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Master's thesis

# Assessing and redesigning processes in the pharmacy to improve pharmaceutical care

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# Summary

Staff and management at the Sint Maartenskliniek want to continuously improve pharmaceutical care. The quality of care has a large influence on the effects of medication-based therapy. It has been shown that the quality of service can be increased by allocating more resources for advice and consultation by pharmaceutical staff to patients in need.

In this study, we assess the current performance of processes in the pharmacy. Furthermore, we redesign these processes to reallocate resources from non-value-creating procedures to value-creating services. Staff perceives two related inefficiencies of patients waiting at the counter while occupying valuable resources: first by not following the correct procedure necessary for fast pickups, and second by not opting for fast pickups at all. Management has supplied a proposal of a locker box implementation for fast medication pickups. This intervention aims to liberate resources from otherwise excessive procedures. The intervention is evaluated as a possible redesign approach, among other proposed interventions.

**Approach** We assess the performance of the pharmacy based on existing data. By cross-checking several databases, we examine and confirm the perceived inefficiencies. We construct a simulation model to assess the influence of these inefficiencies, and implement and evaluate proposed interventions. The objective of proposed interventions is to allow an increase in service duration for patients in need of pharmaceutical care. This possible increase is measured by a new permissible service enhancement (PSE), a factor that multiplies the service duration for these patients artificially to simulate a reallocation of resources.

**Results** We confirm both perceived inefficiencies by data analysis. We find that while 47.95% of medication-requesting patients are eligible for an efficient fast pickup, only 12.65% of these patients actually make use of this option. Furthermore, of all patients selecting the fast pickup, only 56.92% follow the procedure correctly. We use these findings and the simulation model to conclude that a completely efficient pharmacy could either have 25% shorter average waiting times, or allow a 40% increase for service durations of patients in need of pharmaceutical care while still matching the current performance.

We evaluate several proposed interventions. A combined intervention of both electronic identification card and locker box allows an increase of 80% while matching the ambition of the

pharmacy for even better performance. For individual interventions, the electronic identification card is the most promising, allowing an increase in service durations of 40%. The locker box intervention as suggested by management allows an increase of 10%, but notably profits from other approaches that address the inefficiencies directly, as we show using the combined intervention.

**Conclusions and recommendations** Aforementioned inefficiencies result in a considerable waste of resources. Electronic identification alleviates these inefficiencies and allows reallocation of resources. The locker box approach eliminates a non-value-creating procedure, thereby also liberating resources. A combination of both procedures shows promise by allowing a considerable increase in service durations for patients needing pharmaceutical care. Other approaches, such as patient education to reduce these inefficiencies, require further research.

We provide several suggestions and recommendations relating to both practice and future research. As a practical implication, this study provides a trigger for a conscious assessment of pharmacy processes by pharmacy staff. Before, quantitative analysis of process performance was limited to a minimum. Extensive assessment based on existing databases may enhance awareness. We recommend further research into the proposed interventions as we have shown that the pharmacy's capacity could be used more efficiently.

For the scientific community, this study contributes to the growing number of simulation models assessing the performance and allowing the redesign of healthcare and pharmacy processes. We present novel approaches to use existing databases to assess the performance. Additionally, we introduce and evaluate two interventions to redesign the service and product delivery in the pharmacy by using a electronic identification card system or a locker box approach.

# Samenvatting

Medewerkers en management van de Sint Maartenskliniek willen continu de farmaceutische zorg verbeteren. De kwaliteit van de zorg heeft een grote invloed op de resultaten van therapie met medicatie. Onderzoek heeft laten zien dat de kwaliteit van de zorg verbeterd kan worden door medewerkers meer ruimte voor advies en consultatie aan patiënten te geven.

In dit onderzoek evalueren wij de huidige prestatie van processen in de apotheek. Daarnaast herontwerpen wij deze processen om meer resources van niet-waarde-creërende procedures naar waarde-creërende diensten te alloceren. Medewerkers beschrijven twee inefficiënties gerelateerd aan patiënten die aan de balie wachten en zo waardevolle resources bezetten: De eerste, doordat patiënten niet de juiste procedure volgen om snel medicatie op te halen. De tweede, doordat patiënten niet eens voor de procedure van snel ophalen kiezen. Het management heeft een mogelijke interventie aangedragen, bestaande uit een kluisjessysteem voor snelle medicatie dispensaties. Deze interventie probeert resources van niet-waarde-creërende procedures te bevrijden. De interventie wordt samen met overige interventies als een mogelijk herontwerp onderzocht.

**Aanpak** Wij evalueren de huidige prestatie van de apotheek aan de hand van bestaande data. Door het vergelijken en verbinden van verschillende databases onderzoeken en bevestigen wij de geobserveerde inefficiënties. Wij construeren een simulatiemodel om de invloeden van deze inefficiënties te toetsen en om voorgestelde interventies te implementeren en te evalueren. Het doel van deze voorgestelde interventies is het toelaten van een toename van de balietijd voor patiënten die van meer tijd profiteren. Deze mogelijke toename wordt gemeten doormiddel van een nieuw geïntroduceerde toelaatbare service verbetering factor (PSE). Deze factor vermenigvuldigt de balietijd voor deze patiënten kunstmatig in het model om een allocatie van resources te simuleren.

**Resultaten** Wij bevestigen beide inefficiënties doormiddel van data-analyse. Wij laten zien dat 47,95% van alle patiënten die medicatie ophalen in staat zijn om deze medicatie snel op te halen. Slechts 12,65% maakt hier echter gebruikt van. Verder, van alle patiënten die hun medicatie snel ophalen, volgen slechts 56,92% de juiste procedure. Wij gebruiken deze resultaten en het simulatiemodel om te concluderen dat een volledig efficiënte apotheek een 25% lagere gemiddelde wachttijd kan bereiken. Alternatief kan een toename van 40% voor de balietijd van

patiënten die hier baat bij hebben het gevolg zijn.

Wij onderzoeken verschillende voorgestelde interventies. Een combinatie van de kluisjesmuur en een elektronische chipkaart laat een mogelijke toename van 80% balietijd zien. Als het gaat om individuele interventies laat de elektronische chipkaart een toename van 40% zien. De kluisjesmuur laat slechts een toename van 10% toe, maar profiteert zeer sterk van een overige vermindering van de inefficiënties.

**Conclusie en aanbevelingen** De inefficiënties zorgen voor een grote verspilling van resources. Een elektronische chipkaart verhelpt deze inefficiënties en laat een grote herverdeling van resources toe. De kluisjesmuur elimineert een niet-waarde-toevoegend proces waardoor ook resources vrijkomen. Een combinatie van beide interventies laat potentie zien door een grote mogelijke toename balietijd. Andere aanpakken, zoals educatie van patiënten om de inefficiënties te verminderen, eisen verder onderzoek.

Wij presenteren een aantal suggesties en aanbevelingen voor praktijk en verder onderzoek. Voor de praktijk zorgt dit onderzoek voor een bewuster omgaan met prestatiedata in de apotheek. Eerder was kwantitatieve analyse van prestatiedata beperkt tot een minimum. Uitgebreide evaluatie op basis van bestaande databases kan het bewustzijn versterken. Wij bevelen aan om de voorgestelde interventies verder te onderzoeken, gezien de ruimte in de capaciteit van de apotheek bij een betere efficiëntie.

Voor wetenschappelijk onderzoek geeft dit onderzoek wederom een simulatiemodel ter beoordeling en verbetering van de apotheek. Wij introduceren nieuwe aanpakken rondom bestaande databases. Daarnaast beschrijven en evalueren wij nieuwe interventies voor diensten en medicatie dispensatie in de apotheek in de vorm van een elektronische chipkaart en een kluisjesmuur.

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# Terminology

**AGB** Short for *Algemeen Gegevens Beheer* or *general information management*. A national code for care professionals.

**Aposys** Aposys is the electronic pharmacy system used at the Maartensapotheek. Aposys saves pharmaceutical regimes for each patient and is actively used at the counter to enter new information, change existing information, or provide electronic information assistance to staff.

**FTE** Short for *full-time equivalent*, hours worked in full-time employment.

**Gbos queuing system** The queuing system used in the Maartensapotheek, made by the company Gbos. The system is based on the ticket pillar in the waiting room and runs on all terminal computers at the counters to provide up-to-date information about currently waiting patients to staff.

**Mutation** In this thesis, a mutation describes a change in pharmaceutical regime for a patient, triggered by (a) a new patient, (b) a new medication for an existing patient identified by prescription identifier, (c) a changed usage of an existing medication identified by usage code.

**MA** Short for *Maartensapotheek*, the outpatient pharmacy where this project is carried out.

**OR** Short for *Operations Research*, the scientific area this study is situated in.

**Outpatient** Outpatients are patients who do not occupy a bed over night, meaning they leave the hospital on the same day as they enter it.

**PRK** Short for *Prescriptie Kenmerk* or *prescription identifier*. Nationally agreed on identification code for active ingredients of medication, surpassing branding, therefore making it suitable to compare pharmaceutical regimes (Koninklijke Nederlandse Maatschappij ter bevordering der Pharmacie, 2017).

**PSE** Short for *Permissible Service Enhancement*, indicating the allowable increase in service duration of type 5 patients. Used as a performance indicator to evaluate interventions, where the current situation's PSE equals 1.

**Rowa robot** The robot used in the medication warehouse at MA, made by the company Rowa.

**Usage code** A letter-and-number code describing the manner of usage of a medication according to national pharmaceutical agreements, usually of the type number-letter-number-letter where the first pair describes the frequency and the second pair describes the amount to be taken. May be extended by further description and notes.

# Notation

- Times and durations are noted as hours:minutes:seconds, unless specified otherwise.
- Dates are noted as either day-month-year or year-month-day, unless specified otherwise.
- Days of the week may be denoted by numerals, where 1 is Monday, 2 is Tuesday, and so on, unless specified otherwise.
- The gender of a patient or member of staff is never actually implied but for simplicity indicated as male.

# Preface

"We want to improve pharmaceutical care by increasing service durations and maybe eliminate other services by using novel technology." Although not a literal quote, this resembles the content of the first project meeting with Bart and Derya. While it seemed unconventional, it clearly stated the goal: to improve pharmaceutical care for patients visiting the Maartensapotheek. Innovation and ambition immediately convinced me to take up this project for my graduation.

In the past six months I have not only completed this project but also learned a lot about the pharmacy, its staff and patients, performing research, writing a thesis, and about my own capabilities. Now, at the end, I am confident that I am not just able to deliver a sound research but also a useful product.

Before concluding this preface, I want to thank several important people. Derya, your sharp guidance has forced me to stay critical of my own work while also aiming to confidently sell a product of which I am convinced. Erwin, my writing has been greatly enhanced by your unceasing advocacy of succinct style and insisting and inexhaustible avoidance of intricate semantic constructions and passive voice, at least temporarily. Sjoerd, thanks to your expertise within the pharmacy I quickly got to know the relevant details, while also discussing ideas and methods. Bart, your outlook on the future of pharmaceutical service has not only enabled this project but also enriched its execution with remarks and suggestions.

While I want to thank all staff at the pharmacy for their cooperation, I specifically give thanks to Victor, who has contributed to concepts of data analysis, and the managerial support team Sonja, Jeannette, Lisette, Laura, and Esther, who have consistently managed to schedule challenging appointments. I thank my colleague Judith for our talks about our respective projects, which have not only given me insight and valuable feedback but also a possibility for informal and personal reflection on my work.

Finally, I want to thank all friends and family who have supported me during this project in any way imaginable. While I am confident that I have remained sociable, that perception is subjective. Especially my girlfriend Lotte had to endure tedious talks about the nature of mobile units in my simulation model, although the red-faced virtual patients might have alleviated this torment.

R. W. Stuyver, Nijmegen, May 16, 2017

# Chapter 1

# Introduction

The primary focus of this research is the pharmaceutical service delivered in the outpatient pharmacy at the Sint Maartenskliniek, situated in Nijmegen, the Netherlands. Several processes are involved to deliver pharmaceutical care. The purpose of this research is to assess and possibly redesign these processes to achieve better pharmaceutical care.

This chapter presents background information about the project and its context (Section 1.5), including a short description of the Sint Maartenskliniek (Section 1.1), and an overview of the medical background relevant for this project (Sections 1.2 and 1.3). Furthermore, the motivation for this study and the research objective is given (Sections 1.4 and 1.6).

## 1.1 Sint Maartenskliniek

The Sint Maartenskliniek (SMK) is specialized in chronic movement and posture disorders. The organization has four locations in the eastern part of the Netherlands with the main facility situated on the outskirts of the City of Nijmegen. This facility is the focus of this study. It contains centers for orthopedics, rheumatology, rehabilitation, as well as a pharmaceutical department.

Due to its specialization, the hospital's catchment area stretches throughout large parts of the eastern Netherlands and even across the border into Germany. About 60000 patients are treated every year by the hospital's 1300 FTE employees (Sint Maartenskliniek, 2015). Of these patients, more than 40% travel more than 50 kilometers, showing a wide range of the hospital within the Netherlands and bordering nations.

The pharmaceutical functionalities are divided over three departments: Maartensapotheek (outpatient pharmacy), Instellingsapotheek (institutional pharmacy) and Klinische Farmacie (clinical pharmacy). The Maartensapotheek (MA) is the pharmacy specifically for outpatients. At the MA, patients receive prescribed medication after appointments with their healthcare providers at SMK and are also able to pick up repeating prescriptions after they run out of their medication. Additionally, the pharmacy carries over-the-counter medication. A core competence of MA staff is giving advice and education about medication and about combinations of several different medications. For the demographics at SMK, this is considered very valuable as described frequently in customer satisfaction questionnaires (ARGO BV, 2015). About 100 patients visit the MA every day.

## 1.2 Pharmaceutical care

Medication is one of the cornerstones of modern medicine. Consequently, pharmaceutical care, encompassing delivery and advice on the usage of medication, plays an important role in the healthcare path of today's patients. Especially in chronic disorders related to movement and posture, such as rheumatisms and osteoarthritis, medication is an essential part of treatment and often the only valid long-term option. Therefore, pharmaceutical care is of high importance at SMK to ensure patients' quality of life and the clinic's position in the national and international market of orthopedic centers.

The improvement of pharmaceutical care is one of the main targets at SMK. While customer satisfaction for both SMK in general and MA specifically is very high, improvement is seen as naturally possible (Sint Maartenskliniek, 2015; ARGO BV, 2015). Currently, staff is satisfied with their own performance regarding pharmaceutical care, but there are perceived inefficiencies within pharmaceutical processes that might create room for improvement.

Section 1.3 introduces the concept of *medication adherence*. It serves as an exemplary spearhead of the argument to improve pharmaceutical care. While pharmaceutical care encompasses far more than just medication adherence, the direct consequences of adherence on the patient's quality of life make this aspect especially suited to define the motivation for this research in Section 1.4.

## 1.3 Adherence

*Medication adherence* describes the degree of a patient's adherence to a given regime of medical prescriptions as determined by his physician. Nonadherence describes a patient not completely adhering to the determined regime (Osterberg and Blaschke, 2005).

Consequences of insufficient adherence of various degrees can be severe for patients and for the healthcare systems, both in terms of economical damage and quality of care (Osterberg and Blaschke, 2005; Van Den Bemt et al., 2014; Sokol et al., 2005). Unfortunately, adherence is often insufficient, as shown by the large number of medication-related admissions due to faulty adherence (Osterberg and Blaschke, 2005). Especially chronic patients are susceptible to nonadherence, and research has confirmed this for SMK patients (Van Den Bemt et al., 2014).

Measurement of adherence is generally seen as difficult and no gold standards or consistent indicators for nonadherence have been found (Van Den Bemt et al., 2014). While several methods to measure adherence have been proposed, most include frequent and high-quality consults with healthcare staff (Van Den Bemt et al., 2014; Osterberg and Blaschke, 2005).

Predicting nonadherent behavior also generates wide interest. Frequently mentioned indicators are related to patients' lack of belief, presence of bad beliefs, lack of insight and knowledge, and a bad patient-provider relationship (Osterberg and Blaschke, 2005; Van Den Bemt et al., 2014).

Research has shown that possible interventions involving pharmacists to improve adherence usually encompass direct contact. Contact with staff improves knowledge and education about the treatment, thereby enhancing a patient's insight while also enhancing the patient-provider relationship that has been shown to be crucial for prediction of adherence (Van Den Bemt et al., 2014; Osterberg and Blaschke, 2005; Bouvy et al., 2003; Valenstein et al., 2011; McDonald et al., 2002; Haynes et al., 2008; Volino et al., 2014).

A promising approach to improve adherence, prevent nonadherence, advance the patient-provider relationship, and allow further research is consequently based on creating more opportunities for pharmaceutical staff to inform patients and discuss treatments.

## 1.4 Motivation

The motivation for this study is to improve pharmaceutical care for outpatients visiting SMK. As it has been shown that pharmaceutical staff can influence adherence by improving patient education and implementing interventions, a possible approach is to create more opportunities for pharmaceutical staff to deliver care to outpatients.

Opportunities can be created by allowing staff more time with the patient at the counter. Processes in the pharmacy have to be assessed and redesigned as to allow the reallocation of staff working time to pharmaceutical care instead of processes that do not add healthcare value.

## 1.5 Problem description

The management of the MA wants to change the way of delivering service and medication to improve the pharmaceutical service. A redesign of processes in the pharmacy is desired as to create more opportunities for staff to interact with patients in need of pharmaceutical service, while maintaining performance regarding the waiting time of patients.

Observations show that a substantial portion of SMK's patients rely on repeating prescriptions for which they need no or less physical contact with staff. Consequently, some patients get superfluous time for advice while other patients would benefit greatly from additional time. A possible approach could then be to improve this inefficient utilization of resources by reallocating staff working time from time-wasting services to benefit-gaining services.

An assessment of the current situation is necessary before redesigning the pharmacy processes. This assessment can first be used to confirm the existence of possible perceived wasteful processes and observations of patients with repeating prescriptions. Second, the assessment can be used to construct a model of the current situation, which can serve to virtually implement and assess possible interventions. An evaluation of these interventions is also possible using the modified model and performance indicators determined by internal policies.

## 1.6 Research objective

The objective of this research is consequently determined as: *To assess and redesign processes in the pharmacy to reallocate staff time to patients in need of pharmaceutical care in order to improve pharmaceutical service.* This objective leads to a number of research questions, which are addressed in the chapters of this thesis.

1. What are the relevant processes, causal relations, and interdependencies in the pharmacy?
2. What are relevant performance indicators to evaluate the pharmacy's performance?
3. What data is necessary, what data is already gathered and how can the remaining information be collected?
4. Does the data confirm the described perceived inefficiencies and observations?
5. How can the current situation be modeled?
6. How can the processes be redesigned to achieve a better performance in terms of performance indicators?
7. How do proposed interventions perform and do they fulfill the necessary conditions?
8. What intervention performs best and how should the preferred intervention be implemented?

# Chapter 2

# Context analysis

This chapter provides a more detailed description of the context. Section 2.1 presents an overview of relevant pharmacy processes at the MA. Section 2.2 describes the internal data collection methods and performance measurement policies.

## 2.1 Pharmacy processes

Patients can enter the pharmacy seeking a variety of services. Some patients need consultation and detailed pharmaceutical care. Other patients just want to pick up their medication and are not in need of assistance, for example because they have followed the same medical regime for several years. As the MA also sells over-the-counter medicine, some patients visit the pharmacy for these products as well. To accommodate all possible motivations, the MA has installed a waiting room system called *Gbos queuing system* to guide patients, prioritize queuing, and evaluate performance (Sint Maartenskliniek, 2016, 2014). This waiting room system is installed on and served by the ticket pillar situated in the waiting room.

Figure 2.1 displays a photograph of the pharmacy. Some of the counters, the ticket pillar, and the active ticket display are highlighted. These elements are mentioned and explained in the next sections.

### 2.1.1 Tickets

Patients are asked to draw a ticket corresponding to their desired service at the waiting ticket pillar as they enter the pharmacy. This pillar presents eight options, which are given below. The type designations by number are not used in practice but are added here for clarity and used for the remainder of this study. Figure 2.2 displays a picture of the service type selection screen. Table D.2 in Appendix D.1 returns the frequencies of these service types.

**Type 1: Consult with colleagues** Staff members of SMK use this service. Internal policies

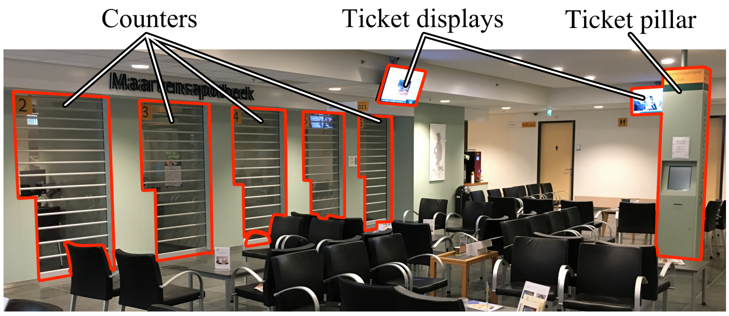


Figure 2.1: Picture of the Maartensapotheek with relevant elements slightly highlighted. Picture was taken after opening hours to protect patient privacy, note the closed shutters. Source: own photography, 03-05-2017.

encourage SMK staff members to visit the MA for private pharmaceutical questions. This service is given the highest priority, so that staff members may resume their usual work as soon as possible.

**Type 2: Medication consult** Patients indicate a desire to discuss their medical regime related to disorders treated at SMK using this service.

**Type 3: Information and advice** This option also indicates a request for information and advice about medication, in this case about over-the-counter medication. This distinction is not explicitly explained to patients.

**Type 4: My medication is ready to pick up** Patients who only want to pick up prepared prescriptions can choose this option. Patients have the option to call beforehand to prepare medication for pickup. A preceding visit to the outpatient clinic may also trigger the preparation of medication. However, due to time constraints, short time between call and visit, or because a patient did not notify the pharmacy at all, medication may not yet be prepared for pickup.

**Type 5: Prescription** This selection is for patients who have been prescribed medication and want to pick up the medication and receive advice about the prescription. For patients picking up a prescription for the first time, this is also the legally required choice.

**Type 6: Return medication and container** Patients who want to return unused medication or possibly hazardous material, for example containers to collect needles, can choose this option.

**Type 7: Needle instruction** Patients who need to use a needle for their medication can get detailed instruction by choosing this type. This type of service may be performed in a separate room if available.

**Type 8: Independent care** As the pharmacy also carries over-the-counter medication, patients can choose this type.

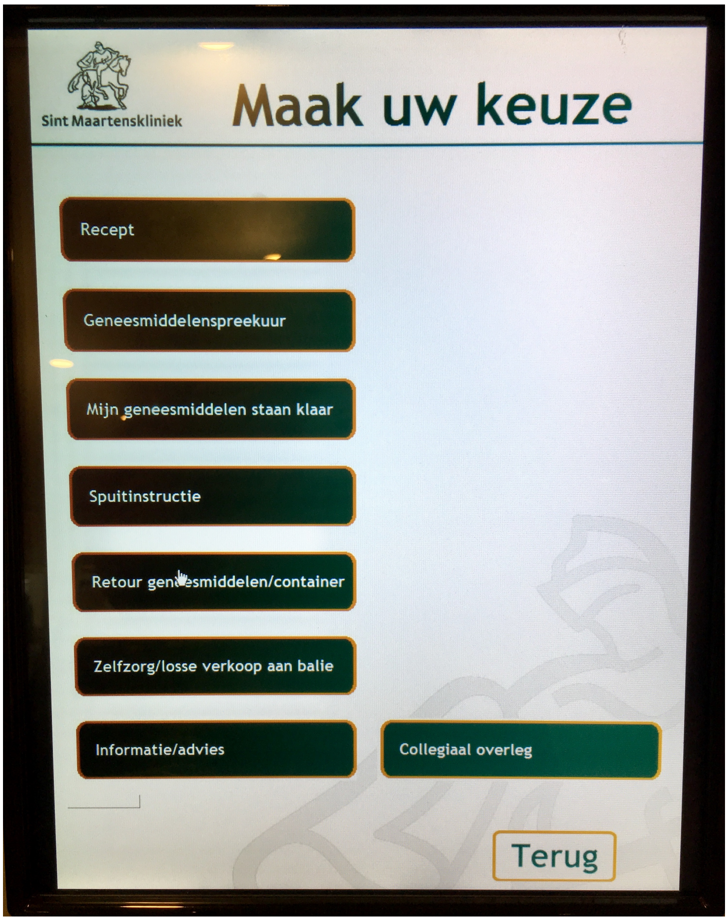


Figure 2.2: Picture of the service type selection screen presented to an arriving patient at the ticket pillar. Order of service types: 5, 2, 4, 7, 6, 8, 3, 1. Number designations are based on alphabetical sorting using the Dutch descriptions. Source: own photography, 03-05-2017.

Patients can enter the pharmacy in two ways: just as they enter the hospital or after a visit to the outpatient clinic. Starting in November 2016, patients coming from the outpatient clinic within SMK draw just one ticket at the start of the day. Before November 2016, a patient had to draw a new ticket for every station of his medical pathway that day. This led to many patients drawing tickets for all their obligations at the start of the day with the intention to minimize waiting time. This behavior, however, then led to a number of people not showing up when it was their ticket's turn because they were already busy at another station. SMK staff decided to give a patient a single ticket to apprehend this. When treatment at one station is finished, staff at that station re-inserts the ticket in the waiting queue for the appropriate next station.

Waiting times recorded after this implementation are unfortunately faulty due to software errors. As this new policy should not affect services, the data from November 2016 onwards can be used only for analysis of service durations. Data up to November 2016 can be used for arrival times, service durations and waiting times. Conclusions drawn in this project are applicable to the new situation as the arrival pattern and service durations do not change. However, the goal of the ticket reinsertion is a reduction of no-shows, which of course influences the pharmacy's performance.

### 2.1.2 Queues

A waiting room system is installed on the ticket pillar. This system controls all waiting instances and governs the queues in which these instances are placed. Section 2.2 provides further information on this software. While there are eight types of service, the waiting room system prioritizes using just four codes that correspond to one or more types. The four codes and corresponding types are given below.

**Code F** Serves types 3, 4, 6 and 8.

**Code R** Serves types 2 and 5.

**Code S** Serves type 7.

**Code Z** Serves type 1.

The motivation for this grouping is not entirely clear, especially considering the perceived overlap between types. There are no policy documents available for this reasoning. However, as data analysis as described in Chapter 6 shows, codes S and Z serve very distinct and uncommon types that need to enjoy a high priority. This is made possible by using own waiting row codes. It can also be shown that service types corresponding to code F do in fact have a shorter average service duration than services corresponding to code R. The code distinction is therefore probably made based on service duration.

### 2.1.3 Counters

The MA has a total of six counters for pharmaceutical care. The number of open counters is determined by the longest waiting time of the currently waiting patients. Audio-visual systems are installed throughout the pharmacy to notify staff of the number of waiting patients and their waiting time. Staff can then quickly react to an increase in number of patients by staffing more counters.

Counters 2 and 3 are always open. Policy dictates that if the waiting time of the longest waiting patient in the queue exceeds five minutes, counter 4 is opened, then counter 5, then counter 6, and finally counter 1. In practice, as members of staff have visual contact with the waiting room, counters 4, 5, and 6 may open more dynamically on own accord and there is no consistently applied policy for this behavior.

### 2.1.4 Priorities

As mentioned earlier, the usage of different codes enables priority queuing. The priority policy at MA is a complex matter because pharmaceutical care should be given for every type of service in a short time. Priorities differ for each counter based on the given codes, as is described in the list below. Corresponding types are given in parentheses.

**Counter 1** Z (type 1), S (type 7), F (types 3, 4, 6, 8), R (types 2, 5).

**Counter 2** Z (type 1), S (type 7), F (types 3, 4, 6, 8), R (types 2, 5).

**Counter 3** Z (type 1), S (type 7), R (types 2, 5), F (types 3, 4, 6, 8).

**Counter 4** Z (type 1), S (type 7), F (types 3, 4, 6, 8), R (types 2, 5).

**Counter 5** Z (type 1), S (type 7), R (types 2, 5), F (types 3, 4, 6, 8).

**Counter 6** Z (type 1), S (type 7), F (types 3, 4, 6, 8), R (types 2, 5).

Code Z for consult with colleagues is always top priority as per internal policy. Colleagues in need of pharmaceutical service are then ensured short waiting times and can return to their regular workstation as soon as possible. Services of code S (type 7 for needle instruction) may be performed in separate rooms based on availability. Consequently, it is possible to restaff the counter if the initial staff member leaves for service in the separate room. Furthermore, this service is fairly uncommon, thus it makes sense to allow these patients a high priority in the queue. Codes F and R alternate at different counters to avoid continuous blocking of one code by another.

### 2.1.5 Waiting period

Patients wait their turn in the waiting room after drawing a ticket and being placed in the queue. Displays show the current active tickets and the corresponding counter number. A new active ticket is announced by a flash of the display and an audio signal to notify patients. The staff member at the counter repeats the announcement if no patient shows up and finally continues on to the next patient in line after sufficient time has passed.

### 2.1.6 Service

The patient can approach the counter for service once his ticket is active. The service is different for every type, but staff members are all equally able to serve different requests. Patients do not have to redraw a ticket if they have chosen a wrong service initially.

Patient's details are confirmed at the start of the service. Then, if the patient has a prescription to pick up, the prescription is entered into the computer system Aposys. Currently, this system is independent of the system used in other departments of SMK. Consequently, for a patient who just came from an appointment at an outpatient department, the prescription has to be manually entered into the pharmacy system as there is no automatic link from the outpatient department system. Outpatient departments are able to forward a patient's prescription but rarely do so due to time constraints on their end.

In general, when a patient wants to pick up medication, either with or without advice, the active member of staff checks whether the medication is already ready for pickup. If this is the case, the medication is presented to the patient. If the medication is not yet ready to pick up, medication is requested from the delivery robot. In seldom cases, medication has to be taken manually from the warehouse. After the arrival of the medication, manually or per robot, the items are presented to the patient. Patients frequently require several different medications in one service.

Advice is given according to the wishes of the patient. Staff is legally required to provide advice for first-time users. Often staff is asked to open the medication or repackage it, as some patients have difficulties opening the packaging. If the patient has no more questions or requests, the service is finished.

There are no time limits for the service duration and members of staff may act on own accord. Internal policy prioritizes quality of service for the current patient over waiting time of other patients.

### 2.1.7 Robot delivery

Management at SMK recently invested in a robot delivery service. The robot is not within the scope of this project and will be treated as a black box servicing the requests from the counters. Medication can be requested at the counters and a robot warehousing system delivers the medication to that counter. Beyond the counters, the back office can also request medication from the robot. Requests from counters are queued for the robot according to a first-come-first-serve principle. They enjoy a higher priority than any back office requests. In idle time, the robot is used to refill the warehouse. At night, the robot autonomously rearranges the warehouse to optimize picking time.

While picking, labeling and transporting a single package takes about 20 seconds, prescriptions often contain several packages, leading to longer picking times as each package is picked individually. Furthermore, during busy periods, several orders are queued and sojourn times for a single request can rise up to five minutes.

### 2.1.8 End of pharmaceutical service

After finishing the service, the patient exits the pharmacy to either leave the hospital or to attend other obligations. The active member of staff at the counter terminates the service session and requests the next ticket.

Some services require small administrative tasks after service, which can be worked on after the patient has left but the service is not terminated, after terminating the service but before requesting the next patient, or after the current work-shift. There is no set policy for staff on how to act regarding this so-called *recovery time*.

### 2.1.9 Perceived inefficiencies

Members of staff perceive inefficiencies at the counter as patients wait for their medication that has been requested from the robot. Depending on the number and types of products requested, robot delivery can take several minutes. If all counters request medication from the robot, the resulting duration can be significant to the overall service duration of the patient. Some medication also needs to be repackaged, further increasing the time the patient is waiting at the counter.

This has several consequences. First, the patient is needlessly waiting, which decreases the quality of his service. Second, the patient occupies a member of staff. Third, the patient takes up the counter, which is a limited resource as well.

A patient waiting for his medication is the result of the patient not needing further pharmaceutical care, which would otherwise be given in the time spent waiting. Such a patient is often a repeating, long-time patient who has been using the same medication for several years and has sufficient knowledge about the usage of his medication and his disorder.

As noted, patients draw a ticket according to the service they request. An unknown portion of patients is eligible to simply pick up their medication, without the need for further advice. However, it is observed by staff that not all eligible patients choose the correct option, which is type 4, but instead select type 5. While this in itself does not increase the patient's service time, the lack of notification to prepare the pickup does.

Furthermore, an unknown fraction of patients selects type 4 even though their medication has not been prepared yet. These patients do not require additional pharmaceutical care and would therefore be able to just pick up their medication. However, they cause inefficiency because their medication still has to be requested from the robot and waiting time at the counter occurs.

Summarizing, there are two perceived inefficiencies. The first inefficiency is the result of patients eligible for type 4 choosing type 4 either too early while their medication is not yet ready for pickup or without notifying the pharmacy at all. This inefficiency leads to wasted time at the counter as the robot has to pick the medication that could have been prepared beforehand. The second inefficiency stems from patients eligible for a quick pickup choosing type 5 for prescription and not notifying beforehand. This again leads to a waste of time at the counter as these patients could have opted for a fast pickup of the medication. Figure 2.3 shows a graphical representation of these inefficiencies and indicates the desired correction.

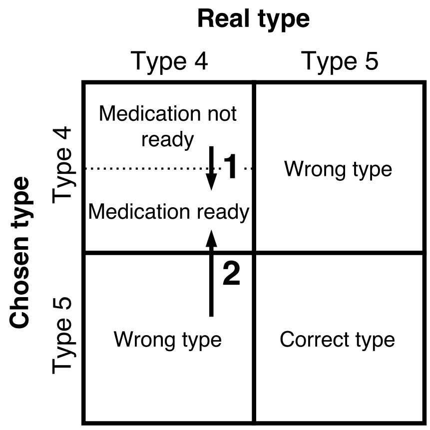


Figure 2.3: Two inefficiencies and corresponding desired corrections. First inefficiency: eligible for type 4, type 4 correctly selected, medication not ready for pickup. Second inefficiency: eligible for type 4, type 5 selected.

### 2.1.10 Suggested intervention

Management has proposed a locker box situated in the pharmacy of the hospital to improve the efficiency of processes. Upon ordering a prescription, staff prepares the medication, places the package in a locker and links the locker to the patient. The manner of linkage is not yet defined. The patient can then open the locker and pick up his medication.

Using this approach, the process for patients who choose to pick up their medication without any pharmaceutical service necessary is basically eliminated from the pharmacy. Note however that staff is still needed to prepare the prescriptions and place them in lockers. These actions may be flexibly scheduled, given on-time requests of medication. Note also that this proposal does not in fact solve the problem of perceived inefficiencies but only eliminates an already efficient process (in terms of the perceived inefficiencies): a patient eligible for a quick pickup choosing and executing a quick pickup.

This formulation is based on ideas and developments in the pharmaceutical service industry, but not supported by further research. Consequently, this thesis serves not only as a scientific exploration of the pharmacy processes and possible redesign concepts, but also as practical assessment of the suggested intervention. In the context of this study, this suggestion will be treated as other proposed interventions. Comparable interventions have been applied in a small number of pharmaceutical environments, notably the Asteres ScriptCenter at Ramstein Air Base military pharmacy. Outside of pharmacies, the concept of a locker box is long-known. Fast food dispensation and postal services may come to mind.

## 2.2 Data and performance measurement

Several data collection mechanisms are at work surrounding the pharmaceutical services at the MA. Some influence the waiting process directly, others serve as performance evaluation systems, and others are unrelated to the waiting mechanism but collect time-stamped information. These databases are not linked, but using common information like time-stamps and counter numbers, manual linking is possible. Chapter 6 further expands on these options.

**Gbos queuing system** The *Gbos queuing system* runs the ticket pillar and its database in the waiting room. Direct output of the database is used to activate inactive counters if patients' waiting time exceeds a certain length as described in Section 2.1. A drawn ticket starts a new instance within the waiting system. For every instance, several properties are recorded, including time of arrival, time that the service is started, time that the service is terminated, the counter at which the service took place, and the selected service type. Note that a patient can have several waiting instances on a single day. Appendix A.1 gives a full list of recorded values.

**Rowa delivery robot** The pharmaceutical storage robot made by *Rowa* also saves various kinds of information to a database, including the corresponding counter and time of the request. Appendix A.2 contains a complete list of information recorded in Rowa output files.

**Aposys pharmacy information system** *Aposys* is the central pharmacy information system in use at the MA. The system contains essential information on every patient of the MA. For reasons of security and privacy, access to and usage of Aposys is limited. One way to extract information from Aposys is using a delivery report, which returns all medication deliveries on a given day or range of days. A description of the information recorded in these reports is located in Appendix A.3.

Another source of information is the daily Aposys snapshot extraction. For security and back-up reasons, policy dictates that an extraction is made at the end of every day. A snapshot consists of a large table containing all patients of the MA and their complete medical profile. Appendix A.4 supplies an overview of the recorded information per patient.

**Performance evaluation** In the MA, the only performance measurement currently used is the waiting time of the patient. As the waiting time of the longest waiting patient exceeds a predetermined limit, policy dictates to try and activate an inactive counter to serve patients. SMK policy dictates that 70% of all patients should be served within five minutes while 90% should be served within ten minutes (Sint Maartenskliniek, 2014).

According to staff, the ambition is to raise this performance to 75% within five minutes and 98% within ten minutes. Consequently, the fractions of patients starting service within five and ten minutes are the basic performance indicators that should also be used for any evaluation of proposed interventions within this project. Table 2.1 gives the current performance with regards to these indicators.

| Indicator | Current performance | Current policy | Ambition |
|---|---|---|---|
| Average waiting time (min) | 4:04 | - | - |
| Fraction $>$ 5 minutes | 32.21% | $<$ 30% | $<$ 25% |
| Fraction $>$ 10 minutes | 9.94% | $<$ 10% | $<$ 2% |

Table 2.1: Current performance, current policy, and ambition of the pharmacy with regards to the relevant performance indicators: the average waiting time and the fractions of waiting instances with a waiting duration exceeding five and ten minutes.

Service durations at the counters are not included in performance evaluations. SMK policy dictates that no compromises are made to forcefully decrease the service duration by evaluating past services. Earlier investments like the robot-based medication delivery system were not made to decrease service time but to instead allow staff members to remain at the counter, delivering direct pharmaceutical care. However, as staff also has to work on back office tasks, staff utilization in terms of total sum of service durations should not increase.

## 2.3 Conclusion

Concluding this chapter, it is clear that the processes at the pharmacy form a complex system, constituted by priority rules, counter activation, and different service types. While customer and staff satisfaction is high and the performance of the pharmacy is regarded as sufficient, the perception of inefficiencies, confusion about service types, and the emergence of proposals are indicators for the possibility of improvements.

Furthermore, the necessity to carefully assess these processes in a quantifiable manner surfaces. While vast collection mechanisms are present, usage is rather limited. As the pharmacy is not an environment for trial-and-error approaches, profound assessment of any suggested intervention is vital to avoid danger to a patient's quality of life.

# Chapter 3

# Literature review

This chapter gives a literature review of existing research. As the declared objective of this study is the assessment and redesign of processes in the pharmacy, literature on process redesign is considered for basic principles and guidelines in Section 3.1. The need for a model emerges and possible modeling methods are presented in Sections 3.2 and 3.3. Earlier scientific endeavors to model comparable systems are described. Appendix B gives an overview of search terms and parameters.

## 3.1 On process redesign

Persson (1995) defines *process redesign* as "a redesign of core processes with the purpose to find and implement breakthrough improvements to those processes". The author argues that process redesign can be applied to any delivery process, whether it concerns a product, a service, or information, assuming that any business is a network or series of processes. Romero (2013) defines the pharmacy specifically as a network of processes.

Persson (1995) supplies several relevant reasons for a redesign: to create a competitive advantage, to improve performance towards customers, and to more efficiently fulfill value-delivering processes. Rosenhead (1978) supplements these reasons specifically for healthcare processes, citing the large costs of healthcare. Furthermore, demographic changes and rising costs for medication are described as specific motivations for pharmacy process redesign (Romero, 2013). Persson (1995) delivers a framework for process redesign, encompassing nine principles of which several are relevant for the current study.

1. **Reduction of lead times** Possible methods include the parallelization of sub-processes, improved synchronization, and the elimination of unnecessary processes. Here it is necessary to address an apparent conflict: a lower service duration for a non-value-creating process does not result in a lower quality of service, as the service does not add value. Instead, reduction of service duration of one service can free up capacity for a longer service

duration and therefore a higher quality in other service types.

2. **Reduction of or adaption to uncertainties** This principle describes the elimination or compensation of uncertain characteristics, such as variance in process parameters. As such, reducing the variance of service durations can be regarded as an intervention stemming from this principle.

4. **Matching supply and demand patterns** Differences between supply and demand can lead to inefficiencies by over- or under-staffing. These differences can be examined for possible elimination by either changing demand or adapting supply.

5. **Simplification of structures, systems, and processes** Networks of processes frequently grow organically and can therefore be subject to increasing complexity, which can lead to inefficiencies.

8. **Improvements of information processing** Improved coordination of processes by increasing the usage of available information can improve efficiency.

To conclude this section, Rosenhead (1978) gives an overview of the application of process redesign techniques, among others, in healthcare environments. Using several examples and listing five characteristics, the author warns of the dangers of simply adapting industrial engineering principles to healthcare services as to avoid *inhumanity*. Three of these characteristics can be used to discuss proposed interventions as the main objective at SMK and MA is to satisfy patients by improving their quality of life.

1. **Single objective** Methods from industry often focus on a single objective to optimize. In the case of human patients, it is difficult to define a single objective. Furthermore, patients may have a different opinion than treating specialists.

2. **Distortion** Models tend to distort reality by simplification. A reduction of choice and uncertainty is therefore implied. Ethical questions arise from impeding a patient's choices.

5. **Static problems** Techniques used in industry formulate problems as static and solving problems is therefore proposed as in one part and at one point in time. In reality, problems are constantly developing and a intervention is implemented gradually in time and in scope with continuous feedback.

Possible conflicts between the objective, the principles described above, and the characteristics listed here are apparent. However, these characteristics do not forbid the use of process redesign in healthcare but instead serve as a warning to proceed with caution, correctly generate interventions, and carefully evaluate their performance.

Hence, it is clear that a model is necessary. Changes in system configuration can not be applied directly in reality, thereby endangering patients' quality of life. The next sections present two ways to model a system. Note that oftentimes researchers do not explicitly select just one method but instead try to combine or confirm findings from one with findings from the other.

## 3.2 On queuing theory

The analytical approach to waiting and service processes is described as queuing theory. This approach is based on the premise that a system can be completely defined by a set of variables, thereby defining the state of the system. In a simple waiting room environment, the number of customers waiting and the number of customers currently in service can be state-defining variables.

A system can transit from one state to another, thereby creating a chain of states, which can be read as the *history* of the system. Each transition from one state to another has a corresponding transition probability. All these probabilities together form a transition matrix, which then again is the basis for further analysis of the system. Depending on the characteristics of the system and the nature of its mechanics, the resulting model can have easily interpretable properties, directly deriving from the mathematical relationships between state variables, transition probabilities, and system characteristics.

Every system can be modeled using a queuing theory approach given the willingness to make assumptions and simplifications. However, complex system mechanics and unwieldy input characteristics can hinder an analytical investigation as the properties of the resulting model require intensive mathematical considerations (Law, 2015).

One issue at hand within this queuing system is the phenomenon of *pooling*. This describes the range of combinations of individual queues with individual service types and specialized servers to a single system with one queue and identical servers, as well as all possible gradual configurations in between these extremes. In the current situation, there are eight service types with differing service characteristics in terms of service durations combined into four queues, being then served by identical servers.

Several authors have described the use of queuing theory to analyze and improve the performance of a network or series of processes with regard to pooling. While several studies are positive about the application of pooling, some researchers note that pooling also has severe disadvantages and its success depends largely on environmental parameters. Large variability in service durations and independent customer decisions can decrease the advantages of pooling (Rothkopf and Rech, 1987).

Vanberkel et al. (2012) give mathematical insight into the efficiency of pooling, outlining the fractional mix of service types, the characteristics of the service durations, the workload, and the resource sharing policy as substantial determinants of the efficiency of pooling. Other research agrees with these determining factors (Van Dijk and Van der Sluis, 2008; Joustra et al., 2010).

Mandelbaum and Reiman (1998) doubt the benefits of pooling based on mathematical analysis, especially with an increase in variability in service durations. According to this work, pooling is beneficial as long as the services have comparable characteristics. Widely differing service durations take away advantages from pooling and favor specialized, de-pooled queues. The same study also notes that the actual mix of service types is important as the effect of increasing variance decreases with a decrease in portion of total instances.

Shimshak et al. (1981) use a queuing theory approach to analyze waiting times for a pharmacy unit with priority rules for certain service types. To simplify the model, the authors choose to assume identically distributed arrival patterns and service durations for all service types and limit the system to two continuously active servers. They note that a queuing theory approach reaches its limits and advise usage of a simulation model for more complex situations.

For the case of the current situation, these findings translate as follows: if the service durations of all service types are similar, a single combined queue is beneficial. With increasing difference between service durations, a specialization of queues and services might perform better. As the goal of this study is to allow an increase in the service duration of one type while possibly decreasing the service duration of another type, the variance of all service durations will obviously increase, therefore making pooling less interesting, performance-wise. However, dependence on type mix is also of interest as this also influences the efficiency of pooling. Furthermore, researchers frequently address the limitations and necessary assumptions related to queuing theory approaches.

## 3.3 On simulation

Simulation models aim to copy real processes and mechanics as accurately as possible or necessary and then insert theoretical instances into the system. These instances themselves are based on historical or empirical data collected from the actual reality. Consequently, simulation models can be seen as an elaborate copy, extracted from reality to facilitate analysis and manipulation *in vitro*. The usage of simulation models requires certain fulfilled conditions. A simulation approach is able to tolerate a wide scale of system mechanics, properties and input characteristics. Of course, with increasing complexity of reality, complexity of a simulation model increases as well (Law, 2015).

One advantage of a simulation study is related to the involvement of the organization. As a simulation model is constructed, members of staff are asked for their opinion, insight and verdict on the underlying processes and the validity of the simulation model. This leads to a more accurate representation of reality and to an increase in acceptance by members of the organization, as they feel that they have contributed to the project (Law, 2015).

Furthermore, as a simulation model creates opportunities for attractive visualizations of the model, an understanding and acceptance of the model by members of the organization is fostered, which increases the probability to adapt resulting conclusions (Law, 2015).

A large number of studies has been conducted using a simulation approach. However, due to the nature of this approach, specific simulation models are generally not suited to simply translate to another real system. Therefore, literature on simulation models can mostly be used for methods and best practices, not for actual models.

Several studies have used simulation to evaluate new staffing policies in the pharmacy, both for outpatients (Reynolds et al., 2011) and inpatients (Spry and Lawley, 2005; Wong et al., 2003). Reynolds et al. (2011) note that consumption of time, potential danger, and staff morale were reasons to use a simulation study instead of simply implementing a new policy for trial. Simulation also allows exploration of the effects of a broad range of possible changes without disturbing the day-to-day work, which was especially beneficial for a study attempting to change the processes in a pharmacy (Wong et al., 2003).

While these studies suffered from inconsistent input characteristics, for example arrival patterns (Reynolds et al., 2011), complex priority rules, and process dependencies (Wong et al., 2003; Spry and Lawley, 2005), researchers were nonetheless able to successfully construct a simulation model. Although there is no explicit mention of any other approach besides simulation, these issues can undoubtedly be seen as further reasons to use a simulation-based approach, as a simulation model is able to accommodate their implementation.

All reviewed studies list a particular set of assumptions, used to simplify the model with respect to individuality of staff (Reynolds et al., 2011), opening hours (Wong et al., 2003), variations in seasons and processes (Wong et al., 2003), and persistence on internal policies (Reynolds et al., 2011; Spry and Lawley, 2005). Furthermore, in a critical review of their own work, researchers give limitations of the model. These include non-standard procedures by staff, unpredictable failures, and extreme outliers in task completion (Wong et al., 2003; Reynolds et al., 2011).

Other papers look beyond pharmacies. Joustra and Van Dijk (2001) use a queuing theory approach for case studies on airport queuing to verify and validate a simulation model, while also giving insights for generating interventions and defining experiments within the simulation model. The authors note that especially a non-constant arrival pattern is problematic for a queuing theory approach. The authors point to dynamic counter staffing as a promising way to increase efficiency in a pooling situation with non-constant arrival patterns.

## 3.4 Conclusion

Usage of a model is advisable, beneficial, and even necessary, as this review shows. Any proposed intervention based on process redesign principles needs to be evaluated using an abstraction from reality to avoid risking day-to-day operations in the pharmacy.

Concerning the nature of the model, while a queuing theory approach promises an extensive theoretical backbone and an environment suited for testing and evaluation, the underlying assumptions and conditions can prove troublesome. Findings on pooling from literature may be useful but the construction of a model for the specific current situation is definitely required.

Simulation, on the other hand, is able to accommodate a much broader range of systems, details, and possible interventions, while of course having its own limitations in design and capacity for generalization. Literature on simulation fails to provide generalizable findings but instead advises on model building practices.

Before a choice of approach can be made, a conceptual model needs to be constructed. This conceptual model should be able to accommodate proposed interventions and allow experimentation. Furthermore, the conceptual model dictates necessary inputs that data analysis should deliver. Based on the conceptual model and results of data analysis, the fit of each approach to the current situation can be judged and an modeling approach is then selected.

# Chapter 4

# Interventions

Redesigning processes in the pharmacy revolves around generating approaches to observed and confirmed problems in the form of interventions to the current situation. In this project, there is a distinction between three types of proposed interventions: upper bound interventions, suggested interventions, and literature-based and creative interventions. This chapter provides an overview of the proposed interventions. Note that while only a single combination is given, other combinations can be feasible in practice.

## 4.1 Upper bound interventions

For this group of theoretical interventions, the perceived inefficiencies are removed from the model as to allow insight into the theoretically optimal performance of the system, *without* even adjusting any processes. While realizations of these interventions are doubtful, the resulting performance can be used as a theoretical upper bound of performance improvement for the current situation. Nonetheless, we give possible approaches to implementation. Both inefficiencies are first assessed individually and also together.

**First inefficiency** For this theoretical intervention, the fraction of patients of type 4 being able to pick up their medication using a fast pickup is set to 100%. This translates to all patients choosing type 4 actually ordering their medication beforehand. This intervention does not change the number of patients per service type. While this intervention constitutes a very theoretical upper bound, gradual implementation may be achieved by educating patients about the possibility of a fast pickup by ordering beforehand.

**Second inefficiency** To assess this theoretical intervention, all patients who are eligible for a type 4 service actually choose this option. To achieve this, patients of both type 4 and type 5 are subject to a probability of eligibility for type 4 services to determine the final service type. The probability for a fast pickup or a robot-assisted pickup is not changed as opposed to the intervention solving the first inefficiency. This intervention is purely a theoretical upper bound as well, but may be gradually achieved by improving patients' knowledge about the eligibility for type 4 services as opposed to type 5 services.

**First and second inefficiency** In this theoretical optimum, both the first and second inefficiency are removed as described in the paragraphs above. This intervention represents an optimal performance of the current situation, given that both inefficiencies are completely eliminated from the system. The resulting performance gives an impression of the theoretical capacity for pharmaceutical care of the current system of processes. As for the individual interventions for the first and second inefficiency, the combined intervention is also mainly theoretical. Improving patients' education and knowledge about their own influence in enhancing the pharmacy's performance might however lead a reduction of these inefficiencies.

## 4.2 Suggested interventions

**Locker box** The locker box is suggested by management (see Chapter 2). To implement this intervention within the simulation model, a separate pathway for patients of type 4 with a fast pickup is set up. These patients are routed to a different service station which does not require any staff time. As such, these patients are essentially eliminated from the system and resources are liberated for reallocation.

While not based on the literature review, this intervention applies principle 1 of the framework by Persson, *reduction of lead times*, by eliminating a process completely from the current scope (Persson, 1995).

## 4.3 Literature-based and creative interventions

Based on the literature review, a framework and related principles for process redesign are used to generate interventions. Practical implementation of these interventions is central in the application of the principles. Furthermore, this group also contains interventions resulting from discussions with staff. While purely literature-based interventions operate top-down from a framework basis, creative interventions are generated bottom-up from operational observations. While a much larger number of possible options is imaginable, we here limit to these interventions as they represent different approaches while also being fairly comprehensible to implement.

**Electronic identification card** This intervention proposes the installation of a card reader at the ticket pillar. Patients receive an electronic identification card which can be used upon arrival to authorize the ticket pillar to order medication for repeating prescriptions. Patients of type 4 receive a ticket which will be activated once the ordered medication has been prepared. This way, patients mimic a type 4 fast pickup. The time spent waiting at the counter for their prescription can now be spent in the waiting room which does not alter the performance for the patient but liberates resources for pharmacy staff. To promote this pickup, type 4 patients are directed in a new queue that receives top priority.

This intervention can be implemented in the model by decreasing the first efficiency and second inefficiency, while at the same time implementing a waiting process for type 4 patients as to ensure that their medication is prepared for a fast pickup. We note here that there is still time and effort required to prepare medications. While this is not within the scope of this model, we assume that back office staff is able to process all requests within their capacity. Referring to the literature review, this intervention shows application of principles 1 and 8, *reduction of lead times* and *improvements of information processing.*

**Counter ordering** This intervention is related to the electronic identification card, but it substitutes the electronic identification with physical ordering at the counter. Here, patients of type 4 are also directed to a new queue with top priority. However, patients of type 4 who have not ordered medication in advance do so at the counter and are then sent back to the queue to wait for their medication to finish preparation. The process of ordering at the counter takes 60 seconds as determined after discussion with staff. Note that there is no recovery time after this ordering process. Forcing the patient to wait two times is not desired according to pharmacy policy, but results of the evaluation of this intervention might motivate a reconsideration.

We implement this intervention analogously to the electronic identification card, except that patients of type 4 without a fast pickup visit the counter twice. We only take the waiting time for their second waiting period into account as they are themselves responsible for the first waiting period.

**Planned staffing** During observation and preliminary data analysis, we observed peak activity moments. As these peaks, around 10.30 am and 2.30 pm, occur consistently, this activity prediction may be used for counter staffing. Instead of using the current dynamic counter activation rules, counters are activated based on the time of the day. This way, counters can be activated before the waiting room fills up and staff may be scheduled more efficiently as the uncertainty of counter activation is greatly reduced.

Of course, an efficient compromise must be found between over- and under-staffing of the counters. As this is outside the scope of this project, a reasonable method is proposed and evaluated. This proposal entails activation of counters 4 and 5 from 10.00 am until 11.30 am and from 2 pm until 3.30 pm. Furthermore, counter 6 is activated from 10.15 am until 11.00 am and from 2.15 pm until 3.00 pm. Counter 1 is permanently inactive as it only accounts for a small fraction of about 2% of services even in the current situation.

This intervention corresponds to principles 2 and 4 of the literature review, *reduction of or adaption to uncertainties* and *matching supply and demand patterns.*

**Combination: locker box and electronic identification card** This intervention is introduced to examine the possible combination of the locker box and the electronic identification card. In this intervention, patients use their electronic identification card and pick up their medication from the locker box. This intervention constitutes a large investment and dual introduction of both interventions. However, as the electronic identification card transitions several patients to one process and the locker box eliminates this exact process, it may show great performance improvements.

# Chapter 5

# Conceptual model

This chapter describes the conceptual model of the pharmacy. The conceptual model is set up to define pharmacy processes and identify necessary knowledge about these processes. Section 5.1 addresses the former by providing an overview of the structure of the conceptual model. Section 5.2 addresses the latter by listing the necessary inputs that data analysis needs to deliver.

## 5.1 Structure

The sequential and logical structure of the conceptual model is illustrated by several figures. In the following paragraphs, these figures are briefly introduced and supplemented with explanation.

**Patient flow** Figure 5.1 outlines the general flow of patients through the pharmacy. As in reality, patients enter the pharmacy and select a service type at the ticket pillar. Patients are placed in virtual queues based on the selected service type. Service is started at one of the six counters. As soon as the service is finished, the patient leaves the pharmacy at the exit.

**Service** Figure 5.2 presents the processes within each service. After each completed service, the procedure to pull the next patient is again triggered (Figure 5.4).

**Counter activation** Figure 5.3 describes the counter activation procedure that is triggered as soon as a patient enters the queue. As Chapter 2 describes, the counter activation method that is actually followed in reality differs from the counter activation method as determined by official policy. The conceptual model applies the method used in reality. As a counter is activated, the procedure to pull the next patient is called (see Figure 5.4).

**Next patient pull** Activated counters and counters that have just finished service and recovery actively pull patients from queues according to their own priority rules. Figure 5.4 displays this process.

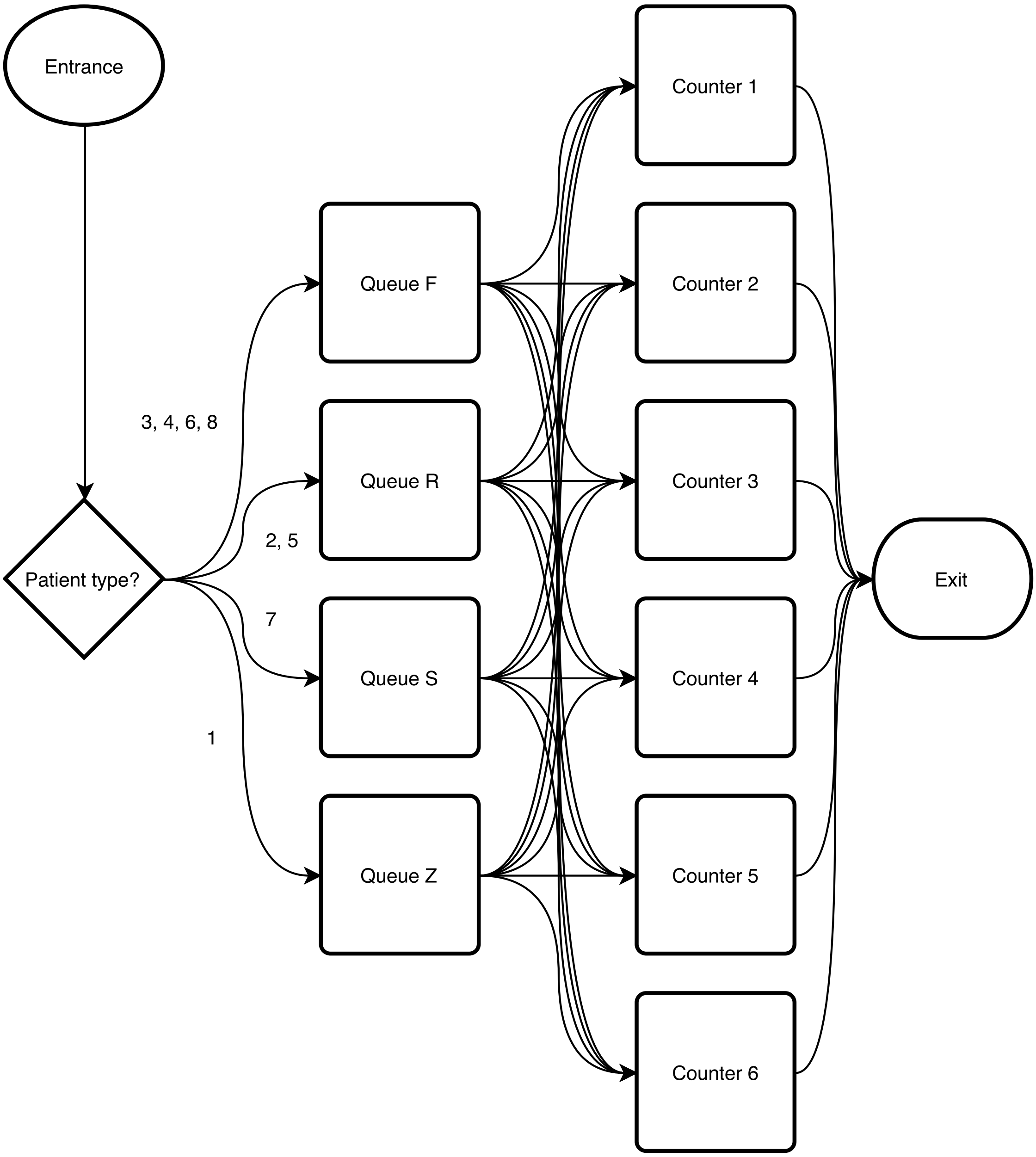


Figure 5.1: Patient flow through the pharmacy. Note that the counter actually pulls patients out of the queue based on its own priority rules. The arrows between queues and counters here indicate that each counter can service each queue. Processes during a service at the counter are indicated in Figure 5.2, procedures triggered by entering the queue are outlined in Figure 5.3.

## 5.2 Required inputs

As the conceptual model suggests, a series of input characteristics are required to define the model. Furthermore, some proposed interventions require additional data analysis. The data analysis described in Chapter 6 is needed to determine these inputs.

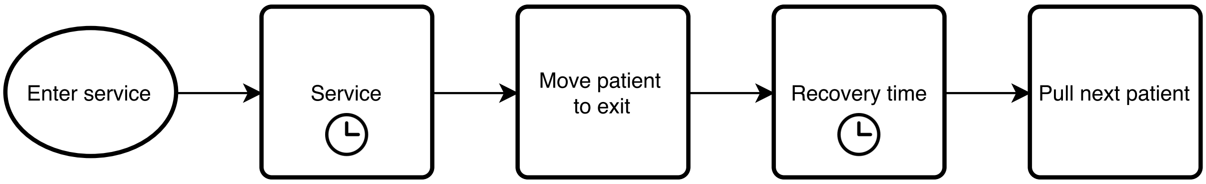


Figure 5.2: Service procedure flowchart for any patient at any counter. The last action, pull next patient, here refers to Figure 5.4.

**Arrival pattern** The model is based on instances of patients. It is necessary to know *how many* patients arrive and *at what time* each patient enters the pharmacy. This may or may not depend on the service type, the day of the week, or other factors.

**Service durations** As patients in the model enter service, the service duration is the determining factor for the length of the service and consequently how long the counter is unavailable for other patients. The service duration may depend on several factors, including service type, day of the week, and others.

**Recovery time** After finishing a service, the counter needs to recover before starting the next service. As mentioned in Chapter 2, there is no set policy for this recovery time and no data collection mechanism in place.

**No-shows** A fraction of patients leaves the queue before service starts. These patients are recorded as no-shows. A probability for this phenomenon needs to be found in existing data to correctly model this behavior.

**First inefficiency** To both confirm and model the first inefficiency, it is of interest to know the fraction of type 4 services being of the fast pickup variety. Furthermore, service durations for both fast and robot-assisted pickup are necessary to correctly model this inefficiency.

**Second inefficiency** For the second inefficiency, it is of interest to know how many patients are eligible for a type 4 pickup without additional advice. Compared to the actual fractions of patients selecting type 4 pickups, this data sheds light on the perceived inefficiency and also allows implementation of the inefficiency in the model.

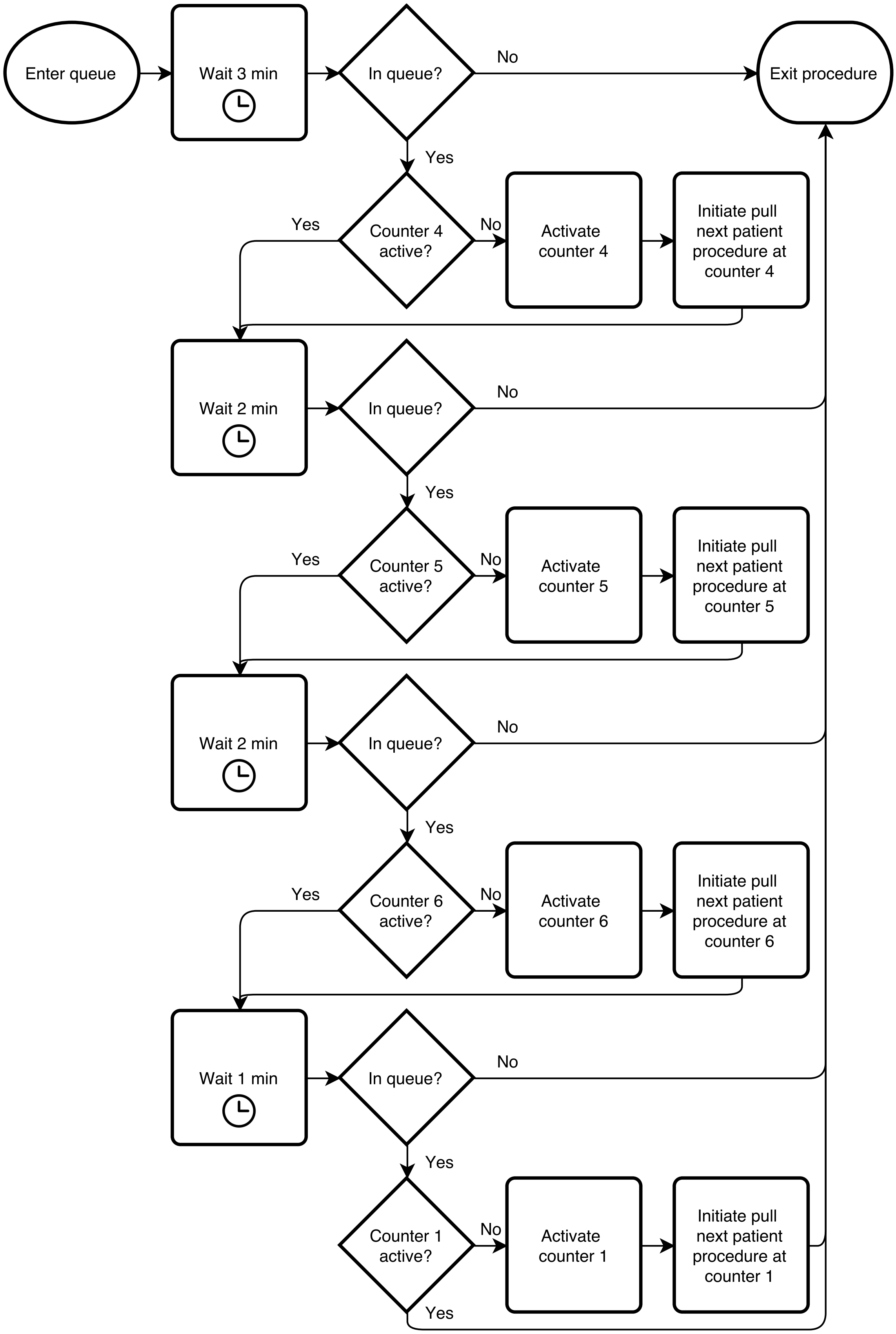


Figure 5.3: Counter activation logical flowchart, triggered by each patient entering any queue. Note that the pull next patient procedure refers to Figure 5.4.

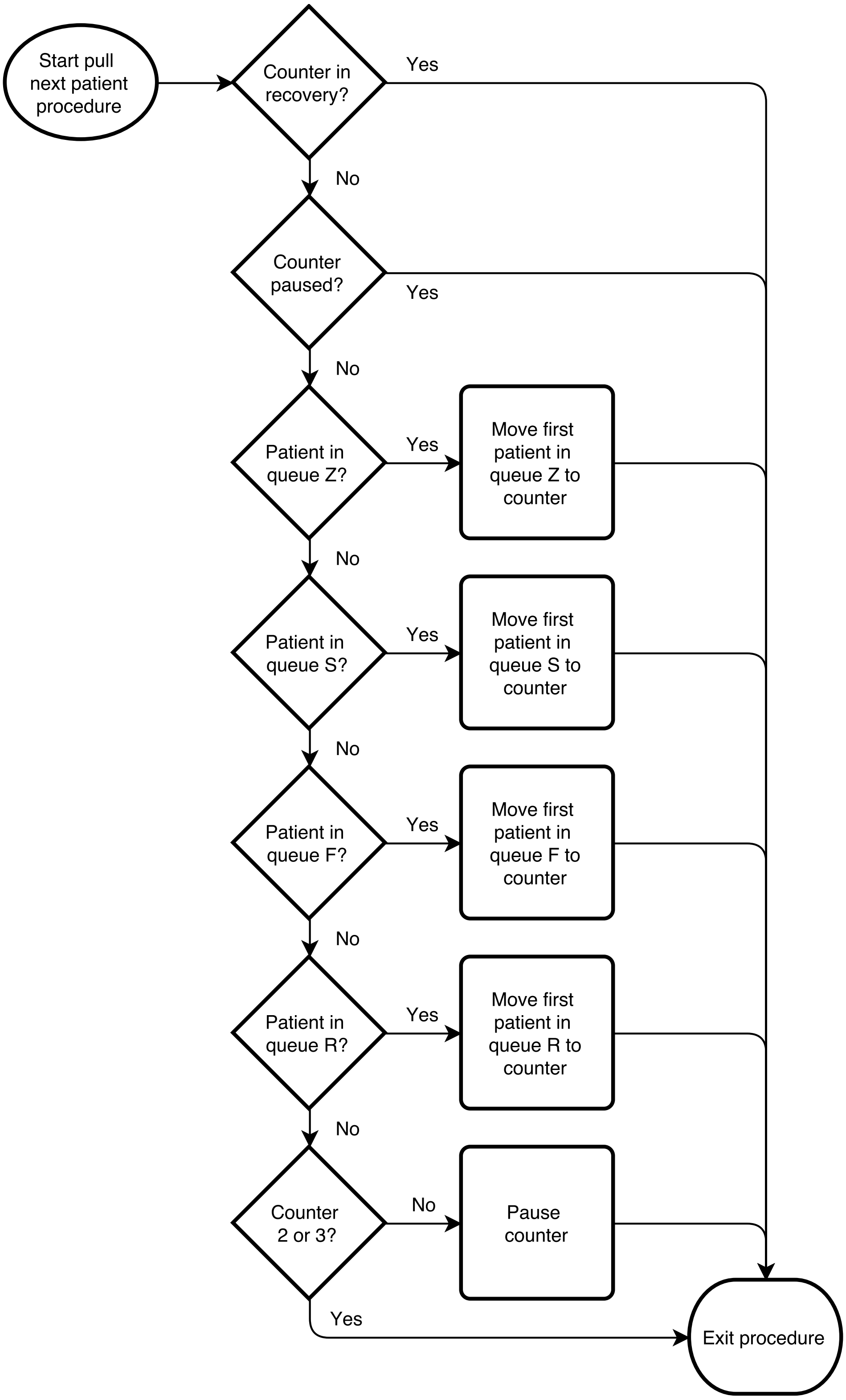


Figure 5.4: Pull next patient procedure logical flowchart, triggered by a counter finishing its recovery time and a counter activation procedure. Note that in this case, priorities of counters 1, 2, 4, and 6 are used as an example. The procedure is identical for counters 3 and 5, except that labels R and F are switched.

# Chapter 6

# Methodology

This chapter describes the steps of data analysis in this study. Section 6.1 formulates the plan of approach. Then, Section 6.2 presents the way data is collected and prepared for analysis. Section 6.3 depicts the data analysis.

## 6.1 Plan of approach

As described in Chapter 5, a conceptual model is constructed. This model allows assessment of the current situation and of proposed interventions. The conceptual model requires a number of input elements (see Section 5.2). These input elements are to be defined by preparing and analyzing available data. Based on the results of this analysis, a choice of approach can be made to translate the conceptual model to either a queuing theory or a simulation model.

This section provides the approach to defining these input elements. Section 6.2 then provides an explanation of the preparation of the datasets, while Section 6.3 gives methodological details on the actual data analysis.

**Arrival pattern** An early survey of the arrival pattern has shown that the arrival frequency is not constant over a day but instead follows a rough two-peaked pattern with peaks around 11 am and 3 pm. This confirms observations by staff according to which patients arrive most frequently around these times. Consequently, the arrival pattern decomposes in two elements: number of patients arriving on a day and the arrival time of a patient.

The number of patients arriving on a day has been shown to depend on the day of the week and the service type (see Figure 6.1). This is a confirmation of observations by pharmacy staff. For each working day of the week and for each type, a distribution should be formulated to determine the number of patients of a given type arriving on a given day of the week, resulting in forty distinct distributions to be used in a modeling environment.

For each patient, an arrival time needs to be randomly determined based on recorded data.

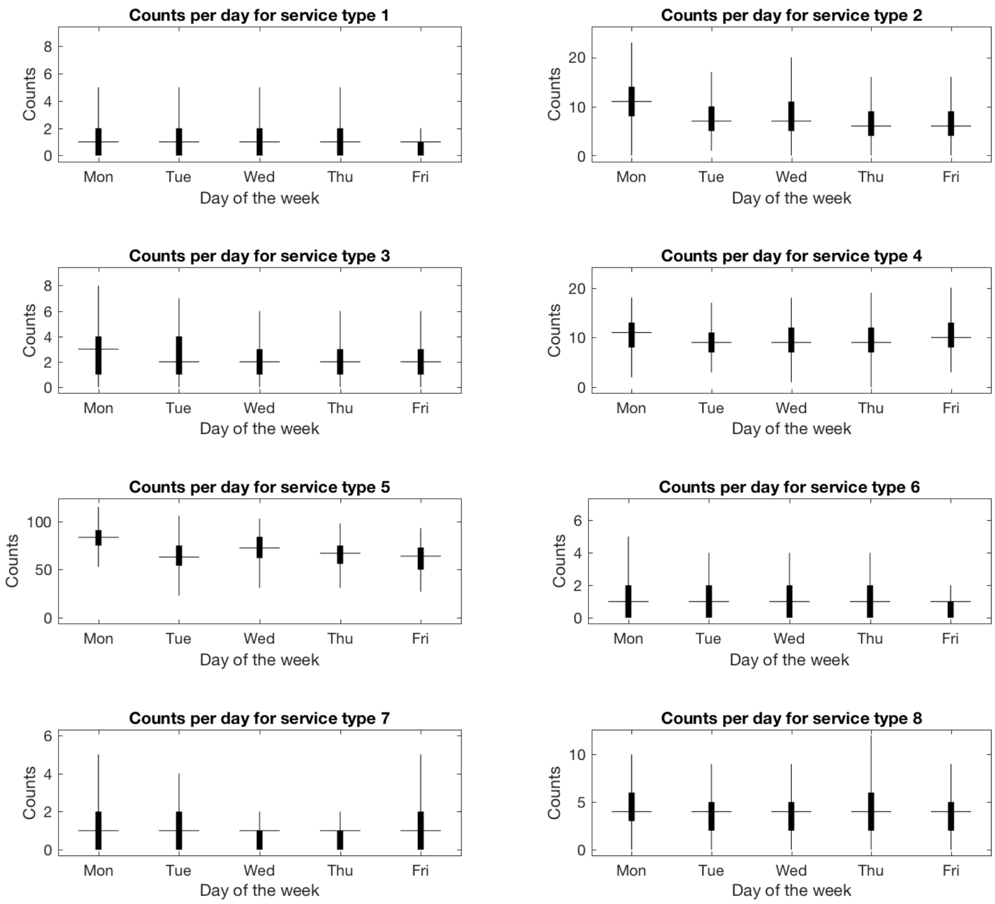


Figure 6.1: Box plots of the number of patients of a given type arriving on a given day of the week. Median and quantiles are indicated. Source: unfiltered Gbos-A dataset, 69272 observations, 10-01-2014 – 21-10-2016.

Data has shown that the arrival time depends on the type of the patient (see Figure 6.2) but not on the day of the week (see Figure D.2 in Appendix D.2). Therefore, for each type of service requested, an arrival time distribution needs to be formulated.

**Service durations** Service durations differ depending on the type of service the patient requests. These durations do not additionally depend on the day of the week (see Figure D.1 in Appendix D.2). Consequently, eight distributions need to be formulated. Figure 6.3 gives histograms for the service durations of each service type.

**Recovery time** Unfortunately, as mentioned in Chapter 2, there are is no consistent policy on recovery time. Observation has shown that the practical implications of recovery time may depend on the member of staff. Even then, the same member may act differently depending on,

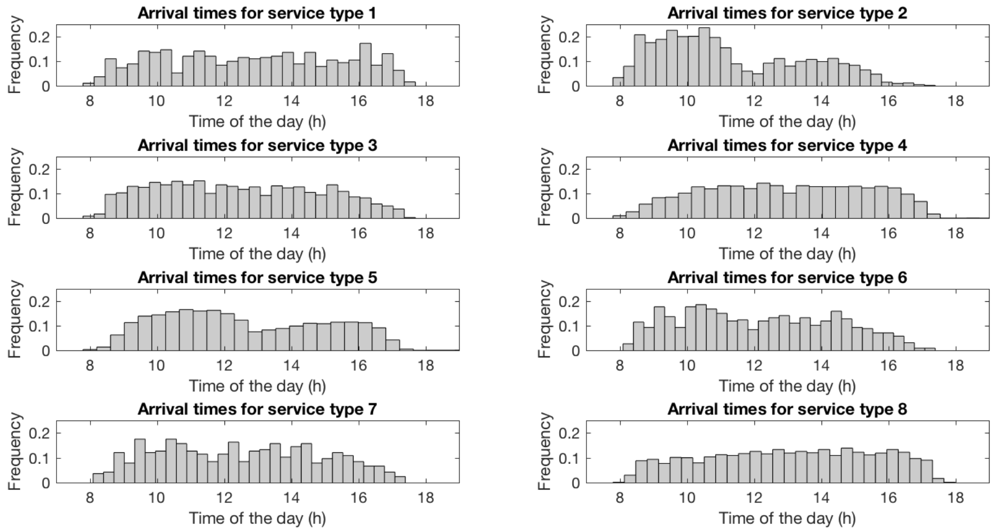


Figure 6.2: Histograms of the arrival times for each service type. The time of the day is set on the horizontal axis, the frequency of occurrence on the vertical axis. Source: filtered Gbos-A dataset, 63359 observations, 10-01-2014 – 21-10-2016.

for example, the time of the day, or the number of patients in the waiting room. Furthermore, sometimes recovery time may be included in the service duration while in other instances, it is clearly distinguishable as a time between services.

As there is no viable method to clearly define and model the recovery time, we have decided to implement the recovery time as an always occurring phenomenon after every service. The value of the recovery time will be determined using a calibration of the model.

**No-shows** No-show patients are implemented as a probability for every patient entering the pharmacy to be a no-show patient. We assume that no dependency on the number of patients waiting in the waiting room or the current waiting time is present, and that no-shows mostly occur as a result of patients drawing several tickets to speed up their waiting process.

**First inefficiency** The first inefficiency constitutes a patient eligible for a fast pickup correctly choosing type 4 while his medication is not yet ready for pickup. In terms of the pharmacy processes, it can be qualified as follows: a patient eligible for a type 4 quick pickup will be recorded as having chosen type 4. During his service at the counter, a patient whose medication has been prepared will not trigger a request to the Rowa robot as his medication has already been requested earlier to prepare the pickup. In contrast, a patient whose medication has not been prepared yet will trigger a robot request.

This assumes that all medication is requested from the robot. According to staff, the fraction of manual picks is as low as 1%. Furthermore, frequently patients need to pick up several

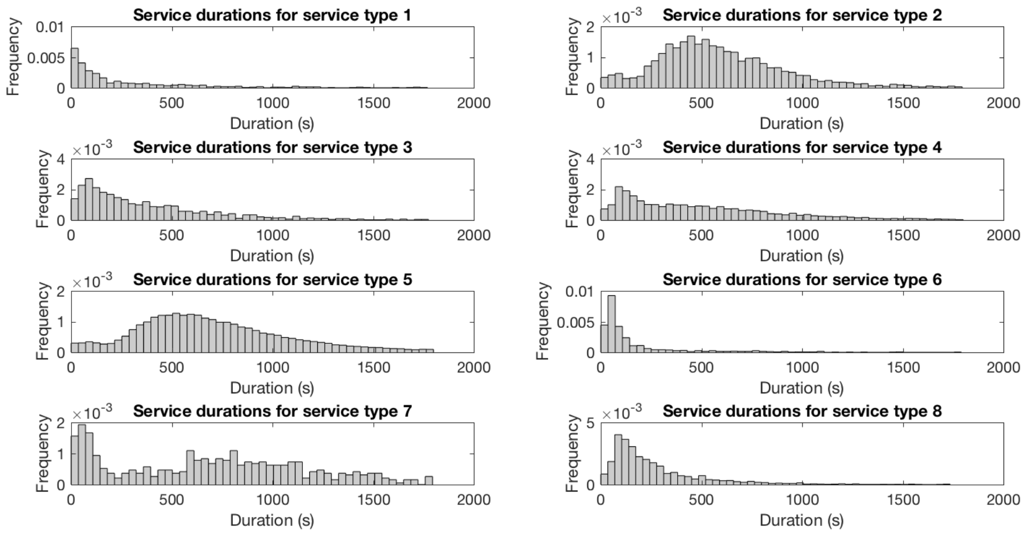


Figure 6.3: Histograms of the service durations for each service type. The time in seconds is set on the horizontal axis, the frequency of occurrence on the vertical axis. Source: filtered Gbos-A dataset, 63359 observations, 10-01-2014 – 21-10-2016.

medications, decreasing the chance that all his medication is picked manually.

To quantify this inefficiency, a daily crosscheck of waiting instances and robot requests is proposed. In practice, for every waiting instance of service type 4 recorded in the Gbos waiting system, a corresponding robot request is to be matched, based on the time-frame and counter of the service and the time and counter of the request. If a match can be found, the waiting instance is qualified as robot assisted. If no match can be found, the waiting instance is qualified as a clean pickup.

Using a crosscheck as described here, a fraction of clean pickups for type 4 services can be determined, leading to an estimation of occurrences of the first inefficiency in terms of a probability for each type 4 patient. Furthermore, an analysis of service durations is made possible. This analysis shows that service duration for clean pickups is shorter than service duration of robot assisted pickups (6:12 minutes and 13:45 minutes on average, respectively).

**Second inefficiency** The second perceived inefficiency, stemming from patients eligible for a type 4 quick pickup choosing a type 5 service instead, can be qualified according to a patient's *necessary* service. If a patient picking up medication has the same medical regime as the last time it was picked up, the patient is eligible for a type 4 quick pickup as advice and consultation has been offered the first time already. In contrast, if a patient is picking up medication as part of a changed regime, the patient should choose a type 5 service, including advice and consultation.

A patient without changes in medical regime choosing type 5 would result in a waste of time of patient, staff, and counter. Therefore, a patient with no changes in medical regime should choose type 4 and notify the pharmacy beforehand to reduce the service duration. Of course, a patient should always have the possibility to choose for a full service consciously if he is in need of advice, any indication of eligibility for type 4 is therefore an upper bound of the actual choice for type 4.

We propose to quantify this inefficiency by comparing Aposys delivery reports of a given day with Aposys snapshot extractions of the day before. For every delivery, it is possible to establish whether the delivered prescription is changed with respect to the prescription saved in the pharmacy system the day before. A patient's complete medical regime may be composed of several prescriptions and thus several deliveries.

A patient's regime is changed, hereby denoted as a mutation, if (a) the patient is new, (b) a new medication occurs within his regime, or (c) the manner of ingestion is changed for an existing medication. If a single prescription mutation occurs, the whole regime is mutated and the patient is not eligible for a type 4 service. In contrast, if no mutation occurs, the patient is eligible for a type 4 quick pickup. Removing a prescription from a patient's medical regime does not register as a mutation.

A prescription is here defined as a combination of PRK code and truncated usage code. The PRK code is a brand-surpassing identification for active ingredients of medication and therefore suited for comparison. The usage code is a coded description of standardized abbreviations for frequency, amount and side-notes for medication ingestion. By truncating the code to only frequency and amount, comparison between two regimes is possible.

In practice, a comparison is based around the Aposys delivery report of a single day. For each prescription in this report, it is checked whether this prescription has a corresponding match in the Aposys snapshot extraction of the day before. If for every prescription for a single patient a match is found, then this patient qualifies as non-mutated. If a single change within all prescriptions for a single patient is found, the patient qualifies as mutated.

Given the total number of mutated patients, non-mutated patients and total patients in a single delivery report, and combining this information from several delivery reports, realizations of the *real* type distributions of type 4 and type 5 can be calculated. Based on these realizations, an estimation of the actual probability of a random patient entering the pharmacy and being either of type 4 or type 5 can be made.

## 6.2 Dataset preparation

As the recorded data can not be simply used in a model as input, several preceding steps are necessary. In this section, the relevant steps are outlined for each of the used databases: Gbos queuing system, Rowa robot database and both outputs of the Aposys pharmacy information system. Furthermore, other remaining parts of data preparation are described. A detailed description of the steps for data preparation can be found in Appendix C.1.

### 6.2.1 Recorded Gbos instances

Data from any desired range of days from the Gbos queuing system is easily extracted using the Gbos back office software. As the system was installed in January 2014 and data is permanently stored, a large amount of data is accessible for analysis. However, due to the necessity to link databases and resulting availability issues with other databases, several datasets are required.

For general analysis of service durations, arrival times, number of patients and type distributions, a dataset starting on January 10, 2014 until October 31, 2016 is used. This dataset is hereby denoted as dataset *Gbos-A*. Gbos data collected after October 31, 2016 is not used for analysis of arrival times as the recording policy is different from earlier dates due to the introduction of a single ticket (see Section 2.1).

For clean pickup analysis, data from the Rowa robot database is needed in addition to Gbos waiting instances. As this data is only stored for 30 days and collection of relevant data was not initiated until halfway November 2016, a dataset from October, 21 2016 until January, 18 2017 is used. The notation for this dataset is *Gbos-B*.

### 6.2.2 Rowa robot requests

The Rowa robot saves several protocol and log files to its internal memory. For the analysis in this study, the log files for output requests are sufficient. As mentioned, Rowa robot data is only stored for 30 days before being purged from internal memory. Therefore, a dataset from October, 21 2016 until January, 18 2017 is used for instance-request crosschecking purposes. This dataset will be referred to as *Rowa*.

### 6.2.3 Aposys snapshot extractions

Aposys analysis is, unfortunately, again constrained by storage policies. While Aposys delivery reports are accessible indefinitely, Aposys snapshots are purged manually by IT staff after about a week. Due to this policy, only Aposys snapshots from November, 29 2016 until January, 18 2017 are available, from here on denoted as *Aposys-snapshots*. A total of 25 days is available for analysis.

### 6.2.4 Aposys delivery reports

Delivery reports are easily available and indefinitely stored. However, due to limitations of the snapshot extraction, a limitation to the dataset is also present here. As a delivery report has to be compared to the extraction of the day before, the relevant delivery report dataset, hereby denoted as *Aposys-delivery*, starts on November, 30 2016 until January, 17 2017.

### 6.2.5 Truncating usage codes

A prescription is defined by the prescribed drug and the prescribed method of usage. Consequently, the usage code is an important part of the prescription. It indicates how much and how often medication needs to be taken, while also allowing room for additional comments and supplementary instructions.

In discussion with pharmacy staff, it was decided that a mutation of a prescription should be triggered if frequency or amount change. Optional comments, however, should not trigger a mutation as this information is usually not essential to treatment and does not require extensive explanation to the patient.

## 6.3 Data analysis

This section outlines the analysis of available data. To be able to set up a model of the pharmacy, recorded data needs to be generalized for valid statistical usage. Below, we describe the basic concepts for each element of the model. Appendix C.2 contains a detailed description of computational steps.

**Real type estimations using temporal comparison (Second inefficiency)** Using the datasets Aposys-delivery and Aposys-snapshots, we establish a comparison between delivered prescriptions and recorded prescription from one day earlier. For each patient picking up medication on a given day, the snapshot from the day before is crosschecked to assess whether the prescription for this patient has changed.

**Clean pickups based on instance-request crosschecks (First inefficiency)** We use dataset Gbos-B and dataset Rowa to assess clean pickup ratio's for type 4 services. A crosscheck is made for every waiting instance to try and match a Rowa robot request. If such a request is found, we label the instance as robot-assisted pickup. If no instance is found, we label the instance as clean pickup. Based on this indicator, two non-overlapping subsets, hereby denoted as *Gbos-clean* and *Gbos-robot*, for clean pickups and robot-assisted pickups, respectively, are created for further analysis.

**Number of patients** Based on the dataset Gbos-A (adjusted to include no-shows), the number of patients of a given type arriving on a given weekday is collected. The result, forty lists of the actual number of patients of a given type on a given day of the week for every day in the dataset, are analyzed using the MATLAB distribution fitting script to try and fit distributions.

**Arrival process** Arrival times for patients were extracted from dataset Gbos-A. Corresponding to the eight types, eight non-overlapping subset of the dataset were selected and arrival times were extracted to be used in the MATLAB distribution fitting script.

**Service durations** We extract service durations from the Gbos-A, Gbos-clean, and Gbos-robot datasets and filter for each service type, thereby creating nine non-overlapping subsets. These subsets are then used with the MATLAB distribution fitting script to match theoretical distributions for service durations.

**No-show patients** We interpret the no-show phenomenon as a probability for each patient to refrain from showing up. No-shows are assumed to be independent of day of the week, time of the day, and service type. Therefore, it is sufficient to estimate the probability from the complete dataset Gbos-A by finding all no-show patients in that dataset and use the fraction of these as an estimator for the actual probability.

**Distribution fitting** Using the maximum likelihood method of distribution fitting, a script for the MATLAB software attempts to find the correct parameters for each theoretical probability distribution. We consider the exponential, gamma, Johnson, logistic, log-logistic, log-normal, normal, Poisson, Pearson, and Weibull distribution for fitting. The script also assesses goodness of fit by performing the Kolmogorov-Smirnov test for continuous distributions and a Chi-Square test for discrete distributions, both at 95% significance. In case of several matches and confirmed goodness of fit, we determine the best match with regards to easy implementation in simulation software. In case of no confirmed match, we construct an empirical distribution.

**Empirical distributions** We use a separate script to create a value-probability table from recorded data. Simulation software is then able to accept this table to draw a value based on these probabilities. For queuing theory approaches, simplifying assumptions have to be made.

# Chapter 7

# Simulation model

This chapter describes the simulation model. Section 7.1 explains and justifies the choice for a simulation approach based on the conceptual model and results of data analysis. Section 7.2 provides a short description of the simulation model. Appendix E presents a more detailed blueprint of the simulation model.

## 7.1 Choice of approach

Referring to the literature review, both queuing theory and simulation approaches have merits, advantages, and disadvantages. In the conclusion of the review, the need for a conceptual model to define the processes in the pharmacy for modeling purposes emerges. The conceptual model then dictates necessary inputs that data analysis should deliver. This section explains a choice of approach based on characteristics of the processes in the pharmacy, results of data analysis, and implications of each approach.

**Arrival pattern** Data analysis has shown that the arrival pattern for patients is not easily describable by theoretical distributions (see Chapter 6). Furthermore, the pattern is dependent on day of the week, time of the day, and the service type of patients. A queuing theory approach requires sweeping assumptions to generate constant arrival distributions. Furthermore, these arrival distributions need to belong to suitable families of distributions to allow analytical examination of the processes. Simulation is able to directly accommodate challenging distributions by using empirical distributions based on historical data. By splitting the arrival pattern in number of patients per day and the arrival time as described in Chapter 6, an easy implementation can be achieved.

**Service durations** Not all service durations can be fitted to theoretical distributions, as is illustrated in detail in Chapter 8. Additionally, not all fitted distributions are suitable for a queuing theory approach, based on their mathematical properties. To approach modeling using queuing theory, assumptions would need to be made for missing distributions. Another way would be to ignore services with low occurrences, thereby diminishing validity of the model. The use of empirical distributions allows a simulation model to easily cater for these service types.

**Priority rules** The priority rules as described in Chapter 2 are possibly implementable using a queuing theory approach, however, literature has not described a combined model of both priorities and multiple servers. A possible simplification could be made by ignoring queues Z and S due to low occurrence as suggested for service durations, and assuming a simple first come, first serve policy based on the alternating priorities for queues R and F at different counters. Simulation, on the other hand, allows implementation of a wide range of priority rules by internal programming, thereby creating resemblance to the actual priority rules used in the waiting room system by reverse engineering based on observation and policy documents.

**Counter activation** The phenomenon of counter activation policies is fully unknown to queuing theory approaches, as queuing theory assumes a steady-state nature of the system. The possibility of programming within the simulation model here again allows implementation of any consistent counter activation policy.

**Implementability of proposed interventions** Queuing theory, although much researched in literature, has a limited range for changes in configurations. Not all changes that would be possible in practice can be implemented in a queuing theory model. A simulation model, however, is expandable for almost any suggested solution using the existing framework of the model and possible extensions, within the wide limits of the simulation software.

**Credibility and involvement** Involvement of members of the organization creates credibility of the model and improves chances of practical implementation. A queuing theory model, being based in a theoretical mathematical environment, cripples involvement by members of staff not educated in this background. Using visualizations, animations, and graphical interfaces, a simulation model can be built together with members of the organization, thereby possibly involving different layers of the organization to construct a widely accepted product.

**Conclusion** Based on the characteristics described in this section, a clear choice can be made for a simulation approach. Results of data analysis, process description, and inherent properties of both approaches make simulation the apparent choice.

## 7.2 Simulation

This section presents a brief summary of the constructed simulation model. Simulation modeling is done following the book *Simulation Modeling and Analysis* by Averill M. Law, which gives clear instructions on simulation models, backgrounds and best-practice methods (Law, 2015). Siemens Tecnomatix Plant Simulation 11 is used as a software basis to construct, run, and analyze the model. The model is realized as a discrete-event simulation, consisting of independent days. The simulation is a terminating simulation as the system is cleared out at the end of the day and there is consequently no carry-over of patients from one day to another. The terminating event is here the end of the day, after every patient has left. Appendix E provides a more detailed description of each element. Figure 7.1 gives a graphical representation of the model.

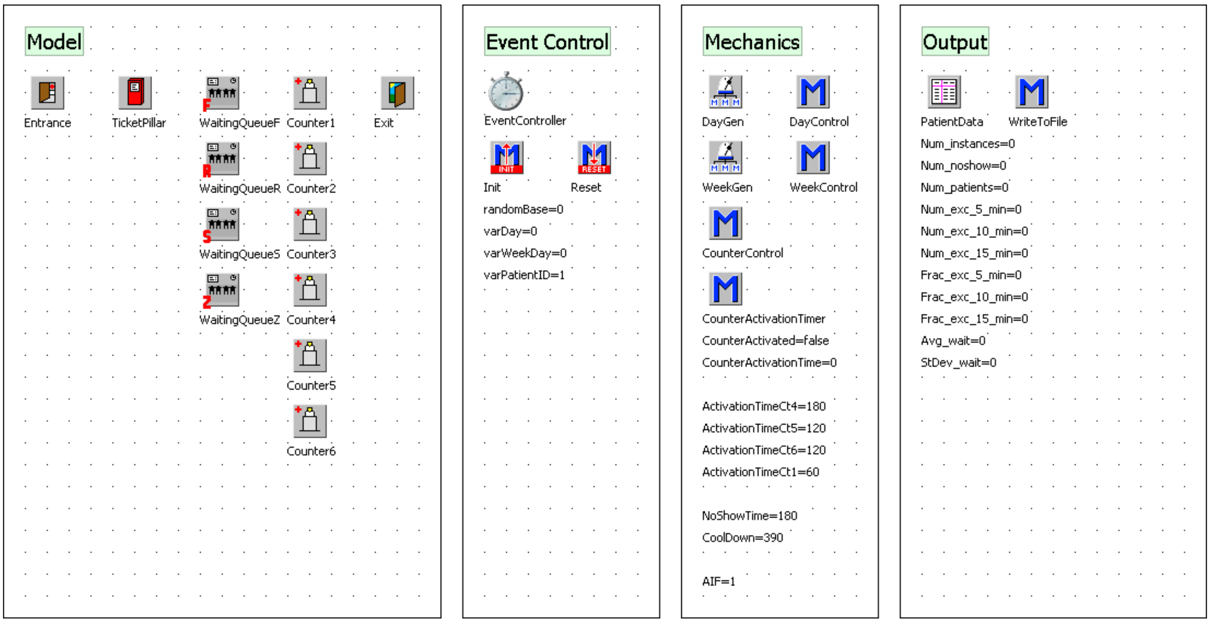


Figure 7.1: Graphical representation of the simulation model in Siemens Tecnomatix Plant Simulation 11.

### 7.2.1 Input

**Time, day, and day of the week** The model uses an internal event controller to keep track of the simulation time. The event controller triggers methods to keep track of the simulation day and the day of the week. A day runs for 24 hours and the day of the week cycles from one to five, thus excluding the weekend.

**Number of patients** As outlined in Chapter 6, the number of patients of a given type on a given day of the week is determined as a realization of a random variable stemming from a statistical distribution. The simulation then creates exactly this number of patients at the start of the day.

**Arrival time** Depending on the type of the patient, the arrival time for a patient is determined as drawn from an empirical distribution, defined by historical data from dataset Gbos-A.

**Service duration** Again, depending on the type of patient, a service duration is drawn from an empirical or theoretical distribution. For type 4, it is first determined whether the patient is of the clean pickup or robot pickup variety, based on the probability extracted from the Gbos-B dataset. Service duration is then determined based on a theoretical distribution fitted to empirical data from Gbos-clean or Gbos-robot datasets. For other service types, the Gbos-A dataset is used.

**Recovery time** Observation of the actual pharmacy has not given conclusive results on the phenomenon of recovery time. In the model, recovery time is implemented after each service and is used as a calibration method to achieve model validity. No actual data is available for the recovery time and any attempt to measure would result in inconsistencies that can not be harbored in the simulation model as it is constructed in this project (due to dependencies on members of staff, for example). We therefore use the recovery time to calibrate the model.

**No-shows** Every patient has a probability to be a no-show, thereby setting the service duration to a set time. We determine the probability based on no-shows in dataset Gbos-A while we set the service duration for no-shows to equal three minutes after consulting pharmacy staff.

### 7.2.2 Output

Output of the simulation is given in the form of one extensive table, containing one row for every patient and including all relevant details for each patient. In a sense, this output resembles the output generated by the Gbos back office software.

In addition to recording information like day of the week, service type, no-show, arrival time, waiting time, and service duration, this table serves to calculate the performance indicators of a configuration: percentage waiting time exceeding five minutes, percentage waiting time exceeding ten minutes, and average waiting time.

### 7.2.3 Elements

The simulation model consists of several sub-frames. They follow actual physical elements of the pharmacy and enable easy identification, credibility, and acceptance.

**Entrance** In this sub-frame, patients are created, wait for their arrival time and finally enter the pharmacy. For modeling purposes, this is the frame where properties for the patients are set to indicate that a patients route through the pharmacy is set before entering.

**Ticket pillar** As in the real physical pharmacy, the model contains a ticket pillar as well. While patients in the physical pharmacy make the selection for a service at this place, the ticket pillar in the model only serves as a guidance system to the correct queue, as the service type is already determined by chance at the time of creation.

**Queues** While the real pharmacy contains only one mixed waiting room, it does in fact make a distinction in virtual queues as defined in the Gbos waiting room system. In the model, each waiting queue is represented as a separate waiting room. As soon as patients enter the waiting room, the countdown timers for counter activations are triggered as well. Contrary to pharmacy policy, which requires counter activation after a waiting time exceeds five minutes, an approach was modeled that resembles the actual counter activation as illustrated in the conceptual model: here, counters 4, 5, 6 and 1 have individual countdowns with different lengths, triggered by each patient entering the queue.

**Counters** As in the real pharmacy, the model contains six counters. Background mechanics ensure that counter activation rules are followed as described above. To ensure correct application of priority rules, a pull-mechanic is implemented so that counters actively pull patients from their preferred waiting queue.

**Exit** In this sub-frame, the patient exits the pharmacy. Here, mechanics are situated to record all relevant data about the patient. Finally, the patient instance is removed from the system.

## 7.3 Conclusion

Based on conceptual model, data analysis results, and literature review, we motivate the choice for a simulation approach. Priority rules, counter activation policy, and the arrival pattern were decisive arguments against a queuing theory approach and for a simulation model. Consequently, we construct a terminating, discrete-event simulation model based on the processes as defined in the conceptual model. In Chapter 8, we define the values and distributions for the input elements of th model and define the experiments to carry out.

# Chapter 8

# Experiment design

This chapter provides information about the experiments that are carried out in the context of this project. Section 8.1 gives results from data analysis as inputs for the model. Section 8.2 contains information on verifying, validating and calibrating the model. Section 8.3 provides an overview of the performance indicators used to evaluate experiments. Finally, Section 8.4 outlines the experiments.

## 8.1 Model input parameters

As described in Chapter 6, data required for model inputs is fitted to theoretical distributions. If no fit can be established, an empirical distribution is constructed. Appendix E provides the exact parameters for every fit.

**Number of patients** For service types 1, 3, 6, 7, and 8, a fit to a Poisson distribution can be made for all days of the week. Number of patients for service type 4 can be fitted to a Poisson distribution on all days except on Thursdays, when a normal distribution provides a fit. Number of patients for service type 5 can be fitted to a normal distribution on all days of the week. Service type 2 number of patients cannot be fitted to a theoretical distribution on any day of the week, so empirical distributions are constructed instead. Note that while the family of fit may be stable, the parameters change for every day of the week and service type.

**Arrival times** None of the arrival time distributions can be fitted to a theoretical distribution. Consequently, eight empirical distributions are constructed instead.

**Service duration** For four service types, it it possible to establish gamma distribution fits: service type 1, service type 3, service type 4 clean pickups and service type 4 robot pickups. For other service types, empirical distributions are constructed.

**Recovery time** As mentioned in Chapter 6, there is no valid way to determine a recovery time. To achieve model validity by calibration, we implement recovery time as a normal distributed time duration after each service ($\mu = 420$ seconds, $\sigma = 120$ seconds).

**No-shows** A no-show percentage of 8.54% has been found in the data. This value is used as a probability for each patient entering the pharmacy to abandon waiting in the queue. In the simulation, no-show patients are modeled as patients having a predetermined service duration of three minutes. As they flow through the system just as normal patients do, their data is included in the waiting time analysis.

This might seem inconsistent as these patients do not really wait. However, we assume that these patients' waiting time is distributed identically to the waiting times of all other patients. Therefore, their waiting time does not influence any averages. To confirm this assumption, the run of 10000 days as used for the graphical method (see below) was analyzed once including no-shows and once excluding no-shows. Table 8.1 shows that the performance indicators stay stable, thereby legitimizing our approach to include no-show patients in waiting time analysis.

| **Indicator** | **Include no-shows** | **Exclude no-shows** |
|---|---|---|
| Average waiting time (s) | 233.7 | 233.5 |
| Fraction > 5 min | 0.31 | 0.30 |
| Fraction > 10 min | 0.08 | 0.08 |

Table 8.1: Results of performance indicators when either including or excluding no-show patient instances in waiting time analysis.

**Clean pickups (first inefficiency)** Based on the Gbos and Rowa database crosscheck, a percentage of 56.92% of type 4 services was able to pick up medication directly. In the model, this is used as a probability for each patient of service type 4. Ideal efficiency would see this fraction at 100%.

**Eligibility for clean pickups (second inefficiency)** We estimated eligibility using the Aposys delivery report and snapshot extraction crosscheck. It was found that of all patients picking up medication on a given day, a percentage of 47.95% is eligible for a quick pickup. In practice, this means that these patients can select type 4 to quickly pick up their medication. In the current situation, a percentage of 12.65% of all medication-requesting instances picks up their medication using type 4.

Table 8.2 provides an overview of the current values and optimal values for both inefficiencies. Note that there is ample room for improvement for both inefficiencies.

**Warm-up time** A warm-up period is necessary if the simulation needs to reach a certain steady state, and data stemming from this warm-up period is then discarded before analysis

| Inefficiency | Currently | Optimal |
|---|---|---|
| Clean pickups (1st) | 56.92% | 100% |
| Type 4 percentage (2nd) | 12.65% | 47.95% |

Table 8.2: Numerical realizations for both inefficiencies, current situation and desired optimal situation.

(Law, 2015). However, as this model is simulated as independent days without inventory carry-over in terms of patients remaining for the next day, no warm-up period is needed.

**Number of runs** As each day constitutes an independent run of the model, the number of runs needs to be specified to be able to accurately evaluate the model. To assess this number of runs, the graphical method of Welch is used (Law, 2015). As the days of the week differ in input, the number of runs for each day of the week is determined. The current situation model is used in this method. Figure 8.1 presents the results of this method. It can be concluded that about 500 runs of each day of the week should be included to reach a stable metric, resulting in a simulation run length of 2500 days.

## 8.2 Verification, validation, and calibration

**Verification** The conceptual model is verified in discussion with pharmacy staff and supervisors. After constructing the simulation model, this is again verified with supervisors by presenting an exemplary run of the simulation and highlighting all relevant model mechanics.

**Validation** Using an overview run of 5000 days, we validate model inputs to check for a correct implementation of theoretical and empirical distribution functions. We choose 5000 days as this was sufficiently above the minimum number of runs as determined using the graphical method. We validate theoretical distributions using Chi-Square tests for discrete distributions and Kolmogorov-Smirnov tests for continuous distributions. We validate empirical distributions using two-sample Kolmogorov Smirnov tests, using the historical data from dataset Gbos-A as the first sample and the simulation data as the second sample.

To validate output data, we compare waiting time data as a resulting characteristic of the model to waiting time data from dataset Gbos-A stemming from the Gbos waiting room system. Descriptive statistics of the waiting time and results of the performance indicators are compared.

**Calibration** The model is calibrated using the recovery time as explained in Chapter 7. By running the model several times and carefully changing the recovery time variable, we determine a suitable value (see Section 8.1). While the model is able to reproduce reality using this value, the phenomenon of recovery time and its numerical value are up for discussion.

## 8.3 Performance indicators

We evaluate each experiment using the performance indicators dictated by policy. Below, we first present the three performance indicators. We then introduce a new performance indicator that allows an increase in service duration for patients of type 5, thereby resulting in improved pharmaceutical care as discussed in Chapter 1.

**Average waiting time** The average waiting time of patients is used as a performance indicator, but no exact goal or limit is set by policy. Instead, this indicator is included in monthly reports of the pharmacy. Management uses the average waiting time to judge the pharmacy's performance.

**Fraction $>$ 5 min** This performance indicator describes the fraction of patients that have a waiting time exceeding five minutes. The goal per policy for this indicator is to be below 30%, while the ambition of the pharmacy is to achieve a value below 25%.

**Fraction $>$ 10 min** Analogously, this indicator gives the fraction of patients that have a waiting time exceeding ten minutes. Per policy, this value should be below 10%, and the ambition is to perform below 2%.

**Permissible service enhancement (PSE)** This performance indicator is introduced in the model to increase the service duration of type 5 patients. In the current situation, the PSE is set to 1. A higher PSE indicates an increase in service duration of type 5 patients and therefore an reallocation of resources to this service type. A PSE value below 1 indicates a decrease in service duration of type 5 and therefore a deterioration of service quality for these patients. The PSE is implemented in the simulation model as a multiplying factor for the service duration of type 5 patients.

## 8.4 Experiments

This section provides an outline of the experiments. We set up three sets of experiments: first, we briefly assess the influence of the no-show probability, as a decrease in no-shows was one of the goals of the recent change in ticket reinsertion as described in Chapter 2. Second, we assess the influence of the values for both inefficiencies. Third, we evaluate the proposed interventions by gradually changing the introduced PSE performance indicator.

**Influence of no-shows** We gradually change the no-show probability to assess the influence of no-show patients. The current value of no-show probability is set to 8.54%. We perform a total of six experiments where the no-show probability ranges from 0% to 10%. We focus on the average waiting time as a result of the simulation as an indicator for the overall system performance.

**Influence of inefficiencies** For this set of experiments, we gradually change the value of both inefficiencies. To assess the first inefficiency, we change the percentage of clean pickups from 50% gradually to 100% (current realization is 56.92%, see Table 8.2). For the second inefficiency, we gradually change the percentage of type 4 patients out of all medication-requesting instances from 10% to 50% (current realization is 12.65%, see Table 8.2).

As we want to combine both inefficiencies, we perform a total of 30 experiments. The PSE in these experiments is set to 1 to copy the current situation. We here again focus on the average waiting time for these experiments.

**Evaluation of proposed interventions** For each proposed intervention, we perform a set of six experiments. We gradually change the PSE from 1.0 to 1.5 in these experiments to model a increase in service duration of type 5 patients. As we propose eight interventions and include the current situation, we perform a total of 48 experiments.

## 8.5 Conclusion

In this chapter, we describe the input parameters for the simulation model as based on analysis of collected data. We present numerical values on the perceived inefficiencies and note that there is indeed room for improvement. We present our verification, validation, and calibration. A critical review of these steps takes place in Chapter 10. We describe the performance indicators as determined by pharmacy policy and introduce a novel indicator to assess the possible enhancement of type 5 services. Finally, we present three sets of experiments to assess the influence of both inefficiencies, the influence of the no-show probability, and evaluate the proposed interventions.

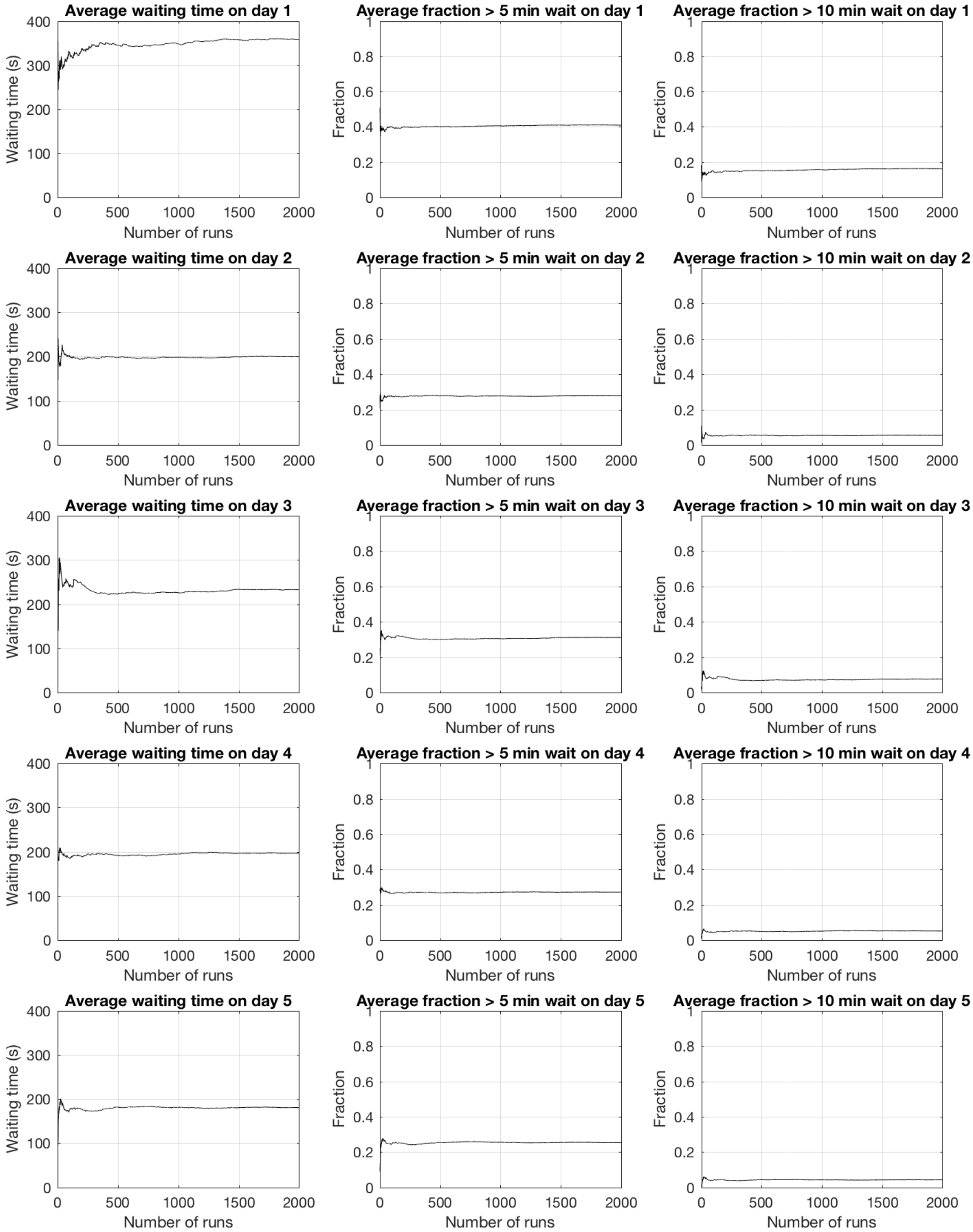


Figure 8.1: Application of the graphical method to determine the necessary number of runs. Average waiting time, average fraction $>$ 5 minutes waiting time, and average fraction $>$ 10 minutes waiting time are plotted versus the number of runs the averages are taken over.

# Chapter 9

# Evaluation

This chapter provides the results of the experiments carried out as described in Chapter 8. Section 9.1 presents the results of the experiments assessing the influence of no-show patients. Section 9.2 gives the results of experiments examining the influence of both inefficiencies. Section 9.3 presents the findings on the evaluation of proposed interventions.

## 9.1 Influence of no-shows

Figure 9.1 displays a graph of the results with regards to the average waiting time. The average waiting time actually *decreases* with increasing no-show probability. Table F.1 in Appendix F.1 provides an overview of the full numerical results.

Within the limits of the model, this result makes sense: each simulated patient has a probability to be a no-show. The service duration for no-shows is set to three minutes. However, three minutes is in fact *lower* than the average service duration for all services (which is a about 10:30 minutes). A no-show is therefore beneficial to the system as he occupies the counter for a shorter period of time than a regular patient.

This model is correct for the case that no-show patients drop out of the system. If a patient however fails to show up for one ticket and then re-draws this failed ticket, this modeling approach does not hold anymore because the patient does not disappear from the system after not-showing up. These results point to a limitation in this model and should be taken into account when modeling no-show behavior in the pharmacy in the future.

## 9.2 Influence of inefficiencies

Figure 9.2 presents a three-dimensional plot of the average waiting time with respects to the fraction of clean pickups and to the fraction of type 4 patients out of all medication-requesting patients. Table F.2 in Appendix F.2 gives full numerical results. Reductions of both inefficiencies

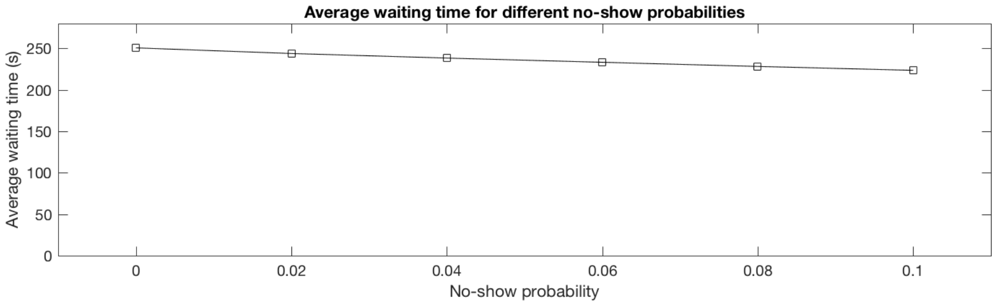


Figure 9.1: Plot of the average waiting time with changing no-show probabilities.

contribute to possible improvement of the average waiting time. An ideal situation, where both inefficiencies are practically removed, results in an average waiting time of 170.4 seconds. Compared to the current situation with 228.1 seconds, this is a reduction of about 25%. These findings confirm the existence of the perceived inefficiencies and indicate the capacity that can be reallocated if these inefficiencies were to be eliminated.

We establish that stepwise improvements of the second inefficiency (related to the fraction of type 4 patients) have a larger influence on the decrease of average waiting time than stepwise improvements of the first efficiency (fraction of clean pickups). However, the influence of stepwise improvements of the first efficiency increases with improvements in the second inefficiency. We explain this as follows: the first inefficiency is applied to all patients of type 4. Therefore, if the fraction of type 4 patients rises, the first inefficiency has a larger influence on the whole system.

However, as the *costs*, or effort, for a stepwise improvements are unknown, we limit our conclusion to the following: improvements in either inefficiency lead to a reduction of average waiting time, and a reduction of 25% is possible given a full elimination of both inefficiencies. Furthermore, reduction of the second inefficiency enhances the results of reduction of the first inefficiency.

## 9.3 Evaluation of proposed interventions

Table 9.1 presents the current performance of the pharmacy and the targets according to policy and ambition with regards to the three performance indicators, average waiting time, fraction of instances with a waiting time exceeding five minutes, and fraction of instances with a waiting time exceeding ten minutes.

Figures 9.3, 9.4, and 9.5 present plots of the performance indicators average waiting time, fraction exceeding five minutes and fraction exceeding ten minutes, respectively, for each proposed intervention with varying PSE. The tables in Appendix F.3 give the numerical values. Note that the results of the timed staffing intervention have been discarded as the performance of the first experiment (see Table F.10) was too low to even consider the intervention in its current implementation.

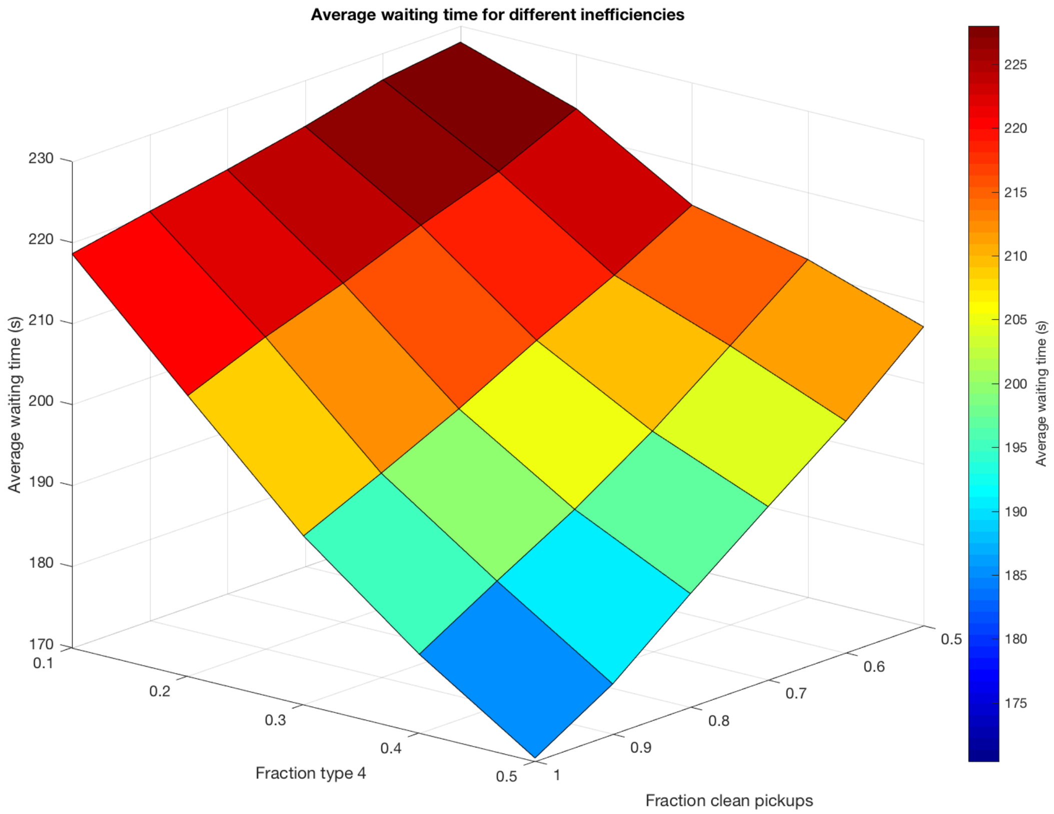


Figure 9.2: Plot of the average waiting time with changing fraction of clean pickups and fraction of type 4 patients out of all medication-requesting patients.

| **Situation** | **Waiting time (s)** | **Fraction $>$ 5 min** | **Fraction $>$ 10 min** |
|---|---|---|---|
| Current | 228.1 | 0.30 | 0.07 |
| Policy | - | $<0.30$ | $<0.10$ |
| Ambition | - | $<0.25$ | $<0.02$ |

Table 9.1: Current pharmacy performance and targets according to policy and ambition, with regards to average waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes

**First inefficiency** As we have shown above, the first inefficiency accounts for some loss of efficiency. With regards to the average waiting time and the fraction exceeding a waiting time of five minutes, we show here that elimination of the first efficiency allows the pharmacy to slightly increase the PSE to a level of about 1.03 while keeping the same performance as the current situation and as dictated by policy. The fraction exceeding a waiting time of ten minutes rises above the current situation but still stays within policy. The targets for ambition can however not be reached by eliminating the first inefficiency for any PSE value.

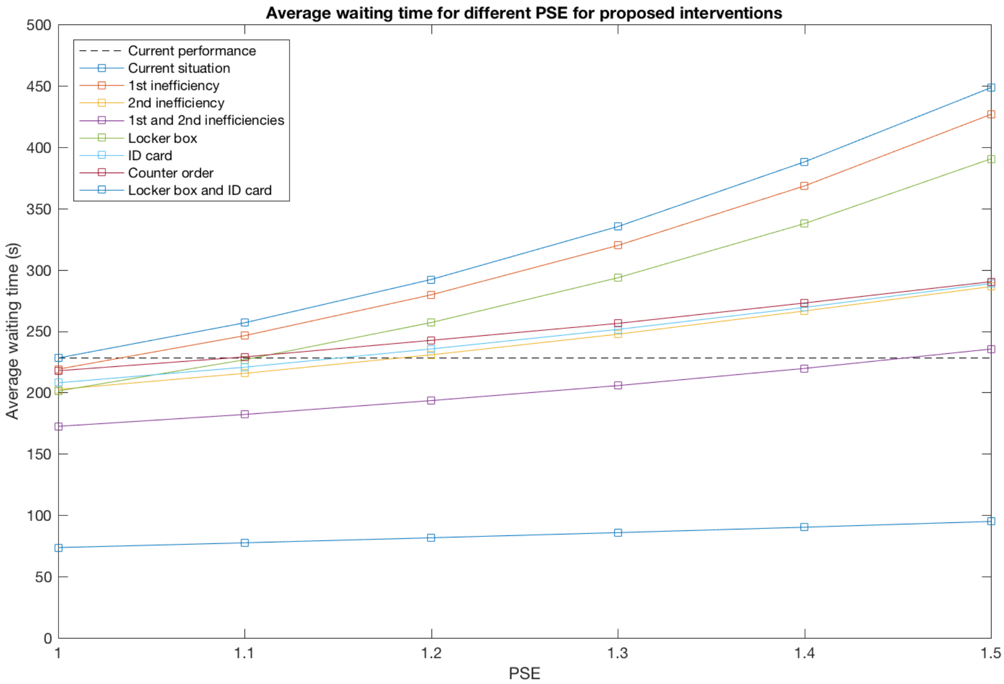


Figure 9.3: Plots of the average waiting time with changing PSE for the proposed interventions.

**Second inefficiency** The second inefficiency contributes to the loss of capacity as well. Here, we show that for a PSE of about 1.2, both current performance and policy requirements can be matched in all three performance indicators by eliminating the second inefficiency. This simulates an increase of service durations for type 5 patients of 20%, which can make a large impact on the quality of care. The ambition can however not be matched for any PSE.

**First and second inefficiency** By eliminating both first and second inefficiency, we liberate a large amount of capacity. With regards to all performance indicators, an increase of the PSE to 1.4 would satisfy both the current situation's performance as well as the policy. An increase of 40% of type 5 service duration can lead to large improvements of pharmaceutical care.

The ambition of less than 25% of instances exceeding a waiting time of five minutes can be reached with a PSE of 1.2, while the ambition of less than 2% of instances exceeding a waiting time of ten minutes can not be reached for any PSE.

**Locker box** Installation of the locker box intervention would allow the PSE to rise to 1.1, thereby resulting in an increase of 10% for the service duration of type 5 patients. The performance would then still match the policy and also the current performance, regarding the average waiting time and fraction exceeding five minutes.

Figure 9.6 indicates the share of each service type of the total service duration for the current situation. The locker box approach focuses on the yellow share, as it practically eliminates

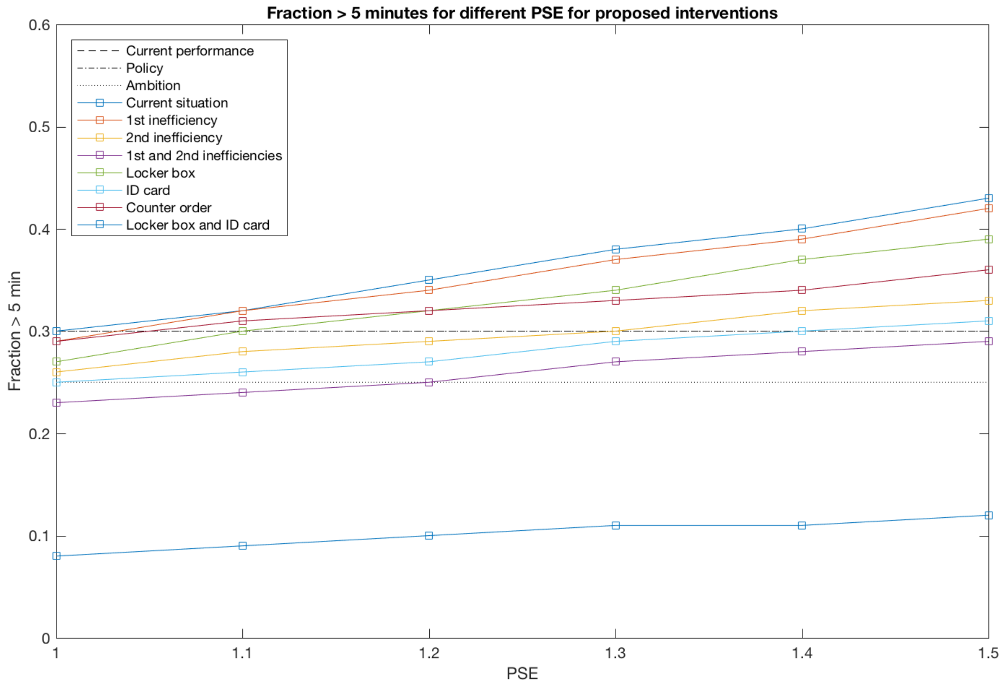


Figure 9.4: Plot of the average waiting time with changing no-show probabilities. Note that current performance and policy are equal and their lines therefore overlap in this graph.

the process related to type 4 patients with a fast pickup. The figure shows that the locker box approach does not address the perceived and confirmed inefficiencies but instead targets a relatively minor process that does not account for a large share of time spent at the counter.

Consequently, the influence of this approach for the current state of both inefficiencies is limited. However, as both inefficiencies diminish, the yellow share increases: more patients select a fast pickup (first inefficiency, red share to yellow share) and more eligible patients choose type 4 fast pickups (second inefficiency, green share to yellow share). Therefore, the locker box approach is very promising if an effort is made to reduce either one or ideally both inefficiencies.

**Electronic identification card** The electronic identification card approach eliminates both the first and second inefficiencies. It creates new processes (waiting for pick and preparation in the waiting room instead of at the counter) that do not waste staff-at-the-counter time. Its performance therefore approaches the theoretical elimination of the first and second inefficiency. A PSE of about 1.4 is possible while still matching the current performance policy, excluding the average waiting time which would increase by 14%.

Analogously to the locker box approach, we use Figure 9.6 to show the large impact that the electronic identification card can have. This approach facilitates both transitions related to the inefficiencies: from yellow share to red share as all type 4 patients are shifted to a fast

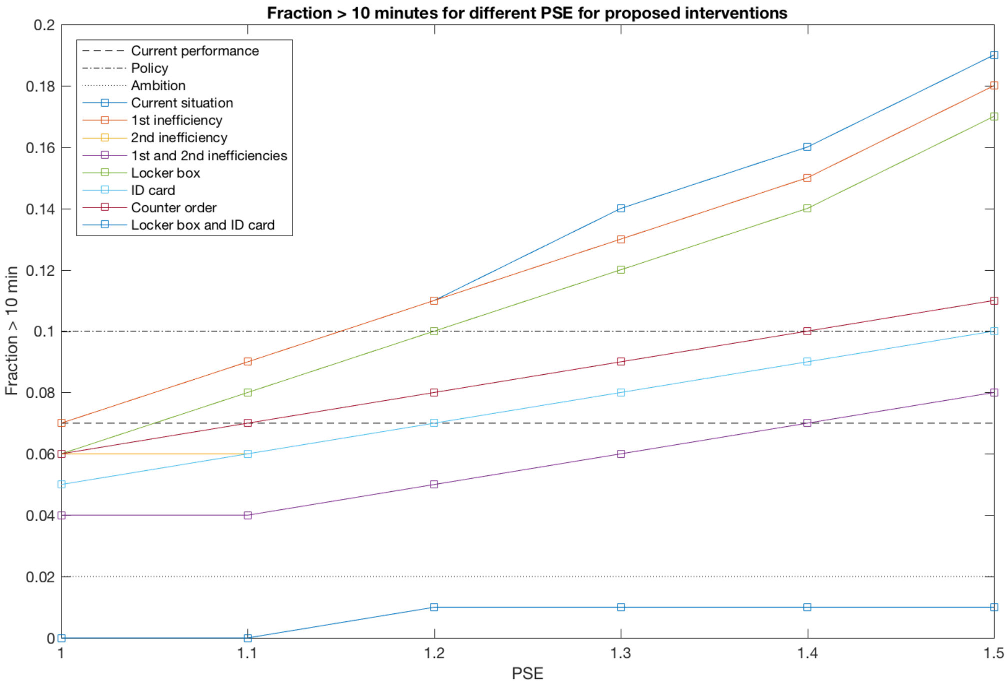


Figure 9.5: Plot of the average waiting time with changing no-show probabilities.

pickup, and from green share to yellow share as eligible patients are automatically relegated to a type 4 fast pickup. Note that the share composition changes as the service durations for these processes are not identically distributed. The additional waiting time of patients that have not requested medication beforehand is not taken into account in this evaluation. We also neglect the necessary back office time required to prepare the medication.

**Counter order** As with the electronic card approach, this approach deals with both inefficiencies. However, as inefficient patients order their medication at the counter before resuming waiting in the waiting room, there still is a process wasting counter time in the system. This

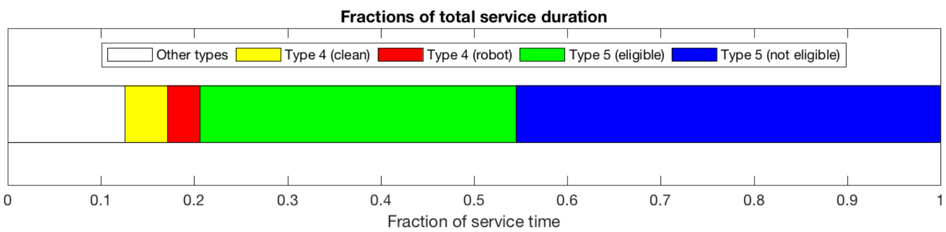


Figure 9.6: Fractions of the total service duration for the current situation. Service types 1, 2, 3, 6, 7, and 8 are summed up as 'other types'. The figure is composed by summing up all durations from all valid services and then plotting the shares of each service type. Divisions of type 4 and type 5 are based on the acquired quantifications for both inefficiencies. Source: filtered Gbos-A dataset, 63359 observations, 10-01-2014 – 21-10-2016.

process is completely eliminated by the electronic identification card (or rather delegated to an electronic procedure). Consequently, the performance of this approach is worse than the electronic identification card. An increase of the PSE to 1.1 can still be managed while matching both policy and current performance. We again ignore both additional waiting time for inefficient patients as well as the required back office time.

Again referring to Figure 9.6, both red and green share are transitioned to the yellow share. However, the transition is not perfect as a counter time wasting process is introduced into the system, which is the patient ordering medication at the counter before returning to the waiting room.

**Timed staffing** The intervention that schedules counter activation instead of allowing dynamic activation was excluded from further analysis after the first experiment. The intervention did not improve but instead sharply deteriorated the performance of the system. Average waiting time increased almost eightfold, the fraction exceeding five minutes waiting time more than doubled and the fraction exceeding ten minutes increased almost tenfold.

While these results are shattering, we conclude that timing staffing based on activity prediction is still an interesting direction for further research. An optimization of the scheduling process can greatly enhance this intervention's performance. Unfortunately, this is not within the scope of this project. Instead, we give suggestions for further examination: day of the week variations, seasonal changes, and outpatient clinic schedules could enhance this approach and lead to more precise predictions. This model may in any case enable a fast and safe evaluation of any timed staffing policy.

**Combination: locker box and electronic identification card** As mentioned before, the locker box intervention has great potential if combined with other interventions that reduce the inefficiencies. This combined intervention of both locker box and electronic identification card shows exactly that. As the electronic identification card eliminates both inefficiencies and transitions all inefficient patients to a type 4 fast pickup, the effect of the locker box is greatly enlarged. The locker box then basically eliminates all inefficient patients as these do not need any counter time at all. Referring to Figure 9.6, the yellow, red, and green share are in principle eliminated by this intervention. Of course, back office time is still required but not within the scope of this project. Furthermore, this intervention assumes a 100% efficiency of transition by the electronic identification card intervention.

This intervention is able to match the ambition of the pharmacy, even for a PSE of 1.5, which results in a 50% increase in service duration for type 5 patients in need of advice. For a PSE of 1, a decrease of 66% of average waiting time and fraction exceeding five minute waiting time is achieved. Additional experimentation (see Table F.11, not displayed in the figure) shows that a PSE of 1.8 is permissible while still matching the ambition of the pharmacy.

**Conclusion** In conclusion, we note that these experiments have again confirmed the large impact of both inefficiencies on the pharmacy's performance. Elimination of both inefficiencies could lead to an PSE of 1.4 and therefore an increase of 40% for the service durations of type 5 patients, thereby creating more opportunities for pharmaceutical staff to deliver quality care.

The combined intervention of locker box and electronic identification card shows immense promise as it allows an increase of 80% of type 5 service duration while still matching the pharmacy's ambition targets. With regards to implementation and reachability, scrutiny is required. First, two novel processes, the locker box and the electronic identification card, would need to be implemented and coordinated. Second, the transition from inefficient patients to efficient patients needs to be realized. Stepwise implementation is, of course, a possibility.

Of all practically possible individual interventions, the electronic identification card is most promising by allowing a PSE of 1.4 while still matching the current performance policy. A PSE of about 1.2 could be achieved while also matching the current performance of the pharmacy in all regards. This represents a large theoretical increase in service quality.

As the counter order intervention is a simpler implementation of the electronic identification card intervention, it shares its characteristics. However, this intervention leads to lower performance improvements as the inefficiencies are not completely eliminated but instead substituted by a new and wasteful process. Nevertheless, a PSE of 1.1 can be achieved by simply adjusting pharmacy policy to send patients waiting at the counter back to the waiting room.

The suggested intervention of the locker box is interesting as well. As it does not address the perceived inefficiencies, but instead eliminates another process, this intervention is well-suited to be combined with another intervention that does approach both inefficiencies. The locker box intervention's improvements increase with a reduction of both inefficiencies. Improvements in patient education to promote fast pickup eligibility can therefore lead to large increases in performance.

Timed staffing has been shown to be a poor approach in the current implementation. However, as it constitutes a completely different approach to pharmacy efficiency, further research may improve the implementation and thereby lead to far better results.

## 9.4 Conclusion

To conclude this chapter, we first note that the no-show analysis has shown limitations of the model. An increase in no-shows leads to a reduction in waiting time as no-shows *cost* less time at the counter than actual patients. However, this is where the model is limited, as no-shows are implemented as instances that leave the system before not showing up. In reality, no-show patients are mostly caused by patients missing their ticket, which they redraw again to get service. The model would need to account for this by adapting the number of patients showing up on a day instead of just applying the no-show probability. Further research and modeling is required to adapt the model to this limitation.

Second, we confirm both inefficiencies as a cause for a loss of efficiency and capacity within the pharmacy. We show that the waiting time could be drastically reduced by 25% if these inefficiencies were to be eliminated. Furthermore, we show that the effect of reducing the first inefficiency increases if the second inefficiency is also addressed.

Concluding the loss of capacity due to both perceived and confirmed inefficiencies, we see that either an increase of the service duration for type 5 patients of 40%, or a reduction of average waiting time by 25% is possible. We therefore argue that both inefficiencies have an enormous impact on the pharmacy's performance and a reduction of either inefficiency can lead to improvements. While these theoretical interventions do not allow direct implementation, we suggest workarounds to decrease these inefficiencies in the next chapter.

Third, we evaluate the proposed interventions and show that a combination of both locker box and electronic identification card is highly promising. The effects may be overestimated due to assumed perfect transitions, ignored back office workload, and negation of possible implementation issues. However, the approach to both eliminate the inefficiencies and address the remaining inefficient process by the identification card and the locker box, respectively, carries a lot of potential as has been shown by a PSE of 1.8 while still matching the ambition targets.

As for the individual interventions, we conclude that the electronic identification card has most impact by allowing a PSE of up to 1.4 while still almost matching the current performance. The simpler variant, the counter order intervention, also carries promise, as it consists of a simple policy change instead of large, structural changes. Its highest PSE while still matching current performance and policy results in an increase of 10% for the service duration of type 5 patients. The locker box, while also allowing a PSE of 1.1, shows promise in another area as it can be easily combined with other interventions that target the efficiencies. This can lead to immense improvements, as has been shown for the combined intervention. Furthermore, the locker box intervention profits greatly from any reduction of inefficiencies. Patient education, a fairly uncomplicated non-technical intervention, could therefore improve the locker box' performance. Timed staffing has performed worse than the current situation and is therefore discarded in this project. However, an improved staff schedule can undoubtedly improve this intervention's performance.

Finally, we note that the ambition targets can only be met by the combined intervention of locker box and electronic identification card. While ambition is a good thing for an organization, the ambition to have just 2% of all patients wait longer than 10 minutes seems unrealistic. We suggest that this ambition is reconsidered to better align with the other targets.

# Chapter 10

# Conclusion and recommendations

This chapter provides the conclusions drawn from this project and presents final recommendations for practice and further research. Section 10.1 presents a critical discussion and conclusion on the basis of the succeeding steps of this project. Section 10.2 finishes this chapter and this thesis with recommendations for practice and further research.

## 10.1 Conclusion

**On scope** The scope of this project was chosen to be counter interaction at the outpatient pharmacy. Clearly, several other processes are relevant at the pharmacy, which were intentionally left out. Back office work, phone advice, contact with medical specialists, and logistical warehousing operations directly influence the pharmacy's efficiency while also having immense impact upon the quality of service for patients.

We have also neglected other dimensions of the scope of this project. Seasonal variance in pharmacy activity was not taken into account and weekly variance was limited to day of the week dependencies of the number of patients. Opening hours and changing schedules of outpatient clinics can lead not only to variance in activity but also to a different composition of service requests. We suggest to further explore these possibilities.

However, we argue that the limits imposed upon this project and its resulting model make sense, especially taking into account the motivation for this research: to improve the pharmaceutical service provided for patients in need of pharmaceutical advice.

**On data analysis** We regard the current data analysis as extensive, especially due to the crosschecks introduced to assess the current performance of the pharmacy. While the perceived inefficiencies have been confirmed and quantified based on these results, the existing databases could provide a further wealth of information to improve modeling and redesigning the pharmacy. Also, the existing databases allow for several extensions of the scope as outlined above.

**On modeling** One striking challenge concerning the modeling of the current situation is clearly the validation. As illustrated earlier, the phenomenon of recovery time had to be introduced to allow calibration of the model. However, recovery time as such is not directly observed in the pharmacy. Instead, it is suggested that inconsistencies in the recording of service durations at the counters lead to a difference between theoretical model and observed reality.

Some services are terminated early when the member of staff waits for the robot to deliver the medication, while in other cases services are terminated late when the patient is already long-gone and the member of staff simply forgot to terminate the service. As there is no pattern in this behavior, it is impossible to correct for these phenomena in the existing dataset. Therefore, it was decided to introduce the recovery time as a compensating factor. However, the recovery time is applied to every service while not every service triggers the aforementioned phenomena.

As a result, the model itself is verified, but only validated through manual calibration. Consequently, results of the model are clearly under scrutiny as an artificial element has been introduced to allow calibration.

**On experiment design** We carried out experiments belonging to three sets: no-shows, inefficiencies, and interventions. Combinations of these sets to assess further influences and relations are possible but surpassed the scope of this research. We argue that using these three sets, we have shown limitations of the model, influences of inefficiencies, and impact of interventions.

For each proposed intervention, six experiments were run to evaluate the intervention's performance. Several more experiments could possibly result in more comprehensive information, especially when combining several interventions as has been done for the locker box and electronic identification card. Furthermore, other interventions are imaginable.

We regard the introduction of the permissible service enhancement, PSE, as pragmatic. While it serves as an easy-to-use evaluation measure, effects of the factor in practice are not clear. An imposed increase in service duration in the model only assesses liberated capacity. This capacity needs to be actually deployed to result in an enhancement of pharmaceutical care for patients.

**On results** We show that both inefficiencies have a large influence on the efficient usage of pharmacy capacity. We note that a reduction of the average waiting time of 25% or an increase of the service duration of type 5 of 40% is possible for optimal efficiency.

Concerning the proposed interventions, we conclude that the combined intervention of both locker box and electronic identification card shows most promise. This intervention leads to an allowable increase of 80% in service durations of type 5 patients, which can have large influence on the quality of care. However, implementation of this intervention is complex as it involves two distinct approaches and is based on several assumptions as outlined at length.

The individual interventions also show promise to various degrees. We conclude that the electronic identification card has most impact if we were to select a single intervention only. We see the counter order intervention, as it is related to the electronic identification card intervention, as a simpler version of the latter. Impacts on performance are accordingly smaller. There are several non-technical interventions related to patient education that favor the implementation of the locker box intervention, which makes this a good candidate for a combined approach of several interventions. The timed staffing approach has proved to be severely lacking, which, in our opinion, is mostly the result of a poorly constructed counter schedule. A better schedule construction method would undoubtedly lead to better results.

**Conclusion** This project has succeeded in assessing the pharmacy's performance with regards to current performance policy and perceived inefficiencies. These inefficiencies are confirmed and we show their large influence on the pharmacy's efficiency. Furthermore, a model is constructed to allow extensive process redesign without endangering day-to-day operations at the pharmacy. Several proposed interventions have been implemented in the model and evaluated with regards to the performance policy and a permissible service enhancement factor, PSE, to assess the capacity available for reallocation to value-creating processes.

## 10.2 Recommendations

Based on the discussion and conclusion presented above and observations made while carrying out this project, several recommendations to the organization can be made. Some recommendations are practical and can be applied directly by management, others suggest further research.

### 10.2.1 Recommendations for practice

**Patient education (1)** The pharmacy's efficiency could be greatly improved if patients are more aware of the possibility of quick pickups. The assessment of the influence of both inefficiencies have proven that a decrease of inefficiency can lead to large performance gains in terms of resource reallocation. Patients relying on repeating medications who are hence eligible for quick pickups could be advised to select this option next time they visit the pharmacy. Notification of pickup beforehand needs to be promoted to reduce this inefficiency.

As addressed before, the service type descriptions can be regarded as vague and overlapping. Furthermore, there is a fairly large number of options and oftentimes patients are not aware of the exact intention for each option. We suggest to reassess the possible types and reduce the number while increasing the specificity of each type's description. In the next section, a related suggestion for further research into patient education is given as well.

**Data policy** Although data collection is already very extensive at the MA, some aspects of the policy are not strictly adhered to. While strict policies can be implemented in any model, validity of the model is diminished if these policies are not followed as strictly in reality.

One apparent realization of lenient policy application is the registration of services at the counter. No-shows should be marked as no-shows instead of starting and directly terminating the service or letting it go on for ever if no other patients are waiting. Service durations should be recorded exactly as the service is started and finished. Recovery time should be included in the service duration and termination of the service should not be necessarily triggered by the patient leaving the counter. Also, members of staff should log on to their own user accounts as to allow individual performance evaluation.

In summary, irregularities in policy application introduce errors and variability in the data. A better application of a strict policy would allow better analysis of the data and increased validity of any modeling endeavors.

**Counter policy** While a coherent counter activation policy has been agreed upon, the way counters are actually activated differs and is often dependent on members of staff present. A vague policy can not be modeled. Hence, a precise and transparent activation policy should be implemented and followed. Non-dynamic activation of the counters, solely based on time of the day, may provide a possible direction, although the proposed configuration in this project showed disappointing performance.

**Performance policy** As has been shown frequently in this project, the performance of the pharmacy depends on the day of the week. Mondays see far more activity than Thursdays and more activity translates to longer waiting times for patients. However, the performance policy does not differ for the different days of the week. While days of the week are taken into account while staffing the pharmacy, the bottleneck in patient services is the number of counters. As this resource does not change and can not be changed depending on the day of the week, performance measures should reflect this discrepancy.

As for performance evaluation, a monthly performance review depends on the days of the week in this month. A month having five Mondays versus a month having four Mondays could result in significant performance differences. Therefore, monthly performance reports should incorporate the days of the week and possibly other factors as well.

**Forecasting (1)** As seen in the data, peak activity in the pharmacy occurs in two points of time during the day: around 10.30 am and around 3.30 pm. Incidentally, this is exactly the time when coffee breaks are usually scheduled. While coffee breaks are designed to not have impact upon the performance of the counters, the pharmacy as a whole operates at a reduced capacity during these breaks. A rescheduling of these coffee breaks or dynamic assessment of the situation may serve to conserve the capacity needed during these activity peaks. A second suggestion related to forecast staffing is given in the next section.

**Information systems** As of right now, the pharmacy and hospital use two different digital patient information systems. While this is already scheduled to be combined in future, this suggestion should highlight possible benefits. Using a combination, direct ordering of medication by outpatient clinics would be possible, allowing staff to prepare medication while the patient travels from the outpatient clinic to the pharmacy. Also, analysis of repeating prescriptions and eligibility for quick pickups could be done on a more consistent and complete basis. Furthermore, repeated entering of personal information and details could be avoided, thereby liberating resources at the counter.

**Robot queue** In the current situation, patients of type 4, requesting a quick pickup, enjoy the same priority in the robot queue as all patients at the counters. A possible reduction in service duration could be achieved if requests stemming from type 4 patients would receive a higher priority in the robot queue. This way, these patients' services could be finished faster, allowing reallocation of resources. This would promote type 4 fast pickups, improving the pharmacy's overall performance.

**Home delivery** An increase in home delivery of medication to repeating prescription patients would directly lead to a decrease in activity at the pharmacy. Promotion of these possibilities towards patients would be beneficial for the pharmacy's efficiency. Of course, any communication towards patients should always include the possibility of personal consultation at the pharmacy.

**Resource expansion** A completely different approach to increasing the service quality can be seen in an expansion of available resources. In practice, this could result in more counters and a more aggressive counter activation policy. Any intervention that expands the base capacity would obviously also benefit from any improvements regarding the inefficiencies.

### 10.2.2 Further research

**Queuing theory approach** As mentioned frequently in this report, a choice has been made to model the pharmacy using a simulation approach. However, a queuing theory approach was a possibility as well. In Chapter 7, a decision has been justified on why simulation was chosen. Future research could be carried out to try and use a queuing theory approach for this model to gain more solid analytical understanding of underlying pharmacy processes.

As outlined in the chapter mentioned earlier, several assumptions would have to be made. An interesting and fairly inexpensive endeavor would be to compare the current situation as modeled using a simulation approach with a simulation model of the simplified reality as required by queuing theory. In the proposed simulation model, arrival pattern and service distributions would be approached with suitable distributions, counter activation would be ignored, and priority rules would be negated, so as to approach a simulation model of the simple queuing theory model. Resemblance between current situation and simplified situation could then lead to an application of queuing theory insights.

**Patient education (2)** Further research should be done into the education of patients to promote fast pickups and type 4 eligibility. Psychology or education science studies could be set up to find ways to enhance patients' awareness about their own influence on the efficiency of the pharmacy. Furthermore, communication science could lead to new service type descriptions at the ticket pillar.

**Forecasting (2)** Regarding the wealth of information recorded at the hospital, extensive forecasting mechanisms might be feasible. Arrival rates at outpatient clinics may be used to forecast periods of activity at the pharmacy, thereby influencing staffing and scheduling back office tasks. As mentioned before, improvements in forecasting could allow an efficient intervention using timed staffing instead of dynamic counter activation. The possibility for details of forecasting is possibly limitless, although for practical reasons it should of course be limited to a comprehensive level.

Another area of forecasting could lead to patient prescriptions. Using the information present in the pharmacy systems, repeating prescriptions pickups could be scheduled without the patient actively engaging with the pharmacy.

**Robot information** In this project, the robot was regarded as a black box element within the model. Further research could include the robot, its workings, its priorities, and its queues. Extensive feedback of information by the waiting room system and the robot queue could lead to load balancing at counters and improved process efficiency.

**Other interventions** While this project contains several interventions for the pharmacy, a wealth of other options is available. Workshops with members of staff to construct interventions with a subsequent implementation and evaluation could lead to surprisingly potent approaches.

**Improvements in modeling** Finally, of course the model presented in this project could be improved further. An inclusion of back office work would enable the researcher to take the costs of counter activation into account while also allowing an assessment of the time needed to prepare medication for quick pickups. An extension of the model into the field of staff utilization would be then be possible.

Any improvement should however first be based on improved data collection, preparation, and analysis. More precise arrival patterns, service durations, and patient characteristics would result in a more accurate model, allowing better evaluations and conclusions. More precise policies and a more consistent application of these policies are needed to achieve this.

### 10.2.3 Implementation plan

Concluding, we suggest the following for the MA: first, patient education needs to be improved to promote the possibility of fast pickups for repeating prescriptions. This process needs to be continuously evaluated with respect to both inefficiencies.

Second, a pilot on the locker box can be organized by setting up a dummy locker box and staffing it with pharmacy personnel. While of course diminishing the pharmacy's performance, this pilot should serve to assess the locker box' theoretical impact. A financial feasibility study should be done to gather implementation information on the locker box approach.

Third, another pilot based on the counter order intervention should assess the possible impact of the electronic identification card intervention. As both interventions share characteristics with regards to addressing both inefficiencies, results from this pilot can be translated to possible results of the electronic identification card intervention. Furthermore, as the counter order intervention requires just a small adaption of policy, it can be easily implemented and reversed. Additionally, a financial and practical feasibility study on the electronic identification card should be done. Integration with the pharmacy system should be a central element of this system.

Fourth, either the locker box or the electronic identification card approach should be implemented, depending on both feasibility studies and pilot results. Implementation should be according to the approach that the other intervention can follow later.

Coupled with a continuous evaluation of the pharmacy's performance, realizations of both inefficiencies, and characteristics of the patient population, this could lead to large improvements. A more efficient pharmacy not only enables improvements in pharmaceutical care. Due to the liberation of capacity, other endeavors not mentioned in this study are possible, for example an expansion of the service portfolio.

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# Appendix A

# Databases

## A.1 Gbos queuing system

**Time of arrival** The time the instance is created as the ticket is drawn. In other words, the waiting period starts.

**Date** The date of the service is recorded. As all services are finished on the day they were started, this day suffices.

**Weekday** The day of the week is recorded as string and as numerical code (where 1 corresponds to Monday, 2 to Tuesday, and so on).

**Waiting code** One of the four waiting codes as described earlier (F, R, S, Z).

**Instance ID** The identification number of this instance. Every day, this number is restarted. On the ticket, the waiting ID is preceded by the letter code.

**Queue** The queue corresponds to the letter of the waiting code.

**Location** This option is not in use.

**Counter** The counter where the service was delivered is recorded as well. Note that no-show instances do not have this value.

**Staff member** This variable gives the name of the staff member that was logged on at the counter during the service. As log-in and log-off discipline is not very high, this data is not valid. It is not used for any processing either.

**Product** Service type (1 through 8).

**Product group** Every product for this study stems from the group *Maartensapotheek*. As the pillar is used for other services besides pharmaceutical care, this group is used to filter out unrelated services.

**Cluster** For the sake of this study, this is a copy of the *product group* variable.

**Pillar** This option is not in use.

**Reception** This option is not in use.

**Status** Here, the status of the instance is recorded. Possible values are *finished*, *no-show*, *waiting* and *busy*. As this study only uses past data and no live recordings, only finished instances and no-shows are of interest.

**Time service started** The time that the service has started is recorded here.

**Time service ended** The time that the service has been finished is recorded.

**Notes** This option is not in use.

**Waiting time** An internal calculation for the waiting time is also given.

**Service time** As well as an internal calculation for the service time.

**Sojourn time** And finally, for the sojourn time of an instance.

**Appointment number** This option is not in use.

**Appointment time** This option is not in use.

**Appointment customer name** This option is not in use.

**Handicap** This option is not in use.

**Customer first name** This option is not in use.

**Gender** This option is not in use.

## A.2 Rowa robot database

**ID** An identification number for every output pick is given. This number resets about every 1400 picks. As the robot receives about 250 pick requests on a given day, unique pick ID and day combinations are given.

**Time** A complete timestamp with date and time of the day is saved for every pick.

**Order** As individual picks can belong to a single order, another identification number in the form of an order number is given.

**Machine** An identification for the machine is recorded for each pick.

**Device** The part of the device performing the pick is recorded. For devices with several picking heads, this allows differentiation.

**Output** The output location is recorded here. When a counter requests a pick, the pick is sent to this counter. The eight possible output locations are listed below.

- 1: Output at the operating screen.
- 16: Output at the prepackaging workplace.
- 2: Output at counter 6.
- 3: Output at counter 5.
- 4: Output at counter 4.
- 5: Output at counter 3.
- 6: Output at counter 2.
- 7: Output at counter 1.

**PC** The PC from where the pick was requested is recorded as well.

**Priority** A priority is given to every pick. Picks requested by the counters are of the highest priority while picks requested from the operating screen and the prepackaging workplace are of the lowest priority. Different counters do not differ in priority nor is there an option for a staff member to increase priority of a request.

**Packs** The date the medication was inserted into the machine is recorded here.

**Codes** A code for every medication is recorded here.

**Names** The name of the requested medication is recorded here for easy identification of orders.

**Channels** Internal routing for precise delivery is set here.

**Status** The state of the pick is recorded here. As this study uses output logs, no live data is visible and therefore all picks are finished.

## A.3 Aposys delivery reports

**Social security number** A patient's social security number.

**Client number** A patient's patient ID as used within the Aposys pharmacy system.

**Delivery date** The date of the delivery listed in this row.

**Packaging name** The name of the medication as listed on packaging, not used in this study as PRK suffices for identification.

**Amount** The number of packages delivered.

**Usage code** The pharmaceutical usage code for this prescription.

**Usage text** The pharmaceutical usage code, decoded for easy reading.

**ATC code** A specific code for medication, not used in this study.

**GPK code** A specific code for medication, not used in this study.

**PRK code** A specific code for medication, used in this study for prescription comparison.

**AGB code** A specific code for care provider, used in this study to filter for location.

**Name complete** The care provider's name, not used in this study as the AGB code suffices.

**Specialization code** A code for the specialization of the care provider, not used in this study.

**Postal code** The postal code of the patient, used in this study to filter for location.

## A.4 Aposys snapshots

**Patient ID** The patient's ID as used by the Aposys pharmacy system.

**Medication name including branding** The name of the medication including the branding of the product.

**Medication name** The name of the medication excluding any branding.

**Usage code** The usage code of this prescription.

**Usage text** The decoded usage code of this prescription, not used in this study.

**Usage manner** The manner of ingestion, not used in this study.

**ATC code** A specific code for medication, not used in this study.

**Care provider code** An employee's ID for the care provider, not used in this study.

**Care provider name** The care provider's name, not used in this study.

**Stop date** The date this prescription was stopped, not used in this study as often not entered or faulty.

**Prescription date** The date the prescription was entered, not used in this study as often not entered or faulty.

**Stopped by** The name of the care provider who stopped the prescription, not used in this study as often used for other comments.

**Indication usage** Indicates whether this prescription is in use or not, not used in this study as often used for other comments.

**HPK code** A specific code for medication, not used in this study.

**PRK code** A specific code for medication, used in this study for prescription comparison.

**Concentration of active ingredients** Extracted from HPK code, not used in this study.

# Appendix B

# Literature search

**Search methods** Using search engines and search terms, a number of scientific articles were found. Furthermore, several articles were found as references in other work. The book Simulation Modeling and Analysis by Law (2015) was extensively used for the simulation study.

**Search engines** The literature search was mainly carried out using the Scopus search engine (https://www.scopus.com/). For literature search stemming from references in other scientific work, the Google Scholar engine (https://scholar.google.com) was used as it provides easy access to a number of source websites. The ORchestra database provided by the CHOIR group at the University of Twente (http://www.choir-ut.nl) was searched on the topic of *pharmacy services*.

**Search terms** For medication adherence, within Scopus the search term *(adherence OR compliance) AND (pharmacist OR pharmacy)* was used to find a large number of medical research on this topic.

On process redesign, literature was searched using the term *logistics AND process AND redesign*.

On general pharmacy logistics, literature was searched using the term *pharmacy AND (logistics OR processes)*. For simulation or queuing theory, the terms *AND simulation* or *AND "queuing theory"* were attached. For queuing theory, another search term was *"queuing theory" AND pooling*, to specifically focus on the pooling phenomenon.

**Selection and exclusion** Literature was selected based on abstracts and their relation to the current project. Literature was actively excluded if the quality was doubtful or the content was not related to the current project.

# Appendix C

# Detailed methods of data preparation and analysis

## C.1 Data preparation

### C.1.1 Gbos instances

- Gbos data was exported using the Gbos back office software installed on pharmacy computer terminals.
- Back office exports were imported using a custom Python script.
- Data was cropped to relevant columns.
- Values were formatted as necessary and textual information was largely recoded to numerical values (counters, service types, days of the week).
- Based on the timestamps for arrival, start of service, and end of service, the corresponding waiting, service, and sojourn durations were calculated and saved to the data table.
- Data was filtered for faulty instances. Faulty instances include: no-shows, incorrectly terminated services as indicated by the Gbos software, instances with a waiting or service duration of zero, instances with a waiting or service duration exceeding 30 minutes.
- The percentage of faulty instances was recorded to correct for these instances in the model.
- All faulty instances were interpreted as no-shows.
- Finally, data was exported for further usage, containing only valid instances that have completed the pharmaceutical service pathway.

### C.1.2 Rowa robot requests

- Rowa robot request data was exported from the Rowa robot terminal after a service request to the contractor for the location of the files.
- Request logs are saved on a day-to-day basis.
- A custom Python script was designed to import daily log files.
- Using the script, relevant columns were selected: timestamp of the request, request ID, output location for that request.
- Values were formatted according to needs and the output location was adjusted to match the counter identifier used in the Gbos system.
- A separate custom Python script was used to stitch all days together as to create on long record of all robot requests.
- Data was exported for further usage.

### C.1.3 Aposys snapshot extractions

- Due to corrupted file export, Aposys snapshots had to undergo extensive correction before usage.
- A custom Python script was used to import the daily snapshot extraction.
- A number of defects may occur during extraction. Reasons for this are unclear as the extraction script was neither accessible nor known during this research.
- It may be assumed that the problem originates with terminating and escaping characters in text fields, triggering new lines or column jumps during the extraction to a comma-separated file.
- Possible line defects include:
  - Single row shift
  - Double row shift
- These may be combined with the following column defects:
  - No column shift
  - Single column shift
  - Double column shift
  - Triple column shift
- These defects may result in a line being cut off half way and continuing on one or two rows below, in the first, second, third or fourth column.

- Identifying each defect is troublesome and correcting the defects is equally extensive.
- Using the custom Python script, it was possible to correct the file to an acceptable level (according to pharmacy staff), so that relevant information was possible to extract.
- Relevant columns were extracted so that a list of all pharmaceutical regimes saved at SMK was accessible.
- Each line consists of the patient ID, the corresponding PRK, the truncated usage code and a hashed combination of these values for easy comparison with delivery reports.

### C.1.4 Aposys delivery reports

- Aposys delivery reports were extracted using a CrystalReports routine.
- Extraction resulted in a table file that was possible to import using a custom Python script.
- The script first selected relevant columns so that patient ID, PRK and truncated usage code were left. A hashed combination of these values was added for easy comparison.
- Several filtering efforts were made to exclude non-valid instances, as the delivery report included other SMK locations as well as Nijmegen.
- To exclude patients picking up medication at SMK location Boxmeer, a filter for postal codes of the patient's address was implemented.
- To exclude patients picking up medication at SMK location Woerden, a filter for the prescribing doctor's AGB was implemented.
- The filtered file was saved for further analysis.

### C.1.5 Truncating usage codes

- Usage codes consist of parts for frequency and amount of ingestion and room for optional comments.
- In some cases, the code may be preceded by an additional comment that indicates reasonable self-medication by the patient.
- Both frequency and amount are defined by a number and a string, consisting of one or two characters. These two pairs are directly joined to form the core of the usage code.
- There are some variations to this pattern, consequently, it is not easily achievable to extract frequency and amount.
- It was decided that this core must be taken as a whole for comparison.
- Appendices to the code are usually separated from the core by a space character.

- Usage codes are truncated using a Python script.
- First, any semi-colons are eliminated as these are prone to disturb the script and later usage.
- Second, any optional comments following the core are truncated by cutting of the code after the first space character.
- In cases where the code is preceded by a self-medication indicator, the second space character is used as a cutting line.

## C.2 Data analysis

### C.2.1 Real type estimations using temporal comparison

- A custom Python script was used to import, for a given day, both the prepared Aposys delivery report and the prepared Aposys snapshot of the day before.
- A list of all unique patient IDs in the delivery report was created.
- For every patient, the following routine was followed:
  - Each entry in the delivery report for this patient was crosschecked, based on the hashed value, whether it was present in the snapshot from the day before.
  - If the entry was present, the script continues on to the next entry for this patient.
  - If this entry was the patient's last entry, the script marks this patient as non-mutated and continues on the next patient.
  - If the entry was not present, the patient is marked as mutated and the script starts with the next patient.
- This way, a mutation is recorded if (a) the patient is new at the MA, (b) an existing patient receives a new kind of medication as identified by PRK, or (c) the truncated usage code of an existing patient for an existing medication has changed.
- A single mutation within a patient's regime is sufficient to label the patient as mutated.
- The script then calculates the total number of patients who have picked up medication on that day and the number of mutated patients.
- This is done for all days where delivery reports and corresponding snapshots are available.
- Data is aggregated to give the average fraction of mutated patients.

### C.2.2 Clean pickups based on instance-request crosschecks

- A custom Python script was designed to import the Gbos records and Rowa request logs of a given range of days.
- Only instances of type 4 are selected for this analysis.
- For every Gbos instance, the following routine is executed:
  - The start and end times of the service are recorded, together with the counter at which the service took place.
  - Using this time window and counter number, the Rowa request log was searched for a matching request.
  - A request matched if the request was formed within the time window and the output location for the request was identical to the counter at which the service took place.
  - If a match or several matches were found, the instance was marked as a robot assisted pickup and the corresponding request IDs were recorded with that instance.
  - If no match was found, a different indicator was appended to mark the request as a clean pickup.
- The complete list of marked Gbos instances was exported for further analysis in three variations:
  - *Gbos-clean*, containing only clean pickups.
  - *Gbos-robot*, containing only robot pickups.
  - *Gbos-all*, containing all pickups, including their markings.

# Appendix D

# Results of data preparation and analysis

## D.1 Descriptive information on Gbos datasets

| Result | Gbos-A | Gbos-B |
|---|---|---|
| Start date | 10-01-2014 | 21-10-2016 |
| End date | 10-31-2016 | 18-01-2017 |
| Total count | 69272 | 6807 |
| No-show count | 2710 | 369 |
| Faulty count | 3203 | 403 |
| Total filtered | 5913 | 772 |
| Percentage filtered | 8.54% | 11.34% |

Table D.1: Results of preparing and filtering Gbos datasets Gbos-A and Gbos-B. Faulty instances include not correctly terminated instances, not correctly started instances, crashed instances, instances exceeding maximum waiting or service duration (30 minutes), instances with zero waiting or service duration.

| Service type | Gbos-A | Gbos-B |
|---|---|---|
| All | 63359 | 6035 |
| 1 | 579 (0.91%) | 41 (0.68%) |
| 2 | 5356 (8.45%) | 495 (8.20%) |
| 3 | 1480 (2.34%) | 103 (1.71%) |
| 4 | 6577 (10.38%) | 701 (11.62%) |
| 5 | 45429 (71.70%) | 4370 (72.41%) |
| 6 | 729 (1.15%) | 69 (1.14%) |
| 7 | 535 (0.84%) | 25 (0.41%) |
| 8 | 2674 (4.22%) | 231 (3.83%) |

Table D.2: Counts and percentages of instances of service types for Gbos datasets A and B.

| **Day of the week** | **Gbos-A** | **Gbos-B** |
|---|---|---|
| All | 63359 | 6035 |
| Monday | 14999 (23.67%) | 1331 (22.05%) |
| Tuesday | 12199 (19.25%) | 1269 (21.03%) |
| Wednesday | 13035 (20.57%) | 1186 (19.65%) |
| Thursday | 11987 (18.92%) | 1141 (18.91%) |
| Friday | 11139 (17.58%) | 1108 (18.36%) |

Table D.3: Counts and percentages of instances on days of the week for Gbos datasets A and B.

| **Counter** | **Gbos-A** | **Gbos-B** |
|---|---|---|
| All | 63359 | 6035 |
| 1 | 820 (1.29%) | 79 (1.31%) |
| 2 | 18567 (29.30%) | 1739 (28.82%) |
| 3 | 17224 (27.18%) | 1470 (24.36%) |
| 4 | 14596 (23.04%) | 1373 (22.75%) |
| 5 | 8344 (13.17%) | 916 (15.18%) |
| 6 | 3808 (6.01%) | 458 (7.59%) |

Table D.4: Counts and percentages of instances on counters for Gbos datasets A and B.

| **Measure** | **Gbos-A** | **Gbos-B** |
|---|---|---|
| Count | 63359 | 6035 |
| Mean waiting time (min) | 4:04 | 3:40 |
| Median waiting time (min) | 2:36 | 2:10 |
| St. dev. of waiting time (min) | 4:07 | 3:48 |
| Waiting time $>$ 5 min | 20408 (32.21%) | 1722 (28.53%) |
| Waiting time $>$ 10 min | 6296 (9.94%) | 468 (7.75%) |
| Waiting time $>$ 15 min | 1389 (2.19%) | 85 (1.41%) |

Table D.5: Descriptive performance measures of instances for Gbos datasets A and B. Note that Gbos dataset B originates after the change in ticket reinsertion.

## D.2 Detailed histograms

In this section, several histogram are given that are mentioned in the main body.

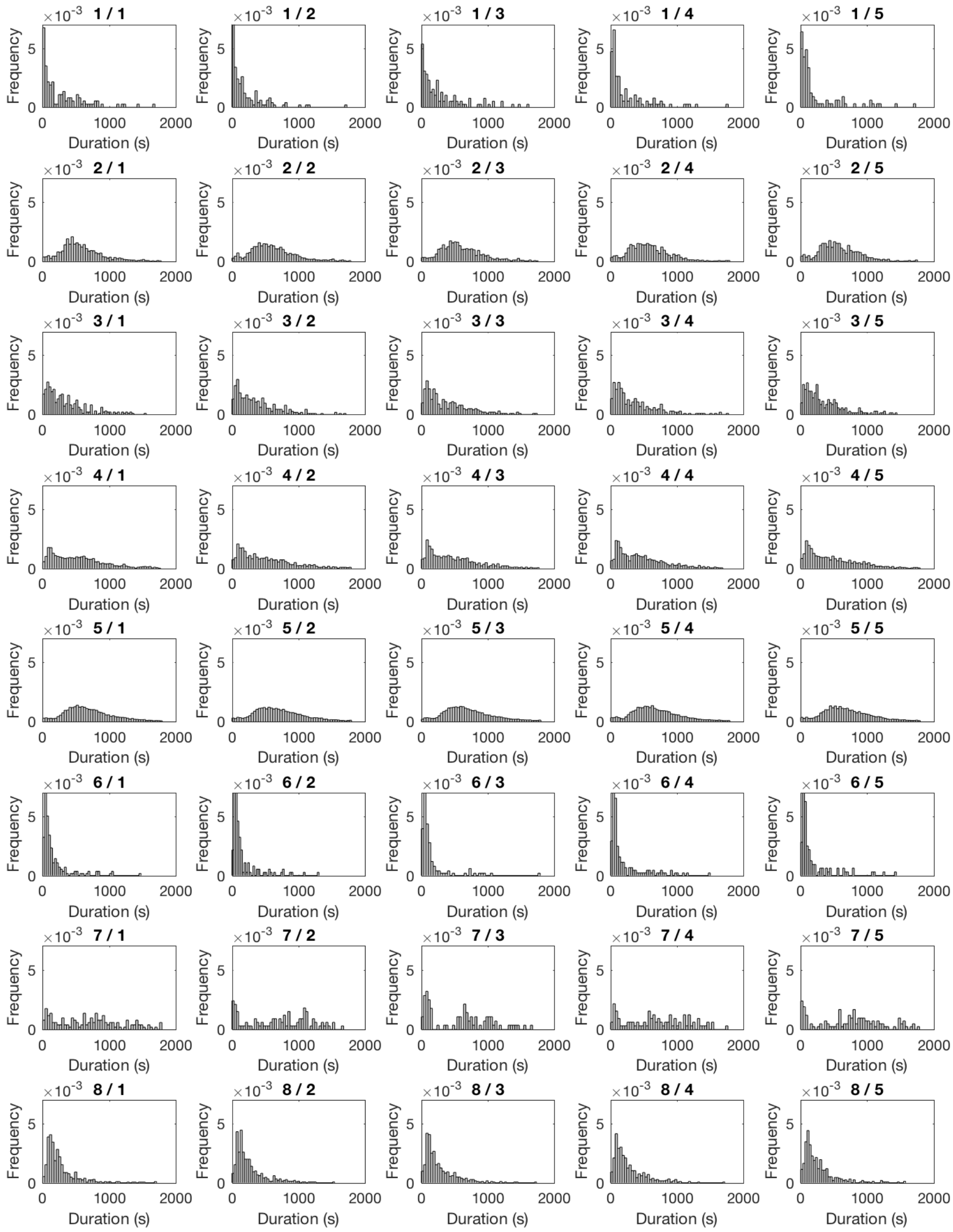

Figure D.1: Histograms of the service durations for each service type and for each day of the week. Figure titles are shortened for layout reasons in the format service type / day of the week. The time in seconds is set on the horizontal axis, the frequency of occurrence on the vertical axis. Source: filtered Gbos-A dataset, 63359 observations, 10-01-2014 – 21-10-2016.

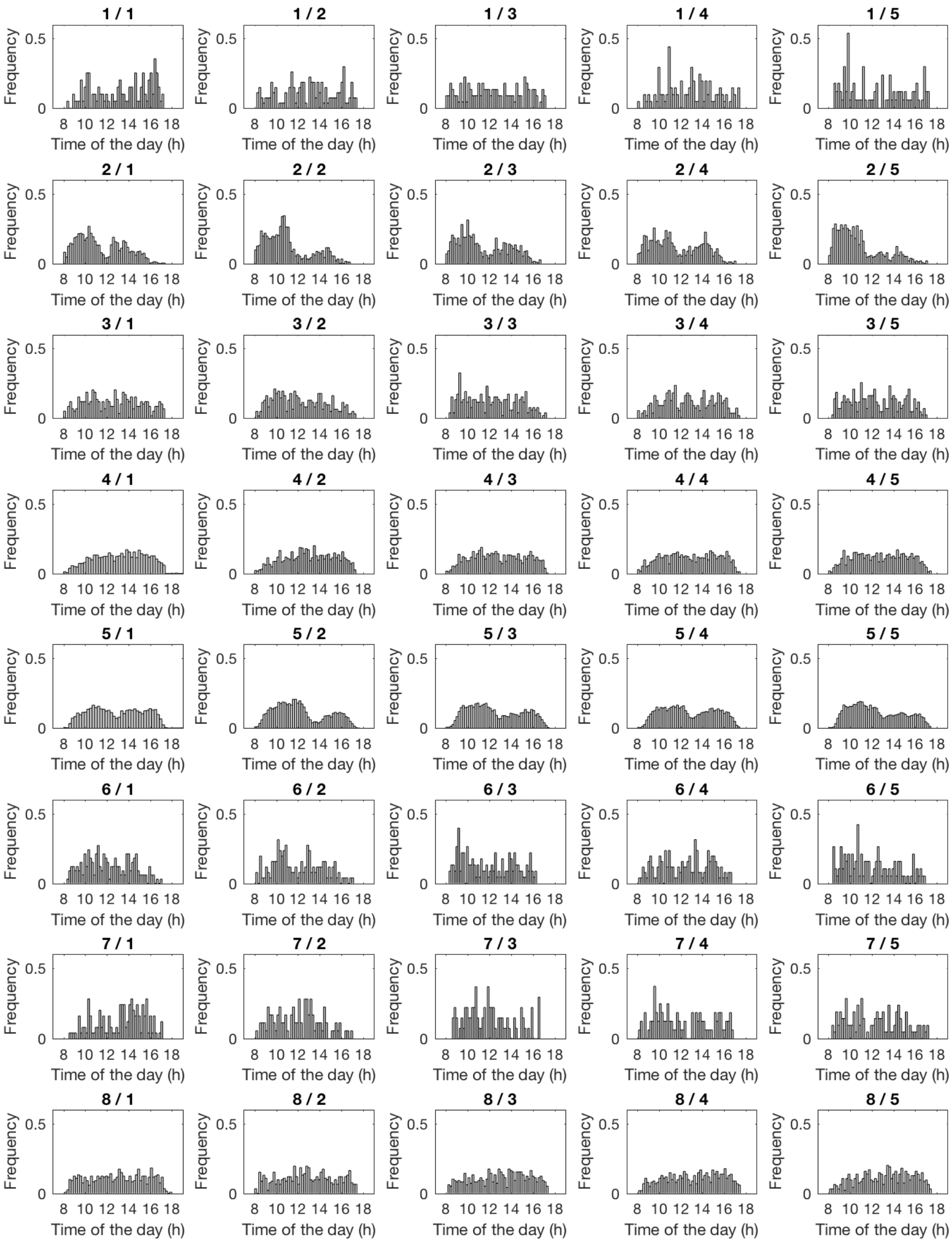

Figure D.2: Histograms of the arrival times for each service type and for each day of the week. Figure titles are shortened for layout reasons in the format service type / day of the week. The time of the day is set on the horizontal axis, the frequency of occurrence on the vertical axis. Source: filtered Gbos-A dataset, 63359 observations, 10-01-2014 – 21-10-2016.

# Appendix E

# Detailed description of the simulation model

## E.1 Input

### E.1.1 Time, day and day of the week

Time is kept by the internal event controller module *EventController* supplied by the software package. A generator triggers the day control method *DayControl* every 24 hours to increase the day counter and the day of the week counter both by one. Another generator triggers the week control method *WeekControl* every 5 days and resets the day of the week counter to 0.

### E.1.2 Number of patients

For every service type, a number is drawn from a determined distribution. This distribution furthermore depends on the day of the week. Discrete distributions directly deliver the number of patients to be created on that day. Values of continuous distributions are rounded to the next integer. Tables E.1, E.2, E.3, E.4, and E.5 give an overview over the used distributions, their parameters and corresponding p-values for a goodness of fit test (Chi-Square for discrete, Kolmogorov-Smirnov for continuous distributions).

### E.1.3 Arrival time

For every service type, an arrival time is drawn from a determined distribution. For the arrival time distributions, all distributions are of empirical nature and therefore not listed here.

| Service type | Distribution |
|---|---|
| 1 | Poisson distribution ($\mu$ = 1.2786, p = 0.12) |
| 2 | Empirical distribution |
| 3 | Poisson distribution ($\mu$ = 2.7429, p = 0.40) |
| 4 | Poisson distribution ($\mu$ = 11.0000, p = 0.14) |
| 5 | Normal distribution ($\mu$ = 83.4000, $\sigma$ = 16.4644, p = 0.22) |
| 6 | Poisson distribution ($\mu$ = 1.5000, p = 0.06) |
| 7 | Poisson distribution ($\mu$ = 1.2857, p = 0.07) |
| 8 | Poisson distribution ($\mu$ = 4.7429, p = 0.01) |

Table E.1: Number of patients distributions on Monday.

| Service type | Distribution |
|---|---|
| 1 | Poisson distribution ($\mu$ = 1.2759, p = 0.13) |
| 2 | Empirical distribution |
| 3 | Poisson distribution ($\mu$ = 2.5793, p = 0.40) |
| 4 | Poisson distribution ($\mu$ = 9.3172, p = 0.36) |
| 5 | Normal distribution ($\mu$ = 64.8483, $\sigma$ = 15.4634, p = 0.79) |
| 6 | Poisson distribution ($\mu$ = 1.0966, p = 0.06) |
| 7 | Poisson distribution ($\mu$ = 0.9379, p = 0.07) |
| 8 | Poisson distribution ($\mu$ = 3.7172, p = 0.09) |

Table E.2: Number of patients distributions on Tuesday.

| Service type | Distribution |
|---|---|
| 1 | Poisson distribution ($\mu$ = 1.1034, p = 0.14) |
| 2 | Empirical distribution |
| 3 | Poisson distribution ($\mu$ = 2.3655, p = 0.40) |
| 4 | Poisson distribution ($\mu$ = 9.4483, p = 0.21) |
| 5 | Normal distribution ($\mu$ = 71.3103, $\sigma$ = 16.5616, p = 0.95) |
| 6 | Poisson distribution ($\mu$ = 1.1241, p = 0.06) |
| 7 | Poisson distribution ($\mu$ = 0.8621, p = 0.07) |
| 8 | Poisson distribution ($\mu$ = 3.9655, p = 0.02) |

Table E.3: Number of patients distributions on Wednesday.

| Service type | Distribution |
|---|---|
| 1 | Poisson distribution ($\mu$ = 1.0704, p = 0.30) |
| 2 | Empirical distribution |
| 3 | Poisson distribution ($\mu$ = 2.3662, p = 0.40) |
| 4 | Normal distribution ($\mu$ = 9.8169, $\sigma$ = 4.0205, p = 0.06) |
| 5 | Normal distribution ($\mu$ = 65.6197, $\sigma$ = 17.5974, p = 0.55) |
| 6 | Poisson distribution ($\mu$ = 1.1056, p = 0.06) |
| 7 | Poisson distribution ($\mu$ = 0.8873, p = 0.07) |
| 8 | Poisson distribution ($\mu$ = 4.1127, p = 0.69) |

Table E.4: Number of patients distributions on Thursday.

| Service type | Distribution |
|---|---|
| 1 | Poisson distribution ($\mu = 0.9286$, p = 0.29) |
| 2 | Empirical distribution |
| 3 | Poisson distribution ($\mu = 2.0214$, p = 0.90) |
| 4 | Poisson distribution ($\mu = 10.6143$, p = 0.27) |
| 5 | Normal distribution ($\mu = 60.7571$, $\sigma = 16.9625$, p = 0.26) |
| 6 | Poisson distribution ($\mu = 0.8929$, p = 0.06) |
| 7 | Poisson distribution ($\mu = 1.2000$, p = 0.07) |
| 8 | Poisson distribution ($\mu = 3.8214$, p = 0.65) |

Table E.5: Number of patients distributions on Friday.

### E.1.4 Service duration

For every service type, a service duration is drawn from a determined distribution. Table E.6 gives an overview over the used distributions, their parameters and corresponding p-values for a goodness of fit test (Chi-Square for discrete, Kolmogorov-Smirnov for continuous distributions). Note that type 4 is split in clean and robot-assisted pickups.

| Service type | Distribution |
|---|---|
| 1 | Gamma distribution (shape = 0.6375, scale = 397.2855, p = 0.01) |
| 2 | Empirical distribution |
| 3 | Gamma distribution (shape = 1.2322, scale = 296.4696, p = 0.09) |
| 4 (clean) | Gamma distribution (shape = 1.4914, scale = 250.3973, p = 0.05) |
| 4 (robot) | Gamma distribution (shape = 5.2370, scale = 158.6259, p = 0.07) |
| 5 | Empirical distribution |
| 6 | Empirical distribution |
| 7 | Empirical distribution |
| 8 | Empirical distribution |

Table E.6: Service duration distributions.

### E.1.5 Clean pickups

For every service of type 4, it is randomly determined whether this pickup is of the clean or of the robot-assisted variety. Corresponding service durations are chosen based on this property. The probability for a service of type 4 to be a clean pickup is 0.5692.

### E.1.6 No-shows

Every patient has a chance to transform into a no-show with a probability determined by historical data. The probability for a patient to be a no-show is 0.0854.

## E.2 Output

Output is generated in the form of a table file *PatientData* containing one row per patient instance. Below, recorded data per patient is described. The table file may be written to disk for further analysis using the *WriteToFile* method.

**Patient ID** Unique patient ID given to every instance in the model.

**Type** The service type of the patient.

**NoShow** Indicates whether the patient is a no-show (value of 1) or not (value of 0).

**CleanPick** Indicates whether the patient is of the clean pick variety (value of 1) or not (value of 0). Only relevant for patients of service type 4.

**GivenServiceDuration** Recording of the determined service duration based on the empirical or theoretical distribution.

**DayNum** The simulation day on which the instance is created and serviced.

**WeekDay** The day of the week on which the instance is created and serviced.

**ArrivalTime** The time of arrival of the patient (in seconds from 0:00:00).

**ServiceStartTime** The time the service is started for this patient (in seconds from 0:00:00).

**ServiceEndTime** The time the service is ended for this patient (in seconds from 0:00:00).

**Counter** The counter at which the patient is serviced.

**WaitingTime** The waiting duration for this patient (in seconds).

**ServiceDuration** The service duration for this patient (in seconds).

**SojournDuration** The sojourn duration for this patient, sum of waiting and service duration (in seconds).

**Exc_5_min** Indicates whether the waiting duration exceeds five minutes (1 for yes, 0 for no).

**Exc_10_min** Indicates whether the waiting duration exceeds ten minutes (1 for yes, 0 for no).

**Exc_15_min** Indicates whether the waiting duration exceeds fifteen minutes (1 for yes, 0 for no).

In the simulation root frame, several variables are displayed for easy overview. These variables are calculated at the end of every simulated day based on the table file. These variables and values are not exported as calculation is fairly simple using the exported table file.

**Num_instances** This variable records the number of instances generated and served during this simulation run.

**Num_noshow** This variable records the number of no-show patients during this simulation run.

**Num_patients** This variable records the number of valid patient instances during this simulation run, which is the total number of instances subtracted by the number of no-show patients.

**Num_exc_5_min** This variable gives the number of patients with a waiting time exceeding five minutes.

**Num_exc_10_min** Analogously for ten minutes.

**Num_exc_15_min** Analogously for fifteen minutes.

**Frac_exc_5_min** This variable gives the fraction of patients with a waiting time exceeding five minutes, based on the number of valid patient instances and the number of patients with a waiting time exceeding five minutes.

**Frac_exc_10_min** Analogously for ten minutes.

**Frac_exc_15_min** Analogously for fifteen minutes.

**Avg_wait** This variable gives the average waiting duration for all patients during this simulation run.

**StDev_wait** This variable gives the standard deviation of the waiting duration for all patients during this simulation run.

## E.3 Elements

See Figure 7.1 for an overview of the graphical representation of the simulation model within the software package.

### E.3.1 Entrance

See Figure E.1.

**Buffer: Creator** In this buffer building block with unlimited capacity, created patients are placed. They automatically proceed to the next block, the processor *GetAttributes*.

**SingleProc: GetAttributes** Created patients enter this processor with a zero processing time. At entrance, the processor triggers the method *SetAttributes* for every patient. Patients continue directly to the parallel processor *AtHome*.

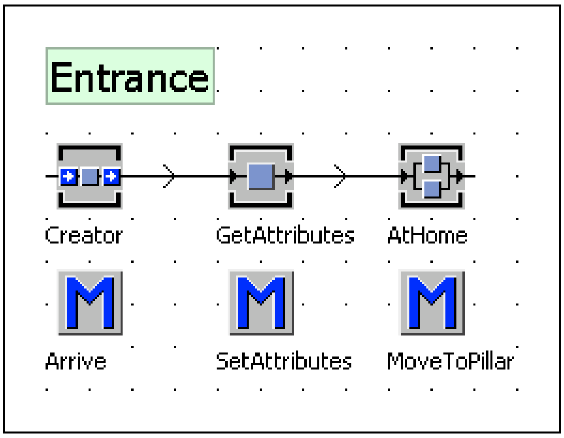


Figure E.1: Entrance frame of the simulation model.

**ParallelProc: AtHome** Patient enter this parallel processor with a service time determined by the arrival time of the patient. The logic is: every patient receives an arrival time at the start of the day, measured in seconds since the start of the day. Consequently, the patient has to wait that amount of seconds before entering the pharmacy. This is implemented by a parallel processor with a service duration of exactly the arrival time in seconds. After the arrival time has elapsed, patients want to exit the parallel processor and are guided by the method *MoveToPillar* to enter the pharmacy.

**Method: Arrive** This method is triggered at the start of the day by the root method *Day-Control*. Depending on the day of the week set by the variable *root.varWeekDay*, a number of patients for every service type is determined based on empirical and theoretical distributions. For every service type, that exact number of patients is then created and the service type is set accordingly for the group. Patients are created in the buffer *Creator*.

**Method: SetAttributes** This method determines and sets attributes for each patient. First, it is determined whether the patient is a no-show or not, based on the probabilities set in the table file *root.NoShow*.

Second, depending on the service type of the patient, an arrival time is determined based on the distributions for arrival times.

Third, the service duration is set for each patient. If the patient is a no-show, the service duration is set to a time period equal to the member of staff waiting at the counter for the patient to show up. In terms of the simulation, the patient is actually serviced for exactly that time, but in terms of reality, the patient did not show up and the member of staff is waiting at the counter for that time.

If the patient is not a no-show, the service duration is determined based on the empirical and theoretical distributions. For service type 4, it is here determined whether the patient is a clean pickup or a robot pickup, based on the probabilities for both varieties.

Fourth, the simulation day and the day of the week are recorded for each patient.

**Method: MoveToPillar** This method sets several attributes and finally moves the patient to the ticket pillar. First, the patient ID is set here based on the root variable *root.varPatientID*. The ID is not set at creation to ensure that the patient ID is increasing with arrival time. Second, the patient is moved to the element *root.TicketPillar.Buffer*. Third, the method increases the patient ID counter *root.varPatientID*.

### E.3.2 Ticket pillar

See Figure E.2.

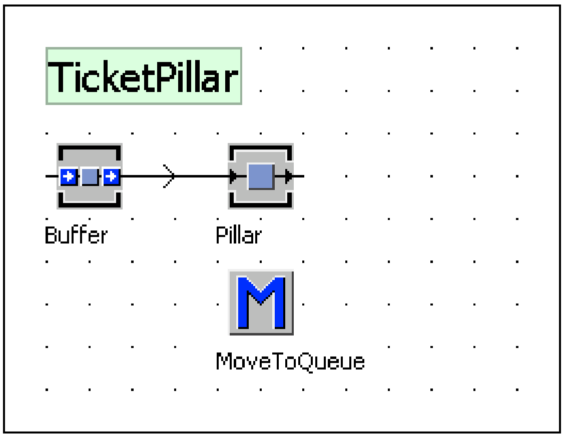


Figure E.2: Ticket pillar frame of the simulation model.

**Buffer: Buffer** This buffer serves as a drop area for patients coming from the entrance. To ensure that patients do not block each other, the capacity is set to infinity.

**ParallelProc: Pillar** This parallel processor is a representation of the ticket pillar in the pharmacy. The service type is already determined so this parallel processor serves mainly to trigger the method *MoveToQueue*.

**Method: MoveToQueue** This method moves each patient to the buffer element of the correct queue, depending on the service type:

**Service type 1** Queue Z.

**Service type 2** Queue R.

**Service type 3** Queue F.

**Service type 4** Queue F.

**Service type 5** Queue R.

**Service type 6** Queue F.

**Service type 7** Queue S.

**Service type 8** Queue F.

### E.3.3 Queues

The four different queues work with identical principles, therefore explanation is limited to one case. See Figure E.3.

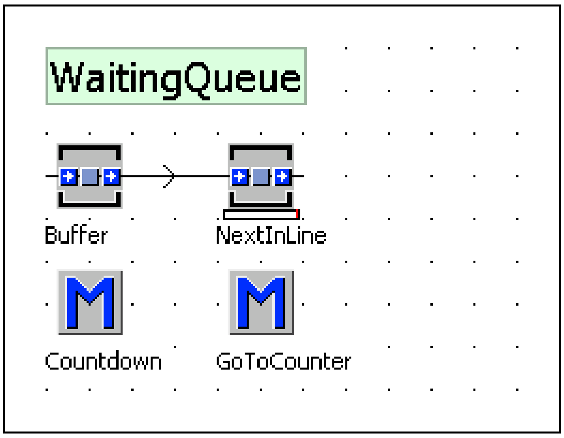


Figure E.3: Queue frame of the simulation model.

**Buffer: Buffer** This buffer elements catches all patients entering the queue with unlimited capacity. It triggers the method *Countdown* at entrance and pushes patients into the next buffer element *NextInLine*.

**Buffer: NextInLine** This buffer element serves to clearly identify the patient waiting next in line in this queue for easy access. At entrance, the buffer triggers the method *GoToCounter*.

**Method: Countdown** First, this method declares that the patient is waiting using an attribute. Second, the method starts a countdown of the activation time for counter 4. After the time has elapsed, it is checked whether the instance still exists, is still in queue, and whether counter 4 is inactive. If all are true, counter 4 is activated and its *NextPatient* method is called to force the counter to pull patients. The countdown continues on for counter 5, counter 6, and counter 1. See Figure 5.3 for the representation of this logic in the conceptual model.

**Method: GoToCounter** This method triggers the counters to pull new patients if possible. By triggering this method at the entrance of a patient into the buffer *NextInLine*, it is announced to counters that a patient is waiting for service. Counters are triggered to pull depending on the priorities for counters, which starts at counter 2, increases to counter 6 and ends with counter 1.

Starting at counter 2, the counter is triggered to pull patients (by using the counter method *NextPatient*). If pulling did not succeed and the patient is still in queue, the next counter is triggered to pull. If no counter is able to pull the patient because the counter is either inactive or busy, the patient continues to wait in the buffer *NextInLine*.

### E.3.4 Counters

The six different counters work with comparable principles, therefore explanation is limited to one case. Note that priorities differ per counter. See Figure E.4.

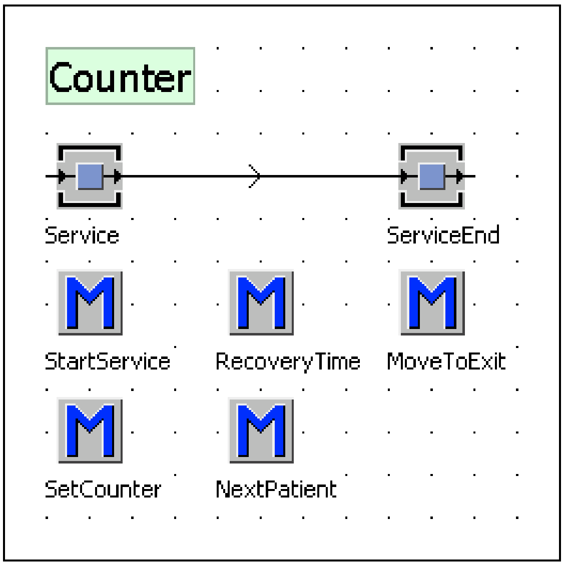


Figure E.4: Counter frame of the simulation model.

**SingleProc: Service** This single processor represents the service at the counter. Service duration is given by the patient's attribute *ServiceDuration*. At entrance, the method *StartService* is triggered. At exit, the method *RecoveryTime* is triggered. Processes patients move to the single processor *ServiceEnd*.

**SingleProc: ServiceEnd** This single processor constitutes a dummy processor, only active to call the method *MoveToExit* when a patient enters this block.

**Method: StartService** This method first sets the patient's attribute *InQueue* to false, to clarify that the patient has entered service and is not waiting in queue anymore. This relates to the methods *Countdown* and *GoToCounter* in the queue frame. Then, this method sets the time the service has started as the patient attribute *ServiceStartTime*, based on the current simulation time. Lastly, the method triggers the method *SetCounter*.

**Method: SetCounter** This method sets the counter at which the patient is serviced. While this could have easily been implemented in the method *StartService*, it was done separately due to inheritance policies for counter frames.

**Method: RecoveryTime** After exiting the single processor *Service*, a patient triggers the method *RecoveryTime*. This method ensures that the single processor *Service* is set as blocked. The procedure then counts down, length depending on the value of the variable *root.CoolDown*, and unblocks the single processor. After unblocking, the method *NextPatient* is called to force the counter to pull patients.

**Method: MoveToExit** This method is called after service has finished. It sets the time of the finished service as the patient attribute *ServiceEndTime* based on the simulation time. Then, it moves the patient to the buffer element in the exit frame.

**Method: NextPatient** This method serves to allow the counter to pull a new patient. Depending on the priority rules, the method differs for the various counters. The method starts at the top priority queue and checks whether there is a patient waiting and whether the counter where this method is called is active. If there is a patient waiting and the counter is not paused, the patient from that queue is moved to the service at the current counter. If there is no patient waiting in that queue, the next queue in the priority is considered.

If no patients at all are present in the pharmacy, the counter is paused, except if it concerns counters 2 or 3, as these are active all day.

### E.3.5 Exit

See Figure E.5.

**Buffer: Buffer** This buffer element with unlimited capacity serves to collect all patients send to the exit without patients blocking one another's path. At exit, it triggers the method *RecordData*.

**Drain: ExitPharmacy** This drain element removes the instance from the system.

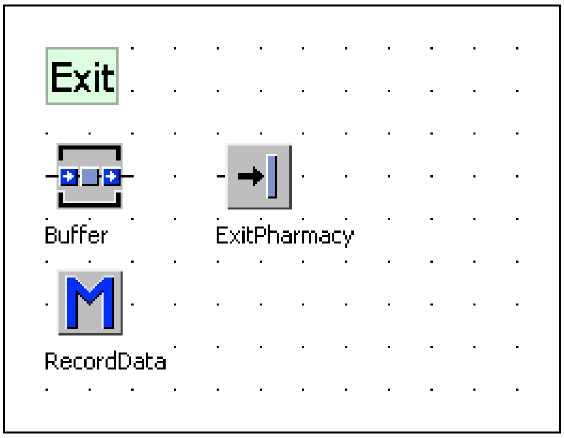


Figure E.5: Exit frame of the simulation model.

**Method: RecordData** This method is triggered to record data the patient has accumulated to the root table file *root.PatientData*. It includes logic to determine whether the indicator for waiting time exceeding five, ten or fifteen minutes should be set or not. After recording data, the patient is moved to the drain element *ExitPharmacy*.

### E.3.6 Event Control

**EventController: EventController** This built-in element ensures that the simulation runs. The element keeps track of the simulation time and event list.

**Method: Init** This method is automatically called by the *EventController* at the start of the simulation. It carries out several tasks. First, all movable units are removed so that any traces of earlier simulation runs are deleted. Second, it resets the variables *varWeekDay* and *varDay*. Third, it sets the variable *varPatientID* to 1 for the next simulation run. Fourth, it clears the table *PatientData*. Fifth, it activates counters 2 and 3 while pausing all other counters. Sixth, it resets the waiting statistics in the graphical output frame to 0.

**Method: Reset** This method is called when resetting the simulation. It directly calls the method *Init*, to ensure that a reset readies the simulation for next deployment.

**Variable: varDay** This variable keeps track of the simulation day. It is governed by the method *DayControl*.

**Variable: varWeekDay** This variable keeps track of the day of the week, ranging from 1 for Monday to 5 for Friday. It is governed by the methods *DayControl* and *WeekControl*.

**Variable: varPatientID** This variable keeps track of the last issued patient ID as used in the frame *Entrance*.

**Variable: randomBase** This variable allows easy randomization of all random-number streams. By changing this variable, all random-number streams are increased by its value and a completely different simulation run is possible.

### E.3.7 Mechanics

**Generator: DayGen** This generator triggers the method *DayControl* every 24 hours.

**Generator: WeekGen** This generator triggers the method *WeekControl* every 5 days.

**Method: DayControl** This method is triggered every day at the start of the day and first increases the variable *varDay* by 1 for the current simulation day and the variable *varWeekDay* by 1 for the current simulation day. Then, to ensure that all patients from the previous day are gone from the system, it removes all movable units. Then, to trigger creation of new patient for the new day, the method *root.Entrance.Arrive* is triggered. Finally, the daily waiting statistics in the graphical output frame are recalculated.

**Method: WeekControl** This method simply resets the day of the week to 0 to start the week anew.

**Variable: NoShowTime** This variable determines the time spent on no-show patients.

**Variable: ActivationTimeCtX** This variable contains the countdown time necessary for a counter X to be activated, X here being 4, 5, 6 and 1.

**Variable: CoolDown** This variable contains the cool-down period for each counter. It is placed here for easy access and manipulation.

**Variable: AIF** This variable represents the PSE as described in the main body of this thesis. AIF was used as an earlier term and has been kept in the simulation for continuity reasons.

### E.3.8 Patient

The patient as the mobile unit in this simulation has several attributes related to simulation mechanics and a realistic depiction of actual patients.

**ArrivalTime** The arrival time of the patient as determined by the entrance method *SetAttributes* based on theoretical or empirical distributions.

**CleanPick** Whether the patient is a clean pickup (1) or a robot pickup (0), set by the entrance method *SetAttributes*.

**Counter** The counter at which the patient is serviced, set by the counter method *SetCounter*.

**DayNum** The simulation day when the patient visits the pharmacy, set by the entrance method *SetAttributes*.

**InQueue** Indicates whether the patient is in queue or not. Set by the queue method *Countdown* and the service method *StartService*.

**NoShow** Indicates whether the patient is a no-show (1) or not (0). Set by the entrance method *SetAttributes*.

**PatientID** The patient ID of the patient within the simulation. Set by the entrance method *MoveToPillar*.

**ServiceDuration** The service duration of the patient as determined by the entrance method *SetAttributes* based on theoretical or empirical distributions.

**ServiceEndTime** The time the service has ended. Set by the service method *MoveToExit*.

**ServiceStartTime** The time the service has started. Set by the service method *StartService*.

**Type** The service type of the patient, set by the entrance method *Arrive*.

**WeekDay** The day of the week on which the service took place, set by the entrance method *SetAttributes*.

# Appendix F

# Results of simulation analysis

## F.1 Influence of no-show probability

| **No-show probability** | **Waiting time (s)** | **Fraction > 5 min** | **Fraction > 10 min** |
|---|---|---|---|
| 0.00 | 250.7 (190.5) | 0.32 (0.13) | 0.09 (0.12) |
| 0.02 | 243.9 (173.6) | 0.32 (0.13) | 0.08 (0.11) |
| 0.04 | 238.4 (165.1) | 0.31 (0.13) | 0.08 (0.11) |
| 0.06 | 233.3 (160.1) | 0.31 (0.13) | 0.08 (0.11) |
| 0.08 | 228.3 (159.1) | 0.30 (0.13) | 0.07 (0.10) |
| 1.00 | 223.6 (150.4) | 0.30 (0.12) | 0.07 (0.10) |

Table F.1: Results of experimentation for the influence of the no-show probability. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

## F.2 Influence of inefficiencies

| **Fraction clean pickups** | **Fraction type 4** | **Average waiting time** |
|---|---|---|
| 0.5 | 0.1 | 228.0 |
| 0.5 | 0.2 | 223.3 |
| 0.5 | 0.3 | 214.9 |
| 0.5 | 0.4 | 211.7 |
| 0.5 | 0.5 | 206.9 |
| 0.6 | 0.1 | 226.7 |
| 0.6 | 0.2 | 218.9 |
| 0.6 | 0.3 | 209.6 |
| 0.6 | 0.4 | 204.4 |
| 0.6 | 0.5 | 198.6 |
| 0.7 | 0.1 | 224.3 |
| 0.7 | 0.2 | 215.6 |
| 0.7 | 0.3 | 204.9 |
| 0.7 | 0.4 | 197.2 |
| 0.7 | 0.5 | 191.4 |
| 0.8 | 0.1 | 222.3 |
| 0.8 | 0.2 | 211.8 |
| 0.8 | 0.3 | 199.8 |
| 0.8 | 0.4 | 190.9 |
| 0.8 | 0.5 | 184.0 |
| 0.9 | 0.1 | 220.5 |
| 0.9 | 0.2 | 208.5 |
| 0.9 | 0.3 | 195.2 |
| 0.9 | 0.4 | 185.4 |
| 0.9 | 0.5 | 176.2 |
| 1.0 | 0.1 | 218.6 |
| 1.0 | 0.2 | 204.6 |
| 1.0 | 0.3 | 190.8 |
| 1.0 | 0.4 | 179.7 |
| 1.0 | 0.5 | 170.4 |

Table F.2: Results of experimentation for the influence of both influences. Waiting time in seconds is given as the average over all runs.

## F.3 Evaluation of proposed interventions

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 228.1 (157.1) | 0.30 (0.12) | 0.07 (0.10) |
| 2 | 1.1 | 256.8 (199.8) | 0.32 (0.13) | 0.09 (0.12) |
| 3 | 1.2 | 292.1 (250.3) | 0.35 (0.14) | 0.11 (0.14) |
| 4 | 1.3 | 335.2 (313.5) | 0.38 (0.15) | 0.14 (0.15) |
| 5 | 1.4 | 387.0 (387.0) | 0.40 (0.16) | 0.16 (0.17) |
| 6 | 1.5 | 448.4 (471.2) | 0.43 (0.17) | 0.19 (0.19) |

Table F.3: Results of experimentation for the current situation as implemented in the simulation model. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 219.0 (145.4) | 0.29 (0.12) | 0.07 (0.10) |
| 2 | 1.1 | 246.3 (184.9) | 0.32 (0.13) | 0.09 (0.11) |
| 3 | 1.2 | 279.6 (233.4) | 0.34 (0.14) | 0.11 (0.13) |
| 4 | 1.3 | 319.8 (292.0) | 0.37 (0.15) | 0.13 (0.15) |
| 5 | 1.4 | 368.3 (363.7) | 0.39 (0.16) | 0.15 (0.17) |
| 6 | 1.5 | 426.6 (443.4) | 0.42 (0.17) | 0.18 (0.18) |

Table F.4: Results of experimentation for the upper bound intervention removing the first inefficiency. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 202.5 (123.0) | 0.26 (0.10) | 0.06 (0.07) |
| 2 | 1.1 | 215.6 (139.4) | 0.28 (0.11) | 0.06 (0.08) |
| 3 | 1.2 | 230.7 (158.9) | 0.29 (0.11) | 0.07 (0.09) |
| 4 | 1.3 | 247.5 (181.4) | 0.30 (0.12) | 0.08 (0.10) |
| 5 | 1.4 | 266.4 (205.7) | 0.32 (0.12) | 0.09 (0.11) |
| 6 | 1.5 | 286.3 (232.0) | 0.33 (0.13) | 0.10 (0.11) |

Table F.5: Results of experimentation for the upper bound intervention removing the second inefficiency. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 172.4 (86.8) | 0.23 (0.09) | 0.04 (0.05) |
| 2 | 1.1 | 182.1 (96.7) | 0.24 (0.09) | 0.04 (0.06) |
| 3 | 1.2 | 193.4 (110.4) | 0.25 (0.10) | 0.05 (0.07) |
| 4 | 1.3 | 205.6 (124.3) | 0.27 (0.10) | 0.06 (0.07) |
| 5 | 1.4 | 219.6 (141.3) | 0.28 (0.11) | 0.07 (0.08) |
| 6 | 1.5 | 235.4 (162.5) | 0.29 (0.11) | 0.08 (0.09) |

Table F.6: Results of experimentation for the upper bound intervention removing both the first and second inefficiency. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 201.2 (133.4) | 0.27 (0.12) | 0.06 (0.09) |
| 2 | 1.1 | 226.7 (171.3) | 0.30 (0.13) | 0.08 (0.11) |
| 3 | 1.2 | 257.0 (216.0) | 0.32 (0.14) | 0.10 (0.12) |
| 4 | 1.3 | 293.5 (269.5) | 0.34 (0.15) | 0.12 (0.14) |
| 5 | 1.4 | 337.6 (334.9) | 0.37 (0.16) | 0.14 (0.16) |
| 6 | 1.5 | 390.4 (410.0) | 0.39 (0.17) | 0.17 (0.18) |

Table F.7: Results of experimentation for the locker box intervention. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 207.9 (121.1) | 0.25 (0.09) | 0.05 (0.07) |
| 2 | 1.1 | 220.6 (136.2) | 0.26 (0.10) | 0.06 (0.07) |
| 3 | 1.2 | 235.5 (155.4) | 0.27 (0.10) | 0.07 (0.08) |
| 4 | 1.3 | 251.4 (177.4) | 0.29 (0.10) | 0.08 (0.09) |
| 5 | 1.4 | 269.3 (201.2) | 0.30 (0.11) | 0.09 (0.09) |
| 6 | 1.5 | 288.8 (228.0) | 0.31 (0.11) | 0.10 (0.10) |

Table F.8: Results of experimentation for the electronic identification card intervention. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 217.7 (100.7) | 0.29 (0.10) | 0.06 (0.06) |
| 2 | 1.1 | 229.0 (113.3) | 0.31 (0.10) | 0.07 (0.07) |
| 3 | 1.2 | 242.5 (129.8) | 0.32 (0.10) | 0.08 (0.08) |
| 4 | 1.3 | 256.3 (145.9) | 0.33 (0.11) | 0.09 (0.08) |
| 5 | 1.4 | 272.9 (167.5) | 0.34 (0.11) | 0.10 (0.09) |
| 6 | 1.5 | 290.3 (190.0) | 0.36 (0.12) | 0.11 (0.10) |

Table F.9: Results of experimentation for the counter order intervention. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 1808.4 (965.2) | 0.75 (0.10) | 0.63 (0.12) |

Table F.10: Results of experimentation for the timed staffing intervention. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses. Only experiment 1 is carried out as the performance is severely lacking.

| Experiment | PSE | Waiting time (s) | Fraction > 5 min | Fraction > 10 min |
|---|---|---|---|---|
| 1 | 1.0 | 73.6 (25.2) | 0.08 (0.05) | 0.00 (0.01) |
| 2 | 1.1 | 77.5 (27.4) | 0.09 (0.05) | 0.00 (0.02) |
| 3 | 1.2 | 81.6 (30.3) | 0.10 (0.05) | 0.01 (0.02) |
| 4 | 1.3 | 85.8 (33.6) | 0.11 (0.05) | 0.01 (0.02) |
| 5 | 1.4 | 90.2 (37.3) | 0.11 (0.06) | 0.01 (0.02) |
| 6 | 1.5 | 94.9 (41.5) | 0.12 (0.06) | 0.01 (0.03) |
| 7 | 1.6 | 99.9 (46.9) | 0.13 (0.06) | 0.01 (0.03) |
| 8 | 1.7 | 105.2 (53.0) | 0.14 (0.06) | 0.02 (0.04) |
| 9 | 1.8 | 111.1 (59.7) | 0.14 (0.07) | 0.02 (0.04) |
| 10 | 1.9 | 117.6 (67.7) | 0.15 (0.07) | 0.03 (0.04) |
| 11 | 2.0 | 124.9 (77.0) | 0.16 (0.07) | 0.03 (0.05) |

Table F.11: Results of experimentation for combination of locker box intervention and electronic identification card intervention. Waiting time in seconds, fraction of instances waiting longer than 5 minutes, and fraction of instances waiting longer than 10 minutes are given as the average over all runs with standard deviation in parentheses. Note that more experiments with higher values of PSE were conducted for this intervention.