the blueprint schedule with seven screeners. A possible reason is that high priority patients have strict restrictions regarding the access time. Consequently, it is more difficult to deal with the fluctuations in demand.



(a) (b)

Figure 6.15. Results of the DES for the performances of the adapted blueprint schedules, for a different percentage of high priority patients. a) shows the percentage of patients that meets the access time criteria and b) shows the daily number of patients overbooked. The error bar indicates the standard deviation

6.7.3 Screening patients with a day treatment online after COVID-19

A second possible future scenario is that the number of surgery requests will increase after COVID-19 and that patients with a day treatment are screened online. An increase in the number of surgery requests is expected because COVID-19 will probably less influence the OR department in future. Then, the characteristics of before COVID-19 will return, which implies a higher number of surgery requests. Table 6.6 gives the mean and standard deviation of the daily number of surgery requests, during and before COVID-19.

Table 6.6. Mean and standard deviation of the daily number of requests, during and before COVID-19

	During COVID-19	**Before COVID-19**
Mean daily number of requests	88.51	121.91
Standard deviation	14.7	19.3

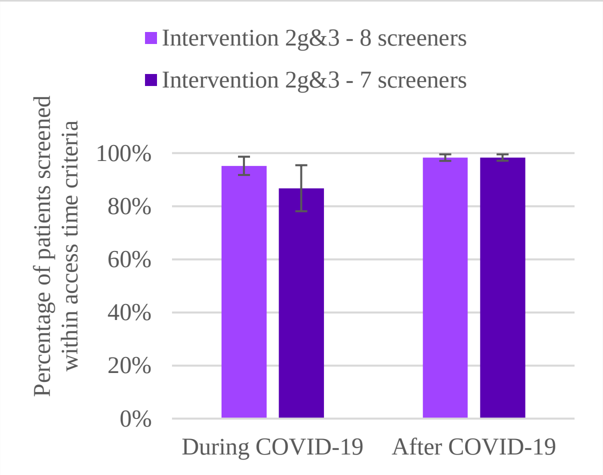
Next, currently, the PAC is investigating the possibilities of screening patients with a day treatment online because these patients are often associated with a low ASA classification. Approximately 49% of the patients have a surgery request for a day treatment. The blueprint schedule should be adapted to this new scenario. The capacity allocation method requires the mean and standard deviation of the daily number of surgery requests per priority group. Table 6.7 shows the current priority distribution, with the percentage of patients per priority group and the mean and standard deviation for each priority group. Next, Table 6.7 gives the future scenario in which patients with a day treatment are screened online. Thus, this priority distribution reflects the priority of patients without a day treatment.

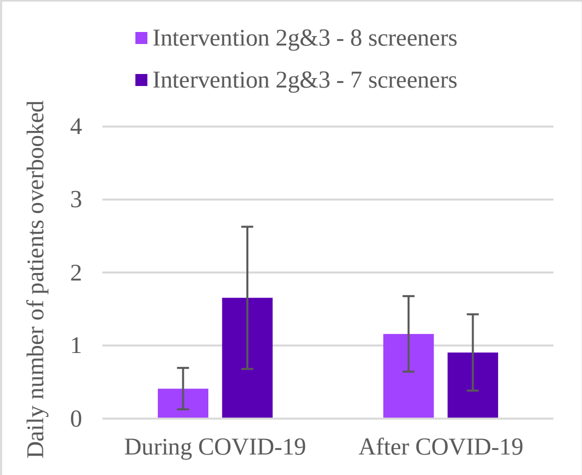
Table 6.7. Priority distribution and mean and standard deviation per priority group, when patients with a day treatment are screened in the PAC (current situation) and when these patients are screened online

	Patients with day treatment screened in the PAC			**Patients with day treatment screened online**		
Priority group	Mean daily number of requests	Standard deviation	Percentage	Mean daily number of requests	Standard deviation	Percentage
< 1 week	26.9	6.3	24.7%	20.0	4.7	37.2%
< 10 days	3.5	2.9	3.2%	1.7	1.7	3.2%
< 3 weeks	14.0	5.6	12.9%	6.4	3.3	11.8%
< 6 weeks	23.9	9.9	22.0%	11.0	5.1	20.4%
< 6 months	40.5	12.2	37.2%	14.8	6.3	27.4%
Total	**108.8**		**100%**	**53.8**		**100%**

Figure 6.16 shows the performances of the adapted blueprint schedules regarding the percentage of patients that are screened within the access time criteria and the daily number of patients overbooked. We expect that the future scenario after COVID-19 does not affect the percentage of patients screened within the access time criteria because the blueprint schedule is adapted to this future scenario. Figure 6.16a shows that both blueprint schedules result in 98.3% of the patients screened on time.

Next, we expect that the daily number of patients overbooked decreases because the number of patients that should be screened decreases and because the blueprint schedule is adapted. Figure 6.16b shows that the daily number of patients overbooked decreases for the adapted blueprint schedule with seven screeners. The fact that both combined interventions result in approximately one patient overbooked daily is probably because the number of high priority patients increased. High priority patients have strict restrictions regarding the access time and consequently, it is more difficult to deal with the fluctuations in demand.





(a) (b)

Figure 6.16. Results of the DES for the performances of the adapted blueprint schedules, before versus after COVD-19. a) shows the percentage of patients that meets the access time criteria and b) shows the daily number of patients overbooked. The error bar indicates the standard deviation

Figure 6.17 shows that the PAC capacity does not match the surgery demand. However, no conclusion can be drawn about whether the capacity is too extensive in this new future scenario because patients who do not have a day treatment require more consultation time. Next, it is not possible to investigate what time is needed to check the screening of the patients who are screened online. Thus, this future scenario results in a situation in which the number of appointment slots does not match the number of requests anymore, however, no conclusion can be drawn about the PAC capacity that is needed.

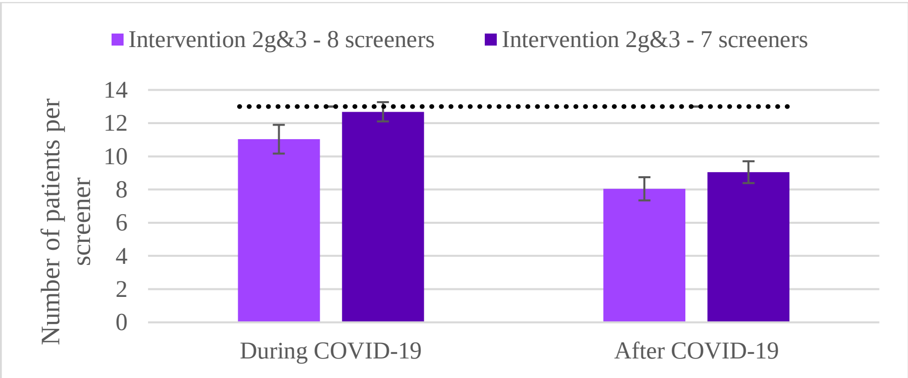


Figure 6.17. Results of the DES for the daily number of patients scheduled per screener with the black dotted line indicating the current capacity of a screener. The error bar indicates the standard deviation

6.8 Conclusion

Chapter 6 discussed the results of three individual interventions and three combinations of interventions.

During intervention 1, the screening capacity is increased by one additional screener. This resulted in a significant increase in the percentage of patients screened within the access time, a significant decrease in the daily number of patients overbooked, and a decrease in the utilization. Next, the variation in the workload for nurses as well as the variation in the workload for screeners decreases significantly. Thus, increasing the screening capacity by one additional screener improved the performances of the PAC.

During intervention 2, multiple blueprint schedules with allocated capacity to priority groups, which vary in the degree of flexibility and the number of priority groups, are designed. Because all blueprint schedules had a capacity of eight screeners, the results are compared with the first intervention. Compared with intervention 1, the percentage of patients screened within the access time criteria increases significantly for all blueprint schedules. Only intervention 2g, where the priority groups were subdivided by the PAC planners, resulted in a significant decrease in the daily number of patients overbooked compared with intervention 1. No significant difference between intervention 2 and intervention 1 is found with respect to utilization and variation in workload for nurses and for screeners. However, compared to the current situation, the blueprint schedules with allocated capacity to priority groups improved the performances of the PAC.

During intervention 3, the offline planning approach is represented by scheduling patients with a priority of six weeks immediately and by scheduling patients with a priority "< 6 months" after two months of their surgery request. This resulted in a significant increase in the percentage of patients screened within the access time, a significant decrease in the daily number of patients overbooked, and a decrease in the utilization. Next, the variation in the workload for nurses as well as the variation in the workload for screeners decreases significantly. Thus, the offline planning approach improved the performances of the PAC.

Three blueprint schedules are combined with the offline planning approach. These blueprint schedules (1) allocate capacity to eight priority groups with a capacity of eight screeners, (2) allocate capacity to five priority groups with a capacity of eight screeners, or (3) allocate capacity to five priority groups with a capacity of seven screeners. The first two blueprint schedules show the most promising results regarding the percentage of patients screened within the access time criteria and the daily number of patients overbooked. However, the third blueprint schedule shows the most promising results regarding the daily number of patients scheduled per screener.

The sensitivity analyses showed that the designed blueprint schedule is sensitive for a change in the percentage of patients per priority group, which is as expected since the blueprint schedule should be adapted then. Moreover, the blueprint schedule is not sensitive to a change in the restrictions on the access time. A possible future scenario is an increase in the number of high priority patients as a consequence of the delayed care as a result of COVID-19. The analyses showed that the blueprint schedule can be adapted to this new future scenario and still shows promising results regarding the percentage of patients screened within the access time criteria and the daily number of patients overbooked.

The results are well received by the management of the PAC. Currently, the PAC of the St. Antonius Hospital is implementing the offline planning approach and is taking the first steps to implement the blueprint schedule with allocated capacity to priority groups. Next, together with the management of the PAC, we are developing a dashboard with multiple KPIs related to the access time, such that the performance of the PAC can easily be monitored.

7 Recommendations and implementation

Chapter 7 discusses the recommendations of this study and the implementation of these recommendations. Recall from Chapter 6 that the combination of the blueprint schedule with allocated capacity and the offline planning approach yields the most promising results. It is by the St. Antonius Hospital to choose whether they are willing to increase the screening capacity by one additional screener. Based on these results, the recommendations from this study are as follows:

1. Implementation of the new blueprint schedule, with slots allocated to priority groups
    a. Adjustment of the number of available appointment slots
    b. Adjustment of the number of priority groups
2. Implementation of the offline planning approach
    a. PAC planners actively call high urgency patients
    b. OR planners create a “patient list” with low priority patients that should be scheduled for a PAC appointment

Section 7.1 discusses the implementation of the new blueprint schedule, followed by Section 7.2, which describes the implementation of the offline planning approach.

7.1 Implementation of the new blueprint schedule

The newly designed blueprint schedule is static and is created under the current circumstances. Therefore, this blueprint schedule can be directly implemented. When St. Antonius Hospital chooses for the current capacity of seven screeners, the capacity allocation from intervention 2g with seven screeners (Appendix D2) should be implemented. When St. Antonius Hospital chooses for eight screeners, the capacity allocation from intervention 2a with an allocation to eight priority groups (Appendix D2), or the blueprint schedule from intervention 2g, with an allocation to five priority groups (Appendix D2) should be implemented. Moreover, the sensitivity analysis in Section 6.6 showed that the blueprint schedule is sensitive for the distribution of the patient characteristic Priority. Especially the blueprint schedule with seven screeners showed an increase in the daily number of patients overbooked when the percentage of high priority patients increase. Thus, to maximize the performance of the blueprint schedule, the blueprint schedule should be adapted when the circumstances change. Section 7.1.1 gives how to adapt the blueprint schedule. Moreover, Section 7.1.2 provides planning rules for the PAC planners to ensure that the newly designed blueprint schedule is fully exploited.

7.1.1 Adaptation of the blueprint schedule

Before we describe how to adapt the blueprint schedule, we first discuss the indicators which imply that the blueprint schedule should be adapted. Then, the adaptation of the blueprint schedule is described in four steps.

Indicators

We advise to review the blueprint schedule every quartile. Next, there are two indicators that imply that the blueprint schedule should be adapted. These indicators are the access time and the daily number of patients overbooked. The blueprint schedule should be adapted when the access time increases and when the daily number of patients overbooked increases, which can have two main reasons:

1. The first reason is that the patient mix changes, and consequently that the blueprint schedule should be adapted.
2. The second reason is that demand increases and that capacity does not meet demand anymore. In this case, the capacity should be increased and the blueprint schedule should be adapted. Capacity can be increased in two ways: (1) increase the number of physical consultations and thereby the number of appointment slots per screeners, or (2) increase the number of screeners (initially by one additional screener).

Because it is difficult to estimate the demand, always first check if the patient mix changed. If the percentage of patients of one of the priority groups changed with more than 20%, the blueprint schedule should be adapted. If the patient mix changed, follow point one and adapt the allocation in the blueprint schedule. If the patient mix did not change, follow point two. The next five parts discuss the adaptation of the blueprint schedule.

1. Input data
The capacity allocation method requires input data. The following input should be collected:

- Daily number of appointment slots in the PAC schedule. This number depends on the number of screeners and the ratio between physical and phone consultations.
- Daily number of surgery requests during weekdays, including the priority of the patients. This data should include the weekdays of approximately 2 months. Example of one weekday:
    - A total of 90 surgery requests daily, of which 20 with a priority "< 72 hours", 10 with a priority "< 1 week", etc.

2. Mean and standard deviation of the priority groups
Calculate the mean daily number of surgery requests per priority group (μ_i) and the standard deviation of the daily number of surgery requests per priority group per priority group (σ_i)

3. Number of appointment slots per priority group
Given the mean daily number of surgery requests per priority group i (μ_i) and the total daily number of surgery requests, the percentage of priority group i is calculated. Then, the number of appointment slots per priority group (C_i) is determined with the use of the percentage of priority group i and the daily number of appointment slots in the PAC schedule (capacity):

- $C_i = \lfloor \text{Percentage priority group } i * \text{capacity} \rfloor$

4. Flexible and allocated appointment slots per priority group
First, calculate the number of flexible appointment slots. Using the number of appointment slots per priority group i (C_i) and the mean (μ_i) and standard deviation (σ_i) of priority group i, we can calculate the number of flexible appointment slots contributed by priority group i (F_i):

- $F_i = \left\lfloor \frac{C_i * \sigma_i}{\mu_i} \right\rfloor$

Second, calculate the number of allocated appointment slots. Using the number of flexible appointment slots contributed by priority group i (F_i) and the number of appointment slots for priority group i (C_i), we can calculate the number of allocated appointment slots for priority group i (A_i):

- $A_i = C_i - F_i$

5. Distribute the appointment slots over the available screening rooms
High priority patients are treated by the screeners treating inpatient patients since inpatient patients often receive a high priority. Thus, the flexible and allocated appointment slots for the high priority patients should be placed by the screeners treating inpatient patients. The remaining flexible and allocated appointment slots should be randomly divided among the screeners working in the PAC. Note that it is not favorable to start the schedule with a flexible appointment slot. Because the capacity allocation method uses formulas which round down numbers, the remaining appointment slots become flexible appointment slots.

7.1.2 New planning rules

During this study, the goal was to support PAC planners by changing the blueprint schedule without changing the current planning rules. The current planning rules did not change, except for the auto planner used in this planning process, see Section 5.6 for a detailed description of the extension of the auto planner. This auto planner tries to find an available appointment slot before the excepted surgery date. This process is extended by first searching for an allocated appointment slot, and then searching for a flexible appointment slot before the access time criteria. If no appointment slot is found, then search for an allocated appointment slot and next for a flexible appointment slot before the expected surgery date. If no appointment slot is found by this extended auto planner, the planner can use the same planning decisions to schedule the patient on another appointment slot or to overbook the patient.

7.2 Implementation of the offline planning approach

The second recommendation of this study is to implement the offline planning approach. The offline planning approach implies that requests are gathered and then patients are scheduled. Next, this intervention implies that the planner actively calls the patient instead of the planner who waits till the patient calls for an appointment. Patients are divided into two groups, and different rules apply to these groups.

Patients with a priority of six weeks

We recommend that PAC planners are going to actively call these high urgency patients. This means that when a patient with a priority of six weeks requests surgery, this patient is called the same day to schedule a PAC appointment.

Patients with a priority of six months

We recommend that OR planners are going to create a patient list with low urgency patients who will probably have surgery in two months. Then, PAC planners are going to actively call the patients from this patient list to schedule a PAC appointment.

8 Conclusion and discussion

Chapter 8 gives the conclusion of this study (Section 8.1) and discusses the study limitations and recommendations for further research (Section 8.2).

8.1 Conclusion

The PAC has the goal to examine the patient and to determine whether the patient is in good condition to have surgery. Thereby, the PAC improves the efficiency of the OR department, resulting in decreased costs and improved quality of care. Since the PAC and the OR department are closely related, the timing of the preoperative screening is important. Currently, the PAC in the St. Antonius Hospital does not succeed in screening patients within their access time criteria. The goal of this study was to develop a capacity allocation method for the St. Antonius Hospital with which a blueprint schedule is designed to increase the percentage of patients that are screened within the access time criteria.

While the focus of this study is on the capacity allocation method, two other interventions were investigated as well. During intervention 1, the screening capacity was increased by one additional screener. During intervention 2, multiple blueprint schedules with allocated capacity which vary in the degree of flexibility and the number of priority groups were designed. During intervention 3, the offline planning approach is applied, and patients are scheduled based on their priority. The performances of the interventions were investigated using a DES, taking stochasticity into account.

Based on the results of the individual interventions, three combined interventions were tested. The combination of the offline planning approach and the blueprint schedule with a capacity of eight screeners resulted in the most promising results regarding access times and overbookings. When the capacity was allocated to eight priority groups, the percentage of patients screened within the access time criteria increased from 60.4% to 95.4%. When the capacity was allocated to five priority groups, the percentage of patients screened within the access time criteria increased from 60.4% to 95.2%. Both combined interventions resulted in a decrease in the number of patients overbooked from 10.4 to 0.4 patients daily. Next, the offline planning approach and the blueprint schedule with capacity allocation to five priority groups using a capacity of seven screeners resulted in the most promising results regarding the utilization of the screeners, namely 12.7 patients scheduled per screener daily.

The analyses showed that the blueprint schedule can be adapted to possible future scenarios. A possible future scenario is an increase in the number of high priority patients as a consequence of the delayed care as a result of COVID-19. The best performing blueprint schedules were adapted to this future scenario. The blueprint schedule with a capacity of eight screeners and seven screeners resulted in 93.7% and 87.5% of the patients screened within the access time criteria respectively.

Currently, the St. Antonius Hospital is implementing the offline planning approach and is taking the first steps to implement the blueprint schedule with allocated capacity to priority groups. Next, together with the management of the PAC, we are developing a dashboard with multiple KPIs related to the access time, such that the performance of the PAC can easily be monitored. Moreover, this study contributes to theory since we are the first to analyse the effects of allocating capacity to priority groups in order to improve the access time to the PAC and improve the patient flow of the preoperative process. Although we specifically focus on the PAC, the proposed capacity allocation method applies to other outpatient clinics where appointments have to be allocated to multiple specialties or priority patients. Thus, by developing an easy-to-implement capacity allocation method and by the use of a case study, this study does not only result in a high practical contribution but also contributes to theory.

To conclude, the results of this study provide a quantitative basis to support a blueprint schedule with allocated capacity to priority groups to improve access times in a PAC. In this way, the PAC supports the OR department in functioning efficiently.

8.2 Discussion

The research presented in this thesis has some limitations and there are opportunities for further research. This section describes the study limitations and the recommendations for further research.

Study limitations

The first limitation of this study is that patient waiting time and physician idle time was not investigated during the interventions. The main reason for this is the missing data regarding the mean consultation time. As a result, patient waiting time and physician idle time could not be calculated. However, since the number of phone consultations increased from 0% to 80%, we expect that patient waiting time does currently not play an important role in patient satisfaction. Moreover, it is already known that as a consequence of the increase in phone consultations, physician idle time increases because patients do not always answer the phone. To conclude, we expect that the new blueprint schedule does not deteriorate patient satisfaction and physician idle time, however investigating the effect of the new blueprint schedule on patient waiting time and physician idle time is advised.

The second limitation of this study is the assumptions that should be made to complement the missing data regarding patient priority. As described in Section 5.3, the missing patient priorities are complemented by the assumption that a patient is operated within the maximum allowable time. In this way, the patients are distributed over the priority groups. By making this assumption, there could be a discrepancy between the priority distribution in reality and the priority distribution in this study. Consequently, it could be that the blueprint schedule for the current situation should be adapted. However, currently, the doctor in the outpatient clinic gives the patient a priority indication more often. The current distribution in combination with the capacity allocation method can be used to adapt the blueprint schedule when the priority mix changed compared to the priority mix used in this study.

The third limitation, which follows the second limitation, is that no distinction is made between patients with a priority "< 2 months", "< 3 months" and "< 6 months". Patients with the priority "< 2 months" and "< 3 months" are added to the priority group "< 6 months" since for these patients the time between the request and surgery strongly depends on the length of the waiting list. It was not possible to determine whether this priority indicates the urgency of the patient or represents the length of the waiting list. However, OR planners indicate that the access time criteria for patients with a priority "< 2 months" differs from the access time criteria for patients with a priority "< 3 months" and "< 6 months". In this study, this is captured by the recommendation that OR planners should make a patient list with patients who will probably have surgery in two months. In this way, a distinction can be made. When the data regarding this priority group is available, the formula to calculate the number of flexible and allocated appointment slots can be used to allocate appointment slots to this priority group.

Fourth, a limitation is that cancellations are not taken into account while 10-15% of the appointments are currently cancelled. Appointments are cancelled by the patient or by the planner and it was unknown by whom the appointment was cancelled. Next, appointments cancelled by the hospital were often a consequence of a schedule that is overloaded. For these cancellations, we assumed that these cancellations will not occur with the new blueprint schedule. However, it should be further investigated which percentage of appointments are cancelled by the patient and what the reasons for these cancellations are. Moreover, we assumed that, because appointments are cancelled at least 24h in advance, PAC planners can schedule a new patient and that it does not affect the performances much. However, further research should investigate the effect of cancellations on the performance of the PAC.

Recommendations for further research

The first recommendation for further research is to investigate the relationship between the developed capacity allocation method and the PAC capacity. In this study, we determined the number of flexible and allocated slots based on the coefficient of variation of the priority groups and tested the degree of flexibility. This calculation was based on a given PAC capacity. The capacity allocation method can be improved when capacity calculations and the relation between capacity, demand and the degree of flexibility are added. Therefore, we advise to improve the capacity allocation method by adding calculations to determine the required capacity.

The second recommendation for further research is to investigate the possibilities to create a dynamic blueprint schedule that is able to adapt to changes in the patient mix. The capacity allocation in this study results in a static blueprint schedule which should be regularly reviewed. However, dynamic blueprint schedules showed already promising results regarding patient access time, resource utilization and flexibility. Therefore, further research could investigate how capacity can dynamically be adapted when the priority mix changes.

The third recommendation follows the first limitation of this study. This study focussed on improving the access time from the outpatient clinic to the PAC and did not take performances regarding patient waiting time and physician idle time in the PAC into account. However, further research could investigate a multi-objective function in which the access times are optimized as well as the performances of the PAC.

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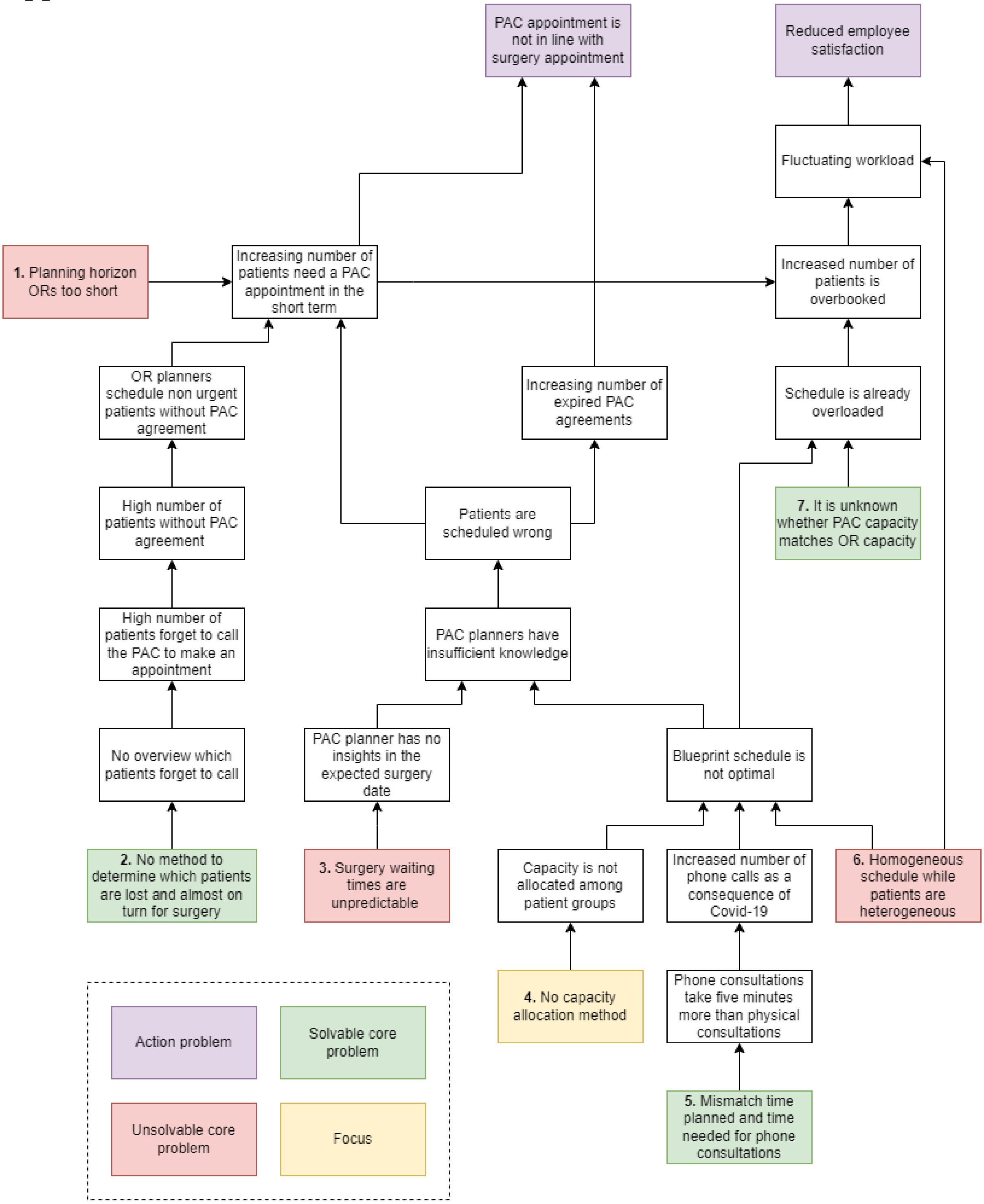
Appendices

Appendix A Problem cluster



Appendix B Systematic literature review

We use PubMed as a database to find the literature that answers the knowledge questions. Some searches are done to get some common knowledge about the topic. Other searches are systematically performed to find all the literature regarding that topic. This study fills a gap in the literature regarding the PAC, therefore, for this knowledge question, a systematic literature study is performed.

What is done in the field of resource capacity planning in the PAC?

We gathered the keywords regarding this topic. These are as follows:

- Preoperative OR preanesthesia
- Screening OR clinic OR evaluation OR assessment
- Organization OR appointment

These keywords are combined in a search string, which is as follows:

((preoperative[Title] OR preanesthesia[Title]) AND (screening[Title] OR clinic[Title] OR evaluation[Title] OR assessment[Title])) AND (organization[Title/Abstract] OR appointment[Title/Abstract])

The search yields 49 results, of which ten were selected based on title and abstract. After reading these articles, seven articles were chosen:

1. (Dexter, 1999)
2. (Edward et al., 2008a)
3. (Edward et al., 2008b)
4. (Edward et al., 2008c)
5. (Edward et al., 2010)
6. (Hawes et al., 2016)
7. (Zonderland et al., 2009)

Moreover, for this topic, two master theses from the University of Twente are selected, which are:

8. (Odijk, 2012)
9. (Schoenmakers, 2008)

Appendix C

Appendix C1 MSER-k

Index	Terminology
k	Number of observations per batch
h	Number of batches for the warmup period
n	Total number of batches
j	Batch number (j = 1 .. n)

Goal

Minimize the sample variance $S^2(n,h)$ of $\bar{Z}_{h+1}(k), \bar{Z}_{h+2}(k), \ldots, \bar{Z}_n(k)$, while maximizing the remaining number of observations $(n-h)$

Procedure

1. Make one long run with length $k \cdot h + k \cdot (n-h)$, consisting of:
   a. warm-up period of h batches of k observations
   b. plus $n-h$ batches of k observations
2. Calculate the mean value $Z_j(k)$ of each batch j of k observations:

$$Z_j(k) = \frac{1}{k} \sum_{i=(j-1)k+1}^{jk} Y_i$$

3. Calculate the mean value $\bar{Z}(n,h)$ of the remaining batches $n-h$, for each warmup period h:

$$\bar{Z}(n,h) = \frac{\sum_{j=h+1}^{n} Z_j}{n-h}$$

4. Calculate the sample variance $S^2(n,h)$, given the total number of batches n and warmup period h:

$$S^2(n,h) = \frac{\sum_{j=h+1}^{n} [Z_j - \bar{Z}(n,h)]^2}{n-h}$$

5. Calculate the $MSER(n,h)$, given the total number of batches n and warmup period h:

$$MSER(n,h) = \frac{n-h-1}{(n-h)^2} S^2(n,h)$$

6. Find h^* which minimizes $MSER(n,h)$

$$h^* = \underset{h=0,1,\ldots,n-1}{\arg\min} \; MSER(n,h)$$

7. If $h^* > \frac{1}{2}\, run\ length$, then increase the run length and repeat the procedure

Appendix C2 Verification

Input	Simulation n	Simulation Mean	Simulation Standard deviation	Historical data n	Historical data Mean	Historical data Standard deviation
Daily number of surgery requests during weekdays	159 days	88.7	14.2	191 days	88.5	14.7
Daily number of surgery requests during weekend days	62 days	12.7	4.0	206 days	12.6	3.6
Type 1 patients & screening	11,102 patients	29.4%		44,020 patients	32.9%	
Type 2 patients & screening	929 patients	21.2%		4,207 patients	20.6%	
Type 1 patients & screening & nursing	11,102 patients	43.8%		44,020 patients	38.1%	
Type 2 patients & pharmacy and screening	929 patients	78.8%		4,207 patients	79.4%	
Patients with a day treatment	14,973 patients	49.2%		55,831 patients	48.7%	
Patients with a priority "< 1 week"	14,973 patients	6.9%		55,831 patients	7.0%	
Patients with a priority "< 2 weeks"	14,973 patients	4.5%		55,831 patients	4.9%	
Patients with a priority "< 4 weeks"	14,973 patients	8.3%		55,831 patients	8.6%	
Patients with a priority "< 6 weeks"	14,973 patients	13.2%		55,831 patients	13.4%	

Appendix D

Appendix D1 Distribution to complement type of patient

Specialty	Type 1	Type 2
General Surgery	0.69	0.31
Anaesthesia	1.00	0.00
Bariatrics	0.27	0.73
Cardiology	0.00	1.00
Cardiothoracic Surgery	0.16	0.84
GE	1.00	0.00
GE Surgery	0.71	0.29
Head Neck Surgery	1.00	0.00
ENT	1.00	0.00
Lung Surgery	0.16	0.84
Lung Diseases	0.57	0.43
Mamma Surgery	1.00	0.00
Neurosurgery	1.00	0.00
Obstetrics and Gynaecology	1.00	0.00
Optometry	1.00	0.00
Orthopedy	1.00	0.00
Pain relief	1.00	0.00
Plastic Surgery	1.00	0.00
Oral Surgery	1.00	0.00
Trauma Surgery	1.00	0.00
Urology	0.90	0.10
Vascular Surgery	1.00	0.00
Other	1.00	0.00

Appendix D2 Capacity allocation intervention 2

Appointment slot	Intervention 2a	Intervention 2b	Intervention 2c
< 72 hours	13	15	13
< 1 week	4	5	4
< 10 days	1	2	1
< 2 weeks	2	3	2
< 3 weeks	4	6	4
< 4 weeks	5	6	5
< 6 weeks	7	10	7
< 6 months	26	31	26
Flexible	35	19	35
Type 2	15	15	15
Total	**112**	**112**	**112**

Appointment slot	Intervention 2e	Intervention 2f	Intervention 2g 8 screeners	Intervention 2g 7 screeners
< 72 hours	13	13		
< 1 week			18	16
< 10 days		6	1	1
< 2 weeks	10			
< 3 weeks		8	8	7
< 4 weeks	9			
< 6 weeks	7	13	13	11
< 6 months	26	26	26	21
Flexible	32	31	31	27
Type 2	15	15	15	15
Total	**112**	**112**	**112**	**98**

Appendix D3 Distributions to determine patient specialty

	Monday	Tuesday	Wednesday	Thursday	Friday	Weekend day
General Surgery	0.14	0.11	0.12	0.13	0.08	0.22
Anaesthesia	0.01	0.01	0.02	0.00	0.00	0.00
Bariatrics	0.00	0.06	0.02	0.02	0.01	0.00
Cardiology	0.01	0.01	0.00	0.01	0.01	0.00
Cardiothoracic Surgery	0.07	0.07	0.07	0.06	0.08	0.07
GE	0.00	0.01	0.00	0.01	0.01	0.01
GE Surgery	0.04	0.03	0.04	0.05	0.04	0.07
Head Neck Surgery	0.00	0.01	0.00	0.00	0.00	0.00
ENT	0.15	0.16	0.14	0.15	0.18	0.01
Lung Surgery	0.01	0.00	0.02	0.01	0.00	0.00
Lung Diseases	0.00	0.00	0.00	0.00	0.00	0.00
Mamma Surgery	0.02	0.02	0.01	0.02	0.02	0.00
Neurosurgery	0.03	0.01	0.00	0.03	0.01	0.00
Obstetrics and Gynaecology	0.08	0.06	0.07	0.07	0.08	0.19
Optometry	0.11	0.10	0.11	0.11	0.10	0.00
Orthopedy	0.11	0.10	0.13	0.10	0.14	0.07
Pain relief	0.00	0.00	0.00	0.00	0.00	0.00
Plastic Surgery	0.03	0.05	0.02	0.04	0.03	0.01
Oral Surgery	0.02	0.02	0.02	0.02	0.03	0.01
Trauma Surgery	0.07	0.06	0.05	0.05	0.08	0.21
Urology	0.07	0.09	0.09	0.08	0.10	0.06
Vascular Surgery	0.03	0.02	0.04	0.03	0.03	0.05
Other	0.00	0.00	0.00	0.00	0.00	0.00
Total	1	1	1	1	1	1
n	10,751	11,884	10,252	10,573	9,700	2,670

Appendix D4 Distributions to determine priority and day treatment

Day treatment > ***Priority >***	**YES** **72 hours**	**YES** **1 week**	**YES** **10 days**	**YES** **2 weeks**	**YES** **3 weeks**	**YES** **4 weeks**	**YES** **6 weeks**	**YES** **6 months**	**NO** **72 hours**
General Surgery	0.04	0.02	0.01	0.03	0.05	0.05	0.08	0.20	0.40
Anaesthesia	0.02	0.07	0.03	0.05	0.10	0.07	0.04	0.38	0.08
Bariatrics	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.02
Cardiology	0.00	0.04	0.03	0.09	0.10	0.09	0.09	0.07	0.25
Cardiothoracic Surgery	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30
GE	0.18	0.02	0.01	0.01	0.01	0.00	0.00	0.01	0.59
GE Surgery	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.04	0.35
Head Neck Surgery	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.02	0.07
ENT	0.02	0.02	0.01	0.03	0.04	0.06	0.12	0.59	0.01
Lung Surgery	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11
Lung Diseases	0.01	0.02	0.03	0.04	0.01	0.01	0.01	0.01	0.19
Mamma Surgery	0.02	0.03	0.03	0.05	0.39	0.11	0.10	0.02	0.01
Neurosurgery	0.01	0.00	0.01	0.01	0.01	0.00	0.02	0.11	0.04
Obstetrics and Gynaecology	0.04	0.02	0.01	0.02	0.02	0.04	0.04	0.08	0.39
Optometry	0.01	0.05	0.03	0.06	0.10	0.09	0.17	0.48	0.00
Orthopedy	0.01	0.02	0.02	0.02	0.03	0.03	0.05	0.13	0.11
Pain relief	0.01	0.02	0.08	0.06	0.16	0.12	0.08	0.30	0.05
Plastic Surgery	0.03	0.02	0.01	0.02	0.03	0.04	0.10	0.35	0.04
Oral Surgery	0.04	0.03	0.01	0.04	0.04	0.06	0.08	0.38	0.04
Trauma Surgery	0.11	0.24	0.06	0.03	0.03	0.04	0.05	0.05	0.31
Urology	0.01	0.01	0.00	0.01	0.01	0.02	0.05	0.15	0.13
Vascular Surgery	0.00	0.01	0.01	0.02	0.01	0.02	0.02	0.01	0.36
Other	0.11	0.03	0.00	0.00	0.05	0.02	0.02	0.05	0.48

Day treatment > ***Priority >***	**NO** **1 week**	**NO** **10 days**	**NO** **2 weeks**	**NO** **3 weeks**	**NO** **4 weeks**	**NO** **6 weeks**	**NO** **6 months**	**Total**	**n**
General Surgery	0.01	0.01	0.01	0.02	0.02	0.02	0.03	1	6,861
Anaesthesia	0.01	0.02	0.01	0.03	0.01	0.00	0.07	1	377
Bariatrics	0.03	0.05	0.07	0.15	0.10	0.15	0.38	1	1,288
Cardiology	0.06	0.03	0.04	0.04	0.02	0.02	0.03	1	280
Cardiothoracic Surgery	0.15	0.03	0.04	0.05	0.08	0.12	0.22	1	3,936
GE	0.11	0.02	0.01	0.02	0.01	0.01	0.01	1	392
GE Surgery	0.05	0.04	0.06	0.09	0.09	0.08	0.07	1	2,344
Head Neck Surgery	0.01	0.01	0.01	0.02	0.06	0.28	0.47	1	163
ENT	0.00	0.00	0.00	0.01	0.01	0.01	0.06	1	8,210
Lung Surgery	0.18	0.23	0.19	0.15	0.07	0.05	0.02	1	419
Lung Diseases	0.16	0.18	0.09	0.14	0.06	0.03	0.02	1	166
Mamma Surgery	0.01	0.01	0.03	0.11	0.04	0.03	0.01	1	945
Neurosurgery	0.03	0.03	0.02	0.03	0.03	0.08	0.59	1	759
Obstetrics and Gynaecology	0.01	0.01	0.03	0.05	0.05	0.06	0.13	1	4,354
Optometry	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1	5,701
Orthopedy	0.03	0.02	0.03	0.03	0.04	0.09	0.34	1	6,281
Pain relief	0.01	0.01	0.01	0.02	0.00	0.04	0.04	1	102
Plastic Surgery	0.01	0.00	0.01	0.03	0.03	0.07	0.20	1	1,932
Oral Surgery	0.01	0.00	0.01	0.02	0.02	0.06	0.17	1	1,170
Trauma Surgery	0.06	0.02	0.01	0.00	0.00	0.00	0.00	1	3,792
Urology	0.01	0.01	0.03	0.06	0.11	0.17	0.22	1	4,678
Vascular Surgery	0.10	0.05	0.08	0.07	0.08	0.09	0.07	1	1,619
Other	0.05	0.02	0.10	0.03	0.02	0.00	0.03	1	61

Appendix D5 Distributions to determine type of patient

Distribution 5A	Emergency	Inpatient	AGE	Type 2	Type 1	n
Day treatment: YES	0.00	0.00	0.00	0.00	1.00	12,855

Distribution 5B	Emergency	Inpatient	AGE	Type 2	Type 1	n
Priority: 72 hours	0.42	0.53	0.00	0.00	0.05	1,996

Distribution 5C	Emergency	Inpatient	AGE	Type 2	Type 1	n
General Surgery	0.04	0.00	0.02	0.29	0.65	443
Anaesthesia	0.00	0.00	0.00	0.00	1.00	6
Bariatrics	0.00	0.00	0.00	0.73	0.27	917
Cardiology	0.12	0.04	0.00	0.84	0.00	25
Cardiothoracic Surgery	0.16	0.17	0.00	0.56	0.11	1,925
GE	0.14	0.14	0.00	0.00	0.71	7
GE Surgery	0.04	0.01	0.10	0.24	0.60	541
Head Neck Surgery	0.01	0.00	0.00	0.00	0.99	90
ENT	0.00	0.00	0.00	0.00	1.00	454
Lung Surgery	0.07	0.01	0.00	0.77	0.15	167
Lung Diseases	0.11	0.04	0.00	0.37	0.48	54
Mamma Surgery	0.01	0.00	0.00	0.00	0.99	132
Neurosurgery	0.00	0.00	0.00	0.00	1.00	418
Obstetrics and Gynaecology	0.00	0.00	0.00	0.00	0.99	1,056
Optometry	0.00	0.00	0.00	0.00	1.00	1
Orthopedy	0.00	0.01	0.00	0.00	0.99	2,073
Pain relief	0.00	0.00	0.00	0.00	1.00	2
Plastic Surgery	0.00	0.00	0.00	0.00	1.00	402
Oral Surgery	0.00	0.00	0.00	0.00	1.00	277
Trauma Surgery	0.05	0.15	0.00	0.00	0.80	148
Urology	0.01	0.00	0.01	0.10	0.88	1,162
Vascular Surgery	0.08	0.01	0.02	0.00	0.89	407
Other	0.00	0.00	0.00	0.00	1.00	3

Appendix D6 Distributions to determine patient routing

Distribution 6A	A	A&N	P&A	P&A&N	n
Inpatient	1	0	0	0	3,155
Emergency	1	0	0	0	3,313
AGE	0.15	0	0.78	0.07	307
Type 2	0.21	0	0.79	0	4,207

Distribution 6B	A	A&N	P&A	P&A&N	n
General Surgery	0.12	0.80	0.05	0.04	2,320
Anaesthesia	0.91	0.00	0.09	0.00	56
Bariatrics	0.17	0.03	0.81	0.00	277
Cardiology	1.00	0.00	0.00	0.00	1
Cardiothoracic Surgery	0.18	0.00	0.82	0.00	205
GE	1.00	0.00	0.00	0.00	8
GE Surgery	0.10	0.42	0.41	0.07	552
Head Neck Surgery	0.01	0.12	0.04	0.83	92
ENT	0.60	0.33	0.00	0.07	5,227
Lung Surgery	0.41	0.00	0.59	0.00	29
Lung Diseases	0.65	0.00	0.35	0.00	31
Mamma Surgery	0.82	0.04	0.13	0.01	675
Neurosurgery	0.01	0.22	0.00	0.77	486
Obstetrics and Gynaecology	0.28	0.35	0.01	0.35	1,719
Optometry	0.41	0.58	0.00	0.01	223
Orthopedy	0.05	0.37	0.00	0.58	3,118
Pain relief	0.87	0.00	0.13	0.00	15
Plastic Surgery	0.13	0.52	0.02	0.33	1,052
Oral Surgery	0.22	0.54	0.02	0.22	863
Trauma Surgery	0.11	0.78	0.00	0.10	1,119
Urology	0.13	0.30	0.04	0.53	1,609
Vascular Surgery	0.05	0.33	0.03	0.59	446
Other	0.50	0.17	0.33	0.00	6

Appendix E

Appendix E1 Statistical analyses percentage of patients within the access time criteria

	Baseline	Intervention 1	Intervention 3
Mean	60.4%	68.9%	67.9%
Variance	0.15%	0.34%	1.06%
n	28	28	28
p-value		0.00	0.00

	Inter-vention 1	Inter-vention 2a	Inter-vention 2b	Inter-vention 2c	Inter-vention 2e	Inter-vention 2f	Inter-vention 2g
Mean	68.9%	82.2%	81.8%	76.3%	80.3%	78.5%	84.1%
Variance	0.34%	0.16%	0.14%	0.31%	0.11%	0.18%	0.11%
n	28	28	28	28	28	28	28
p-value		0.00	0.00	0.00	0.00	0.00	0.00

	Inter-vention 2g	Inter-vention 2a	Inter-vention 2g	Inter-vention 2b	Inter-vention 2g	Inter-vention 2e
Mean	84.1%	82.2%	84.1%	81.8%	84.1%	80.3%
Variance	0.11%	0.16%	0.11%	0.14%	0.11%	0.11%
n	28	28	28	28	28	28
p-value	0.06		0.02		0.00	

Appendix E2 Statistical analyses daily number of patients overbooked

	Baseline	Intervention 1	Intervention 3
Mean	10.43	2.21	3.56
Variance	12.87	2.02	4.80
n	28	28	28
p-value		0.00	0.00

	Inter-vention 1	Inter-vention 2a	Inter-vention 2b	Inter-vention 2c	Inter-vention 2e	Inter-vention 2f	Inter-vention 2g
Mean	2.21	1.59	2.73	1.56	2.13	1.87	1.39
Variance	2.02	1.03	2.99	0.89	1.71	1.32	0.88
n	28	28	28	28	28	28	28
p-value		0.18	0.22	0.25	0.40	0.43	0.05

	Inter-vention 2g	Inter-vention 2c	Inter-vention 2g	Inter-vention 2a	Inter-vention 2g	Inter-vention 2f
Mean	1.39	1.56	1.39	1.59	1.39	1.87
Variance	0.88	0.89	0.88	1.03	0.88	1.32
n	28	28	28	28	28	28
p-value	0.18		0.34		0.08	

Appendix E3 Statistical analyses variation in workload for nurses

	Baseline	Intervention 1	Intervention 3
Mean	9.26	6.64	6.26
Variance	13.43	5.81	4.29
n	28	28	28
p-value		0.00	0.00

	Inter-vention 1	Inter-vention 2a	Inter-vention 2b	Inter-vention 2c	Inter-vention 2e	Inter-vention 2f	Inter-vention 2g
Mean	6.64	6.36	5.25	6.22	5.45	5.96	6.04
Variance	5.81	5.42	8.89	5.82	5.35	7.53	7.15
n	28	28	28	28	28	28	28
p-value		0.65	0.06	0.52	0.06	0.33	0.38

	Inter-vention 2b	Inter-vention 2e	Inter-vention 2b	Inter-vention 2f	Inter-vention 2b	Inter-vention 2g
Mean	5.25	5.45	5.25	5.96	5.25	6.04
Variance	8.89	5.35	8.89	7.53	8.89	7.15
n	28	28	28	28	28	28
p-value	0.78		0.36		0.31	

Appendix E4 Statistical analyses variation in workload for screeners

	Baseline	Intervention 1	Intervention 3
Mean	8.19	5.64	5.72
Variance	7.22	6.31	3.12
n	28	28	28
p-value		0.00	0.00

	Inter-vention 1	Inter-vention 2a	Inter-vention 2b	Inter-vention 2c	Inter-vention 2e	Inter-vention 2f	Inter-vention 2g
Mean	5.64	5.27	5.44	5.81	5.66	5.08	5.24
Variance	6.31	5.33	6.53	4.84	4.22	4.97	4.51
n	28	28	28	28	28	28	28
p-value		0.56	0.76	0.79	0.97	0.38	0.52

	Inter-vention 2f	Inter-vention 2g	Inter-vention 2f	Inter-vention 2a	Inter-vention 2f	Inter-vention 2b
Mean	5.08	5.24	5.08	5.27	5.08	5.44
Variance	4.97	4.51	4.97	5.33	4.97	6.53
n	28	28	28	28	28	28
p-value	0.78		0.75		0.58	