organizing acute care

Logistic optimization of an integrated emergency post using discrete event simulation

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ORGANIZING ACUTE CARE

LOGISTIC OPTIMIZATION OF AN INTEGRATED EMERGENCY POST USING DISCRETE EVENT SIMULATION

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MANAGEMENT SUMMARY

In April 2010, the emergency department (ED) of ZGT Almelo and the after hours general practitioners post (CHPA) merged into a single integrated emergency post. To benefit most from this collaboration, a research project started in April 2011. This project is called "Optimal logistics and patient preferences in acute care: the general practitioners post and emergency post in one integrated emergency post". The goal of this project is to find an optimal design of an integrated emergency post where the right patient arrives at the right care provider without unnecessary delays and with an optimal allocation of means, while accounting for patient preferences (Doggen, Hans, Snel, Velde, & Verheij, 2010). As part of this project, a computer simulation model is designed (Visser, 2011).

This thesis is part of the research project, and details the use of the simulation model to evaluate possible organizational interventions. The goal of this study is *to assess possible organizational interventions for the integrated emergency post and to optimize over these interventions using simulation.* To reach this goal we first further modify, verify and validate the simulation model, such that it correctly reflects the conceptual model, as well reality. Following this, possible organizational interventions are evaluated using experimental designs in an iterative approach, such that the effects of interventions, a well as their interaction on each other are analyzed.

From the intervention analysis, we conclude that several changes have a positive effect on the patient length of stay. These are the treatment of ED patients in GP post rooms, the direct ordering of pre-diagnostic tests for patients that likely need them, direct bed admission requests, using a single triage system, and letting physician assistants (PA) work at both ED and GP post. Furthermore, the pooling of resources such as sharing of rooms and simultaneous employment of staff allows for a reduced length of stay, while sharing costs. The greatest reduction on length of stay is seen when staff is added that treats either low urgency GP post, surgical specialty ED patients, or both, reflected by the desired ZGT roster, or addition of a PA during the weekends, or IEP starting hours.

Overall, we conclude that the interventions show a significant improvement over the current situation, and that combining them results in the greatest length of stay reductions, for both ED as well as GP post patients, by increasing flexibility through the pooling of resources, while maintaining similar workloads.

SAMENVATTING

In April 2010 is een samenwerkingsverband gestart tussen de spoedeisende hulp van ZGT Almelo en de Centrale Huisartsenpost Almelo. Om zoveel mogelijk uit deze samenwerking te halen is in april 2011 een onderzoeksproject gestart, genaamd: "optimale logistiek en patiënt voorkeuren in de acute zorg: de huisartsenpost en eerste hulp in een geïntegreerde spoedpost". Het doel van dit project is om een optimale inrichting van de geïntegreerde spoedpost te vinden, waarbij de juiste patiënt bij de juiste zorgaanbieder terecht komt, zonder onnodige vertragingen, en met optimale inzet van middelen, rekening houdend met de voorkeuren van de patiënt (Doggen et al., 2010). Als onderdeel van dit project is een computer simulatiemodel ontwikkeld (Visser, 2011).

Dit verslag is een onderdeel van het onderzoeksproject en beschrijft het gebruik van het simulatiemodel om mogelijke organisatie interventies te evalueren. Het doel van dit onderzoek is *het beoordelen van mogelijke organisatie interventies voor de geïntegreerde spoedpost, en te optimaliseren over deze interventies, gebruikmakend van simulatie.* Om dit doel te bereiken hebben we eerst het simulatiemodel verder aangepast, geverifieerd en gevalideerd, zodat correct het conceptuele model en de realiteit wordt nagebootst. Hierop zijn mogelijke organisatie interventies geëvalueerd, met behulp van experimental designs in een iteratieve aanpak, zodat het effect van interventies, alsmede de interactie tussen interventies geanalyseerd wordt.

Uit de interventie analyse concluderen we dat verschillende veranderingen een positief effect hebben op de verblijfsduur van patienten. Dit zijn het behandelen van spoedeisendehulp patienten op huisartsenpost kamers, het direct aanvragen van diagnostiek en bed opname van patienten die dit waarschijnlijk nodig hebben, het gebruik van een enkel triage systeem, en het inzetten van de physician assistant (PA) op zowel huisartsenpost als spoedeisendehulp. Het delen van staf en middelen heeft een verlagend effect op de verblijfsduur, terwijl kosten gedeeld kunnen worden. Het grootste effect op de verblijfsduur is het toevoegen van staf die chirurgie patienten op de spoedeisendehulp, laag urgente huisartsenpost patienten, of beide, kan behandelen. Dit is terug te zien in het effect van het toekomstige ZGT rooster, alsmede het toevoegen van een physician assistant tijdens weekenden, of weekdagen als de huisartsenpost opstart.

Onze conclusie is dat de interventies een significante verbetering laten zien over de huidige situatie, en dat het combineren van de interventies de grootste verblijfsduurreductie laat zien, voor zowel huisartsenpost als spoedeisendehulp patienten.

TABLE OF CONTENTS

List of abbreviations

The list below gives the translation and abbreviations of the most commonly used terms in this study.

- ED nurse = Spoedeisende hulp verpleegkundige
- ED specialist = Spoedeisende hulp specialist
- Emergency Department (ED) = Spoedeisende hulp
- General Practitioner (GP) = Huisarts
- General Practitioners post (GP post) = Huisartsenpost
- GP assistant = Doktersassistente
- Integrated Emergency Post (IEP) = Spoedpost
- Medical resident = Arts assistant interne geneeskunde
- Nurse Practitioner (NP)
- Physician Assistant (PA)
- Surgical resident = Arts assistant chirurgie

PREFACE

In February 2012, I started my master thesis assignment, and now, eight months later, this assignment marks the end of my six-plus years of study. During my bachelor assignment I was introduced to the health care environment, and this made me choose the health care track for my master. When it was time to start a master's internship, this assignment jumped out, as it combined the two aspects I really liked as I followed courses, computer simulation and health care. While I was hesitant at first, as this assignment was part of an ongoing project, I am happy with how it turned out.

Working at this project for the last eight months, I had a great time, and for that I would like to thank everyone at the IEP, as well as my supervisors Manon, Martijn and Ingrid for all the feedback and support. In addition I would like to thank the other project members, Janke, Arlette, Carine and Erwin, for giving feedback during the monthly meetings.

Finally, I want to thank Hilde and my family for supporting me during these last eight months, I had my ups and downs during all of this, however you helped me get through.

I hope you will enjoy reading this report.

Nardo Borgman

October, 2012

1 INTRODUCTION

In April 2010, the emergency post of ZGT Almelo and the after hours general practitioners post (CHPA) merged into a single integrated emergency post. Through merger of these two care providers, an increased efficiency is achieved as patients that would originally go to the emergency post (a secondary care provider) are now seen at the general practitioners post (GP post), and only if necessary referred to the emergency post. Question remains as to how this delivery of acute care may be better organized in terms of resource allocation. In this chapter, an introduction is given detailing the involved organizations and the research project this study is part of, followed by the research objective, research questions and report structure.

1.1 ZGT

Ziekenhuisgroep Twente (ZGT) consists of two hospitals, one in Hengelo and one in Almelo. ZGT is a general hospital with over 3500 employees and a service area of 300.000 inhabitants. In 1998, ZGT was formed after a merger of Twenteborg Ziekenhuis in Almelo and Streekziekenhuis Midden-Twente in Hengelo. Table 1 details some key figures of Ziekenhuisgroep Twente (ZGT, 2010).

Key Figures	
Service area	300.000 inhabitants
Turnover	255.661.584 euros
Bed capacity	1085
Admissions	38.209
Outpatient visits	599.038
employees	2520.15 FTE
Medical specialists	189.47 FTE

Table 1: Key figures ZGT 2010

1.2 CHPA

The Centrale Huisartsenpost Almelo (CHPA) delivers after hours primary care. This general practitioners post (GP Post) was created to deliver acute care to patients that cannot wait for an appointment during regular office hours. The CHPA covers over 203.000 inhabitants in Almelo and surrounding regions. 85 general practitioners work at the CHPA and it employs 35 GP assistants and 15 drivers. The CHPA was built next to the emergency post of

ZGT Almelo to create the integrated emergency post. Table 2 details some key figures of CHP Almelo (CHPAlmelo, 2010).

Key Figures	
Service area	203.000
Turnover	3.285.449 euros
consultations	58.283

Table 2: Key figures CHP Almelo 2010

1.3 INTEGRATED EMERGENCY POST

When people are confronted with an acute care demand (outside regular office hours) they are often uncertain which health care provider to contact. While officially emergency departments are secondary care providers, meaning patients should only get there via referral, many do not treat it as such. Patients assess their own acute care demand and decide to visit the GP post or emergency department. These self referring patients, or walk-ins, that arrive at the emergency department could often have been seen and treated by a general practitioner (GP) at the GP post. Given the cost of emergency care and the problem of overcrowding in emergency departments caused by self-referrals (Kool, Homberg, & Kamphuis, 2008) the integrated emergency post (IEP) is created with the purpose to provide the appropriate treatment for patients with an acute care demand and alleviating emergency department overcrowding by shifting back primary care problems from the secondary care provider.

In April 2010, the emergency department of ZGT Almelo merged with the CHPA. Patients that now arrive at the IEP as self-referrals, and would previously go to the ED, are seen by a GP assistant and their care demand is assessed after which they are referred to the emergency department or get an appointment with a GP at the GP post. In effect this lets health care providers determine where patients should go to in order to receive care and eliminates the possibility of patients self-referring to the emergency department.

1.4 ZONMW

This study is part of the research project "Optimal logistics and patient preferences in acute care: the general practitioners post and emergency post in one integrated emergency post" funded by ZonMw. The goal of this ZonMw project is to find an optimal design of an integrated emergency post where the right patient arrives at the right care provider without unnecessary delays and with an optimal allocation of means, while accounting for patient preferences (Doggen et al., 2010).

The goal of this research pertains the overlapping research question of the ZonMw project:

How can the efficiency of processes in the integrated emergency post be optimized? To which organizational interventions does this lead, and how may these be supported, implemented and evaluated?

To this end we use computer simulation to predict and evaluate outcomes of possible organizational interventions. A simulation model has been designed (Visser, 2011), and will be used to evaluate the interventions.

1.5 RESEARCH OBJECTIVE & QUESTIONS

The objective of this study is:

To assess possible organizational interventions for the integrated emergency post and to optimize over these interventions using simulation.

To answer the research question formulated in the ZonMw project, we follow the steps in a simulation study, as formulated by Law (2007). These steps describe the process from formulating problems to the documentation and implementation of results. Appendix 1 gives a complete overview of all steps. Prior to this study, a simulation model has been developed (Visser, 2011). This model aims to give a valid representation of the current integrated emergency post. This study builds upon this by further improvement of the model and by incorporating various interventions and experimental designs to assess, analyse, and optimise possible organisational interventions. In a sense, the steps in a simulation study have been partly completed, from problem formulation to model construction and preliminary validation. Step seven and onwards, from the design of experiments to the analysis of interventions, are the focus of this study. This study starts with the steps by Law (2007) and expands upon that by not only using the simulation model as an evaluation tool, but also using experimental designs and a sequential approach to find the optimal solution. Figure 1 details the research steps in this study, the grey blocs represent the steps seven through ten, as described by Law (2007).

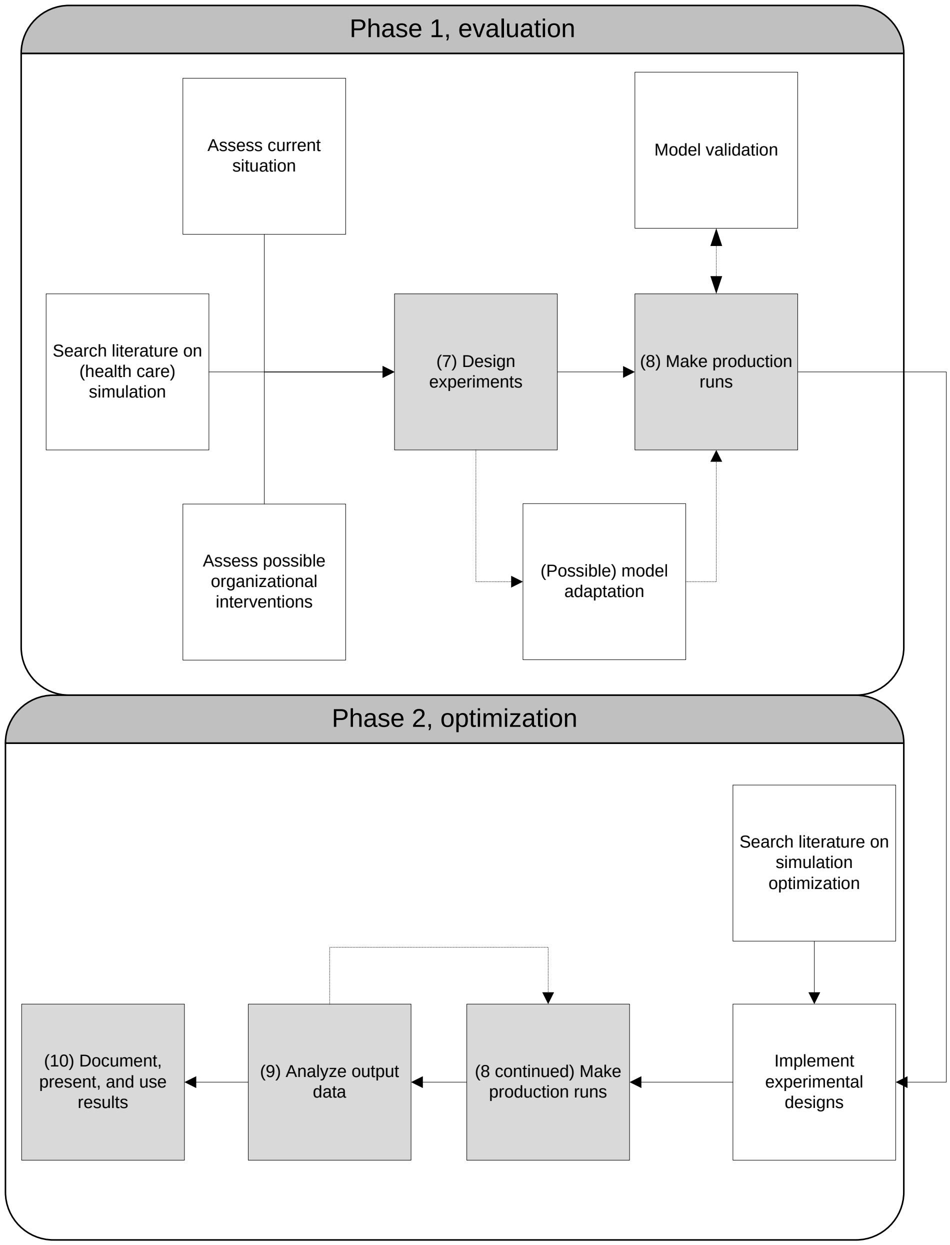


Figure 1: Research steps

In order to better organise resources used, organizational interventions are designed. An example of such a change is the number of nurses working at a given point in time. These changes may be expressed by a set of decision variables together with their values. This design step raises two important questions, what interventions are feasible and relevant in practice and how can we optimize over these interventions. While it may be possible to create interventions that score very well on a given set of performance indicators, they may be completely irrelevant and unobtainable in practice. In designing the experiments, it may be beneficial not only to use literature and organisational analysis but also let stakeholders that work with and in the integrated emergency department generate possible interventions.

As the current simulation model may be unable to simulate all decision variables created in the design step, possible adaptations to the model are done, as well as validation of the adapted model. Following this phase, we evaluate areas of interest and use simulation optimization literature to implement optimization techniques that help optimize the defined decision variables.

In order to complete the steps in the research model we formulate several research questions.

The first research question enables the design of interventions and possible simulation optimization techniques. By reviewing the literature, relevant information may be gathered and implemented.

1. *What is known about simulation and simulation optimization in health care logistics?*
   a. What can we learn from literature on simulation in health care?
   b. What can we learn from literature on simulation of emergency departments?
   c. What can we learn from literature on simulation optimization in general?
   d. What can we learn from literature on simulation optimization in health care?
   e. What can we learn from literature on simulation optimization in emergency departments?

Before being able to list potential interventions, we first look at the processes and resources of the integrated emergency post. By looking at the integrated emergency post's processes and resources, it is possible to deduce potential interventions.

2. *How are IEP's characterized?*
   a. What does the IEP at ZGT look like?
   b. Which processes can be identified in the IEP?
   c. What resources are used in the IEP?
   d. What kind of employees work at the IEP?

In comparing interventions, the establishment of important performance indicators (for stakeholders) has already been conducted within the ZonMw project (Fransman, 2011;

Reinders, 2012). Using performance indicators, established both by employees and patients, organizational interventions are compared.

3. *How may organizational interventions be compared?*
    a. Who are the stakeholders?
    b. What are the key performance indicators?

Ideally, all organizational interventions would be compared, however many possible interventions will be infeasible because of restrictions that prohibit their implementation. By looking at the restrictions that are in place, together with literature on simulation and input from the organizational stakeholders, an inventory of realistically possible interventions can be constructed.

4. *What organizational interventions are possible?*
    a. What feasible interventions are considered in the literature?
    b. What are the organizational restrictions?
    c. What feasible interventions are seen by stakeholders?

Building off the evaluated organizational interventions, promising interventions, or decision variables, may be further optimized using simulation optimization. Using the key performance indicators to evaluate interventions, some may prove a more suitable candidate for optimization.

5. *What are the most promising interventions?*
    a. Which interventions have the greatest impact on the key performance indicators?
    b. What are the effects of the individual interventions?
    c. Are there interactions between interventions?
    d. What interventions are most promising?
6. *What simulation optimization techniques are useable to optimize over the interventions?*
    a. What feasible optimization techniques are available?
    b. Which optimization techniques are suitable to our problem?
7. Which interventions may be used at the integrated emergency post?

1.6 DATA GATHERING

The data gathered and used in this study will be both qualitative and quantitative. Stakeholder interviews and/or surveys will generate qualitative information to be used to assess and compare organizational interventions. Quantitative data will be gathered as input for the simulation model as well as for use of validation. Additionally, a literature study is conducted to find relevant information for this study.

1.7 RESEARCH LIMITATIONS

Within the research objective, this study confines itself to evaluation and optimization of the emergency- and general practitioners post only. Patients that arrive at the integrated emergency post may be admitted to the hospital after treatment, however these processes fall outside the boundaries of this study. While it is plausible that changes in the follow-up process may influence the IEP (e.g., quicker hospital admittance after treatment), these interventions require changes outside the integrated emergency post and as such are omitted.

1.8 REPORT STRUCTURE

Chapter 2 contains the theoretical framework used in conducting this study. Chapter 3 gives a description of the integrated emergency post's processes and resources. Chapter 4 describes the data analysis conducted to specify the simulation model input. In Chapter 5 we describe the simulation model, as well as the verification and validation thereof. Chapter 6 contains the organizational interventions that are investigated based on identified processes and resources from Chapter 3. Following this, the results of simulation and data analysis are given and evaluated in Chapter 7 and 8. Chapter 9 contains the discussion and conclusions from this study. Finally, in Chapter 10, we give a discussion on future work and possible improvements.

2 THEORETICAL FRAMEWORK

In this chapter, an overview of literature on simulation (optimization) as well as its use in health care is given. First, we briefly touch upon collaboration initiatives of GP posts and emergency departments followed by the use of simulation and simulation optimization in general and in health care. We conclude this chapter with potential simulation optimization techniques relevant to this study.

2.1 OUT OF OFFICE HOURS CARE

The reorganization of out of office hours care in the Netherlands, with general practitioners (GPs) collaborating and joining larger organizations to provide after hours care, has been preceded by similar reorganizations of care provision in the UK and Denmark. Prior to these reorganizations, GPs worked with small scale rotations to deliver care outside office hours. Now, this provision of primary care is rolled into large GP cooperatives (van Uden, Giesen, Metsemakers, & Grol, 2006).

These primary care providing GP cooperatives, or GP posts, perform telephonic consultations and triage, as well as physical consultations and visitations. Patients themselves however remain the decider of where to go to with their acute care demand. As such, patients are also able to visit an ED instead of a GP post. An often noted problem facing EDs is overcrowding through self-referring patients that could have been treated at a GP post. The gatekeeper function of a GP post ideally ensures that patients receive the appropriate care for their demand (Dale, Green, Reid, & Glucksman, 1995; Kulu-Glasgow, Delnoij, & de Bakker, 1998; van Uden et al., 2006).

While the Dutch health care system in effect is a gatekeeper system, i.e., all specialized care is through referral, acute care providers do not reject patients. This is where Integrated Emergency Posts may serve to assure patients end up at a proper care provider.

2.2 IEP CHARACTERISTICS

The IEP aims to provide acute complex care through the ED and less complex acute care through the GP post part of the IEP. The level to which an ED and GP post are integrated may differ. A division based on degree of collaboration focusing on ED and GP location and triage processes has been made (Vermue, Giesen, & Huiberts, 2007). In this characterization there are four models of collaboration ranging from no collaboration to an integration of a front-desk and triage processes. These models are:

- No collaboration
- Collaboration, all triage of patients through emergency department
- Collaboration, GP post as (triage) gatekeeper
- Shared front office and triage

This view of integrated emergency posts corresponds with the initiative that GP posts serve as a gatekeeper to refer patients to secondary (acute) care providers if needed. The degree of collaboration is defined by the degree to which patients are directed to the appropriate care provider. Additionally, Coenen (2009) argues, that collaboration drawbacks are based on organizational differences and financial constructions and that integration faces barriers based upon human aspects.

In the most integrated form, the collaboration remains confined to triage activities. This means that after triage a patient is sent to the GP post or ED depending on urgency. From an organizational perspective this still leaves two separate organizational entities that share a front office, and as such, integrated little. A more interesting definition of collaboration, from an organizational perspective, may be the degree to which resources, expertise, and organizational strengths are shared. If staff, resources, and information would be freely available, both organizations could be considered as one from an outside view.

2.3 SIMULATION

Simulation is the creation of a model that represents a system, and using this model to better understand the system it represents (Law, 2007). In this study, simulation is used to better understand the integrated emergency post and to test different organizational interventions. Given the use of simulation to better understand systems, it is used as an evaluation tool for answering "what-if?" questions and more importantly to answer these questions prospectively, before any actual implementation and without disturbing the actual system.

While this study makes use of the constructed model which is currently in its validation stage (Visser, 2011), the adaptations needed to model organizational interventions need to be validated as well. As such the verification and validation of these modifications is an important step in this study.

Following the objective of gaining knowledge about a system, simulation enables the comparison of different interventions and thus the use of simulation as a supportive tool in decision making. This has led to the application of simulation in many different areas, one of which is health care.

2.4 SIMULATION IN HEALTH CARE

A substantive number of studies have been done concerning the simulation of health care processes. Several comprehensive literature studies on the use of simulation in health care have been conducted, such as the those of Jun et al. (1999), Jacobsen et al. (2006), Brailsford et al. (2009) and Mielczarek (2012). Some of the articles give structured methodologies on using simulation in health care such as Mahachek (1992) and Eldabi et al. (2002). Interesting is that while the use of simulation goes back decades, it's use and acceptance in health care is minor compared to commercial and governmental applications seen by studies detailing the problems that arise when using simulation, such as Lowery et al. (1994), Lowery (1996), Young (2009) and Jahangirian et al. (2010). Examples of these problems are historical disincentives to control costs, the technical nature of simulation, undefined stakeholders and hard to define measures in cost-effectiveness studies such as quality-adjusted life years (QALY's). Performance indicators often used in simulation such as throughput times, perceivably reduce patients to numbers, which may cause aversion with health care providers. This dehumanizing effect of patients, together with often used time measurement periods may create additional friction in a health care environment, as patients and their care needs are placed first.

Simulation studies may be categorized over several domains such as simulation type used (discrete, continuous, hybrid, monte carlo), study objective area (resource allocation, patient flows) and application area (epidemiology, health and care systems operation, health and care systems design, medical decision making, extreme event planning). Given that we are interested in the use of simulation in (integrated) emergency departments, we focus on studies concerning acute care delivery.

Sinreich and Marmor (2005) give a methodology to develop a simulation tool for emergency departments. The objectives of their research is to a) create a flexible and general model able to model different ED settings, b) create a simple and intuitive to use tool, and c) to include reasonable default values for many system parameters (Sinreich & Marmor, 2005). Additionally, Jurishica (2005) gives a discussion of proven practices used in developing emergency department simulation models and formulates key elements that are important in a simulation study. Similarly, Connelly and Bair (2004) explore the use of discrete event simulation in emergency department operations.

One of the important motivators for change in emergency departments is overcrowding. Paul, Reddy, and Deflitch (2010) conduct a literature review on the use of simulation to investigate overcrowding of emergency departments and analyze the studies with respect to goals, techniques used, data sources and collection methods, patient classification and flows and study findings. Most of the articles found, focus on the (reduction of) waiting times for patients (Paul et al., 2010). This coincides with waiting times being one of the key performance indicators for acute care providers. The scenarios they evaluate are divided over resource related, process related and environmental related scenario testing (Paul et al., 2010).

With regards to resource allocation, several studies focus on the allocation of staff in the emergency department, both varying alternative staff schedules and numbers of staff available. For example, Rossetti, Trzcinski, and Syverud (1999) evaluate alternative staffing schedules and find that the total average stay of patients can be reduced by over 14 minutes with an additional physician assignment (Rossetti et al., 1999). Other examples are the studies of Blasak, Starks, Armel, and Hayduk (2003) and Samaha, Armel, and Starks (2003) who evaluate staffing levels to see if increases influence length of stay. Alternatively Komashie and Mousavi (2005) evaluate the change in bed availability in an emergency department, and Takakuwa and Shiozaki (2004) study a process planning procedure to reduce patient waiting times.

Another resource allocation method is the use of fast-track pathways to reduce patient waiting times. Here, a minimal number of resources and staff is reserved to treat specific disease types or urgencies. Examples of these studies are the works of Garcia, Centeno, Rivera, and DeCario (1995), Kirtland, Lockwood, Poisker, Stamp, and Wolfe (1995), Samaha et al. (2003) and Maulla, Smarta, Harrisb, and Karasnehc (2009). Other process changes simulated are allowing the (triage) nurses to order tests and/or conduct treatment without the consultation of a physician (Kirtland et al., 1995) or nursing policy changes where, for example, nurses are no longer assigned to specific rooms in the emergency department (Zeng, Ma, Hu, Li, & Bryant, 2011).

While emergency departments are not closed systems, modeling not only emergency departments but also the other departments it interacts with, greatly increases the complexity of such a simulation study. As such, waiting times for, for example, lab results or patient intakes, are based on historical data. Storrow et al. (2008) study the effects of lab turnaround times on patient throughput times. Gunal and Pidd (2006) look at the X-ray times for patients. Bair, Song, Chen, and Morris (2010) study the boarder-released ratio, the number of patients that have to be admitted into the hospital after their ED visit. More studies regard patient demand and the effects these have on an emergency department (Baesler, Jahnsen, & DaCosta, 2003; Lane, Monefeldt, & Rosenhead, 2000). Now that we have a basic view of the simulation studies done regarding acute care, we look at the use of simulation optimization in general, in health care and in acute care.

2.5 SIMULATION OPTIMIZATION

Within a (generic) optimization problem the goal is to find a set of controllable input parameters that lead to the best possible outcome regarding a specific objective function. This objective function is often also subject to one or more constraints creating a finite set op possible outcomes, or combination of input parameters. In essence this entails that optimization aims to find the best solution to a problem in a structured and (in general) sequential manner. This is reflected in many optimization approaches which take a solution to a problem, compare it to some criteria (e.g., best solution found so far) and decide what to do next, in an iterative manner. Whereas “standard” optimization problems deal with deterministic outcomes, simulation optimization deals with situations where the outcomes are measured with noise. Specifically, the outcomes follow from a simulation run which is seen as an estimate of the objective function. Using the definition of Law (2007), simulation is used *“to evaluate a model numerically, and data are gathered in order to estimate the desired true characteristics of the model.”* This means that a simulation model is a function that evaluates a set of input variables, or factors, and simulation optimization techniques use the output estimates of simulation runs to max- or minimize an objective function, as visualized in Figure 2.

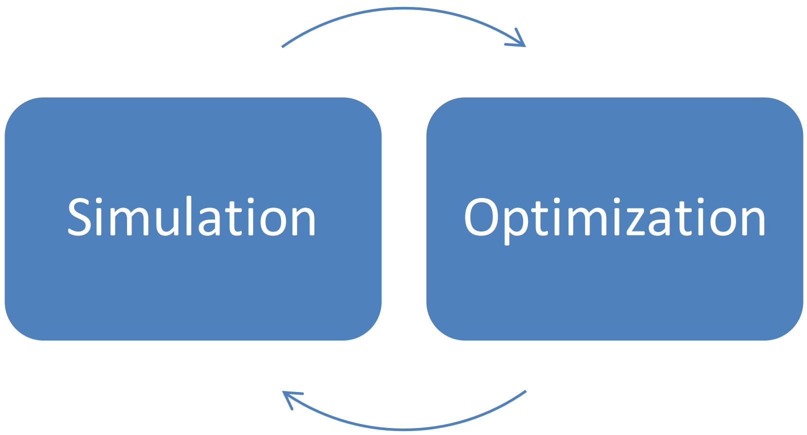


Figure 2: Cyclical input - output approach to simulation optimization

A different approach is to investigate which parameters and settings have the greatest influence on a performance indicator in a simulation model. In experimental designs, the goal is to find such factors, and to do this with the least amount of simulation time (Law, 2007). A difficulty in finding which factors, or changes, have the greatest effect on an objective function is the existence of interaction effects between changes. An interaction effect causes the effect of a factor on a performance indicator to be influenced by one or more other factors. For instance, adding diagnostic equipment and an extra staff member may both individually reduce patient length of stay by a certain amount. There is an interaction effect if the outcome of both interventions combined differs from the added individual outcomes. Examples of accounting for these interaction effects in experimental design are the use of 2^k factorial- and 2^{k-p} fractional factorial designs (Montgomery, 2008). Based on finding what factor (combinations) are most influential, it is possible to predict model responses for configurations that were not simulated, and to find the combination of inputs that optimize the objective function (Law, 2007).

Optimization similarly seeks to find the best possible combination of factors (Fu, Glover, & April, 2005). Fu et al. (2005) give an overview of the different approaches to simulation optimization, being ranking & selection (R&S), response surface methodology, gradient-based procedures, random search, sample path optimization and metaheuristics (Fu et al., 2005). Depending on the objective function and input variable set characteristics, certain simulation optimization strategies are more applicable than others (Andradottir, 1998; Barton & Meckesheimer, 2006).

Within a simulation optimization setting, R&S may be used to screen large sets of interventions and for comparing among alternatives (Boesel, Nelson, & Kim, 2003; Fu et al., 2005). Random search optimization works by moving from a current best solution (a combination of input variables) iteratively. This move is drawn probabilistically from the neighborhood of the current solution. The success of such a random search strategy is heavily dependant upon the strategy for selecting a neighborhood solution (Andradóttir, 2006; Fu et al., 2005). Compared to the deterministic optimization variant of random search, an extra problem arises in determining which candidate intervention is the best. As noise is inherent in a simulation model, this means that the current iteration is not necessarily the best. The metaheuristic approach is based on viewing the simulation model as a black box function evaluator, and as such, the optimization strategy chooses a set of input values for the simulation model and uses the outcomes of the simulation to determine new input values (April, Glover, Kelly, & Laguna, 2003).

Examples of metaheuristic algorithms are simulated annealing, genetic algorithms, tabu search and scatter search (April et al., 2003). The definitions of metaheuristics and random search however seem to overlap, as for example tabu search has also been categorized under random search (Andradóttir, 2006) and indeed random search techniques that attempt to "guide" the search process may be seen as trying to optimize using a black box function evaluator.

2.6 SIMULATION OPTIMIZATION IN HEALTH CARE

In early health care studies, simulation optimization has been used for finding optimal resource allocations. Carlson, Hershey, and Kropp (1979) use a recursive method that combines linear programming and simulation to minimize annual costs, waiting times and evaluate the effect of skill levels in a hypothetical outpatient clinic setting. Using linear programming under assumptions such as constant utilization, a yearly planning is constructed. This planning is then evaluated on a day-to-day basis using a simulation model, which' output again is used in the next optimization step (Carlson et al., 1979). This recursive method has also been tested in other studies. Although, only in hypothetical situations (D. Kropp & Carlson, 1977; D. H. Kropp, Carlson, & Jucker, 1978). Another study combines monte carlo simulation and an heuristic optimization technique to evaluate emergency ambulance placements (Siler, 1979).

In more recent work, Baesler and Sepulveda (2001) use a multi-objective simulation optimization model in a case study of a cancer treatment facility using genetic algorithms and multiple comparison statistic techniques (Baesler & Sepúlveda, 2001). De Angelis, Felici, and Impelluso (2003) use simulation, target function estimation and optimization to determine optimal server configurations in a blood transfusion clinic (De Angelis et al., 2003). Wijewickrama and Takakuwa (2006) simulate an outpatient department of internal medicine to examine doctor schedule mixes and appointment schedules in which they use an optimization program OptQuest, which uses tabu and scatter search, to evaluate both doctor- and appointment schedules. Similarly, Pérez, Cardona, Gómez, Olarte, and Escudero (2008) use a simulation model to reduce waiting times in a health care center and use OptQuest to optimize staff scheduling and Klassen and Yoogalingam (2009) use simulation together with scatter- and tabu search algorithms to optimize outpatient appointment schedules. Tànfani and Testi (2010) use discrete event simulation and optimization to determine optimal surgery schedules. In their study, they first minimize the required surgery blocks and then simulate that configuration, at which point re-optimization is done.

2.7 SIMULATION OPTIMIZATION OF EDS

The use of simulation optimization in acute care facilities is limited. Kilmer, Smith and Shuman (1997) use discrete event simulation and metamodels (a model of the simulation model) to evaluate an emergency department and compare results of the metamodel with the simulation model itself. Baesler, Janhsen and Dacosta (2003) propose a simulation model combined with design of experiments for estimating the maximum capacity in emergency rooms. Rico, Salari, and Centeno (2007) use the OptQuest optimization program to determine nurses needed in an emergency room during influenza outbreaks and Yeh and Lin (2007) use simulation together with a genetic algorithm for nurse scheduling to reduce patient queue times. Fruggiero, Lambiase, and Fallon (2008) use discrete event simulation and swarm intelligence to reduce an emergency departments' waiting times and increasing utilization. Ahmed and Alkhamis (2009) use simulation and optimization to determine the optimal number of staff in an emergency department to optimize patient throughput and reduce waiting times (Ahmed & Alkhamis, 2009). In their optimization heuristic, they randomly draw an intervention to test and compare with the current iteration. The results of these paired comparisons are tallied and if a set number of better or worse outcomes for the new intervention is exceeded, the new intervention is respectively accepted or rejected.

2.8 OUR CONTRIBUTION

In this study we aim to assess possible organizational interventions not through comparing a predetermined set of interventions determined by stakeholders, but instead by creating an inventory of possible decision variables, or simulation inputs, that may be changed in order to increase the efficiency of the IEP. We will use experimental design to investigate the effects of input variables on performance indicators in order to steer an optimization process of finding “good” solutions. Additionally we use simulation in a relatively new aspect of health care, being the integrated emergency post, where care providers have merged in their provision of care.

From literature, we use often cited performance indicators and interventions to help formulate the evaluation and formation of interventions as well as simulation optimization techniques to further optimize interventions.

3 MODELING THE INTEGRATED EMERGENCY POST

In order to create a set of interventions, we first describe the collaboration between GP post and emergency department in the integrated emergency post in Almelo, and describe the current situation regarding processes, resources, and dependencies. Additionally, we describe the model adaptations needed to further validate the simulation model, and facilitate the comparison of interventions. Finally, we look at the key performance indicators that are used to measure and compare interventions.

3.1 CURRENT SITUATION

Placing the IEP of Almelo into one of the four collaboration models proves to be difficult. Coenen (2009) defines four states of collaboration: no collaboration, triage of patients through the ED, a GP post with a (triage) gatekeeper function, and finally a shared front-office and triage system. The third model corresponds most with the current situation at Almelo. Patients that self-refer to the hospital only have access to the GP post part of the IEP. After triage, patients are referred to either the GP post or ED. If patients are referred to the ED, a second triage process takes place as currently the GP post and ED use different triage systems, NHG and MTS respectively. In the collaboration model of Coenen (2009), only one triage takes place.

3.1.1 PROCESSES

In order to design interventions, an understanding of the current situation is desired. Looking at the IEP as a black box function, there is an input of patients who enter the IEP, are treated and then leave the IEP, subject to resources and control mechanisms.

There are several ways in which patients may enter the IEP: by calling the IEP, going to the IEP as a self-referral, and by being referred to the ED by an external care provider. When a patient calls the IEP, a telephonic triage takes place and depending on the urgency of care demand the patient gets a consultation at the IEP, a doctor visits the patient, the patient is referred straight to the ED (by ambulance) or the patient receives medical advice by phone. Self-referring patients first undergo physical triage by a GP assistant, after which they are then sent home with medical advice, scheduled for a GP consultation or referred to the ED. Finally external referrals are sent directly to the ED.

Patients that receive an appointment via telephone or self-refer and enter the IEP, are first seen at the GP post. In most cases this treatment is sufficient after which a patient goes home. Possibly, the patient may require an X-ray diagnostics test, after which, depending on the results, a patient goes home, or in case of a fracture, is referred to the ED. Similarly, other patients that cannot be treated at the GP post, or require additional treatment, are further referred to the ED.

In the simulation model, patients that enter the ED are first triaged again, given the different triage systems, and then the patient history is registered by an ED nurse or physician assistant. Afterwards, a patient might undergo multiple diagnostic tests and receives treatment. After all treatment is finalized, the patient leaves the system and continues his care path outside the ED or goes home. In reality, the order in which conducting diagnostic tests, taking patient history (by resident) and treatments take place, depends upon the symptoms of the patients. An example of this is that some patients always undergo a lab blood test and this may take place prior to the taking of patient history (by a resident). Additionally some patients require multiple diagnostic tests with treatment after each test. Regarding diagnostics, there are 5 types of diagnostics specified, being X-ray, Laboratory research, ECG, ultrasound and CT scans.

Visser (2011) created a conceptual model in her thesis of the IEP at Almelo. Figure 3 is based on this and shows all possible processes and pathways a patient may take (Mes & Bruens, 2012; Visser, 2011).

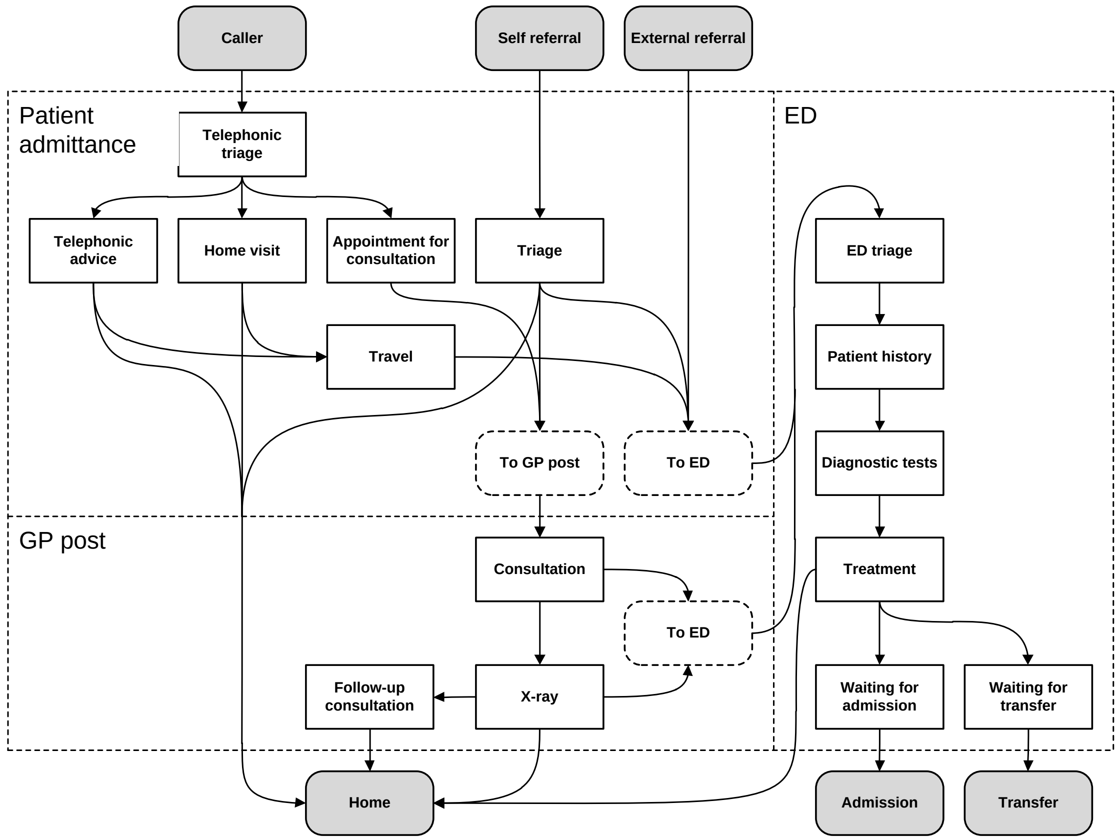


Figure 3: IEP processes (Mes & Bruens, 2012)

3.1.2 Patients

In order to fill in dependencies regarding patients and their need for specific diagnostics and treatments, patients are categorized over 10 simulation groups, which are based on the eight most common diagnostic related groups (DRG's) and two rest groups (Visser, 2011). Depending on the patient category, either a surgical- or internal resident treats these patients. These ten groups are:

1. Surgical – trauma - fracture
2. Surgical – trauma - wound
3. Surgical – trauma - other
4. Surgical - abdomen
5. Surgical – rest
6. Cutting specialties – other
7. Neurological - stroke
8. Pulmonary medicine

9. Internal medicine
10. Contemplative specialties – other

The first six simulation groups are treated by surgical residents, and the latter by internal medicine residents.

3.1.3 Resources

Patients that go through the IEP and undergo treatment also require resources. Three types of resources may be defined, being rooms, staff and equipment. Staff resources are based on responsibilities and qualifications (Visser, 2011). These are:

1. GP assistant
2. Triage assistant
3. General practitioner
4. ED Nurse
5. Resident
6. Physician assistant

In addition there are two types of external staff members that are called when needed, being diagnostic nurses and medical specialists. Staff members perform tasks based on authorizations. For example, general practitioners visit and consult with patients.

For staff to treat patients and perform tasks certain rooms are required. The following rooms are modeled (Visser, 2011)

Room type	Available
Call centre	1
Triage room GP post	1
Triage room ED	1
GP room	6
ED room	8
X-ray room	2
CT room	1
Plaster room	2

Table 3: Available room resources

Regarding medical equipment needed, a ECG and ultrasound equipment is modeled, which are portable so that tests are taken in the ED room of a patient. Other equipment is directly linked to a room, as shown in Table 3. Figure 4 shows a map of the IEP with the described rooms.

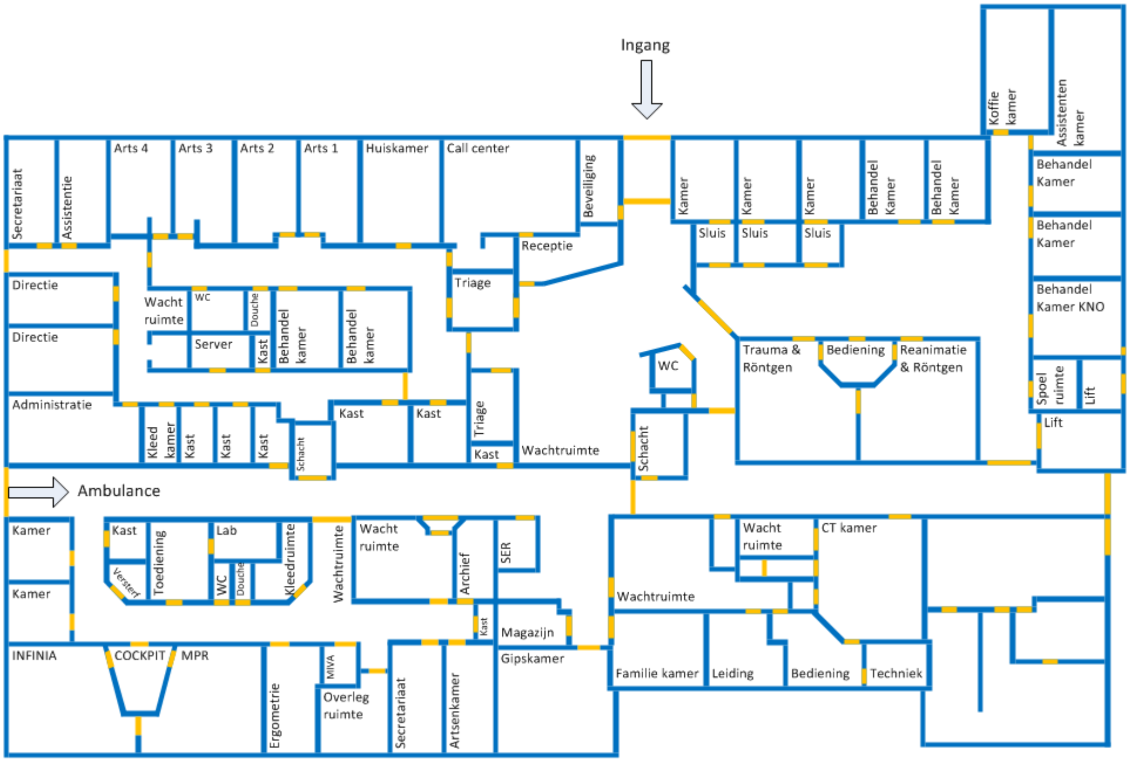


Figure 4: Map of the integrated emergency post

The upper left portion of the map depicts the GP post, left of the entrance ("ingang"). Right of the entrance is the emergency department. As the map shows, the integrated emergency post has a shared waiting room ("wachtruimte") and front office ("receptie").

3.1.4 Dependencies

In reality there are many dependencies that exist between patient arrivals, attributes, processes and more. For example, the ED urgency is dependent on the GP post urgency. After all it is unlikely that low urgency patients are referred to the ED after GP consultation. Figure 5 shows the dependencies between involved variables in the simulation model (Visser, 2011).

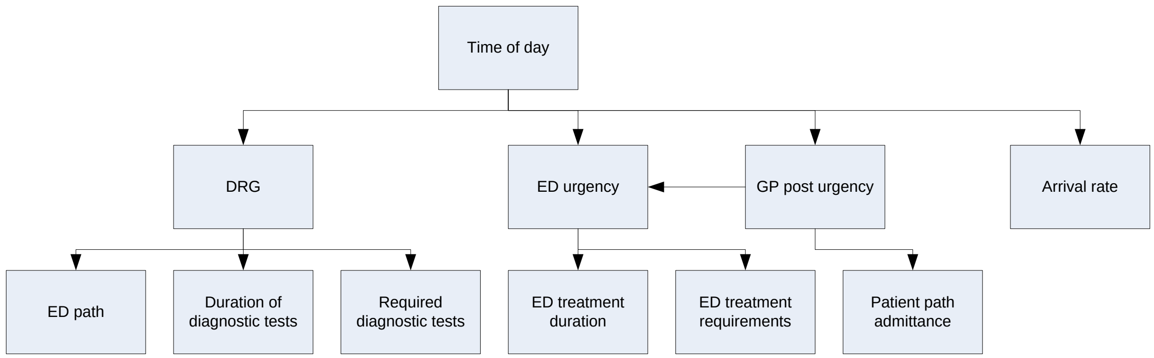


Figure 5: ED dependencies

As can be seen, the time of day determines the number of patients that arrive, those patients' urgency and simulation group. The GP post urgency determines the path a patient takes though the IEP, and in case of a GP post to ED referral patient, the ED urgency is dependent upon the GP post urgency. The simulation group determines the time needed for treatment, a patient's path through the ED, as well as the number and types of diagnostics test required. Finally, the ED urgency determines extra treatment requisites, such as needing a medical specialist.

3.2 MODEL CHANGES

Several changes within the simulation model are made, in order to increase the representativeness of the simulation. By further defining how processes, resources and dependencies are used and combined, these changes help increase the validity of the simulation model.

GP post consultation appointments

Similar to reality, when a patient calls the IEP, is triaged, and needs a consultation, an appointment is scheduled. The time of this appointment, in reality, depends on the urgency, the needed travel time of the patient, and other patients already scheduled for an appointment. In the original simulation model, the time of an appointment is based on the patients already scheduled for an appointment, and travel time for patients. Any patient that needs a consultation is scheduled as soon as an appointment slot is available, based on number of GPs working, and patients already scheduled, as long as a minimum time required for traveling to the IEP is met. This means that, in the simulation model, high urgency patients are also scheduled for an appointment.

In reality however, high urgency patients (U1 and U2) that call the IEP are asked to visit as soon as possible, bypassing the patient appointment schedule. To model this, patients that call the IEP receive an appointment time based on their urgency, as well as other patients already scheduled. U1 and U2 patients that call the IEP are scheduled for an appointment as soon as possible, only accounting for time needed to travel to the IEP. U3 and U4 patients are scheduled similar to the original model, based on patients already scheduled. This means that high urgency patients now immediately travel to the IEP, and “bump down” lower urgency patients that are already scheduled for an appointment.

Office to our-of-office hour transitioning of patients

As the model is used to simulate the operations of the integrated emergency post, the simulation skips time during office-hours. This means that at the start of a transition from office-hours to out-of-office hours the model is empty. However, in reality the ED is always operational and as such always has patients visiting. Indeed, using historical data on the number of patients at the ED over an entire year, we see the ED was never empty at 5pm.

In order to reduce computation times, we opt not to simulate office-hours, but use the data on patient numbers to create a probability distribution to fill the IEP with patients when opening at 5 pm. Using Minitab, the best fit distribution for the number of patients in the IEP at 5 pm is gamma distributed, with parameters 7.45 and 1.56. On average there are 11.6 patients at the ED around 5 pm. Appendix 2 shows the complete results of the data analysis.

The number of patients in the IEP is discrete, however the best found fitting distribution is continuous. Therefore we decide to round the outcomes to the nearest integer, with a minimum of zero. From the historical data, it is not possible to determine at what steps patients are at 5 pm. Therefore, we create care pathways for these patients, and randomly place them at a point in this pathway, such that at 5 pm, the ED is filled with patients that are at various stages of their care pathway.

Additional staff types

Added to the simulation model is a new type of specialist currently working at the ED during office hours, called the ED specialist. This ED specialist focuses on acute care and differs from the residents currently modeled. The ED specialist is able to treat any patient regardless of diagnostic related group. While this specialist only works office hours at the moment, there are residents training for this specialty and utilizing ED specialists during out-of-office hours is a stated goal of ZGT. As such we included the ED specialist in the model to evaluate as an intervention. The effect of this increased flexibility may have a significant effect on the IEP. In addition, a nurse practitioner (NP) is added as a staff type. This NP works at the GP post and treats patients with lower urgency during the weekend. This is similar to the tasks done by the physician assistant at the GP post, however the physician assistant is also able to treat patients at the ED, for which a NP is not authorized.

Staff and task authorizations

Several tasks carried out by staff have been changed in the model. For example, GP assistants no longer treat low urgency patients. In addition the physician assistant treats both GP post and ED patients. Figure 6 lists all staff types and their respective task authorizations.

Location	Task	GP assistant	Triage assistant	GP	Nurse practitioner	ED nurse	Resident	Physician assistant	Medical specialist	Diagnostic nurse
GP post	telephonic triage	U1 - U4	U1 - U4	-	-	-	-	-	-	-
GP post	triage	-	U1 - U4*	-	-	U1 - U4*	-	-	-	-
GP post	consultation	-	-	U1 - U4	U3 & U4	-	-	U3 & U4	-	-
GP post	visit	-	-	U1 - U4	-	-	-	-	-	-
ED	ED triage	-	-	-	-	Blue - Red	-	Blue - Red	-	-
ED	take patient history (1)	-	-	-	-	Blue - Red	-	Blue - Red	-	-
ED	take patient history (2)	-	-	-	-	-	Blue - Red	Blue - Green	Blue - Red	-
ED	X-ray/ultrasound/CT scan	-	-	-	-	-	-	-	-	Blue - Red
ED	ECG / lab test	-	-	-	-	Blue - Red	-	-	-	-
ED	review diagnostic tests	-	-	-	-	-	Blue - Red	-	Blue - Red	-
ED	treatment at ED	-	-	-	-	-	Blue - Red	Blue - Green	Blue - Red	-
ED	cast application	-	-	-	-	Blue - Red	-	Blue - Red	-	-
ED	patient discharge	-	-	-	-	Blue - Red	-	-	-	-

*The triage assistant triages walk-in patients from 8AM to 11PM, outside these hours the ED nurse performs triage

Figure 6: Task authorizations, based on Visser (2011)

Ordering diagnostics

Another process change is related to the ordering of diagnostic tests. In reality, depending on a patient's symptoms or means of arrival, some diagnostic tests are ordered immediately before resident contact. This means that the first resident contact (taking patient history) does not have to take place prior to some diagnostic tests, as was assumed in the model of Visser. As such, patients are able to enter diagnostic queues without first having been seen by a medical specialist.

In the original model, patients were seen by a resident, then had all their diagnostic tests done, followed by treatment. In practice however there are more break-in moments, or interruptions, where a resident does part of a patient's treatment, followed by ordering extra diagnostics and additional treatment based on those diagnostic results. To model this, we created a new treatment process at the ED with a pre- and post-treatment diagnostic phase, as shown in Figure 7.

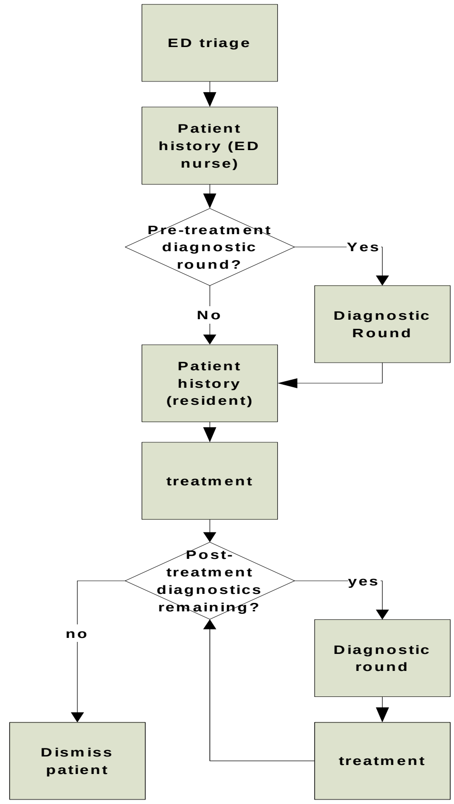


Figure 7: Revised ED patient path

In the revised process, patients that enter the ED undergo (based on their simulation group) some of their diagnostic tests immediately in a pre-treatment diagnostic phase. Depending on their simulation group, zero to multiple tests take place. Any residual tests a patient needs take place in the post-treatment phase. Here every diagnostic round is defined as a single test, followed by treatment. Table 4 details which diagnostic test – simulation group combinations take place per phase.

Patient Group	Lab	ECG	echo	X-ray	CT
1	Pre	Pre	Pre	Pre	Pre
2	Pre	Post	Post	Post	Post
3	Post	Post	Post	Post	Post
4	Pre	Post	Post	Post	Post
5	Post	Post	Post	Post	Post
6	Pre	Post	Post	Post	Pre
7	Pre	Post	Post	Pre	Post
8	Pre	Post	Post	Post	Post
9	Post	Post	Post	Post	Post
10	Post	Post	Post	Post	Post

Table 4: Diagnostic-DRG combinations

In effect this means that there are more break-ins, when a resident or medical specialist is treating a patient and requests more diagnostics, this specialist is able to start or continue treatment of another patient. Regarding medical specialists that arrive from outside the ED, if a patient needs a medical specialist, and there are several treatment stages in a patient's care path, the specialist is only needed during the first treatment process.

Additional tasks ED nurses

The tasks performed by ED nurses are also expanded upon. In the model by Visser (2011), ED nurses perform triage, take patient history, ECGs, ultrasounds and apply casts. In practice however nurses also assist residents and specialists in treating patients. This supporting function consists of many different tasks. Additionally an ED nurse prepares patients for hospital discharge. At the ED patients are assigned an ED nurse similar to a resident. Based on the complexity of care an ED nurse can support several patients simultaneously (by switching between patient-related tasks).

To mimic this in the simulation model, ED nurses have to be present during some of the treatments performed by specialists. In the simulation model we have given a patient a 20% probability of also needing a nurse present during a treatment step. As treatments are now split into multiple rounds, for each of these rounds a requirement for a nurse to be present is determined. In addition there is now a discharge process from the ED, which requires an ED nurse and an available room.

Task authorization changes

In addition to new tasks, task authorizations are also changed, defining what tasks a certain staff member carries out. In the original model, patients with an appointment at the GP post are either seen by a general practitioner, a triage assistant, or a physician assistant/nurse practitioner. The treatment of patients by a triage assistant however is only based on some patients needing urine sample tests, which are carried out by the triage assistant. In the model treatment allocation is based on urgency and letting triage assistants treat (U3 & U4) patients results in a much higher number of consultations than reality. Therefore we no longer let triage assistants treat patients at the GP post.

During the night, self-referring patients are triaged by an ED nurse before having a GP consultation. In the original model this was reflected by letting ED nurses triage self-referrals at all times, resulting in ED nurses triaging patients during the daytime. This is changed so that ED nurses can only triage patients from 11pm-8am, similar to the times at which ED nurses triage patients in reality.

ED treatment room allocation

Another procedural change is the possibility for patients to be placed back in the waiting room after a pre-diagnostic test is performed. This is based on urgency and type of diagnostic performed. Table 5 shows which patients are placed back in the waiting room.

urgency	lab	X-ray	Echo	CT	ECG
Red	no	no	no	no	no
Orange	no	no	no	no	no
Yellow	no	no	no	no	no
Green	yes	yes	no	no	no
Blue	yes	yes	no	no	no

Table 5: Waiting room placement after pre-treatment diagnostics

Patient prioritization

In the original model, patients are prioritized based on urgency and waiting time. As such, a higher urgency patient will always precede a lower urgency patient, and in the case of two equal urgency patients, the patient that has waited longer is prioritized. In reality, patient prioritization is based on a combination of these two factors simultaneously. When a lower urgency patient has been waiting for a long time, at some point the patient will precede a higher urgency patient. This was not possible within the original model.

As a new prioritization mechanic we added a "fake" waiting time to patients based on their urgency, equal to four hours minus their maximum allowed waiting time till physician contact (i.e., triage code waiting time). This added waiting time is listed in Table 6.

Urgency	Added Wait (min)
U1	225
U2	180
U3	60
U4	0
Red	240
Orange	230
Yellow	180
Green	120
Blue	0

Table 6: Added waiting time per urgency

3.3 KEY PERFORMANCE INDICATORS

In order to compare interventions, we must measure an intervention's performance. The performance indicators that are often used in simulation studies are patient waiting times, throughput, length of stay and utilization of resources. Broadly speaking, performance indicators fall under quality of care, quality of labor and efficiency.

Earlier work at the IEP, by Fransman (2011) and Reinders (2012), looked at patient and internal stakeholder performance indicators respectively. The highest ranked patient preference is waiting time, followed by medical accessibility and caregiver type. As mentioned, waiting times are an often used performance indicator in simulation, and its' valuation by patients affirms its use.

From an organizational perspective the most valued performance indicators for the GP post are a correct urgency classification of patients and telephonic call response waiting time. For the ED the most valued performance indicators are triage waiting time and waiting time for first resident contact (Reinders, 2012). While the organizational respondents give function specific performance indicators (e.g., GP assistants value telephonic response times), it can be seen that waiting times at some point in the health care process are valued. A measure such as a correct urgency classification is, in this simulation study context, impossible to measure, as the urgency allocation is assumed to be correct in the simulation model. The waiting times for individual processes are measured as well as the total length of stay of patients, incorporating all waiting time, as well as process times.

In trying to minimize waiting times without regarding cost and resource constraints it is likely that simulations which have a high number of resources available yield the best results. Therefore, in addition to waiting times and length of stay, resource utilization is also used as a performance indicator. Utilization gives both an indication of workload for staff as well as the efficiency of a resource's usage.

In this chapter we describe the integrated emergency post regarding processes, resources, and dependencies, and the level of integration and cooperation between emergency department and GP post. Additionally we describe the changes made to the original simulation model, in order to better represent the current situation at Almelo. Finally, the work already conducted regarding performance indicators for both patients, and staff, enables us to use these to formulate performance indicators to compare and evaluate possible interventions. Besides changes to the model itself, a data analysis is also conducted to further validate and specify the input data of the simulation model. In the next chapter the data analysis is described, concluding all changes made to the original simulation model.

4 DATA ANALYSIS

To create a simulation model that better reflects reality and to better test interventions, process, waiting, and patient arrival times are analyzed. We first give an overview of the measurement period that was carried out. This measurement period was conducted to gather additional data, besides historical, to further validate simulation model input. With the data gathered from this period, previously made assumptions regarding input are evaluated, and possibly changed. Additionally we describe how the patient arrival rates are constructed using four years of historical data. This is done by normalizing the historical data over the years, as well as weeks and days, such that all data points are useable for simulation input.

4.1 MEASUREMENT PERIOD

In order to validate and further specify the simulation model, a two-week period of measurements has been conducted. At the GP post, the arrival and triage times for self-referring patients have been measured as well as the waiting times for the GP, the GP assistant and PA consultations. In addition, we asked GPs on visitation routes to register visitation and travel times. At the ED we distributed forms and asked residents and ED nurses to register diagnostic preliminary results, plaster times, medical specialist waiting- and consultation times and intake waiting times. Appendix 3 shows an example of the used measurement forms. These measurements were conducted from 6-02-2012 to 19-02-2012. These measurements are used, in addition with observations, to change the input values for the simulation model as well as to adapt and validate the model to reflect the current situation at the IEP.

4.1.1 INPUT CHANGES

Using an Anderson-Darling test in Minitab, we fit probability distribution functions to the measured data to use as input for the simulation model. This results in input functions for the following processes.

- Travel time of GPs doing visitations: the time needed to travel between patients and the IEP, as well as time between patients.
- Duration of GP visitations: the time needed for a GP to consult a patient at home.

- Triage time HAP: the time needed for the triage of self-referring patients that enter the IEP.
- Waiting time for hospital admission: the time between a patient's discharge from the ED and admission into a hospital bed. During this time a patient waits at the ED, in one of the treatment rooms.
- Cast application time: the time used to apply casts to patients with fractures.
- Diagnostic process time: the time between start of a diagnostic test and a resident receiving results
- Diagnostic waiting times: the time between a request for diagnostics and the start of diagnostics.

Table 7 gives the resulting best fit distributions using the Anderson-Darling test that are changed in the simulation model, together with the minimum value (if applicable) and parameters. Appendix 4 shows the complete results of the Minitab data analysis.

Simulation input	Best fit distribution	Original distribution
GP travel time visits	Weibull (1.93; 16.21)	Normal (22; 8.67)
GP visit duration	Lognormal (21.09; 15.61)	Gamma (5; 2.34; 8.93)
Triage time self-referrals	Gamma (3.59; 1.32)	Gamma (4; 1.89; 1.11)
Waiting time hospital admission	Weibull (0.91; 23.09)	Gamma (2.63; 11.93)
Cast application time	Weibull (2.41; 9.9)	Gamma (10; 2.67; 11.93)

Table 7: Best fit distributions for simulation inputs

For the diagnostic processes, and patient external admission times (e.g. waiting time for transfer to another hospital), there were insufficient or incorrect measurements to conduct an analysis and we kept the original values used in the simulation model.

4.2 HISTORICAL DATA ANALYSIS

In order to quantitatively validate, and create a more reliable model, we look at both the arrival rates of patients and the length of stay of patients, consisting of process- and waiting times. With regards to patient arrivals, these are assumed to be hour, day and week dependent and drawn using poisson distributions, which is a single parameter distribution. In the original simulation model, these arrivals are based on one year of historical data. To create more reliable patient arrival numbers, we use four years (2008 – 2011) of historical data, and evaluate the differences between years, weeks, days, and hours. In the patient arrivals a distinction is made between IEP arrivals (i.e., patient that call or self-refer to the Post), and external arrivals (i.e., patients that bypass the GP post, such as ambulance arrivals).

4.2.1 YEAR EFFECTS

In order to use all four years of data, we evaluate the differences between the yearly arrivals, and correct for these. Figure 8 shows the arrivals of IEP and external patients per year. In the figure a distinct increase of external patients is visible, while the IEP arrivals seem stable.

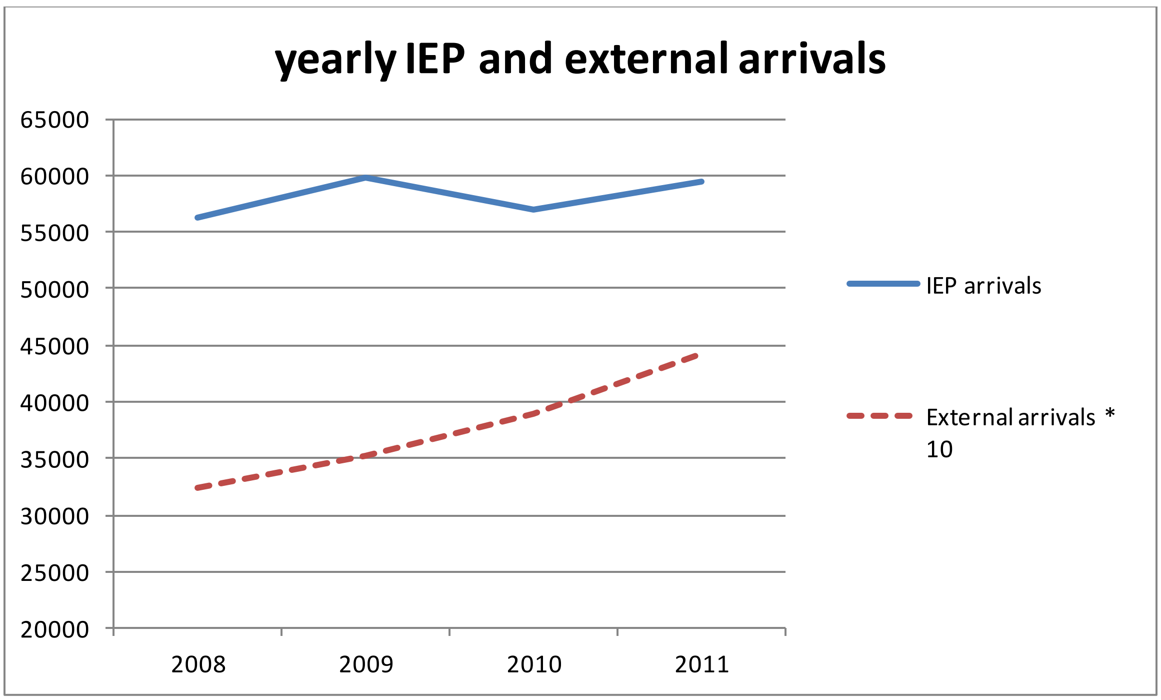


Figure 8: Patient arrivals per year (2008 - 2011)

If we use all four years of data directly, the lower arrival numbers for the earlier years cause the average arrivals to be lower than in reality. In order to use all four years of data, we normalize the arrivals from 2008 – 2010 to 2011. This is done by dividing the number of arrivals in a year by the relative number of arrivals of the year to 2011. The total and relative arrivals are shown in Table 8. Using this method, the total number of patient arrivals is based on 2011, however 2008 – 2010 still play a role in determining patterns within years, such possible seasonal fluctuations. This normalization enables the comparison of time periods between years, and if there are recurring patterns, these should repeat itself over the years. As such, using four years of data gives a more reliable representation of patient arrivals than a single year, as more data points are used.

year	arrivals	arrivals/2011
2008	3248	0.734
2009	3526	0.797
2010	3899	0.882
2011	4423	1.000

Table 8: (relative) Arrivals per year

4.2.2 Week effects

With normalized years, we look at the differences between weeks (i.e., seasonal effects). To do this week factors are calculated. A week factor is the number of arrivals in a week, divided by the average number of arrivals in a week (taken over a year). If a week's factor is greater than one, this indicates the week is busier relative to the average of that year. As there are four years of data, this gives four week factor measurement points per week. Figure 9 shows average week factor over all years with standard deviation for the IEP arrivals.

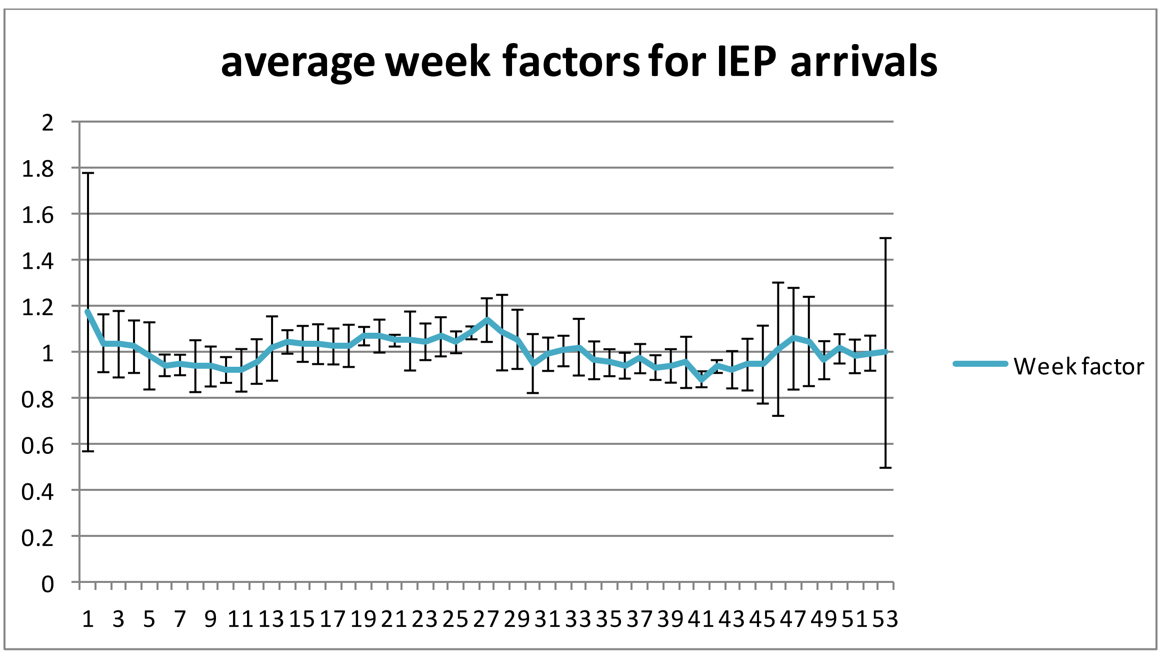


Figure 9: Average week factors and standard deviation for IEP arrivals

From the graph, we calculate there is no distinct seasonal effect visible. Week 1 and 53 seem to differ greatly between the years, however this is caused by errors in data retrieval, as the days in these weeks are not properly divided, and some weeks only have one or two days, while others have more. What does stand out is that the number of arrivals seems to decrease around week 30, and that on average, week factors in week 13 to 27 are higher than other parts of the year. The overlapping standard deviations however indicate that over individual week factors, there have also been busy weeks during the perceived dip, and quiet weeks during the peak. In addition, the standard deviation increases in week 43 to 48, indicating that the number of arrivals fluctuated greatly between years. Figure 10 shows the average week factors and standard deviation for the external patients. Similar to Figure 9, the first and last week are erroneous due to data retrieval. Compared to the IEP arrivals, there seems to be more fluctuation in patient arrivals between the years. Additionally, there is a similar decrease in patient arrivals around week 30. Here too, we see no discernible seasonal effect.

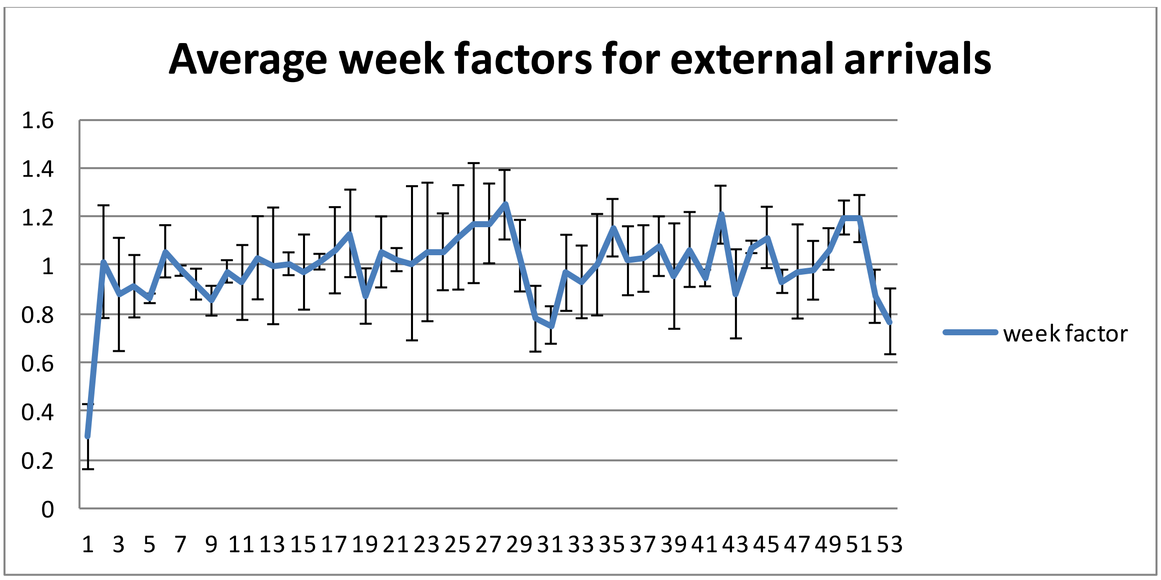


Figure 10: Average week factors and standard deviation for external arrivals

In addition, looking at the historical data there is a discrepancy between the average and variance in the number of arriving patients per week. This indicates that a two-parameter distribution may be more suitable. The average number of weekly patient arrivals is 477.20, with a variance of 2698.15.

4.2.3 Day effects

Assuming all weeks are similar, we calculate day factors for the weekdays, such that we can use a single distribution for all weekdays. For Saturday and Sunday we use separate distributions. The day factors are calculated by dividing the number of arrivals during a day with the average number of arrivals per day, in the week. To determine whether weekdays differ from one another, we use two sample t-tests (95%) between every pair of weekdays. Table 9 shows the outcomes of the t-tests.

	IEP arrivals	External arrivals
comparison	p-value	p-value
mon-tue	0	0.781
mon-wed	0.046	0.093
mon-thu	0.013	0.271
mon-fri	0	0.254
tue-wed	0.037	0.152
tue-thu	0.184	0.409
tue-fri	0	0.145
wed-thu	0.523	0.494
wed-fri	0	0.004
thu-fri	0	0.017

Table 9: Two sample t-test outcomes

From the tests we see that the external patient arrival comparisons all have a high p-value, indicating there is no significant difference. Two exceptions to this are Wednesday-Friday and Thursday-Friday, which have a lower p-value, and differ significantly (alpha = 0.05), indicating that Friday may differ from the other days in the week.

The p-values of the IEP arrivals are all considerably lower. From all comparisons, we see that Monday and Friday differ significantly from any other day of the week, that is, they have a significant p-value in every comparison. From these observations we assume that Monday through Thursday are equal with regards to the number of external arrivals, with Friday having its own distribution. We also assume that Tuesday through Thursday are equal regarding IEP arrivals, and Monday and Friday each have their own arrival distributions. Using Anderson-Darling tests, the probability distribution functions are determined for the day factors, shown in Table 10.

Day	IEP arrivals			External arrivals		
	Distribution	**P1**	**P2**	**Distribution**	**P1**	**P2**
Monday	lognormal	0.99	0.0967	lognormal	0.98	0.43
Tuesday	gamma	105.84	0.0091	lognormal	0.98	0.43
Wednesday	gamma	105.84	0.0091	lognormal	0.98	0.43
Thursday	gamma	105.84	0.0091	lognormal	0.98	0.43
Friday	Lognormal	1.11	0.0098	gamma	7.20	0.15
Lognormal: p1=mean, p2=st. deviation; gamma: p1=shape, p2=scale						

Table 10: Day factor probability distributions

4.2.4 *Hourly arrivals*

Using the day factors, we are able to normalize all patient arrivals over the weekdays. This is done by dividing the number of hourly arrivals by the average day factor. For example, every hourly IEP arrival on a Monday is divided by the Monday factor, 0.993. This allows the use of all weekday hourly arrivals for a single probability arrival distribution. With Minitab, we use Anderson-Darling tests to find the best fitting probability distribution for every hour of each day. The table below shows the average arrivals for every hour, for both IEP and external arrivals.

	IEP arrival			External arrival		
Hour	weekday	Saturday	Sunday	weekday	Saturday	Sunday
0-1	3.144	3.952	4.409	0.218	0.251	0.298
1-2	2.249	2.741	3.861	0.138	0.237	0.301
2-3	1.912	2.405	2.976	0.110	0.248	0.293
3-4	1.597	1.872	2.376	0.096	0.223	0.181
4-5	1.353	1.752	2.342	0.097	0.162	0.238
5-6	1.235	1.665	2.078	0.074	0.106	0.171
6-7	1.357	2.616	2.607	0.080	0.110	0.109
7-8	1.275	7.774	6.452	0.168	0.114	0.131
8-9		13.531	12.724		0.489	0.340
9-10		22.157	22.899		1.513	1.150
10-11		31.880	24.635		1.558	1.425
11-12		18.546	16.813		1.019	0.858
12-13		25.861	14.487		0.878	0.822
13-14		23.990	19.553		0.808	0.911
14-15		13.881	11.385		0.942	0.693
15-16		14.718	14.817		0.955	0.525
16-17		21.130	16.130		0.908	0.685
17-18	13.616	16.484	13.105	0.607	0.726	0.450
18-19	13.491	20.293	16.313	0.472	0.642	0.504
19-20	14.493	12.111	14.654	0.485	0.578	0.479
20-21	9.476	15.269	10.070	0.477	0.531	0.446
21-22	7.580	13.438	6.668	0.423	0.479	0.498
22-23	6.994	7.434	5.306	0.328	0.410	0.366
23-24	5.220	6.644	5.120	0.248	0.391	0.251

Table 11: Average patient arrivals per hour

From the Anderson-Darling tests, the best fitting distributions are continuous, either normal or gamma. The average number of arrivals however, during quiet hours, is well below one, as can be seen in Table 11. For example, during weekdays from 1am to 2am, on average of 0.138 external patients enter the ED. Using the proposed continuous distribution during these hours, and rounding to the nearest integer, does not give a good representation of the actual arrivals during these hours. As such, it may be better to use poisson distributions for hours during which few patients arrive, similar to the original model. Figure 11 shows the average external arrivals and variance per hour measured over all the Saturdays during 2008-2011. Appendix 5 shows the average arrival and variance per hour for external arrivals during other days, as well as IEP arrivals.

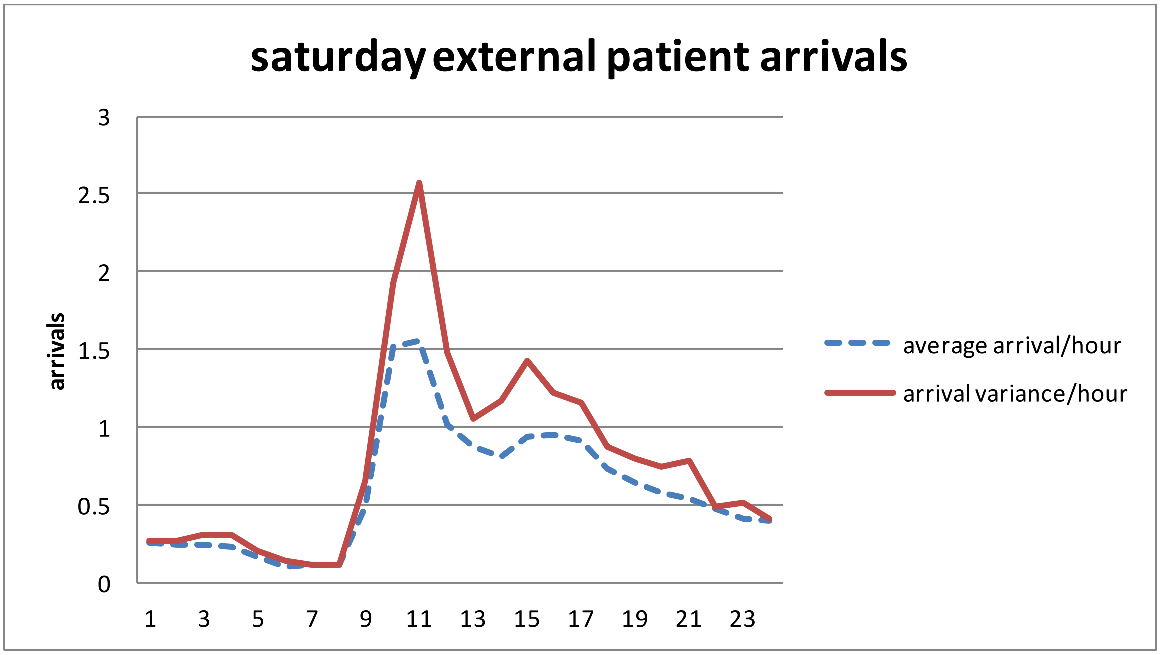


Figure 11: Hourly external patient arrival average and variance

From Figure 11, and Appendix 5, the variance over hourly arrivals for all days show a pattern where during busier hours, the variance and average number of arrivals starts to differ. This indicates that the patient arrivals may be better modeled using a two parameter distribution for the busy hours, and poisson distribution during the quiet hours.

In the original model, based on one year of historical data, there is a seasonal effect, where the first half of the year has more patient arrivals than the second half. This means that, in order to evaluate overall effects of interventions on the IEP, a single simulation run would have to simulate at least one year of operations. In the four year data analysis however, we see that during the years there are no distinct seasonal patterns, which means that, on average, no group of weeks is busier than any other group of weeks. From this we conclude that, if weeks are similar to each other, we may compare over weeks instead of years, to evaluate overall effects of interventions on the IEP. This means that a single simulation run may now be set at one week, instead of one year, reducing computational time needed for simulation.

Fitting a probability function for the hourly arrivals proves difficult, as the best fitting distributions are continuous, while patient arrivals are not. Therefore, to correctly model patient arrivals, a combination of poisson distributions for quiet hours, and two parameter distributions for busy hours seems best. However, as the actual number of arrivals is determined by a mixture of multiple probability distribution functions, tuning is needed such that this combination of distribution functions properly reflects the four years of historical data. In addition to the time needed to tune the new patient arrivals, the average arrivals for IEP patients are almost identical to the original arrivals, and the external arrivals are lower than those of the original one year analysis. As the original arrival distributions have been tuned, such that they accurately reflect 2011, and are, for all hourly average arrivals equal or higher than the four year data analysis arrivals, we choose to use the original values, as these may serve as a "worst-case" scenario.

With the four year historical data analysis, as well as the changes made to the simulation model in Chapter four, we now must verify and validate the simulation model, to ensure that it reflects both the conceptual model, as well as the current situation in Almelo. In the next chapter we give an overview of the simulation model, as well as the steps taken in verification and validation of the simulation model. Following this, we formulate interventions, and evaluate these in Chapter six and onwards.

5 SIMULATION MODEL

In this chapter we give a brief overview of the simulation tool used and how the conceptual model is translated into the computer simulation model. Additionally, we detail the verification and validation steps. The simulation model is created using the discrete event simulation program Plant Simulation, by Siemens.

5.1 MODEL OVERVIEW

The simulation model is graphically represented by a map of the integrated emergency post, with color coded patients, and staff members moving around on this map. Figure 12 gives a screenshot of the simulation model.

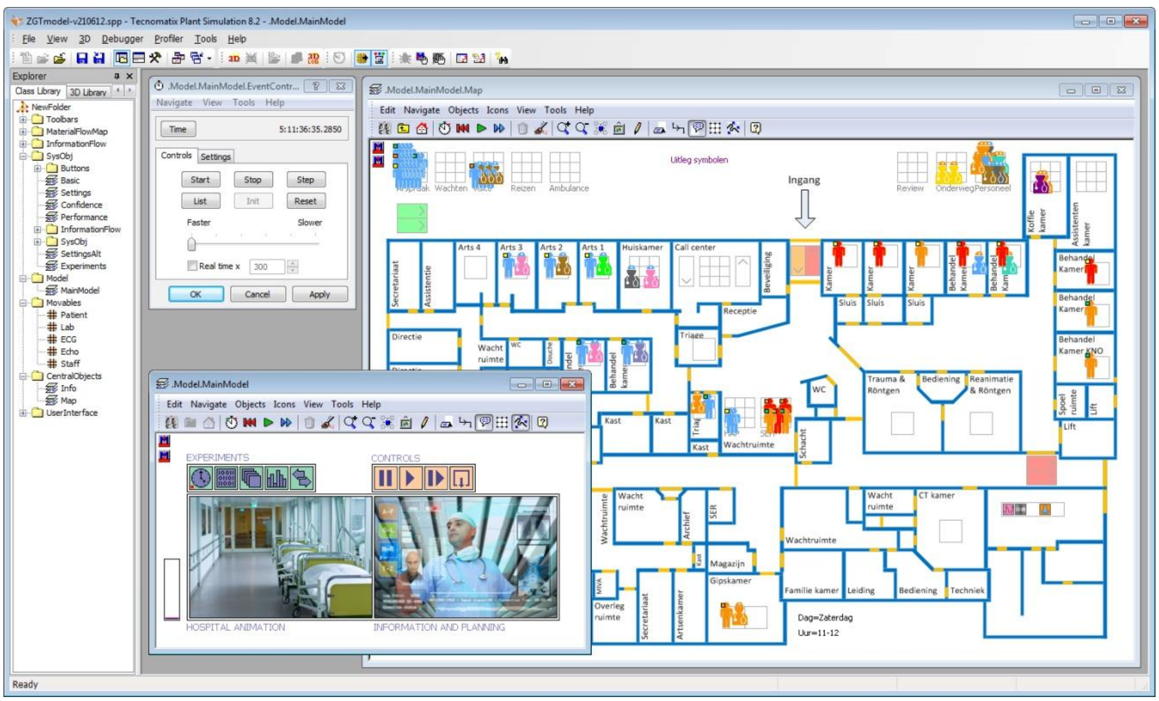


Figure 12: Screenshot of the simulation model

On the map, patients, diagnostic equipment and staff come together in rooms to complete process steps. In addition, actors that are outside the IEP, such as patients traveling to the IEP or GPs on visits are placed outside the IEP (upper left). Based on available rooms, staff, resources and priorities tasks, or events, are started. In addition to the tasks that require the presence of a patient, offline tasks are also defined, such as reviewing tests.

As input to the simulation model patient arrivals, pathways and process times are drawn from probability functions best representing realistic arrival numbers. As output from the simulation model, individual patient information is stored, such as pathway, urgency and diagnostic tests required. Additionally, process times and waiting times process steps are recorded. These may be used not only in comparing interventions, but also in model verification and validation.

5.2 MODEL VERIFICATION

Law (2007) states several techniques for model verification. A given technique is debugging the program so that it runs without errors. In the final build the model runs without errors. A second technique is letting the simulation model be reviewed by more than one person. The simulation model has been verified by several persons, including one of the stakeholders from ZGT. Another technique is observing animations of the simulation model in order to detect strange or unrealistic behavior. As the model has a detailed graphical representation this was extensively observed and no unexpected behavior is observed. A final verification step is comparing the input probability distributions with the observed outcomes of the model. To do this, we simulate three years in the simulation model and compare the patient arrivals, process times and patient pathways with the model input. In this comparison we use the process time outcomes and fitted a distribution in Minitab, as well as storing the mean and variance of the process times. In addition, the patient pathway percentages and probabilities are deduced and compared with the input tables. All outputs are similar to the input distributions, Appendix 6 gives an overview of the pathway verification tables.

5.3 MODEL VALIDATION

After the verification we are able to validate the model. For this step law (2007) lists six different techniques for increasing the validity and credibility of the simulation model:

1. Collect high-quality information and data on the system
2. Interact with the manager on a regular basis
3. Maintain a written assumptions document and perform a structured walk-through
4. Validate components of the model by using quantitative techniques
5. Validate the output from the overall simulation model
6. Animation

For validation, we use the research Visser (2011) conducted within the ZonMw project, the work done by van der Linde (2012), and use historical data from both organizations and the two week measurements period. In addition, model changes are discussed with stakeholders such that assumptions and changes made are agreed upon and documented. Regarding high-quality data on the system, we used four years (2008-2011) of patient arrivals to base our arrival rates upon, which was preciously based on one year, Chapter four details this data analysis.

As part of the measurement period, additional times are recorded to further validate the simulation model. By comparing these measurements with the simulation model outputs an evaluation of the simulation model validity is possible. For validation, the following measurements were done:

- Waiting times diagnostics: the time between a request for a diagnostic test and the start of a diagnostic test.
- Length of stay patients (ED): the total time a patient was in the ED, including treatment, waiting and diagnostic process times.
- Waiting time for GP/NP consultation: the time between the scheduled and actual start of a consultation.
- Waiting time for triage self referrals: the time between a self-referring patient arriving at the IEP (first contact at the front-office) and the start of triage.
- Medical specialist waiting: the time between request and arrival of specialist at ED.

The waiting times for the diagnostic tests were insufficiently measured to be used in validating individual diagnostic waiting times. Expert opinion however, does correspond with the diagnostic waiting times from the simulation model.

Another validation point is the waiting time for the GP and NP consultations. In these waiting times there is a discrepancy between the measurement period times and simulation model, 17 minutes on average in the simulation model, and 14 in reality. From expert opinion, this is caused by the process times for GP post consultations taking too long (on average). Therefore, we tune the parameters of the consult process times for the GP post, this results in a new average consultation time of 11 minutes, and an average waiting time of 14 minutes (Van der Linde, 2012). This corresponds with the measurements period waiting time.

In validating the length of stay of patients, we used data from the ED, where patient registration and discharge times are recorded. The ED average length of stay from the original simulation model is 140 minutes, while average historical length of stay is 100 minutes. Looking at the length of stay per urgency type we see a considerable difference between model and reality. Most noticeable are that the lower urgency (green & blue) patients spend a considerable amount of time longer at the ED in the model than in reality. At the ED the most time consuming tasks are treatment and the taking of patient history. These process times are established using expert opinion and depend only on the simulation group of the patient. In effect this means that a low urgency patient in simulation group 2 has the same (on average) treatment and patient history times as an orange urgency patient in simulation group 2.

In addition, the waiting times for medical specialists are measured, Table 12 below shows the measured outcomes per urgency type. Comparing these measurements with the current waiting times per urgency type in the simulation model, which are 15 minutes for orange, and 60 minutes for yellow and green patients, the average measured time for green patients stands out most. The average waiting time was 45 minutes, while in the model the waiting time is 60 minutes. Unfortunately, in total there were 21 measurements done, with five measurements regarding green patients, and of the measurements conducted, all were done during weekday office hours. Based on this we choose to use the original expert opinion input data for specialist waiting times.

urgency	average waiting time (min)	number of measurements
red	n/a	0
orange	17.8	6
yellow	53	10
green	44.8	5
blue	n/a	0

Table 12: Medical specialist waiting times per urgency

To reduce the length of stay of specific urgency types, we assume the treatment and patient history times are not only simulation group dependent, but also urgency dependent, which is validated by experts. In the model we give a patient's process- and taking history times a factor based on urgency, Table 13 shows these factors.

Urgency	ED factor
Blue	0.35
Green	0.35
Yellow	0.86
Orange	0.86
Red	0.72

Table 13: ED treatment and patient history factors

As can be seen in the table, all factors are lower than one, meaning that the average process times decrease for all urgencies. This is done as normalizing from the most common urgency groups still produced an average length of stay exceeding 110 minutes. Using these values, the average length of stay is under 103 minutes, with the proportional average length of stay per urgency being similar to the historical data.

During validation, the processes that are tuned, to better reflect the current situation, are based on measurement period outcomes and expert opinions. After validating individual processes, the ED length of stay in the simulation model is still higher than in reality. This is caused by lower urgency patients staying at the ED for a disproportionate amount of time compared to higher urgency patients. In addition, the measured waiting times for specialists during the measurement period indicates that these too may better reflect reality if more extensive measurements are done. Based on this, and expert opinion, we opt to modify the process times, such that the length of stay for patients is more urgency dependant, and also better reflects reality.

Finally, another important validation method is the validation through animation, which is also used to validate the simulation model (Van der Linde, 2012). Based on the changes made to the simulation model and validation thereof, we conclude that is model is valid, and is useable for the overall comparison of different organizational interventions. However, both waiting times for specialists, as well as process times, are still mainly based on expert opinions. By conducting a more extensive measurement period, and data analysis, the validity of the simulation model may be further improved.

6 INTERVENTIONS

In this chapter we discuss and formulate the interventions used in optimizing the integrated emergency post. We divide possible interventions over process interventions, resource interventions and environmental changes. Process interventions are interventions that are procedural in kind, such as changing process orders or process authorizations. Resource interventions entail changes in available resources in the IEP. Environmental changes, or external factors, concern the effect these may have on an IEP. Indeed it has been found that, for example, inpatient bed availability has a strong correlation with ED length of stay (Paul et al., 2010).

Following this categorization of interventions, we use an experimental design to determine the influence of individual changes in processes and resources, as well as the combined effects of different interventions. After determining what process and resource interventions are promising, we evaluate their (interaction) effects, and combine interventions to find an optimal intervention set . Finally we use the environmental changes in a sensitivity analysis to compare the best found solution with the current situation.

6.1 PROCESS INTERVENTIONS

Process interventions are interventions based on procedural or authorization changes. An example of such a procedural change is putting the ordering point of diagnostic tests earlier in the process pathway (Kirtland et al., 1995), (Samaha et al., 2003). In addition to such procedural changes, another aspect of process changes are on a task related level. Such interventions may arise from problems such as filing lots of paperwork which bogs down certain tasks in the overall health care process. These interventions however fall outside the scale of the simulation model, where assumptions are made such as an instant notification, or awareness, of diagnostic test result availability.

A higher level of detail in a simulation model might result in a more accurate representation of reality. However, any lack of detail is included in all simulated interventions and this creates an equal estimation error for every intervention. Interesting is that many process interventions have been implemented to certain degrees by the construction of an IEP. For example, the GP post acts as a gatekeeper and primary acute care provider and may be seen as a fast-track pathway, siphoning patients that do not belong at an ED (low urgency) to the GP post.

As mentioned, fast-track care pathways are a dedication of resources to a subset of patients. The IEP however already created such a division of patients by redirecting the high urgency patients into the ED. Furthermore the employment of a physician assistant and nurse practitioner create an additional division in patients, as they treat the (relative to physician/resident) lower complexity patients. Therefore an additional form of fast-tracking patients seems unnecessary, as especially from an ED point of view, all patients that enter the ED require the attention of a resident or medical specialist.

The following list details the potential process interventions we consider, followed by their implementation in the simulation model.

- Using a single triage system for both the GP post and the ED.
- Letting triage nurses order diagnostic tests through protocol.
- Priority only given to high(est) urgency patients.
- Prioritization of staff assignment to patients.
- Direct admission requests for patients with high admission probabilities.

Using a single triage system for both GP post and ED

Currently, patients that enter the ED are triaged by an ED nurse. In the future both the GP post and ED are expected to use the same triage system and this would allow patients to be triaged only once when they enter the IEP, either when they call the IEP, or on walk-in for self-referrals.

Letting triage nurses order diagnostic tests through protocol

Through protocol it is possible to immediately start diagnostic tests without requiring a resident to order the diagnostic test. An example would be the drawing of blood for lab analysis after triage. Normally a patient would wait for a physician consultation after which a need for diagnostics is established, creating a new delay for diagnostic results. A direct ordering of diagnostics may immediately start both waiting times. In reality this already happens at the IEP, as mentioned in the model adaptations in 3.4.2. Patients with a high probability of needing specific diagnostics, based on their DRG, are immediately queued for these diagnostic tests. In theory a perfect assessment of needed diagnostics on triage would enable medical treatment to take place without interruptions and potentially reduce length of stay. As an intervention we add all diagnostics to the pre-treatment diagnostic round that are required in more than 50% of the cases. Table 14 shows the pre-treatment diagnostic tests per simulation group, changes from the current situation are highlighted.

DRG	Lab	ECG	echo	X-ray	CT
1	Pre	Pre	Pre	Pre	Pre
2	Pre	Post	Post	Post	Post
3	Pre	Post	Post	Pre	Post
4	Pre	Post	Post	Post	Post
5	Pre	Post	Post	Post	Post
6	Pre	Pre	Post	Post	Pre
7	Pre	Pre	Post	Pre	Post
8	Pre	Post	Post	Post	Post
9	Pre	Post	Post	Post	Post
10	Pre	Post	Post	Post	Post

Table 14: Increased pre-treatment diagnostics

Arguably it is not always possible to discern what diagnostics are needed without stopping triage and starting to diagnose a patient and thus starting treatment. This means that in reality this increase in needed diagnostics detection would come at a cost; increased triage time, increased knowledge needed to determine diagnostics (triage conducted by Physician assistant or resident), increased unnecessary diagnostics (ordering tests without being certain such a test is needed), or a combination of these factors. Evaluating this intervention however enables us to determine whether there is a potential waiting time reduction in increasing pre-treatment diagnostic tests.

Priority only given to high(est) urgency patients

A problem arising from patient prioritization through urgency designation is that potentially low urgency patients are constantly added to the back of the waiting queue as higher urgency patients enter the IEP. A green patient almost waiting for two hours is pushed back by an entering yellow patient who can, going by urgency definitions, wait for one hour.

In the simulation model a patient may encounter extra added waiting time based on their urgency, as described in 3.4.2. Using the simulation model we can evaluate whether a change in such delays is possible without violating higher urgency waiting times. As an intervention, we change the added waiting time for lower urgencies. In effect this means all lower urgency patients (U3, U4, Blue, and green) are equal in prioritization, as can be seen in Table 15.

Urgency	Current added waiting time	Intervention waiting time
U1	225	225
U2	180	180
U3	60	120
U4	0	120
Blue	0	120
Green	120	120
Yellow	180	180
Orange	230	230
Red	240	240

Table 15: Patient prioritization (added waiting time in minutes)

Prioritization of staff assignment to patients

For certain process steps, where several staff types are authorized to perform these steps, there is a prioritization in which employee to assign to which task. These process steps are treatment (depending on urgency) and cast application. In these steps, the most qualified staff type is preferred. Given that there is uncertainty in what patients (and the process steps they require) may enter the IEP, it may be beneficial to keep the most flexible staff type available to ensure flexibility. As an intervention we invert the prioritization order, as seen in Table 16.

	Physician	NP	ED nurse
Current prioritization treatment GP post	1	2	n/a
Intervention prioritization treatment GP post	2	1	n/a
Current prioritization cast application	n/a	1	2
Intervention prioritization cast application	n/a	2	1

Table 16: Task reprioritization

Direct admission requests for patients with high admission probabilities

When a patient is to be admitted into the hospital, there is often a delay before exiting the IEP. This delay may be caused by multiple factors, such as waiting for a nurse to pick up the patient, or waiting till a bed is available. During this time a patient stays in an ED room and as such occupies that room, preventing other use of that resource. Whether a patient goes home, is admitted to the hospital, or exits the ED otherwise, depends on the simulation group, as described in 3.3.2. These admission probabilities are shown in Table 17.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Exit home	0.807	0.833	0.670	0.529	0.487	0.091	0.175	0.284	0.619	0.350
Transfer	0.002	0.017	0.018	0.005	0.002	0.036	0.011	0.006	0.004	0.026
Admittance	0.191	0.150	0.312	0.466	0.511	0.874	0.815	0.710	0.377	0.624

Table 17: Exit destination probability per DRG (Visser, 2011)

Looking at the admittance ratios, a considerable number of patients from simulation group six (neurology patients) and seven (pulmonary patients) are admitted into the hospital. A way to reduce waiting for patient admittance is to immediately request admittance for patients within that group. In reality this can be achieved by early notification of wards that a patient has entered the IEP that will most likely require admittance, such that wards may prepare for a patient arrival before the patient is ready for admittance. In the simulation model we start the hospital admittance waiting time as soon as a patient enters the IEP and is triaged to represent a direct admission request. After treatment a patient either exceeds the waiting time for admittance and is admitted immediately (bed is available) or there is some time remaining before admittance (bed is available soon).

A consequence of this intervention however is that in reality beds would also be requested for patients that may go home after ED treatment. Comparing the average waiting time for an available bed (24 minutes) to the length of stay at the ED (100 minutes) however shows that it is not necessary to immediately request a bed admittance upon triage, but that possibly after some diagnostic and treatment steps requesting a bed would still be effective while reducing the probability of requesting unneeded admittance. Therefore, we do consider this intervention to evaluate the effect of the hospital admittance times on the IEP.

6.2 RESOURCE INTERVENTIONS

Resource interventions may entail changing staff numbers, rooms and equipment. Potential resource interventions we consider are:

- Varying the number of rooms and diagnostic equipment available.
- Alternate staff available (staffing levels).
- Alternate staffing schedules.
- Using ED specialists.
- Using dedicated medical specialists.
- Staff resource pooling.

Varying the number of rooms and diagnostic equipment available

The number of rooms available in this situation is constrained by the number of rooms built. However, in the current situation, the ED and GP rooms are seen as resources that are used only by the ED and GP post respectively. The sharing of resources may potentially reduce the forming of waiting times for either the ED or GP post. An example of this would be using the rooms of the GP post for ED patients when the ED is overcrowded. Similar to increasing the number of rooms, an increase of diagnostic equipment may be evaluated. Table 18 gives the current number of rooms and diagnostics available. As interventions we increase the number of ultrasound and ECG equipment available by one, as well as adding a (virtual) CT and X-ray room to evaluate the effects of added diagnostic tools. In addition, we let ED patients with low urgency (green/yellow) be treated in a GP room.

resource	available
GP room	6
ED room	8
X-ray room	2
CT room	1
Plaster room	2
ECG	1
Ultrasound	1

Table 18: Resources currently available

Alternate staffing levels

Varying staffing levels is also an often explored intervention in simulation studies. The availability of staff is determined per hour in the simulation model. All staff types have a given minimum that should be present. In reality this corresponds with the night shift staffing levels shown in Table 19.

Staff type	Number required
GP assistant	0
Triage assistant	1
GP	2
ED nurse	2
Resident (AI)	1
Resident (AC)	1
Physician assistant	0

Table 19: Mminimum (night time) number of staff required

Currently the number of staff types and shifts allows for many possible staffing level combinations. To explore the effect staff types have on the IEP, we use interventions where we increase the number of staff available by one, during the peak hours, being the daytime Saturday and Sunday shifts.

Changing staffing schedules

In addition to staffing levels, another intervention could be a shift in staffing schedules. An example of this is the shifting of a schedule in order to better fit health care demands. Looking at other simulation studies that evaluated staffing schedules using simulation, an often used approach to generate schedule alternatives is to compare staffing levels with the number of patients arriving in the system (Draeger, 1992); (Rossetti et al., 1999); (Coats & Michalis, 2001); (Tan, Gubaras, & Phojanamongkolkij, 2002). Looking at the number of GP consultations per hour in Figure 13, it becomes clear that around 8 AM patients start entering the IEP until around 6PM. The exception to this are of course the weekdays, when the GP post opens at 5PM, where the number of patients immediately starts at a level slightly below Sunday arrivals.

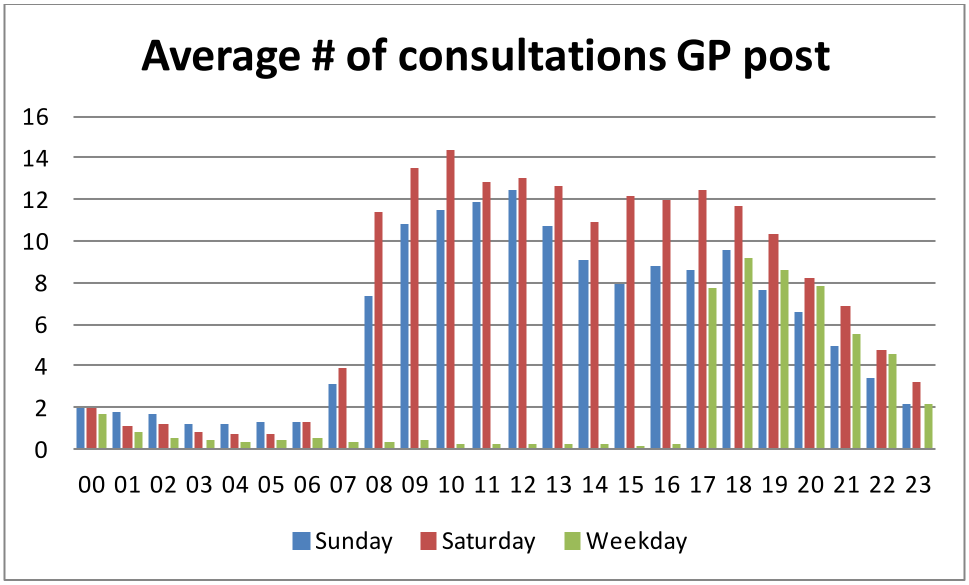


Figure 13: Number of consultations GP post (14-4-2010 to 13-4-2011)

The number of staff working per hour shows this similar trend, most shifts start around 8AM and last until 4-6PM. As an intervention we create a new schedule for the busiest day, Saturday, for the staff types of which more than one person is working. This gives an indication if such a shift change has a positive or negative effect on the IEP, and what type of shift changes may be further investigated. As alternatives we propose a time-shift creating an early and delayed version of these shifts for one of these staff members, as shown in Table 20.

Staff	Shift	Early version	Late version
GP	8:00-17:00	7:00-16:00	10:00-19:00
GP assistant	8:00-18:00	7:00-17:00	10:00-20:00
ED Nurse	8:00-16:00	7:00-15:00	10:00-18:00

Table 20: Shift alternatives

Using ED specialists

A stated goal of ZGT is to use ED specialists outside office hours as well as during office hours. Table 21 shows the desired ED specialist roster. In the table, an SA is an ED specialist, PA a physician assistant, and RES a surgical resident.

Shift	mon	tue	wed	thu	fri	sat	sun
08.00-16.00	SA	SA	SA	SA	SA	SA	SA
10.00-18.00	SA+PA	SA+PA	SA+PA	SA+PA	SA+PA	SA+PA	SA+PA
16.00-00.00	SA+RES	SA+RES	SA+RES	SA+RES	SA+RES	SA+RES	SA+RES
00.00-08.00	SA	SA	SA	SA	SA	SA	SA

Table 21: ED specialist roster

As an intervention we use this roster to evaluate the effects of using ED specialists. In addition we use the current roster and replace residents with ED specialists to evaluate the impact of a staff type that can treat patients regardless of simulation group.

Using dedicated medical specialists

Having dedicated medical specialists at the ED may have profound effects on the ED, as treatment times are reduced, and requesting medical specialists are no longer applicable. Depending on the urgency type of a patient, a medical specialist arrives at the IEP with a certain delay (or waiting time). In reality we see that at times patients (of medium-low urgency) have to wait for a considerable amount of time before a medical specialist arrives. As an intervention we use medical specialists at the ED instead of residents. This gives an insight of waiting times for external specialists.

Staff resource pooling

Currently, the physician assistant performs tasks during out-of-office hours at the GP post, and tasks at the ED during office hours. In reality, these GP post tasks during out-of-office hours are the same as those carried out by nurse practitioners, such that during some weekends a PA is working, and during others a NP. A nurse practitioner however does not work at the ED. In the simulation model the PA working out-of-office hours is modeled as an NP, as they perform the same tasks. As an intervention we let the PA also carry out their tasks at the ED during out-of-office hours, and replace the NP in the roster with a PA.

Another occurrence at the integrated emergency post is that at times either the ED or GP post is getting overcrowded with patients. Currently, both organizations are split, and "helping out" in practice does not occur. In theory a staff member, such as the physician assistant, could help and treat patients at both the ED and GP post, depending on the situation.

Further pooling of staff resources may be beneficial, as having medical staff that can perform a diverse set of tasks at both the ED and GP post enables them to treat patients where necessary. As interventions we give cross-organizational task authorizations to certain staff types as follows:

- Physician assistants can perform both their ED tasks, as well as GP post tasks simultaneously.
- ED nurses can treat/consult with U4 patients at the GP post, similar to the physician assistant or nurse practitioner ED nurses, with additional training, could treat lower urgency patients at the GP post.
- ED specialists/residents can treat/consult with patients at the GP post. In the original situation, any patient that self-referred to the ED was seen by one of the residents, PA, or specialists. As an intervention we again let ED specialists and residents treat patients at the GP post.

6.3 SENSITIVITY ANALYSIS

Given that the IEP is interacting with many other care providers and patients often continue their health care pathway at another care provider, the influence of environmental factors may give considerable insights into the performance of the IEP. An often explored factor is the patient demand itself, and insights into this effect may indicate "tipping" points when overcrowding appears. Potential environmental changes we consider are:

- Varying patient demand
- Varying patient urgency types (e.g., varying number of "true" acute care patients)

Modeling environmental changes in the intervention set can give insight into the effect on the IEP. These changes however are not interventions. If one could choose values for these environmental factors there would be values best for all interventions. These variables are to be discarded in an optimization search, as good solutions would gravitate toward beneficial environmental factors. They can however indicate the effects of potential changes, and as such are included in the list of simulation inputs. As environmental changes we place a modifier on the current environmental values of the IEP.

6.4 EXPERIMENTAL DESIGN

In order to evaluate all these interventions we may use an experimental design, as our goal is to find which interventions have the greatest influence on the IEP. Ideally we wish to run as little simulations as possible, as a single intervention takes a considerable amount of time to run. A solution to this is to use a "base" version of the simulation model, that is the current situation of the IEP, and modify one input variable at a time. For process interventions this means we run all possible interventions as these are defined as a single procedural change from the current situation. This gives a one factor at a time approach that disregards interaction effects (Montgomery, 2008). There is however a probability that these process interventions interact. Changing test protocols, such as immediately ordering ECG tests for DRG group 6 an 7 patients, theoretically increases patient throughput. The direct admission request of patients in group 6 and 7 also aims to reduce length of stay at the IEP. It is possible that these effects may interact even further decreasing (or increasing) average length of stay.

Process experimental design

In order to account for interaction effects we use a 2^k factorial design, shown in Table 22. Here we define the status quo as "-" and the process intervention change as "+". The responses in an experimental design are the simulation outcomes, or performance indicator results. To evaluate the interventions we look at the length of stay at the GP post, the length of stay at the ED, and the overall waiting time for patients. The process interventions are listed below, followed by a table depicting the experimental design with all combinations of interventions.

1. Using a single triage system for both the GP post and the ED.
2. Letting triage nurses order diagnostic tests through protocol.
3. Priority only given to high(est) urgency patients.
4. Prioritization of staff assignment to patients.
5. Direct admission requests for patients with high admission probabilities.

Factor combination	Single triage system	Pre diagnostic tests	Prioritization low urgency patients	Staff assignment	Direct Admission requests	Response
1	-	-	-	-	-	R1
2	+	-	-	-	-	R2
3	-	+	-	-	-	R3
4	+	+	-	-	-	R4
5	-	-	+	-	-	R5
6	+	-	+	-	-	R6
7	-	+	+	-	-	R7
8	+	+	+	-	-	R8
9	-	-	-	+	-	R9
10	+	-	-	+	-	R10
11	-	+	-	+	-	R11
12	+	+	-	+	-	R12
13	-	-	+	+	-	R13
14	+	-	+	+	-	R14
15	-	+	+	+	-	R15
16	+	+	+	+	-	R16
17	-	-	-	-	+	R17
18	+	-	-	-	+	R18
19	-	+	-	-	+	R19
20	+	+	-	-	+	R20
21	-	-	+	-	+	R21
22	+	-	+	-	+	R22
23	-	+	+	-	+	R23
24	+	+	+	-	+	R24
25	-	-	-	+	+	R25
26	+	-	-	+	+	R26
27	-	+	-	+	+	R27
28	+	+	-	+	+	R28
29	-	-	+	+	+	R29
30	+	-	+	+	+	R30
31	-	+	+	+	+	R31
32	+	+	+	+	+	R32

Table 22: 2^k factorial design of process interventions

Effectively this means that, for the process interventions, we evaluate all possible combinations (disregarding resource interventions).

Resource experimental designs

Using a similar 2^k factorial design for resource interventions leads to an undesirable number of possible combinations. Listing all (combinable) resource interventions there are 14 factors, being four diagnostic tools, six staff types, and four resource pooling interventions. If we let every factor have two possible values this means there are still 2^14 (=16384) combinations.

To reduce the number combinations, we divide the resource interventions over multiple experimental designs. This gives three experimental designs to evaluate, respectively, (additional) staff member effects, diagnostics equipment, and resource pooling. The fourth experimental design evaluates variations in the staff schedule, such as using the desired ZGT roster or dedicated medical specialists. These interventions are not combined, as they are mutually exclusive. Using dedicated medical specialists means the ZGT roster is not used, as this roster does not use dedicated specialists.

Resource experimental design A

The first experimental design looks at the effects of adding staff members. There are six staff types most likely to have a positive effect, for these staff types we define the intervention as adding such a staff type during the Saturday and Sunday busy hours. This gives a 2^6 experimental design with 64 experiments.

1. ED nurse
2. Resident AC
3. Resident AI
4. Physician assistant
5. General Practitioner
6. ED specialist

Resource experimental design B

The second experimental design looks at the effects of diagnostic equipment. There are four types of diagnostic tools that may be added. As interventions we add one extra piece of equipment available for the diagnostics mentioned below, this gives a 2^4 experimental design with 16 experiments.

7. X-ray
8. CT-scan
9. ECG
10. Ultrasound

Resource experimental design C

The third experimental design combines resource pooling and allocation interventions. With four defined pooling interventions this gives a 2^4 experimental design with 16 experiments.

11. Using GP rooms for ED patients
12. Letting physician assistants perform ED tasks during the weekend
13. Letting ED nurses treat U4 patients
14. Letting ED specialists and residents treat GP patients

Resource experimental design D

The fourth experimental design evaluates schedule alternatives, as these are not combined this gives, in addition to the current situation six experiments.

15. Dedicated medical specialists
16. ED specialist roster
17. Resident-ED specialist replacement
18. Early shift change
19. Late shift change

Table 23 shows the five experimental designs formulated, we look at a total of 24 interventions, divided over process, staff, equipment, schedule and resource allocation changes. This gives an insight not only in the effect of the individual interventions, but also if these interventions influence each other.

Experimental design	Number of interventions	Number of experiments
Process design	5	32
Resource design A	6	64
Resource design B	4	16
Resource design C	4	16
Resource design D	5	5
Summed over all designs	**24**	**133**

Table 23: Number of experiments per experimental design

Table 24 lists all interventions, over both processes and resources. Appendix 7 lists all the experimental designs as they are used in the simulation model. Based on the experimental design outcomes we take the most promising interventions, and combine these experiments to find the best combination of interventions. After evaluating the process and resource interventions we use the environmental changes as a sensitivity analysis to determine their effects on the best found solution and the current situation.

Process interventions	Resource interventions
1. Single triage system 2. Extra tests during pretreatment diagnostic round 3. Reprioritization of low urgency patients 4. Changed staff allocation to patients 5. Direct admission requests	1. Added ED nurse 2. Added resident AC 3. Added resident AI 4. Added physician assistant 5. Added general practitioner 6. Added ED specialist 7. Added X-ray 8. Added CT-scan 9. Added ECG 10. Added ultrasound 11. Using GP rooms for ED patients 12. Letting physician assistants perform ED tasks during out-of-office hours 13. Letting ED nurses treat U4 patients 14. Letting ED specialist/resident treat GP patients 15. Using dedicated medical specialists 16. Using desired ZGT roster 17. Replacing resident AI with ED specialist 18. Early shift change 19. Late shift change

Table 24: List of all evaluated interventions

From these interventions, and the defined experimental designs we will evaluate the most promising interventions. The most promising interventions are combined into new intervention combination sets. From these sets, a best configuration of interventions is picked. The best set is, again, evaluated using an experimental design, to determine how the most promising interventions interact. This gives insight not only in the individual effects of all interventions, it also shows which combination of interventions is the best found. Additionally, by evaluating this set in a new experimental design, this gives insight in the (interaction) effects of the most promising interventions.

6.5 SIMULATION MODEL SETTINGS

As the outcome of a single simulation run is an estimate of true performance indicators, it is imperative to determine the number of required simulation runs (or data points needed) to make informed decisions regarding the simulation outcomes. An important aspect of computer simulation is using terminating or non-terminating simulations. In terminating simulations there are events that reset or clear the simulation model, such as closing hours, which are absent in non-terminating simulations, where operations never stop.

The integrated emergency post is part terminating, and part non-terminating, the GP post closes during office-hours, while the ED stays open at all times. In the simulation model however, office-hours are not simulated. When the GP post opens, the ED is seeded with patients based on historical data, reflecting the patients that are already at the ED when the GP post opens (and the simulation starts). This characterizes the simulation of the IEP in total as a terminating simulation, there is an event that stops simulation (the start of office hours). Additionally, this circumvents the usual needed warm-up time simulation for non-terminating simulations before a steady state is reached.

From the data analysis we concluded that there are no differences between weeks regarding patient arrivals, that is, there are no seasonal effects. There are differences however within a week, as not all weekdays and weekend days are equal with regard to patient arrivals. As we are (initially) interested in the general effects of interventions, regardless of parameters such as the day of the week or time of day, a single simulation run may be set at one week, with a simulation of one year yielding 52 data points of weekly averages. This means that after simulating a year, we have 52 data points, instead of a single data point accounting for seasonal effects, greatly reducing simulation time needed. In Appendix 8 the number of needed runs is determined per experimental design.

In this chapter the possible interventions are described, as well as how these interventions may be tested and compared in the simulation model. In order to draw conclusions from the possible interventions, we look at the interaction between interventions in Chapter 7, and based on this we evaluate the most promising interventions in Chapter 8.

7 INTERACTION OUTCOMES AND RESULTS

In this chapter we evaluate the outcomes from the experimental designs using interaction effects. By assessing interaction effects, the outcomes per experimental design are evaluated, and based on these results, the most promising interventions are defined.

7.1 EXPERIMENTAL DESIGN OUTCOMES

To compare interventions, we use the performance indicator length of stay for patients, incorporating both treatment, as well as waiting times.. As some interventions target the emergency department or GP post specifically, we split the length of stay in both the length of stay at the ED and the GP post.

Some interventions however only target a specific patient group or time frame. For example, the pre diagnostic test increase only affects patients in simulation groups 1, 5, 6, 7, 9 and 10 for some diagnostic tests. The length of stay at the emergency department decreased as a result of this overall, however it is not clear whether this effects only the mentioned simulation group patients, or also perhaps negatively influences other patients.

Another set of interventions targets specific times only, with the performance indicators being averaged over all days and times of the week. In the staff experimental design, staff was added during the weekend busy hours. Around 45% of GP post, and ED patients (outside office hours only) arrive during the weekdays, whose performance is not influenced, yet used in the performance indicators. The outcomes, in this regard, however are a conservative estimate of a more fair performance indicator. When not taking weekdays into account, experiment results would only be lower (relative) to the current situation.

7.1.1 PROCESS EXPERIMENTAL DESIGN

The process interventions evaluated are: using a single triage system (P1), ordering direct diagnostic tests for certain patient groups (P2), redistributing lower urgencies (P3), changing the staff allocation to patient prioritization (P4), and direct bed admission requests of certain patient groups (P5) (section 6.1).

To evaluate the interventions, we look at the main effects and two factor interaction effects with 95% confidence intervals. The main effect of an intervention is the difference between the average outcome of experiments using the intervention and experiments not using the intervention. For example, to calculate the main effect of direct bed admission requests (P5), we take the average length of stay of experiments 1 through 15, and experiments 16 through 32, and calculate the difference between these two averages. The two-way interaction effects (e.g., P1xP2), gives the average effect of using an intervention, if a second intervention is also used. This interaction result may be interpreted as two interventions amplifying, dampening, or not influencing each other.

Emergency department length of stay

In Figure 14, the first five plots are the main effects, followed by the two-factor effects. We see that the two-factor interaction effects are either not statistically significant, or are extremely small. The main effects of single triage, direct diagnostic requests, and direct bed admission (effect 1, 2 and 5 respectively) all decrease the ED length of stay with an average of approximately 5, 4.5, and 2 minutes, while reprioritizing patients (P3) and staff (P4) has no effect on the ED LOS.

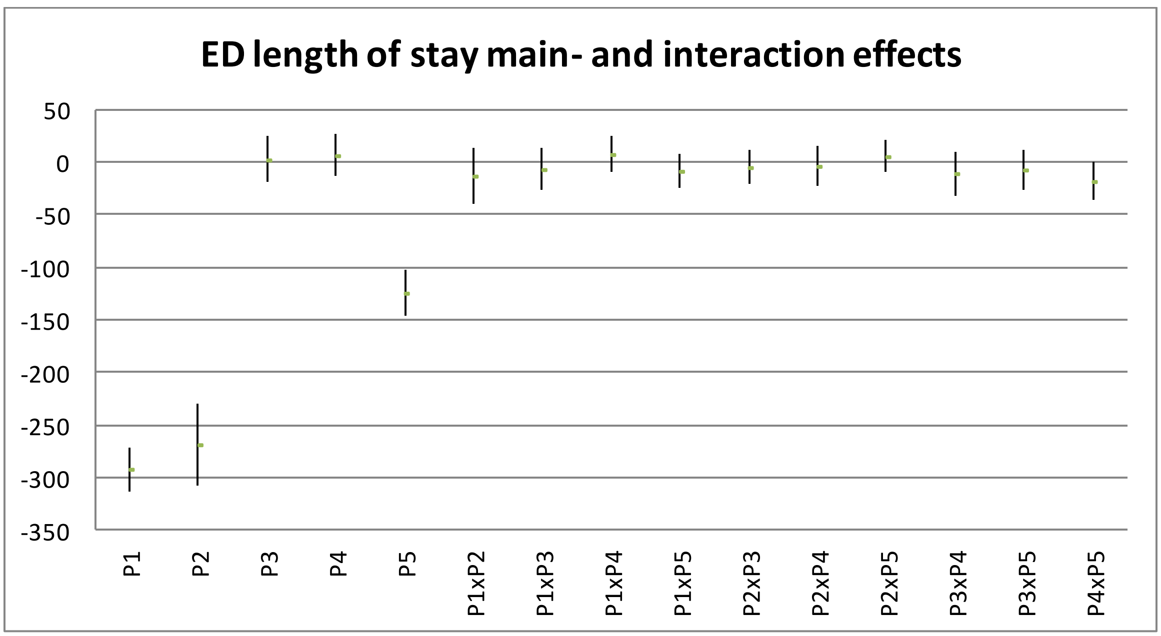


Figure 14: ED length of stay (seconds) main and two-factor interaction effects with confidence interval

With an impression of the interaction between interventions, we evaluate the relative effects of beneficial interventions. Figure 15 shows the relative change in length of stay for single triage (P1), more pretreatment diagnostics (P2), direct bed admission (P5), and the possible combinations of these interventions.

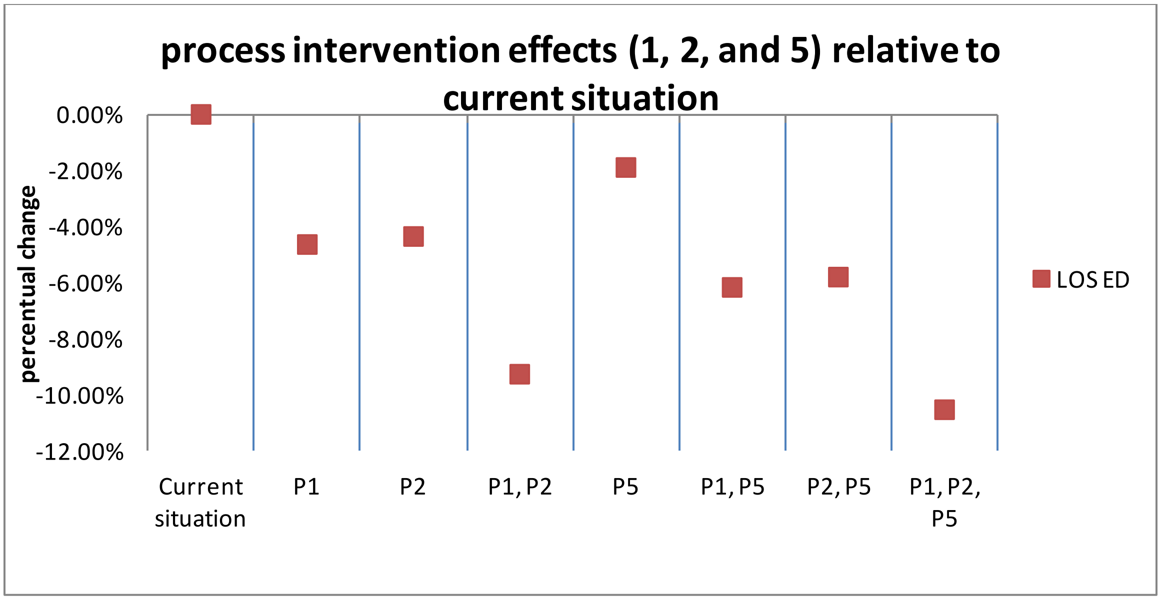


Figure 15: Relative change in ED length of stay compared to current situation

Figure 15 shows effects similar to the interaction effects from Figure 14, a single triage system (P1) and more pretreatment diagnostics (P2) both reduce the ED LOS by approximately 4.5%, and direct bed admissions (P5) reduce LOS by around 2%. When the interventions are combined, there is no interaction, and the outcome from a combination of interventions is the same as the sum of the individual intervention outcomes.

GP Post length of stay

Figure 16 shows the main- and interaction effects of the process interventions on the GP post length of stay. The two main effects that are significant, are reprioritizing low urgency patients (P3), and direct bed admission requests (P5), which respectively reduce the LOS on average by 20 seconds, and increase the LOS by 10 seconds. In addition, there is an interaction effect between these interventions, where the interventions combined reduce the length of stay more than each individually.

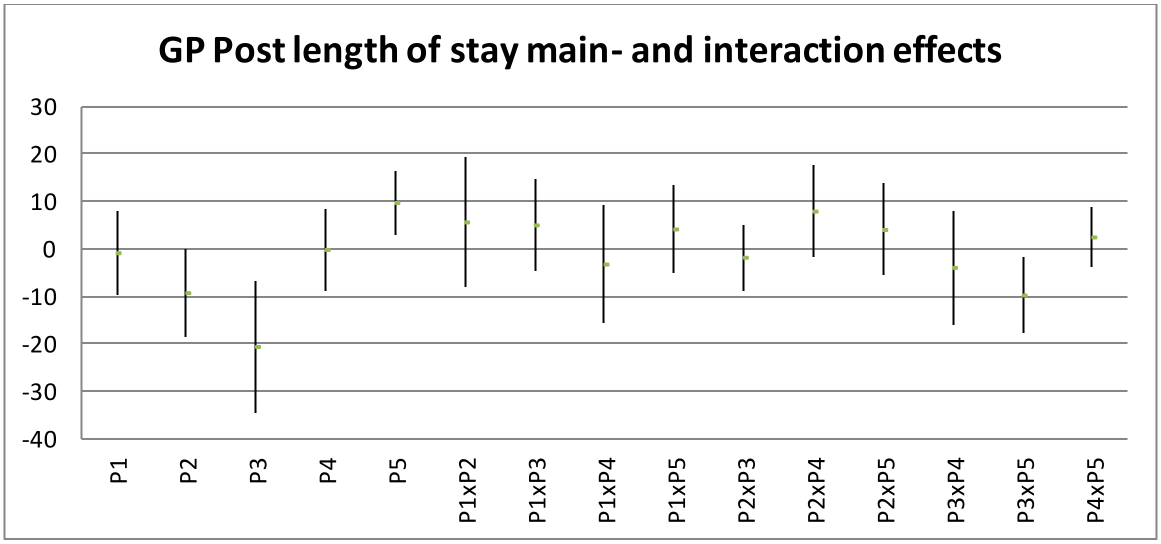


Figure 16: GP post length of stay (seconds) main and two-factor interaction effects with confidence interval

The GP post patient reprioritization means that U3 and U4 patients are no longer prioritized based on urgency, but only on waiting time, such that an U4 patient that waits longer than an U3 patient is treated first. Lower urgency patients at the ED are similarly reprioritized. Presumably, this reprioritization causes lower urgency patients to spend less time at the GP post, at some expense, for higher urgency patients. Table 25 shows the average GP post length of stay per urgency type, for both the current situation, and the patient reprioritization (P3).

Urgency	Current situation	Intervention P3	Relative change
U1	747	742	-0.6%
U2	1162	1203	+3.5%
U3	1217	1432	+17.6%
U4	1601	1436	-10.3%

Table 25: GP post length of stay (seconds) average per urgency type

As can be seen from Table 25, while the average length of stay for U4 patients reduces, this comes mostly at an increase in length of stay for U3 patients. This means that, while the average length of stay may decrease at the GP post, looking only at U3 and U2 patients, the average length of stay increases.

Additionally, direct bed admission requests at the ED increase the GP post length of stay on average with 9.5 seconds. A cause for this may be that patients that are to be admitted, occupy a room at the ED, while they are not waiting for any other resource. This may cause a bottleneck at the ED, where there are less rooms available for patients, which in turn means that shared resources, such as X-ray diagnostics, are requested less by the ED, giving more “X-ray time” to the GP post. As the intervention removes this potential bottleneck, the ED will request more diagnostics in a given time frame, reducing the available diagnostic time for GP post patients.

Figure 17 shows the relative change, compared to the current situation, for both the patient reprioritization (P3), as well as the direct bed admission for ED patients (P5). As can be seen, the reprioritization reduces the LOS by around 20 seconds (-1.3%), direct admission requests increase the LOS by around 10 seconds (+0.6%), and both interventions combined decrease length of stay by 14 seconds (-1%).

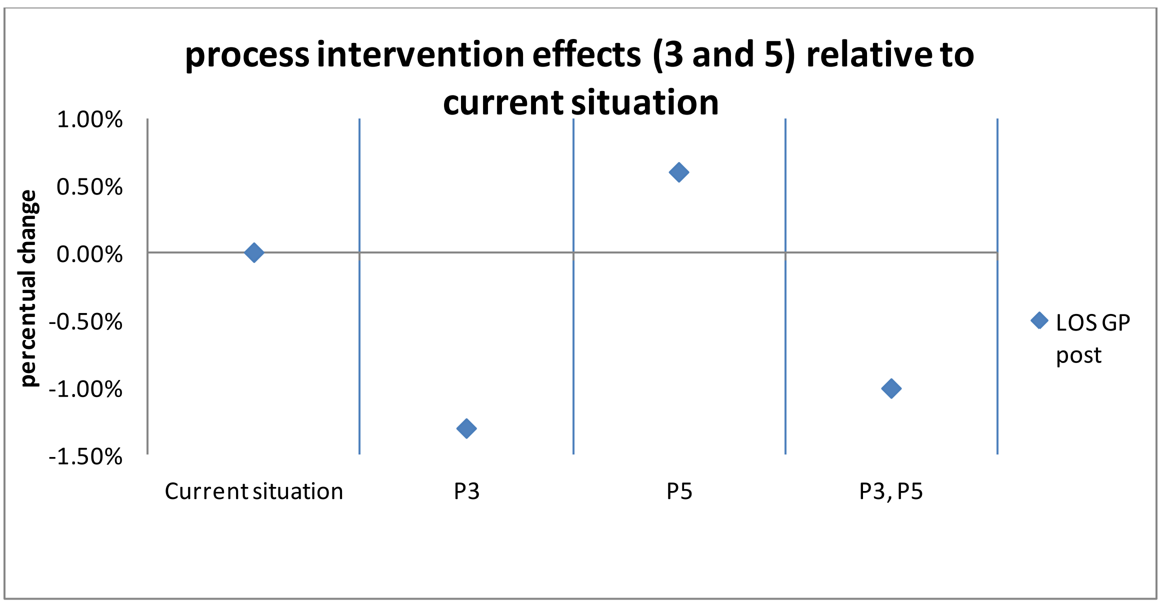


Figure 17: Relative change in GP post length of stay compared to current situation

From both the interaction effects, as well as the relative effects, it shows that, while the process interventions to some extent influence the GP post, this influence overall is small.

Summarizing we see the following effects for the ED and GP post:

- Both a single triage system (P1) as well as a direct ordering or diagnostic tests (P2) reduce the length of stay at the ED by approximately 4%.

- A direct admission of certain patient groups (P5) slightly reduces the length of stay at the ED by approximately 2%.
- These effects seem to work regardless of other intervention settings, i.e., the interventions seem to stack in length of stay reduction.
- Reprioritizing patients (P3) reduces the average GP post LOS by 1.3%, and looking at the LOS per urgency type, the LOS for U4 patients decreases by approximately 10%, while it increases for U2 and U3 patients (4% an 18% respectively).
- Direct bed admission requests at the ED increase the average GP post LOS, while significant however, this increase is quite small (0.6%).

Appendix 9 details all average outcomes of the process experimental design interventions and experiments.

7.1.2 Resource experimental designs

The resource interventions are split over several experimental designs to reduce the number of combinations and computation costs. A division is made over staff, resource, and resource allocation interventions. Additionally, several mutually exclusive (i.e., not combinable) resource interventions are evaluated as well.

Staff interventions

For staff interventions we added extra staff in the simulation model during the busiest times of the week, specifically the ED nurse (R1), surgical resident (R2), internal resident (R3), Physician assistant (R4), General Practitioner (R5) and ED specialist (R6). These busiest times are on Saturdays and Sundays, specifically during the 8AM to 4PM shift at the ED for medical residents, ED nurses and physician assistants and the 8AM to 5PM shifts at the GP post for physicians and GP assistants. Appendix 9 contains all staff experimental design outcomes.

Figure 18 and Figure 19 show the interaction effects for both GP post and ED length of stay. The biggest influence on reducing GP post length of stay is a physician assistant (R4), followed by a general practitioner (R5). In addition we see that the two-way interaction effect between these staff types is positive, interpreting this, the combination of these staff types has a diminished effect of reduction on the length of stay. Adding both a PA (average LOS reduction of 65 seconds) and GP (42 seconds) reduces the GP post length of stay with less that their individual effects combined. For the emergency department we see that the biggest influence is the ED specialist (R6), followed by surgical resident (R2) and physician assistant (R4). These reduce the average length of stay (on average) by respectively 115, 60 and 36 seconds.

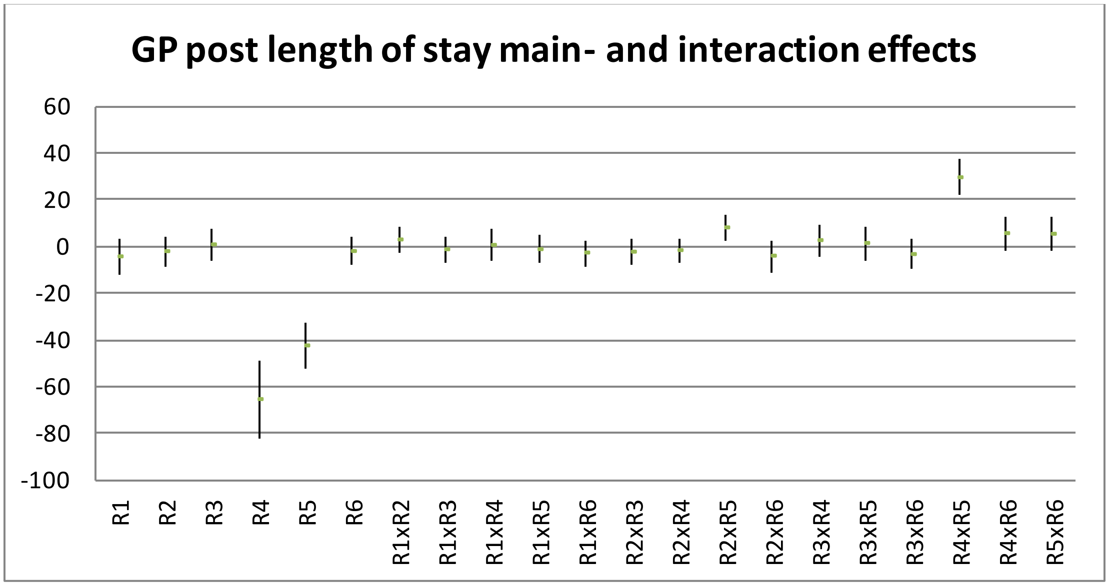


Figure 18: GP post length of stay interaction effects (seconds) and confidence intervals

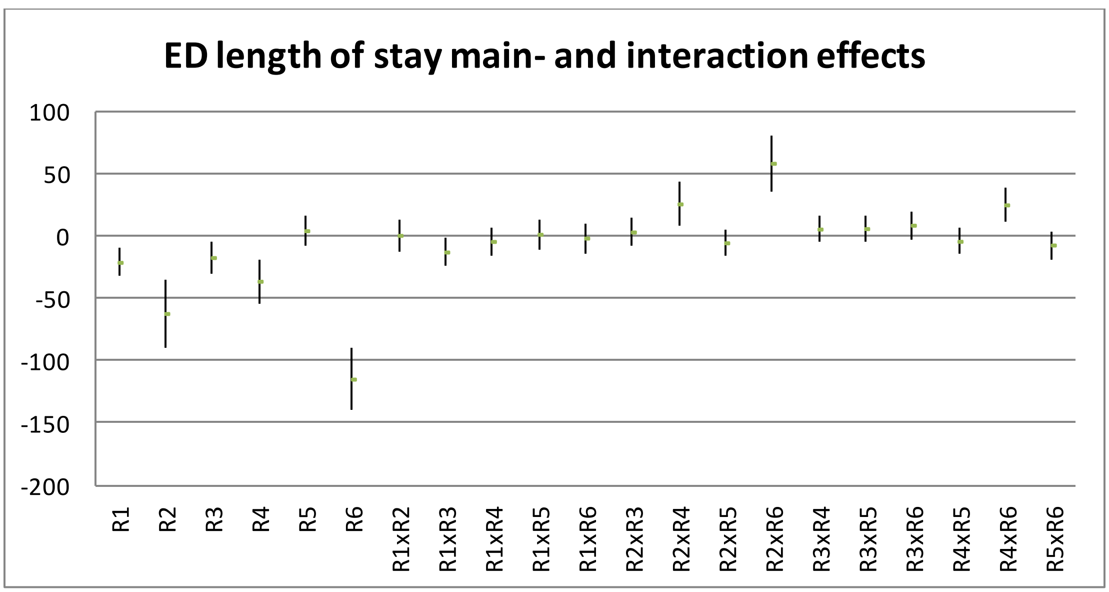
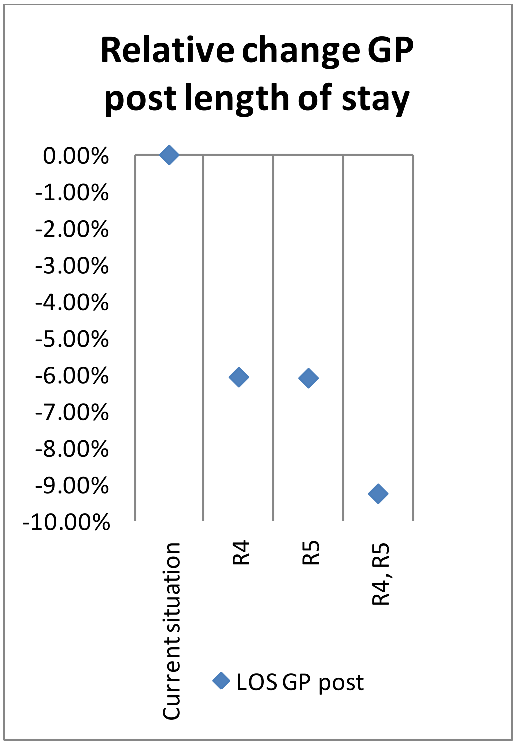


Figure 19: ED length of stay interaction effects (seconds) and confidence intervals

Based on these interaction plots, we look at the relative effects of the changes on the GP post and ED. Figure 20 details the percentual effects of the addition of staff during the weekends.



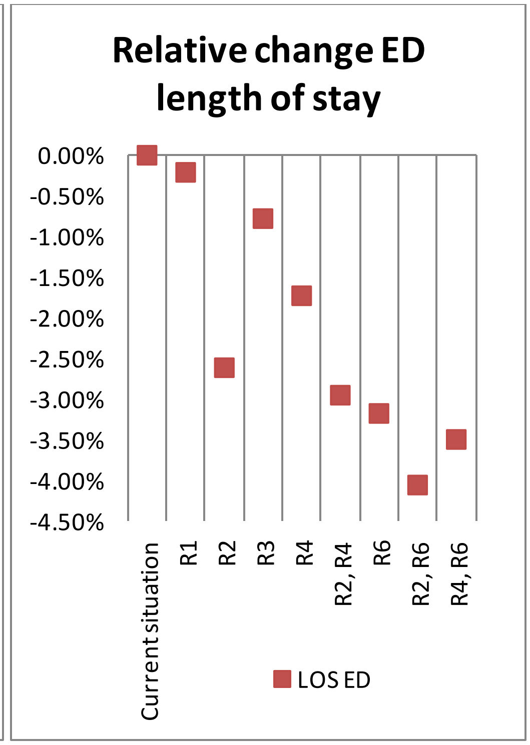


Figure 20: Relative change in GP post and ED length of stay compared to current situation

Similar to the interaction effects figure, the reduction in average length of stay is seen for every staff type, as well as the combinations where staff additions interact. Whenever more than one staff type is added, such as both a GP and PA (R4, R5), the addition of the second staff member reduces the LOS less. Either an extra PA or GP reduces the length of stay by 6% (87 seconds), and both reduce the LOS by 9.5% (133 seconds). For the ED, the greatest single effects are adding an ED specialist (-3.2%, 197 seconds), followed by the addition of a surgical resident (-2.6%, 162 seconds), and a PA (-1.7%, 107 seconds). Here too the effects of interaction are visible, as the addition of an ED specialist has a greater effect on the average length of stay than a surgical resident and PA combined.

What stands out from both actual and interaction effects, is that, while the main effect of the PA addition is greater than the GP, they are equal in a direct comparison. When more staff is added at the ED, the PA gets relatively more time to treat GP post patients, increasing the average effect over all possible intervention combinations.

Diagnostic equipment interventions

For the diagnostic equipment interventions we added extra X-ray (R7), CT-scan (R8), ECG (R9), and ultrasound (R10) tools, and in the case of the X-ray and CT scan also a virtual room where these diagnostics may take place. Appendix 9 contains all diagnostic equipment experimental design outcomes. Figure 21 shows the interaction effects for the extra diagnostics equipment.

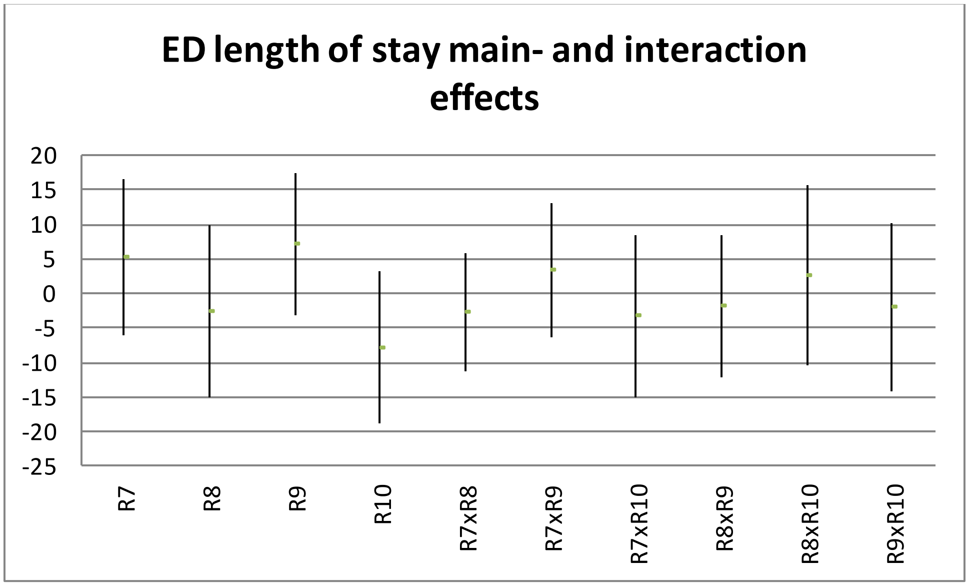


Figure 21: ED length of stay interaction effects (seconds) and confidence intervals

Going by the interaction effects, the addition of diagnostic equipment has no significant effect on the length of stay, indicating that diagnostic equipment is not a bottleneck for the IEP. To be sure adding diagnostics has no significant effect on either the GP post or ED, we evaluate the differences between the simulation runs where diagnostics are added, and the current situation, using t-tests and their resulting p-values. Table 26 shows the outcomes of these tests, for the ED length of stay, GP post length of stay, and average overall waiting time.

p-value	x-ray (R7)	CT (R8)	ECG (R9)	Echo (R10)
waiting time	0.789	0.870	0.709	0.562
LOS ED	0.938	0.993	0.890	0.947
LOS GP Post	0.951	0.831	0.796	0.444

Table 26: T-test outcomes of added diagnostics, compared to current situation

Using a standard significant level of 5%, none of the tests would mean rejecting the null hypothesis assuming there is no difference. As such, the slight differences between the simulation outcomes may be attributed to randomness in the simulation model, and not to changes in diagnostic equipment. This too, indicates that the current number of diagnostics equipment is currently enough and are not a bottleneck.

Resource allocation interventions

As resource allocation changes we let low urgency ED patients be treated in GP post rooms (R11), changed the nurse practitioner in the current roster to a physician assistant (R12), let ED nurses treat low urgency (U4) GP post patients (R13) and let ED residents treat GP post patients (R14). Figure 22 and Figure 23 show the interaction effects on both ED and GP post length of stay.

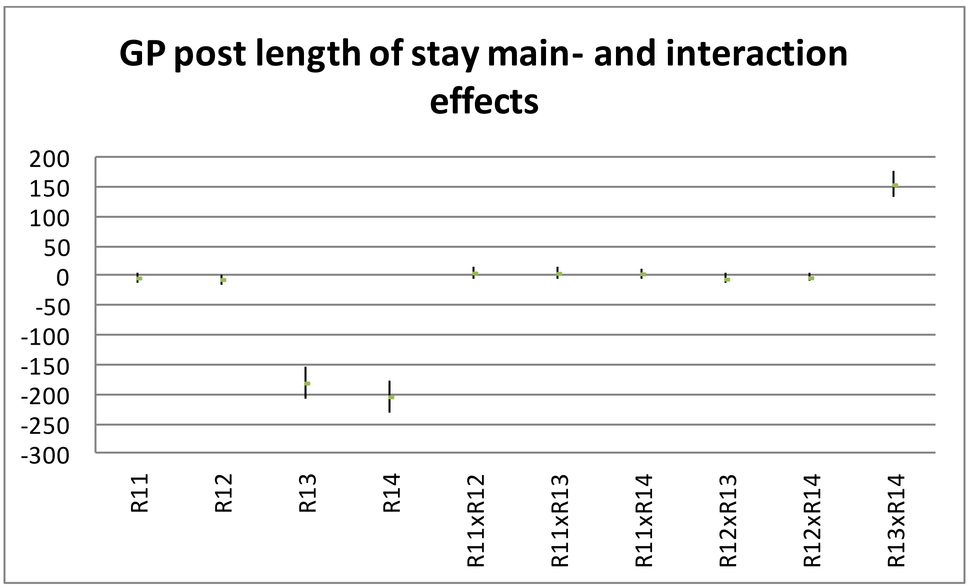


Figure 22: GP post length of stay interaction effects (seconds)

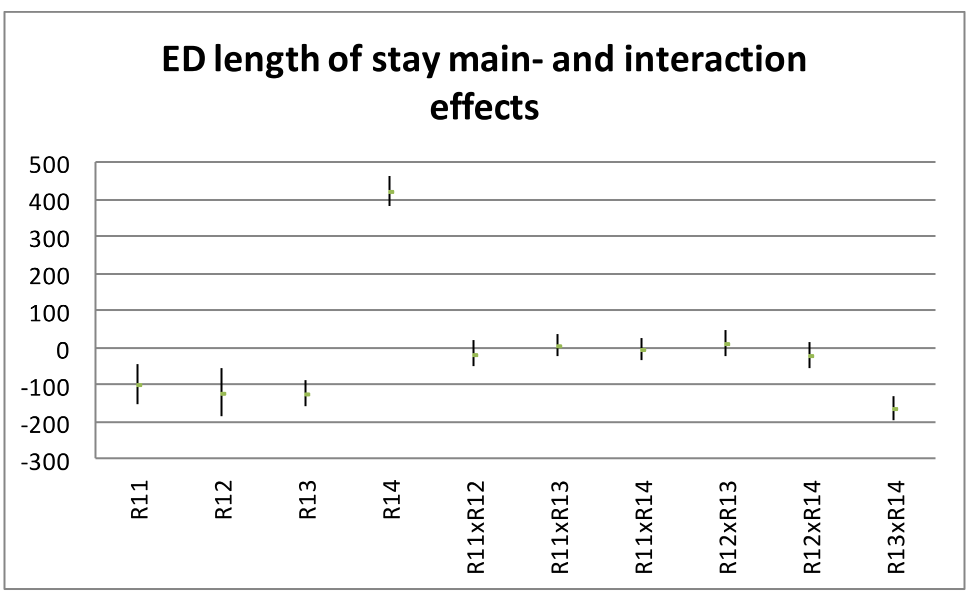


Figure 23: ED length of stay interaction effects (seconds)

Looking at the interaction effects on the GP post and ED length of stay we see that, corresponding to Figure 22, the biggest reduction on GP post LOS is letting ED staff treat GP post patients (R13 & R14). Additionally, there is an interaction effect between these interventions, where the interventions have a dampening effect on each other. This makes sense, as with both interventions all ED staff is able to treat (some) GP post patients, making it likely that the bottleneck has shifted from staff availability to another resource type, or that there are no longer enough patients entering the IEP to see a significant reduction in length of stays.

The ED length of stay is slightly improved by letting ED patients be treated in a GP post room (R11), changing the nurse practitioner in the current roster to a physician assistant (R12), and letting ED nurses treat low urgency (U4) GP post patients (R13). Finally, letting medical specialists treat GP post patients (R14) greatly increases the ED length of stay, while reducing the GP post LOS. In addition there is a positive interaction effect between letting ED nurses and specialists treat GP post patients, indicating that if both treat GP post patients, the ED patient length of stay decreases more. This can be explained as when ED nurses also treat GP post patients, this enables specialists to again treat more ED patients, bringing the ED LOS back to the original value (of not letting specialists treat GP post patients).

From the interaction effects alone, letting ED nurses treat GP post patients (R13) seems beneficial for both patient groups. However, the effect that this intervention has on the ED length of stay is unexpected, as ED nurses work at the GP post, at best the length of stay for ED patients would remain the same. This is explained by the calculation method for interaction effects, and the fact that the length of stay averaged over all the experiments is higher than the length of stay of the current situation. Because letting specialists treat GP post patients has a large negative effect on the ED, this is taken into account when calculating the main effects. As such, to get a proper indication of the effects of a single intervention, we also look at the relative change per intervention compared to the current situation, Figure 24 shows these effects.

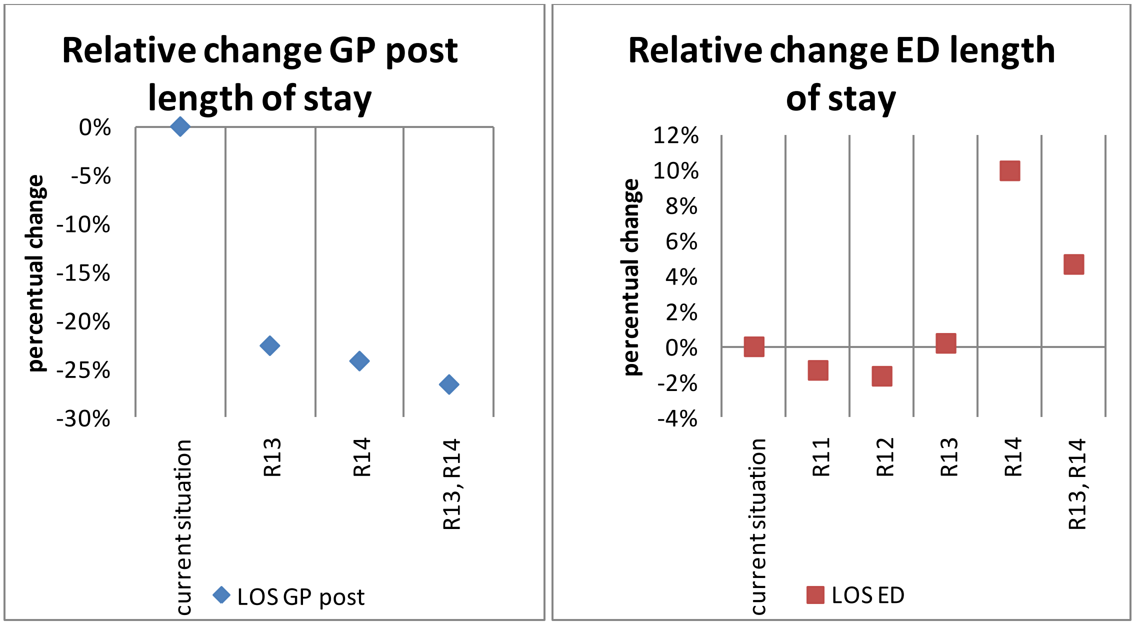


Figure 24: Relative change in GP post and ED length of stay compared to current situation

As can be seen, when either ED nurses or specialists treat GP post patients, the length of stay average reduces over 20%, both interventions simultaneously however, only slightly reduce the length of stay over the individual changes. Different from the interaction effects is that letting ED nurses treat GP post patients (R13) has no effect on the ED length of stay, indicating that this intervention has no effect on the ED.

Mutually exclusive interventions

In addition to the experimental designs we tested five mutually exclusive interventions, these are using dedicated medical specialists instead of the residents (R15), using the desired ZGT roster (R16), replacing the internal specialty resident with an ED specialist (R17) and creating an earlier (R18) and later shift (R19) version of the Saturday schedule for the staff types that have more than one person working at that time. As these interventions are not combined, there are no interaction effects to evaluate. Figure 25 shows the effects of these interventions compared to the current situation.

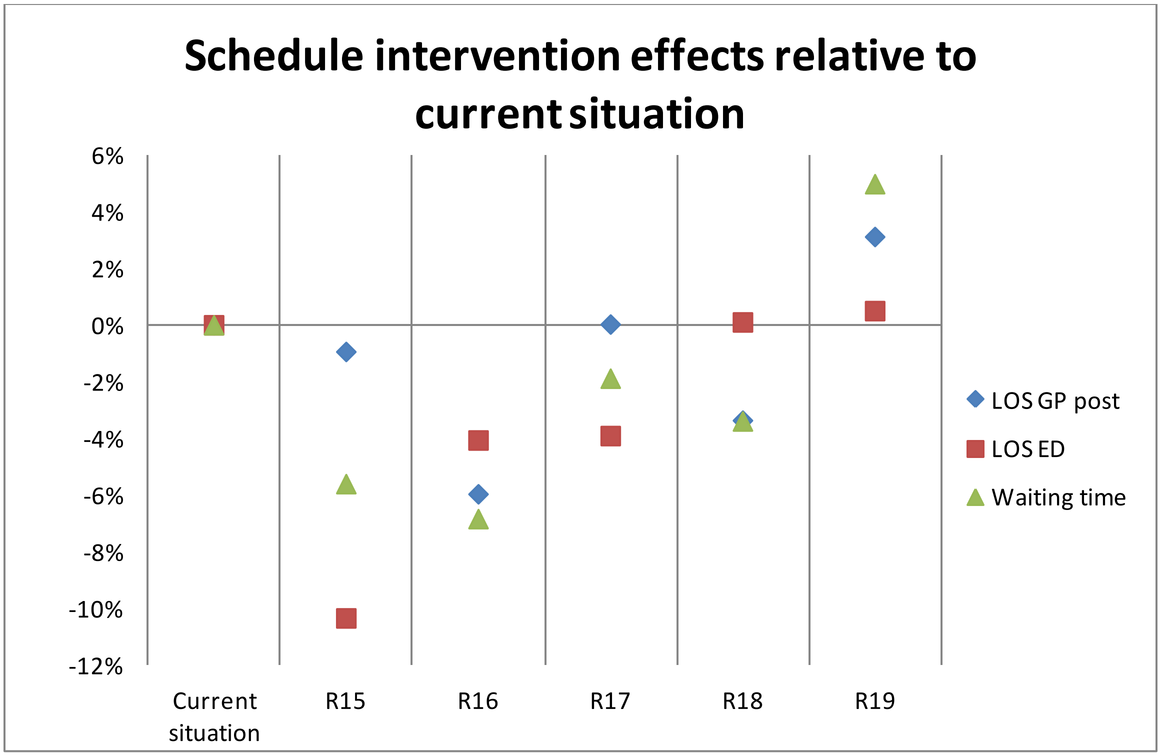


Figure 25: Schedule experimental design results

Scheduling dedicated medical specialists (R15) reduces the ED length of stay by approximately 10% while reducing overall waiting times with 6%, these reductions are caused by the reduced treatment times of specialists, and the lack of a waiting time before specialists arrive at the IEP. The ZGT roster (R16) and replacing internal residents with ED specialists (R17) show overlap, as the ZGT roster is similar to R17 with an additional physician assistant during the weekend. This shows that the effect of the extra PA has little effect on the ED length of stay, while reducing the waiting time and GP post LOS by around 6%. Experiment R18 and R19 are respectively a earlier and later shift of the GP during Saturdays. A later schedule only decreases performance and the earlier shift seems to slightly reduce the GP post LOS and waiting time.

7.2 THE MOST PROMISING INTERVENTIONS

The experimental designs and outcomes give an insight into the individual effects interventions may have on the patient's length of stay. Based on these outcomes, as well as associated costs and feasibility, we are able to discern which interventions seem promising. Table 27 gives the absolute outcomes of the individual interventions that effect the GP post or ED.

	effect on GP post LOS	effect on ED LOS
Current situation	1440	6197
P1	-20.8	-287.4
P2	-21.1	-269.7
P5	8.6	-117.2
R2	-36.4	-162.1
R3	-2.9	-48.3
R4	-87.5	-107.2
R5	-87.9	13.1
R6	5.0	-197.0
R11	-8.2	-82.7
R12	8.0	-103.3
R13	-325.6	12.1
R14	-348.4	617.1
R15	-13.3	-637.9
R16	-84.3	-250.7
R17	0.4	-241.1

Table 27: Absolute difference (seconds) per intervention compared to current situation

Considerable length of stay reductions for both ED and GP post are found in either the addition of staff types that treat surgical or low urgency GP post patients (R2, R4, R5, R6), or resource pooling that lets staff treat other patient types (R11-R14). In addition, several process changes have a positive effect on the ED length of stay, namely the direct admission requests of patients that are likely to be admitted, adding more diagnostic tests to the pre-treatment diagnostic round, and using a single triage system (P1, P2, P5). Even though performing more diagnostic tests before treatments potentially increases the number of unnecessary tests and thus costs, it is an interesting intervention to further explore, as a length of stay reduction seems possible.

While the greatest effect on the ED length of stay is using medical specialists (R15), this would also be a costly intervention, as specialists cost considerably more than residents. Similarly for the GP post length of stay the biggest influence is letting ED staff treat patients, followed by adding more staff. While letting residents treat GP post patients has a positive effect on the LOS, the emergency department length of stay increases, making this a less promising intervention. Summarizing, the most promising interventions are:

- P1 - Using a single triage system.
- P2 - Ordering pre diagnostic tests for patients that likely need them.
- P5 - Direct bed admission requests for patients that are likely to be admitted.
- R11 - Let (low urgency) ED patients be treated in a GP post room.
- R14 - Letting physician assistants treat both ED and GP post patients (i.e., use a physician assistant instead of a nurse practitioner that performs ED tasks as well).
- R2,R4-R6, R15-R17 – Addition of staff that treats low urgency GP post patients or surgical specialty related ED patients.

Most interventions have, compared to the ED, no effect on the GP post length of stay. The process interventions, as well as the dual use of rooms and staff have a positive effect on the ED length of stay, while not influencing the GP post. This sharing of staff and resources however, could also effect the GP post in other aspects. If rooms and staff may be used by the ED as well, this could result in a cost reduction for the GP post.

Some promising interventions entail the employment of more staff members that are able to treat surgical specialty patients and/or low urgency GP post patients. The interventions that add staff, however, have associated costs as well as interaction effects, indicating that the addition of staff has a diminishing effect on length of stays.

As there is still a large combination of different staff numbers possible (each with their associated costs) we take the desired ZGT roster (R16) as a baseline. ZGT has expressed that they wish to use this schedule in the future, and as such we use this schedule as a base for allowed costs, and formulate several variations on this roster roughly maintaining overall costs. With regard to the schedule variations, these are constrained by a schedule needing staff types such that every type of patient may be treated, as such replacing the general practitioners with physician assistants may influence the emergency department length of stay, there are no more staff types that can treat high urgency GP post patients. Accounting for this, we formulate five schedules, listed below.

- S1 - Use the proposed ZGT roster (Chapter 6.2), main difference from the current situation is that an ED specialist is at the ED instead of a resident, in addition there is a physician assistant during the weekends.
- S2 - Schedule two physician assistants during the Saturday and Sunday busy hours instead of a general practitioner.
- S3 - Schedule a surgical and internal medicine resident instead of the ED specialist during the Saturday and Sunday busy hours.
- S4 - Schedule a physician assistant instead of an ED nurse during the Saturday and Sunday busy hours.
- S5 - Schedule a physician assistant instead of an ED nurse during the first opening hours of the IEP (5pm-8pm).

As more combinations would be possible (for example replacing 2 GPs with 4 PAs), these five schedules will give insight into the effect of the staff replacements that are possible. These different schedules are simulated together with the promising process and resource pooling interventions (P1, P2, P5, R11, R14).

In this chapter we evaluated the possible interventions using experimental designs, from these interventions we defined a set of most promising interventions, consisting of both process, as well as resource changes. In the next chapter we will further analyze these most promising interventions, in order to gain further insights into the individual interventions, as well as the possible effects between these interventions.

8 PROMISING INTERVENTION RESULTS

In this chapter we evaluate the most promising interventions defined in Chapter 7. By assessing these interventions, not only the effects of the individual interventions are evaluated, but their combined effects as well.

8.1 POSSIBLE INTERVENTION COMBINATIONS

In Chapter 7 five possible schedule variations are defined, combining these with the promising process and resource pooling interventions (P1, P2, P5, R11, R14), there are five new intervention combinations possible, being:

1. S1, P1, P2, P5, R11, R14
2. S2, P1, P2, P5, R11, R14
3. S3, P1, P2, P5, R11, R14
4. S4, P1, P2, P5, R11, R14
5. S5, P1, P2, P5, R11, R14

Depending on the intervention, either the weekdays or the weekend is affected. To evaluate the effect of every intervention, we not only make a distinction between length of stay at the ED and GP post, but also in length of stay during weekend and weekdays. Additionally we look at the length of stay for high (U1 & U2, and red & orange) and low (U3 & U4, and yellow-blue) urgency patients.

8.1.1 LENGTH OF STAY

To compare the interventions, we evaluate the outcomes per performance indicator. As intervention set one to four affect the weekend, we compare the weekend length of stays for these interventions. Similarly, intervention set five affects the weekdays, and we look at the weekday length of stays. Table 28 shows the average length of stays per intervention set, as well as 95% confidence interval half width, giving an overview of the simulation outcomes.

		Current situation	1	2	3	4	5
weekend LOS	Low urgency ED LOS	6300	5102	5080	5064	5161	
	95% conf half width	90.6	48.0	46.1	48.5	48.6	
	High urgency ED LOS	6196	5426	5467	5398	5493	
	95% conf half width	83.2	66.2	70.5	71.4	71.0	
	Low urgency GP post LOS	1356	1238	1166	1235	1171	
	95% conf half width	34.4	26.4	21.1	24.7	21.3	
	High urgency GP post LOS	1151	1103	1125	1122	1084	
	95% conf half width	41.7	40.9	38.8	39.7	37.4	
weekday LOS	Low urgency ED LOS	5913					5206
	95% conf half width	60.7					47.5
	High urgency ED LOS	6414					5706
	95% conf half width	163.7					163.3
	Low urgency GP post LOS	1553					1295
	95% conf half width	39.0					24.8
	High urgency GP post LOS	1183					1179
	95% conf half width	47.1					49.3

Table 28: Performance indicators and 95% confidence intervals (seconds)

From these values we see that every combination is significantly better than the current situation regarding length of stay, the effects however, depend considerably on the performance indicator. In Figure 26 and Figure 27 we plot the average results of the weekend outcomes.

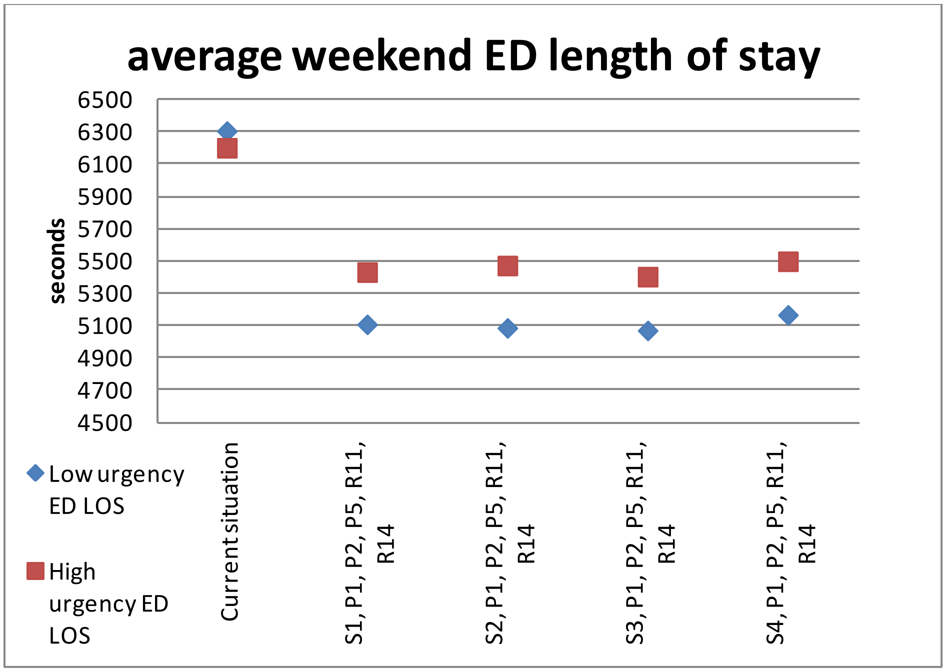


Figure 26: Weekend average ED LOS per intervention

It is clear that all intervention combinations improve upon the original situation, which is as expected, as not only the procedural interventions are implemented, there is also an additional staff member working during the busy hours. Only judging sets, the best combination is scheduling two residents instead of an ED specialist. Comparing it with the worst set however, the differences are small. While significant, the decrease in length of stay is for both urgencies less than 100 seconds.

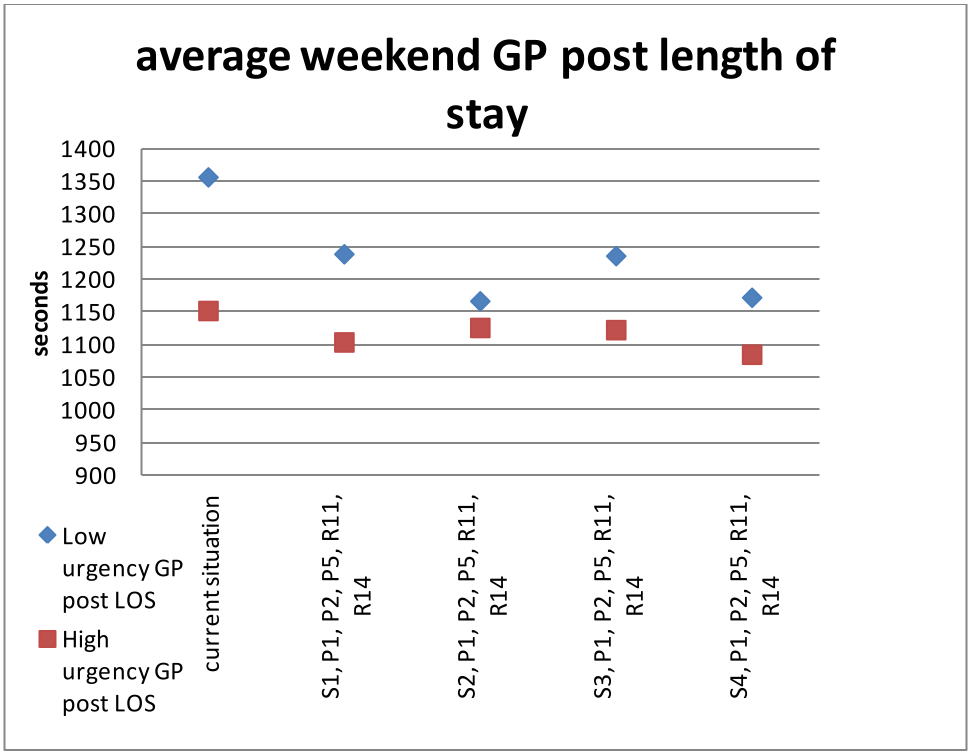


Figure 27: Weekend average GP post LOS per intervention

Similar to the ED results, we see a decrease in length of stay at the GP post, the effects however on high urgency patients is markedly lower than at the ED. Replacing a GP with two physician assistants has the greatest effect on lowering the low urgency patient LOS, while the high urgency LOS is lower than in the current situation. Based on these two figures, the differences between combinations are all minor, the length of stay at the ED between best and worst differs 100 seconds, and at the GP post the differences are all around a minute or less.

Two intervention combinations (S1, P1, P2, P5, R11, R14) and (S5, P1, P2, P5, R11, R14) affect weekdays, as a physician assistant replaces an ED nurse during the starting hours of the IEP in schedule S5 and the ZGT roster has an ED specialist and surgical resident instead of two residents during the weekdays. The other schedules are similar to the ZGT roster (S1) during the weekdays. For these combinations Figure 28 and Figure 29 show the average length of stay for ED and GP post patients. The figures show that both high and low urgency patients at the ED have reduced throughput times compared to the current situation, but replacing an ED nurse with a PA has no further effect. On average a reduction of 700 seconds, or 11.5 minutes, indicates that adding a PA during the starting hours of the

IEP does further influence the ED length of stay, which points to interaction between the ED specialist and PA during the weekdays.

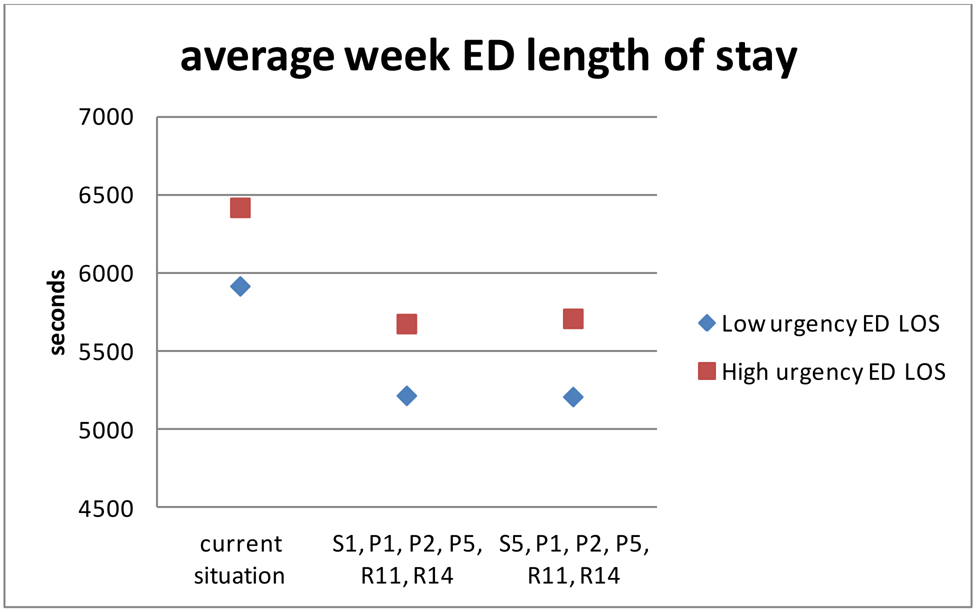


Figure 28: Weekday average ED LOS per intervention

Figure 29 shows a decrease in length of stay for low urgency GP post patients when a PA replaces an ED nurse during the weekday starting hours, and that the ZGT roster does not differ from the current situation regarding weekdays. The difference for high urgency patients between the two intervention sets are minor, on average patients are treated four seconds faster. Low urgency patient throughput is reduced with 258 seconds, or slightly more than 4 minutes. From these figures we conclude that replacing an ED nurse with a physician assistant during weekdays at the start of the IEP decreases the length of stay for low urgency GP post patients, while having no further effect on the ED length of stay.

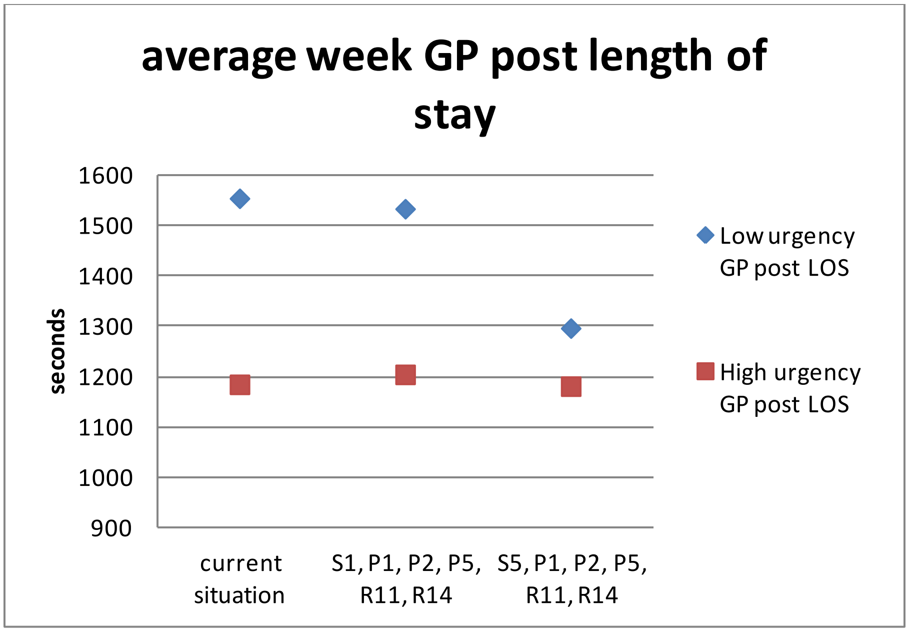


Figure 29: Weekday average GP post LOS per intervention

Based on the different length of stay indicators, the best combination seems to be the fifth intervention set (S5, P1, P2, P5, R11, R14). During the weekends the differences between the ZGT roster and the variations are minor, and the ZGT roster is already planned to be implemented in the future. During the weekdays the ED nurse replacement reduces the length of stay for GP post patients by several minutes, making it the best set regarding length of stay indicators.

8.1.2 OCCUPANCY

In addition to evaluating lengths of stay, we look at the occupancy rate for staff. From these we can determine whether an intervention (negatively) affects staff working conditions. Table 29 shows the occupancy rates for the current situation, the (S1, P1, P2, P5, R11, R14) and (S5, P1, P2, P5, R11, R14) intervention sets.

	current situation	S1, P1, P2, P5, R11, R14	S5, P1, P2, P5, R11, R14
ED nurse	0.26	0.21	0.22
Surgical resident	0.25	0.26	0.26
Internal resident	0.23	n/a	n/a
Nurse practitioner	0.43	n/a	n/a
Physician assistant	n/a	0.39	0.38
GP assistant	0.45	0.46	0.46
Triage assistant	0.28	0.28	0.28
General practitioner	0.56	0.55	0.55
ED specialist	n/a	0.32	0.32

Table 29: Occupancy rates per staff type

The occupancy rates show that there is little deviation from the current situation. Direct comparison between all staff is difficult, as certain staff types are missing from interventions or current situation. The ED specialist is, compared to the internal resident, busier, which is expected as the ED specialist also treats surgical patients, which together with low urgency GP post patients are the biggest groups. Looking at the staff types that are present in all settings, there is little negative deviation from the current situation, only the GP assistant occupancy increases with one percent.

8.2 SENSITIVITY ANALYSIS

To compare the robustness of the best found interventions, we increase the number of patient arrivals, for intervention five, and the current situation. In addition, we look at the effect of increasing the ratio of high urgency patients that enter the IEP.

The patient arrivals are increased with five percent intervals, up to 200% (twice as many patient arrivals as the current situation), shown in Figure 30 and Figure 31. For the urgency ratio we increase the number of high urgency patients up to approximately 300%, three times as many high urgency patients as in the current situation, shown in Figure 32 and Figure 33.

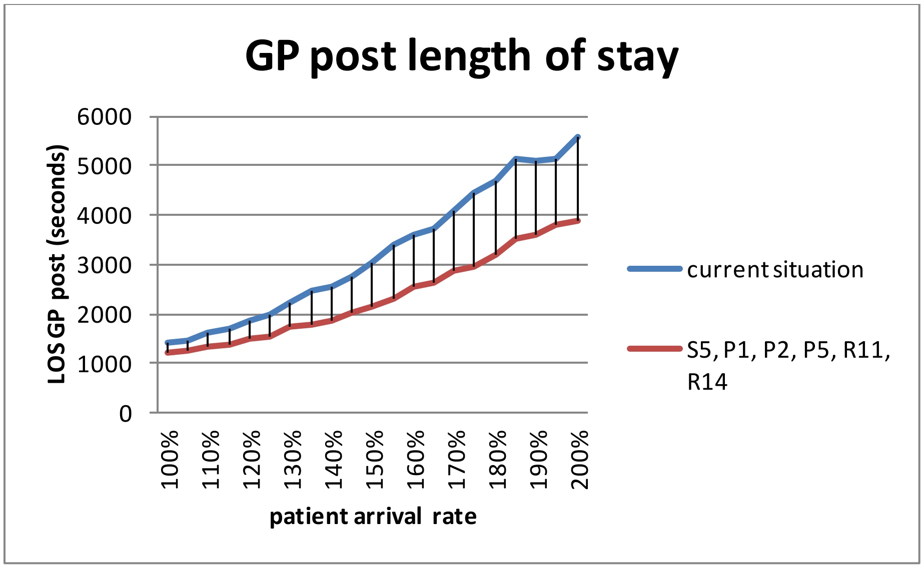


Figure 30: GP post length of stay as patient arrivals increase

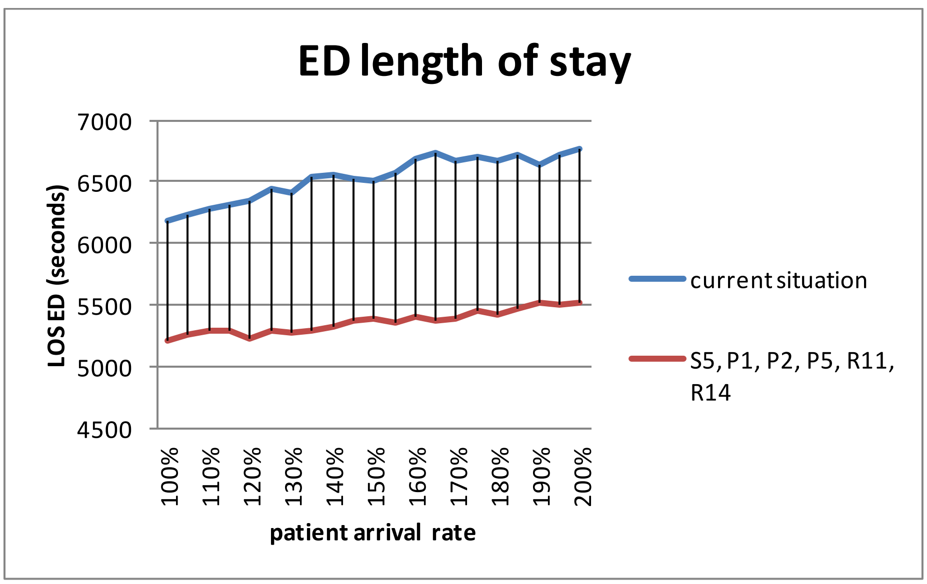


Figure 31: ED length of stay as patient arrivals increase

Looking at the figures, we see that for the GP post the intervention set is more prepared for a patient arrival increase, as the difference between the current situation and intervention set length of stay increases as more patients enter the IEP. Both lengths of stay however seem to increase exponentially, as the length of stay more than doubles as the patient arrivals double. This differs from the ED length of stay, where the LOS increases similarly for both the current situation as well as the intervention set. Of note is that when the patient arrival rate is at 200%, the intervention set is still significantly better than the current situation, with a length of stay approximately 600 seconds shorter.

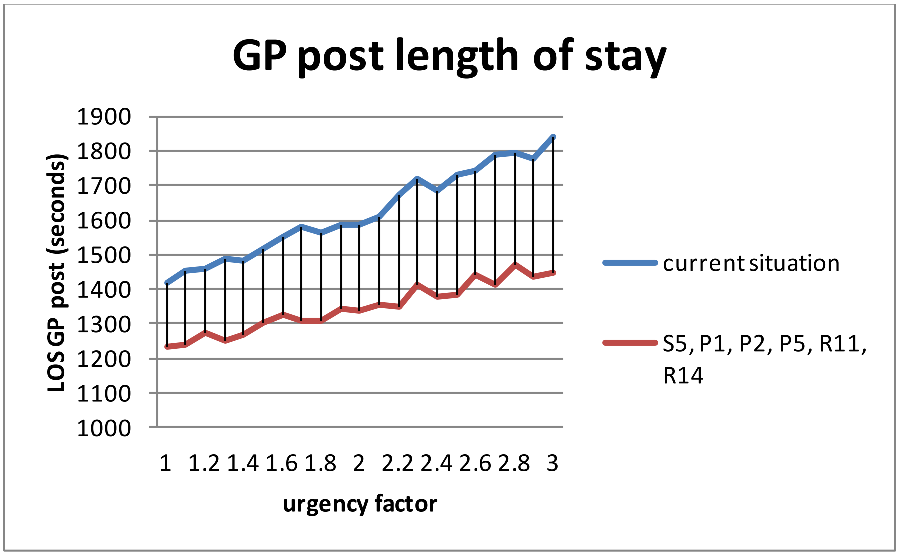


Figure 32: GP post length of stay as patient urgencies increase

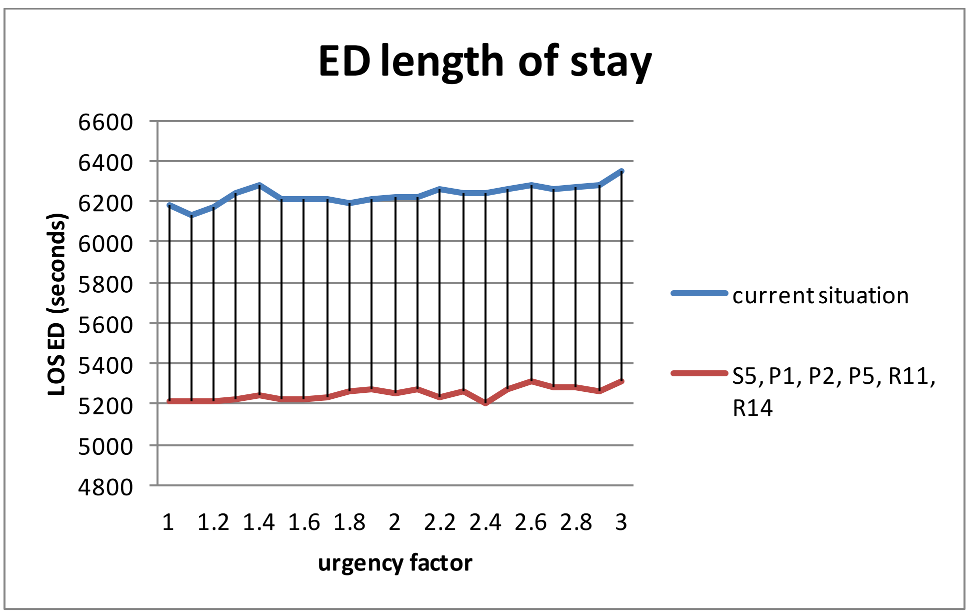


Figure 33: ED length of stay as patient urgencies increase

Looking at Figure 32 and Figure 33, we see a similar trend as more high urgency patients enter the IEP. The intervention set is more robust with regards to the GP post length of stay, as the urgency factor increases, the difference increases as well. When the urgency factor is at its highest, the intervention set performs equal to the current situation with current patient urgency ratio. This indicates that, to the length of stay, the intervention sets have a greater (positive) effect on the length of stay than the (negative) effects of increasing patient arrivals and high urgency patients. Indeed, if the current situation is acceptable, with regards to lengths of stay, the intervention set (S5, P1, P2, P5, R11, R14) is able to treat twice as many ED patients or receive three times as many high urgency ED and GP post patients. As the GP post sees, by far, the most patients the increase in length of stay makes sense, as currently there are around 5 GPs during the weekends, and with the intervention set the difference is an extra PA that treats patients. Using a similar GP to patient arrival ratio the expected number of staff to maintain the current LOS time would be around ten GPs and PAs (assuming a different resource, such as treatment rooms, would not become a bottleneck).

8.3 INDIVIDUAL INTERVENTION EFFECTS

As we evaluate the effects of the combined intervention sets, it is also interesting to look at the interaction effects in this best intervention set (S5, P1, P2, P5, R11, R14). Figure 34 and Figure 35 show the main and two factor interaction effects of the most promising interventions combined. Figure 34 shows that the only influence on the GP post length of stay is the S5 schedule intervention, that is an added PA during the weekends and starting hours of the weekdays. This is expected, as the GP post is not constrained by other resources such as available rooms. On average, an extra PA during the busiest hours (that also treats ED patients) reduces the length of stay by 175 seconds.

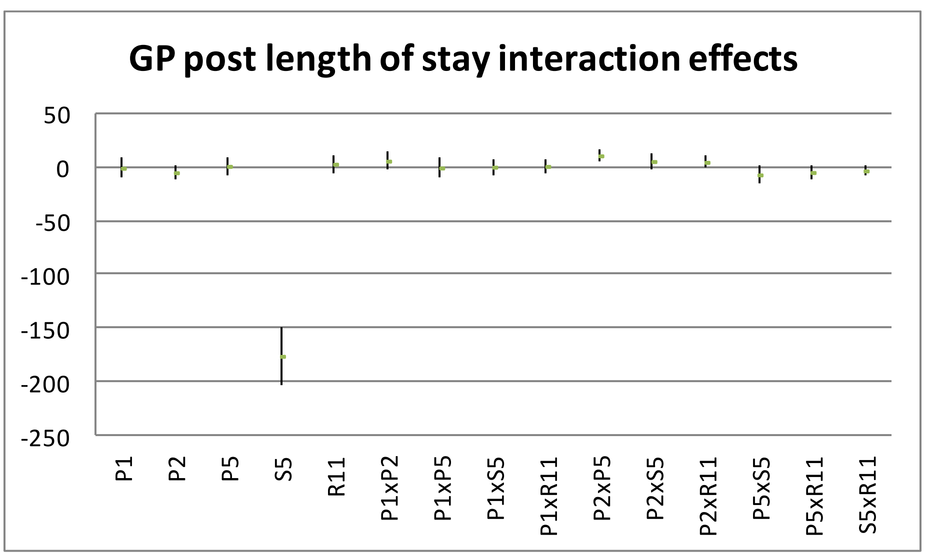


Figure 34: GP post length of stay interaction effects

The ED length of stay interaction effects, depicted in Figure 35, show that all interventions have a positive effect on the ED. The greatest reduction on the length of stay is not the addition of staff, as seen at the GP post, but the use of a single triage system (P1) and adding more diagnostic tests to the pre-diagnostic round (P2), reducing the length of stay by approximately 240 seconds. Following this the direct admission requests (P5) and the ZGT roster (S5) reduce the length of stay by approximately 150 seconds. Finally treating ED patients in GP post rooms reduces the length of stay on average with 70 seconds.

Regarding effect interaction, there are no significant interaction effects at the 5% level. Looking at the position of the intervals however, using a single triage system together with the ZGT roster and weekday PA (P1xS5) indicates a potential interaction effect, indicating that these interventions strengthen each other, however this effect stays small.

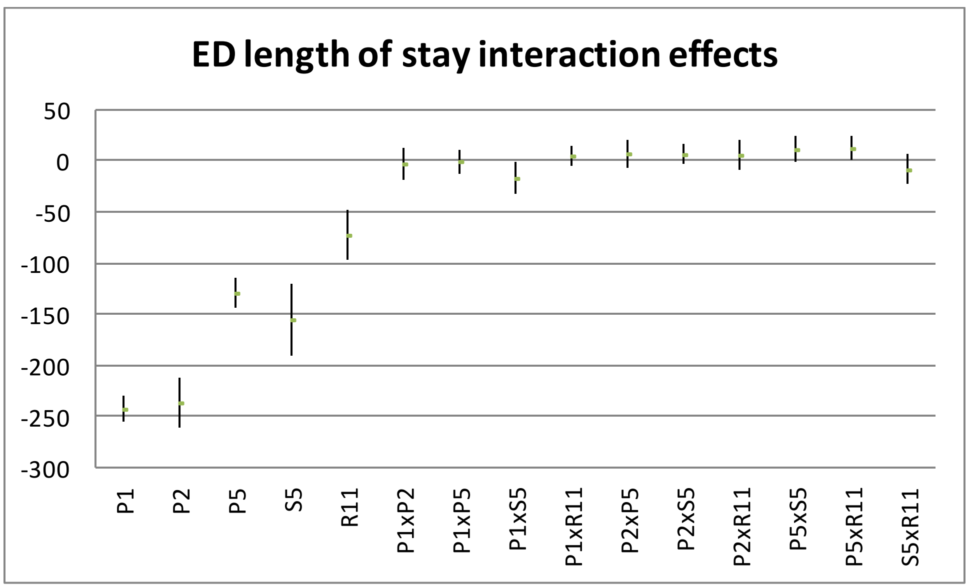


Figure 35: ED length of stay interaction effects

Based on the main and interaction effects, the biggest length of stay reduction for the GP post is an added PA during the busiest hours, being the starting hours (5PM-8PM) during the weekdays and 10AM-5PM during the weekend. Letting this PA treat ED patients has no negative effect on the GP post LOS, while still reducing the ED LOS.

The biggest length of stay reductions for the ED are seen when using a single triage system with the GP post, as this means that for many patients the GP post effectively takes over triage tasks for the ED, and adding more diagnostics to the pre-diagnostic round. This enables specialists and residents to treat patients with less interruptions, resulting in reduced waiting times, as patients wait less for diagnostics, which still occupying a treatment room. Additionally, the use of the ZGT roster, where an ED specialist is present, as well as an extra PA during the weekend (that also treats GP post patients) reduces the ED LOS. Finally, the use of GP post rooms by ED staff treating ED patients has positive effects for ED patients, without increasing GP post LOS, indicating a potential resource pooling option from which both ED and GP post may benefit, either through length of stay or cost reductions.

To directly compare the individual interventions, similar to the comparison of intervention sets, we look at the absolute effects of the individual interventions over several performance indicators. The list below summarizes the interventions.

1. Weekend NP replacement with PA.
2. Treating low urgency ED patients in GP post rooms.
3. Ordering pre-diagnostic tests for ED patients that likely need them.
4. Direct bed admission requests for ED patients that are likely to be admitted.
5. Using a single triage system.
6. Using the ZGT roster.
7. Adding a PA during the weekend.
8. Replacing an ED nurse with a PA during weekdays (5pm-8pm).

As the ZGT roster adds both an ED specialist, as well as a physician assistant during the weekend busy hours, the seventh intervention is also defined, to evaluate the combined effect of both the specialist and PA, compared to a single added staff member. For every intervention, the length of stay for both GP post and ED is evaluated, over type of day (weekend or weekday) as well as urgency type (high (U1, U2, red, orange) or low (U3, U4, yellow-blue). The bolded outcomes are statistically significant, using two sample t-tests (α=0.05). Appendix 10 contains all simulation outcomes.

	GP post weekday high urgency	GP post weekday low urgency	GP post weekend high urgency	GP post weekend low urgency
current	1186	1557	1151	1356
1	+8 (+0.7%)	-38 (-2.4%)	-32 (-2.8%)	+12 (+0.9%)
2	+29 (+2.4%)	+3 (+0.2%)	-8 (-0.7%)	+4 (+0.3%)
3	+11 (+0.9%)	+14 (+0.9%)	-32 (-2.8%)	-5 (-0.4%)
4	+33 (+2.8%)	+19 (+1.2%)	-28 (-2.5%)	-14 (-1%)
5	+4 (+0.4%)	+9 (+0.6%)	-28 (-2.5%)	-16 (-1.2%)
6	+19 (+1.6%)	-34 (-2.2%)	-21 (-1.8%)	***-122 (-9%)***
7	+48 (+4%)	+7 (+0.5%)	-50 (-4.3%)	***-161 (-11.8%)***
8	-8 (-0.7%)	***-274 (-17.6%)***	-7 (-0.6%)	-7 (-0.5%)
All	-7 (-0.6%)	***-262 (-16.8%)***	-48 (-4.2%)	***-118 (-8.7%)***
	ED weekday high urgency	**ED weekday low urgency**	**ED weekend high urgency**	**ED weekend low urgency**
current	6421	5901	6201	6299
1	+5 (+0.1%)	-15 (-0.3%)	-71 (-1.2%)	***-236 (-3.7%)***
2	+36 (+0.6%)	***-119 (-2%)***	-18 (-0.3%)	-108 (-1.7%)
3	***-366 (-5.7%)***	***-203 (-3.4%)***	***-381 (-6.1%)***	***-290 (-4.6%)***
4	-215 (-3.3%)	***-126 (-2.1%)***	***-141 (-2.3%)***	-109 (-1.7%)
5	-193 (-3%)	***-287 (-4.9%)***	***-183 (-2.9%)***	***-349 (-5.5%)***
6	+17 (+0.3%)	-46 (-0.8%)	***-238 (-3.8%)***	***-476 (-7.5%)***
7	-32 (-0.5%)	+8 (+0.1%)	-40 (-0.6%)	***-241 (-3.8%)***
8	+26 (+0.4%)	-11 (-0.2%)	-28 (0.4%)	-7 (-0.1%)
All	***-715 (-11.1%)***	***-695 (-11.8%)***	***-775 (-12.5%)***	***-1197 (-19%)***

Table 30: Absolute outcomes (seconds) per intervention

Table 30 shows that all PA additions (6-8) have a significant effect on low urgency GP post patient length of stay, and that the pooling of resources (1-2), have a positive effect on the ED, while not negatively impacting the GP post. The process interventions (3-5) too, all reduce the average length of stay for ED patients. Combining all interventions (1-6 and 8), has the biggest impact, as the effects of the individual interventions are roughly stacked.

9 DISCUSSION AND CONCLUSIONS

The goal of this study was to build upon an earlier developed simulation model, and to use that model to optimize the efficiency of processes in the integrated emergency post. To reach this goal, we used experimental designs to combine and compare individual interventions, as well as evaluating interaction effects between interventions. To further validate the model we conducted a measurement period, as well as a data analysis, using four years of historical data of both the GP post and the ED.

Using experimental designs and a sequential approach to search for an optimal solution, the outcomes of the simulation runs showed that several interventions proved effective, which are listed below.

1. Weekend NP replacement with PA.
2. Treating low urgency ED patients in GP post rooms.
3. Ordering pre-diagnostic tests for ED patients that likely need them.
4. Direct bed admission requests for ED patients that are likely to be admitted.
5. Using a single triage system.
6. Using the ZGT roster.
7. Adding a PA during the weekend day shift.
8. Replacing an ED nurse with a PA during weekdays (5pm-8pm).

Based on the observed interaction effects these interventions do not greatly affect each other, meaning that they may be evaluated individually, and combining them results in the best solution.

Using a single triage system allows the ED to use the GP post expertise, as many patients that go to the ED do so through the GP post, where they have already been triaged. This intervention of course requires the change to a single triage system, as well as a dedicated cooperation such that the telephonic triage, possible combined with GP post consultation observations, are sufficient for the ED.

Adding more diagnostic tests to the pre treatment diagnostic round also reduces the ED length of stay. As residents and specialists are able to treat more patients with no, or less, interruptions. This in turn ensures that an ED patient spends less time in an ED room waiting for a diagnostic test. This intervention does have the costs associated with conducting more unnecessary diagnostic tests, which may be a valid concern to ordering more tests in advance.

Directly requesting a bed admission for a patient that most likely needs it also reduces the ED length of stay. Similar to the added diagnostic tests, this means that for some patients a bed is requested while the patient will not be admitted, with all associated costs. There is some leeway however regarding the point in time of requesting a bed admission, as the current average length of stay is 100 minutes, and the average waiting time for a bed is 24 minutes. This means that a bed may also be requested further in the treatment process, such that the certainty of knowing whether a patient needs to be admitted increases, while still being so timely with the request that patients do not wait for a bed at the ED.

Treating low urgency ED patients in GP post rooms has a beneficial effect on the ED length of stay, while there is no noticeable negative effect on the GP post length of stay. For the ED this is a quick solution when all treatment rooms at the ED are full, while the GP post has empty rooms. A difficulty to overcome in this situation is that the GP post rooms are separated from the ED by the waiting room, such that ED staff would have less overview of patients in a GP post room. Coordinating with GP post staff, or ensuring patients at the GP post can be monitored from the ED may take away this barrier.

Comparing the nurse practitioner and physician assistant, the PA reduces the ED length of stay while not increasing the GP post length of stay. As both staff types are equal in costs, using PAs instead of NPs gives both organizations reason to pool this staff type. This staff type can be used at both ED and GP post, depending on where he or she is needed, while costs may be shared among organizations. This pooling of resources, however, introduces financial, as well as medical and legal questions. Sharing resources such as rooms (and the materials inside), as well as staff require financial agreements or compensations. In addition, the use of staff that treats patients at both ED and GP post means that agreements have to be made regarding medical and legal responsibility, determining which organization is responsible for a patient at certain moments in time.

Looking at the ZGT roster, the difference from the current situation is that a PA is added, as well as the replacement of an internal resident with an ED specialist. This ED specialist has a positive effect on the ED length of stay, as this specialist may treat surgical patients as well as internal patients. Given that the busiest staff type currently is the surgical resident, the addition of this specialist means that during the busy hours there is both a surgical resident, as well as an ED specialist, available to treat surgical specialty patients, greatly reducing the ED length of stay. In addition, the ZGT roster employs an extra PA during the weekend, with the replacement of an NP with a PA there are two PAs available to work at either the GP post or ED. Increasing the flexibility of both organizations. Finally, replacing an ED nurse with a PA during the starting hours of the IEP (weekdays) reduces the GP post length of stay for low urgency patients considerably, while having no negative effect on the ED. This is another possibility to pool resources, as this is attractive for both organizations from a cost perspective, as well as a performance perspective. The table below summarizes the effects of all interventions.

	GP post weekday high urgency	GP post weekday low urgency	GP post weekend high urgency	GP post weekend low urgency
current	1186	1557	1151	1356
1	+8 (+0.7%)	-38 (-2.4%)	-32 (-2.8%)	+12 (+0.9%)
2	+29 (+2.4%)	+3 (+0.2%)	-8 (-0.7%)	+4 (+0.3%)
3	+11 (+0.9%)	+14 (+0.9%)	-32 (-2.8%)	-5 (-0.4%)
4	+33 (+2.8%)	+19 (+1.2%)	-28 (-2.5%)	-14 (-1%)
5	+4 (+0.4%)	+9 (+0.6%)	-28 (-2.5%)	-16 (-1.2%)
6	+19 (+1.6%)	-34 (-2.2%)	-21 (-1.8%)	***-122 (-9%)***
7	+48 (+4%)	+7 (+0.5%)	-50 (-4.3%)	***-161 (-11.8%)***
8	-8 (-0.7%)	***-274 (-17.6%)***	-7 (-0.6%)	-7 (-0.5%)
All	-7 (-0.6%)	***-262 (-16.8%)***	-48 (-4.2%)	***-118 (-8.7%)***
	ED weekday high urgency	**ED weekday low urgency**	**ED weekend high urgency**	**ED weekend low urgency**
current	6421	5901	6201	6299
1	+5 (+0.1%)	-15 (-0.3%)	-71 (-1.2%)	***-236 (-3.7%)***
2	+36 (+0.6%)	***-119 (-2%)***	-18 (-0.3%)	-108 (-1.7%)
3	***-366 (-5.7%)***	***-203 (-3.4%)***	***-381 (-6.1%)***	***-290 (-4.6%)***
4	-215 (-3.3%)	***-126 (-2.1%)***	***-141 (-2.3%)***	-109 (-1.7%)
5	-193 (-3%)	***-287 (-4.9%)***	***-183 (-2.9%)***	***-349 (-5.5%)***
6	+17 (+0.3%)	-46 (-0.8%)	***-238 (-3.8%)***	***-476 (-7.5%)***
7	-32 (-0.5%)	+8 (+0.1%)	-40 (-0.6%)	***-241 (-3.8%)***
8	+26 (+0.4%)	-11 (-0.2%)	-28 (0.4%)	-7 (-0.1%)
All	***-715 (-11.1%)***	***-695 (-11.8%)***	***-775 (-12.5%)***	***-1197 (-19%)***

Table 31: Absolute outcomes (seconds) per intervention

Overall, we conclude that the interventions show a significant improvement over the current situation. Of these, the roster alternatives are specific to the setting in Almelo, and show the greatest effect. However, the pooling of resources is effective in all tested resource settings, indicating that more organizations may benefit from such a cooperation.

Looking at the interventions, the easiest, short term implementable, are the process and pooling interventions. Adding staff means attracting new employees, which also need to be trained, making it a more long term intervention. Sharing rooms may be easily implemented, as well as letting PAs work at both the ED and GP post. This pooling of resources, as well as using a single triage system such that referred patients from the GP post going to the ED are no longer triaged, requires cooperation and collaboration between both organizations. If this can be achieved however, a reduction of both length of stays and overall costs could be achieved. Two recommended interventions for implementation within the ZonMw project are the use of a single triage system, and employing the PA at both ED and GP post, both interventions are, with collaboration, possible without requiring significant additional resources.

10 FUTURE WORK

Concluding this study, we found that there are still improvements to be made. In this section we elaborate on the research that may build upon this study.

In the simulation model, GP post patient characteristics are based upon their urgency. Relative to the intervention, these distinctions may be too indistinct to properly investigate an alternative, using simulation groups similar to ED patients may help improve the accuracy in testing interventions of different staff types treating patients. For example, in the current model GPs treat all urgency types, and Physician assistants the lowest two patient urgency types. A possible intervention could be to let ED nurses treat specific low urgency types, which showed promise resource pooling experimental design. This poses the question however, to what extent an ED nurse could treat all U4 patients, which account for over half of the patients that enter the IEP.

Another possibility of improvement is the handling of trauma patients. In the simulation model there are eight ED rooms usable for treatment, with the trauma rooms used for X-rays. While there are red patients within the simulation model, these patients are helped only when there are staff and resources available, while in reality such a patient would be treated immediately.

The arrival of medical specialist in the current model is deterministic, based on the urgency of the patient needing a specialist. In reality, a medical specialist will arrive as quickly as possible, and in the case of a high urgency patient, immediately travel to the ED. The simulation model differs from this by always having a given (long) waiting time for low urgency patients. During the measurement period, some waiting time measurements for medical specialist arrival were conducted, a more comprehensive measurement period and data analysis of specialist arrivals may be used to model a probability function based on historical data. With these functions a more realistic representation of the interaction between ED and hospital may be created.

In the simulation model, all tasks are added to a task list, and based on this list, the patient that has been waiting the longest, with the highest urgency, for his or her step in the care pathway is treated next. This differs from actual prioritizations made in the health care organization, where time waiting for triage, as well as a maximum total treatment time determine the priority of a patient. In the model, only the waiting time for the current process step is used, without considering total length of stay of a patient, possibly letting a low urgency patient wait a long time for every process step. An incorporation of this total length of stay would increase the validity of prioritization, giving a better representation of reality.

Another point of improvement is the interaction of the integrated emergency post with other departments in the hospital. For example, for lab tests blood is drawn from a patient, and sent to the lab for testing. As every ED patient undergoes a blood test, increasing patient arrivals at the IEP would mean that the lab gets busier, increasing the waiting time for test results. This is not taken into account in the current simulation model. Investigating the interaction between, and the effect these departments have on each other may give insights in causes for bottlenecks, as well as lead to possible interventions to be analyzed using the simulation model.

Currently, patients that call the GP post receive telephonic triage and are scheduled for an appointment if needed. The time of this appointment depends on multiple factors, such as urgency, the travel time needed to go to the IEP, as well as the already scheduled appointments. In reality appointments are made mainly based on urgency type. U1 and U2 patients are scheduled immediately and as a result "bump" down the lower urgencies. U3 and U4 patients are scheduled at the next available appointment time. During peak hours the waiting times for patients tend to exceed their appointment times, as more higher urgency patients enter the IEP as well as self-referrals. An intervention to schedule patients with a lower urgency outside these peak hours may help to divert patients from peak hours. Depending on urgency, there are time criteria in which a patient must be seen. Figure 36 shows the distribution of all patients that had a consultation at the GP post from 14-4-2009 to 13-4-2011.

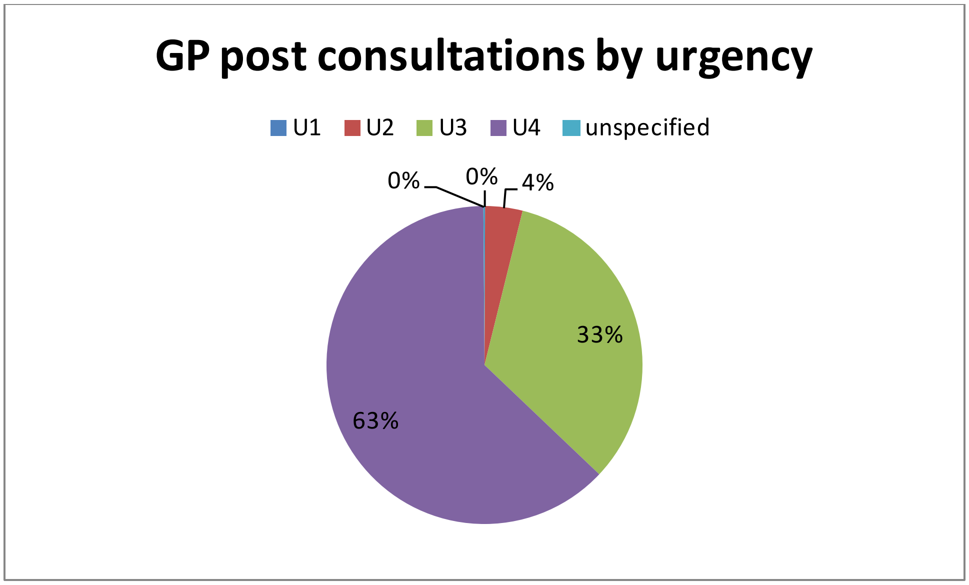


Figure 36: GP post consultation by urgency type: 14-4-2009 to 13-4-2011

Out of all the patients that had a consultation, 63% was triaged as U4. Given that these patients have no time criterion in which they must be seen by a GP post employee, the scheduling of these patients may have great effect on the performance of the IEP, redirecting them away from busy moments.

With the recommendations done, a follow-up step would be to implement one, or several, of the interventions. This would allow an intervention to be monitored and compared with the simulation model results, increasing validity. With the flexible design of the simulation model, it is possible to quickly change and test interventions. This enables not only ZGT and the CHPA to make informed decisions using the simulation model, but would also enable other health care providers with acute care provision to use and tune the model to their situation, and test interventions, or scenarios. This general applicability also allows a comparison of actual health care providers, and as such may also be used in benchmarking. As such, expanding the study beyond Almelo, in similar situations is of interest, hopefully this will allow the knowledge gained to be used in other health care organizations.

A final improvement is the use of simulation optimization heuristics to find the optimal process design of the integrated emergency post. In our current systematic approach, we used multiple experimental designs to investigate interaction between interventions, and based upon these, we created combinations of alternatives. As the number of interventions increases, so does the number of required simulation runs, as well as experimental designs.

This means that not every possible combination has been tested, and that the designs are created using informed assumptions. In addition, fact that the simulation model does not account for costs means that more of any resource is always better, as there is no downside to adding resources. To counter this, we defined roster alternatives that did not vary from a set cost, limiting the number of possible interventions. Using a simulation optimization heuristic, costs may be incorporated in the search process. An example would be a heuristic similar to simulated annealing, where a neighbor solution is randomly drawn and compared with the current solution. If the neighbor solution is better, the alternative is accepted, if it is worse, it is accepted with a declining probability. An added difficulty to this problem is that every simulation run is an estimation of a true performance indicator, that is, there is noise in every outcome. To cope with this, a solution could be to perform multiple runs for an intervention set, comparing confidence intervals, or incorporating the certainty of a solution's true outcome into the decision to reject or accept itself.

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12 APPENDICES

APPENDIX 1

The figure below shows the Steps in a Simulation study by Law (2007)

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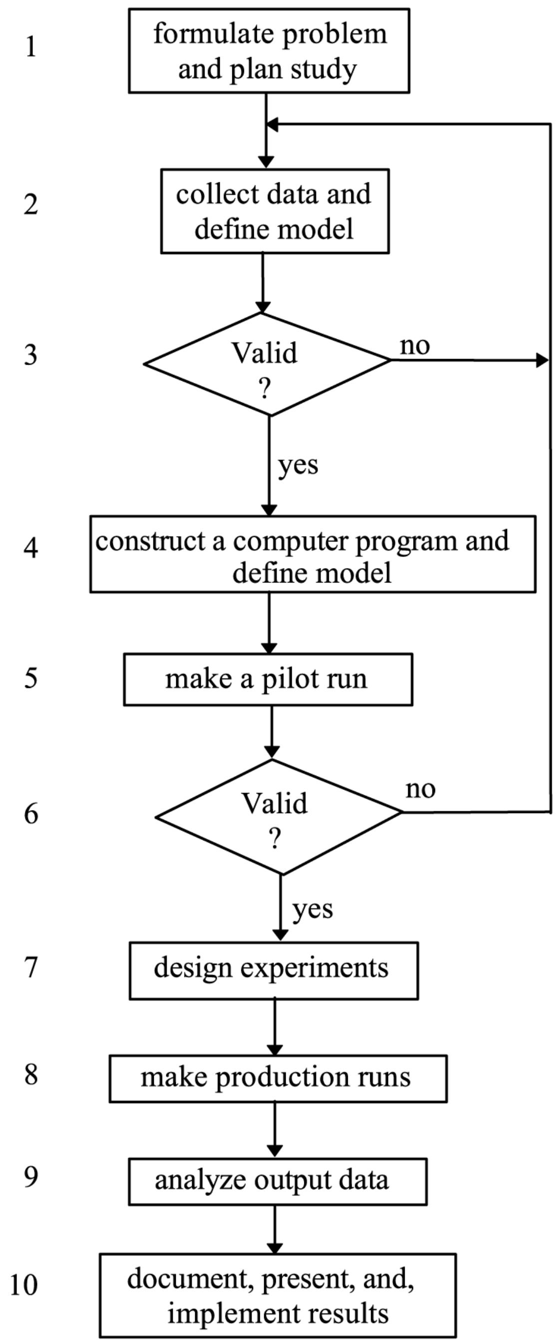


APPENDIX 2

Minitab analysis of number of patients at ED (5pm), comparing the number of patients at the ED at 5pm per day, only Monday is busier than other days of the week. To normalize all arrivals, such that one distribution may be used for all days, we divided the number of patients with the relative day factor for each day. The tables below list the day factors and summary statistics.

day	Factor
Monday	1.147
Tuesday - Friday	0.963

N	mean	stdev	min	max
259	11.63	4.22	2.07	35.3

in Minitab we compared Anderson-Darling tests for the following distributions: normal, lognormal, weibull, gamma, exponential, logistic and loglogistic. In comparing distributions we chose the test with the lowest A-D statistic and highest p-value. Using this the best found distribution is a gamma distribution, detailed below.

distribution	mean	shape	Scale
gamma	11.634	7.456	1.56

The used distribution is continuous, however the number of patients at the ED is discrete. Discrete distributions however have a considerably worse fit. Therefore we choose to use a continuous distribution function with rounding to the nearest integer. Additionally it is not possible to have a negative number of patients at the ED, so the minimum number of patients is 0.

APPENDIX 3

The forms below were used during the two week measurement period.

GP post measurement form

Meetweek Spoedpost 2012

centrale huisartsenpost almelo

Naam patiënt:

………………………………………………

Geboortedatum patiënt: .. .. - .. .. - .. ..

Datum: maandag 6 februari 2012

Tijd binnenkomst Spoedpost: …………………………………..

Tijd start triage doktersassistente: …………………………………..

Tijd einde triage doktersassistente: …………………………………..

Binnenlopers:

Tijd start afspraak huisarts: …………………………………..

Tijd einde afspraak huisarts: …………………………………..

ED measurement form

Meetweek Spoedpost 2012

SEH

Achternaam patiënt:
Geboortedatum patiënt:

Datum: maandag 13 februari 2012

Arts-assistent

Tijd voorlopige uitslag röntgen:	………………………………..
Tijd voorlopige uitslag CT:	………………………………..
Tijd voorlopige uitslag echo:	………………………………..
Tijd voorlopige uitslag ECG:	………………………………..
Tijd telefonisch overleg specialist	………………………………..
Tijd inroepen specialist:	………………………………..
Tijd aankomst specialist SEH:	………………………………..
Tijd vertrek specialist SEH:	………………………………..
Tijd einde behandeling arts(-assistent):	………………………………..

SEH verpleegkundige

Tijd aanvraag nabepaling lab:	………………………………..
Tijd start ECG:	………………………………..
Tijd start gipsen:	………………………………..
Tijd einde gipsen:	………………………………..
Tijd uitslag controle foto:	………………………………..
Tijd einde behandeling:	………………………………..

GP post visitation measurement form

MEETWEEK Spoedpost	**Visites**	centrale huisartsenpost almelo
Datum:	maandag 6 februari 2012	

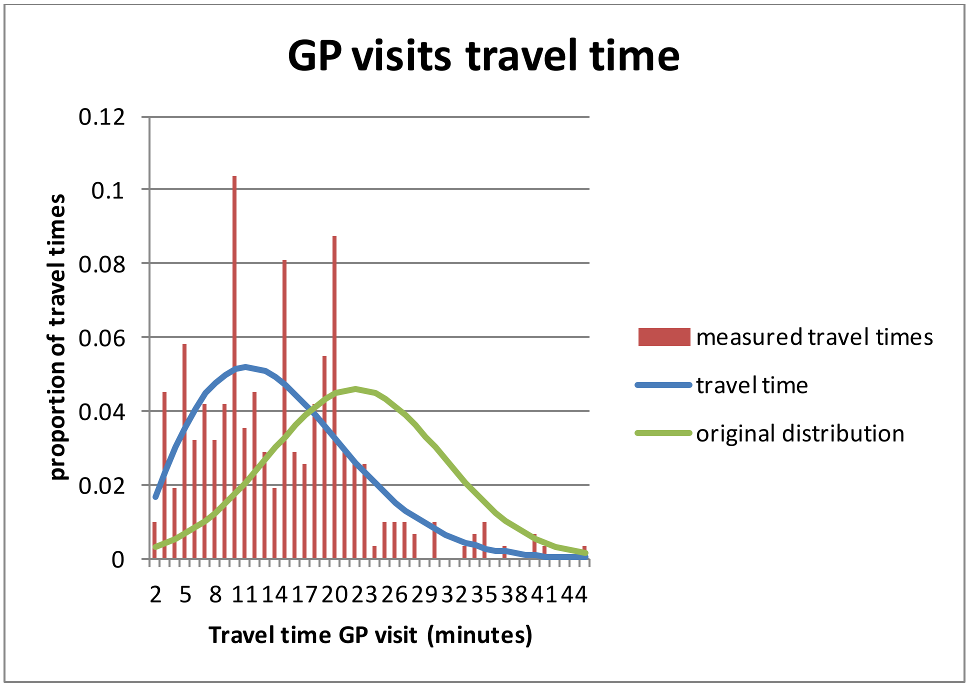
Patiënt achternaam	Geboortedatum	Vertrektijd Spoedpost	Starttijd visite	Eindtijd visite	Naar volgende patiënt	Aankomsttijd Spoedpost
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	
					ja / nee	

Appendix 4

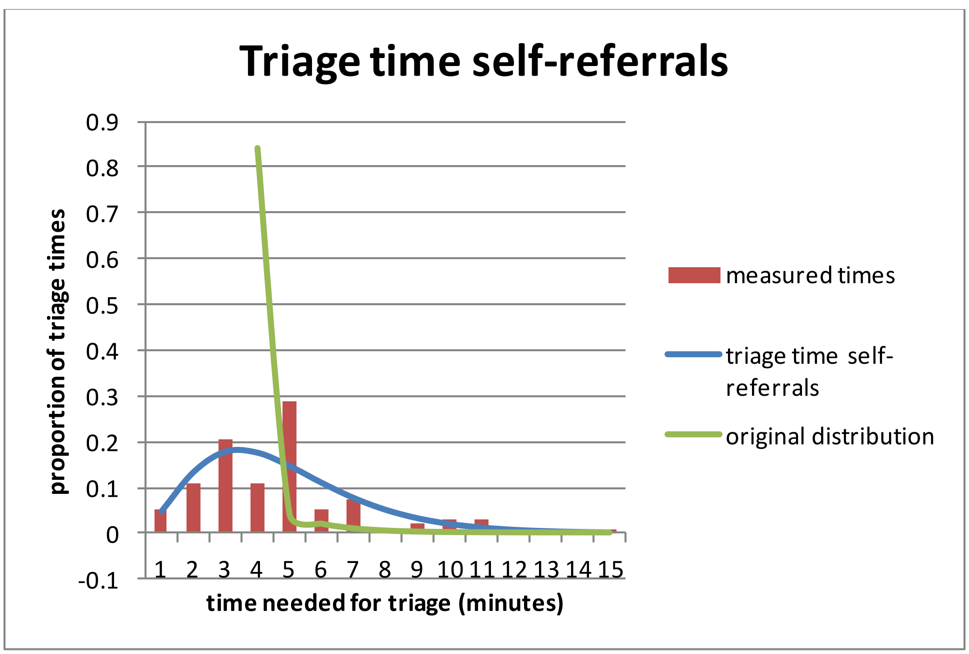
Minitab data analysis simulation model inputs, in Minitab we compared Anderson-Darling tests for the following distributions: normal, lognormal, weibull, gamma, exponential, logistic and loglogistic. In comparing distributions we chose the test with the lowest A-D statistic and highest p-value. For distributions with a low p-value (<0.05) we compared the proposed distribution with the currently used distribution.

Measurement	GP travel time	GP visit duration	Triage time self-referrals	Waiting time hospital admission	Cast application time	Waiting time medical specialist	Treatment time medical specialist
N	309	220	93	73	59	23	28
Min	2	5	1	1	3	1	3
Max	45	135	15	134	25	120	150
Median	14	18	5	16	10	31	16
Average	14.35	21.1	4.731	24.21	8.780	38.70	30.18
St.dev	7.8	15.61	2.567	26.96	3.819	34.59	33.42
Location		2.86893					2.95204
Shape	1.93832		3.58939	0.90921	2.41928	1.28999	
Scale	16.21022	0.58291	1.3181	23.09899	9.90861	29.99682	0.96148
Distribution	Weibull	Lognormal	Gamma	Weibull	Weibull	Gamma	Lognormal
p-value	<0.01	0.174	<0.005	>0.25	<0.01	0.128	0.242
A-D statistic	1.406	0.530	1.634	0.341	2.613	0.621	0.460
Use in model	yes	yes	yes	Yes	yes	No	No

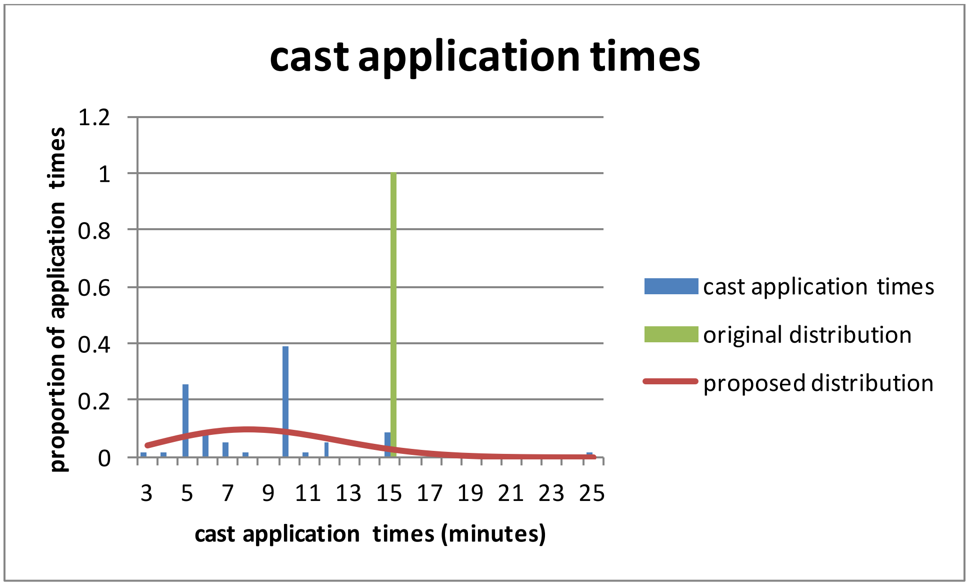
Based on the Minitab results the distributions for GP travel time, self-referral triage and cast applications still have a small p-value and large A-D statistic. Based on a plot of the proposed distribution, the original distribution and measurements of the GP travel times we decide to use the new probability distribution function. The waiting and treatment times measured for specialists are aggregated over all patient DRGs and urgencies. Given the number of measurements it is not possible to analyze waiting and treatment times per sub-section of patients. Therefore we use the original distributions.



Based on a plot of the proposed distribution, original distribution and measurements of triage times we find the proposed distribution is the best fit.



The same analysis for the cast application times shows that there is a very high number of 5 and 10 minute registrations. This may be because ED nurses rounded their cast application times. The original assumed duration of 15 minutes however is very rare. Therefore we use the proposed probability distribution.

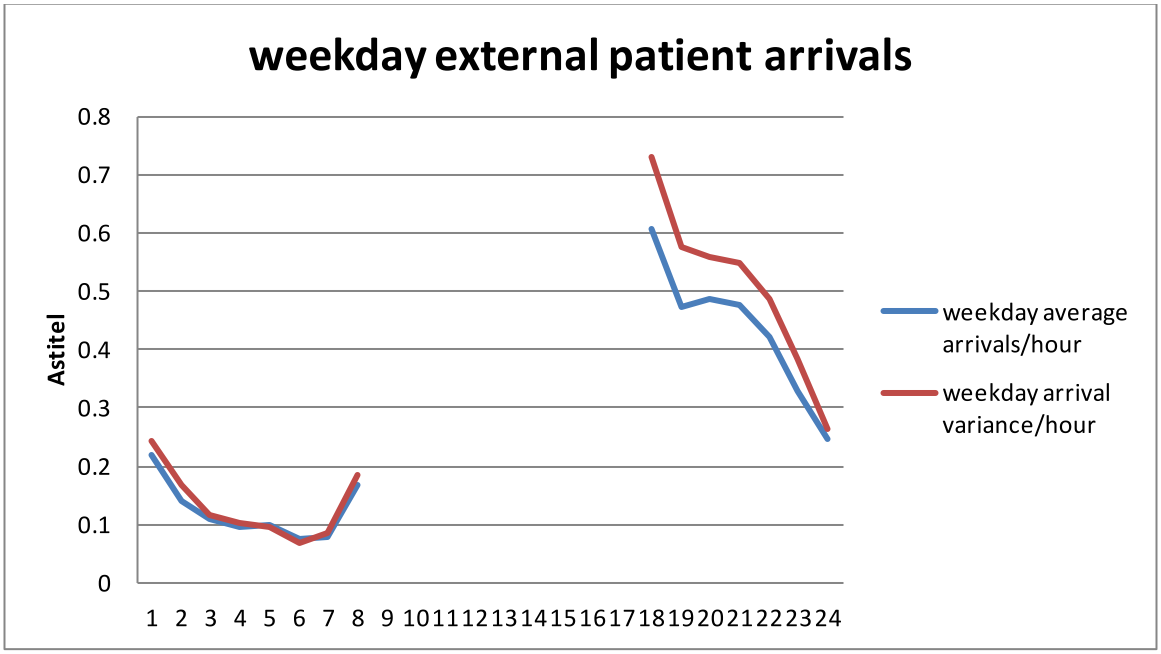


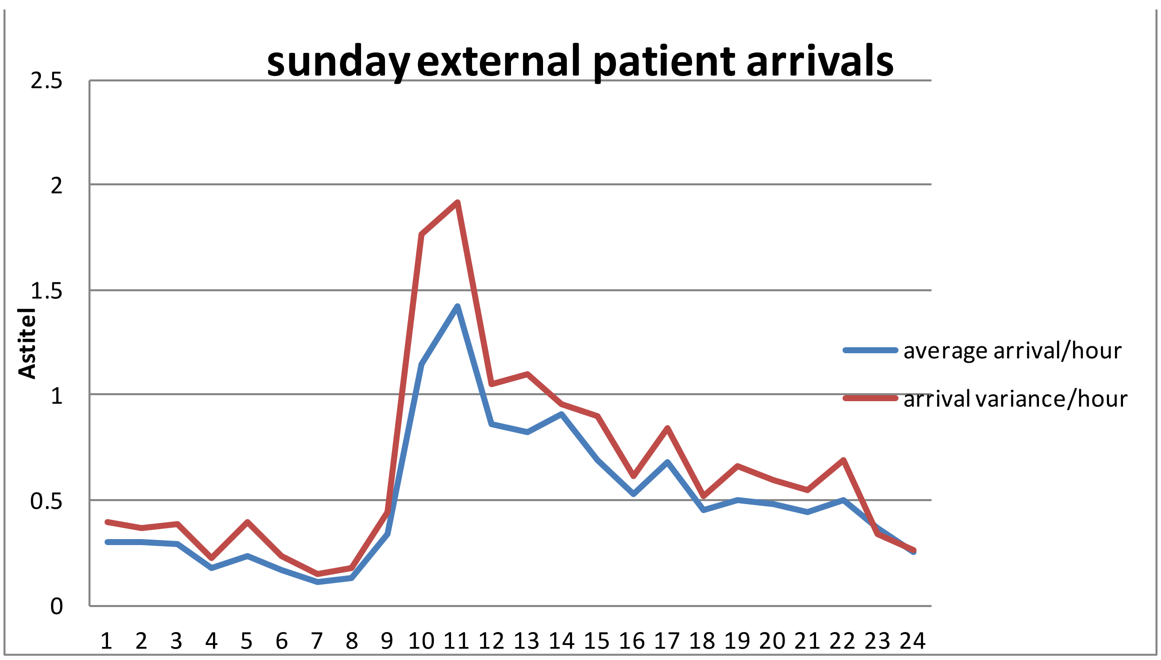
The diagnostic process times are measured as the time between the start of a diagnostic test, retrieved from EZIS and the review of results by medical specialists/residents. Looking at the X-ray process times they originally were estimated by staff to be deterministic with a 5 minute duration. The measurements however have an average duration of 29 minutes. This may be explained by the fact that part of the process time may be the waiting time of results before a resident is available for review. Paired with the low number of measurements, and p-value we choose to use the original deterministic distribution.

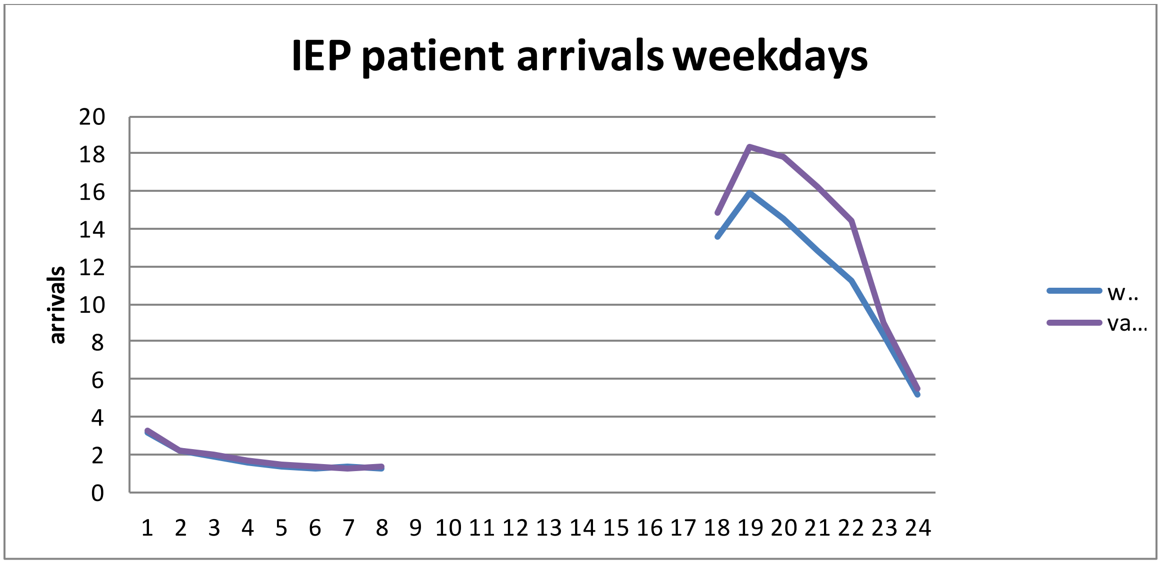
Regarding the echo- and ECG process times there were insufficient measurements for analysis and the original distributions are retained. The CT process times are similar to X-ray times said to be deterministic, estimated at 20 minutes. The measurements however show a much higher average and the proposed distribution based on said measurements reflects this. For example the probability that a CT scan takes 50% longer than the original 20 minutes is 70%. Given that the process times registered face the same problems as those of the X-ray process potential waiting times on medical staff is included. Because of this and the considerable discrepancy between estimated and measured times we choose to use the original estimated CT process times.

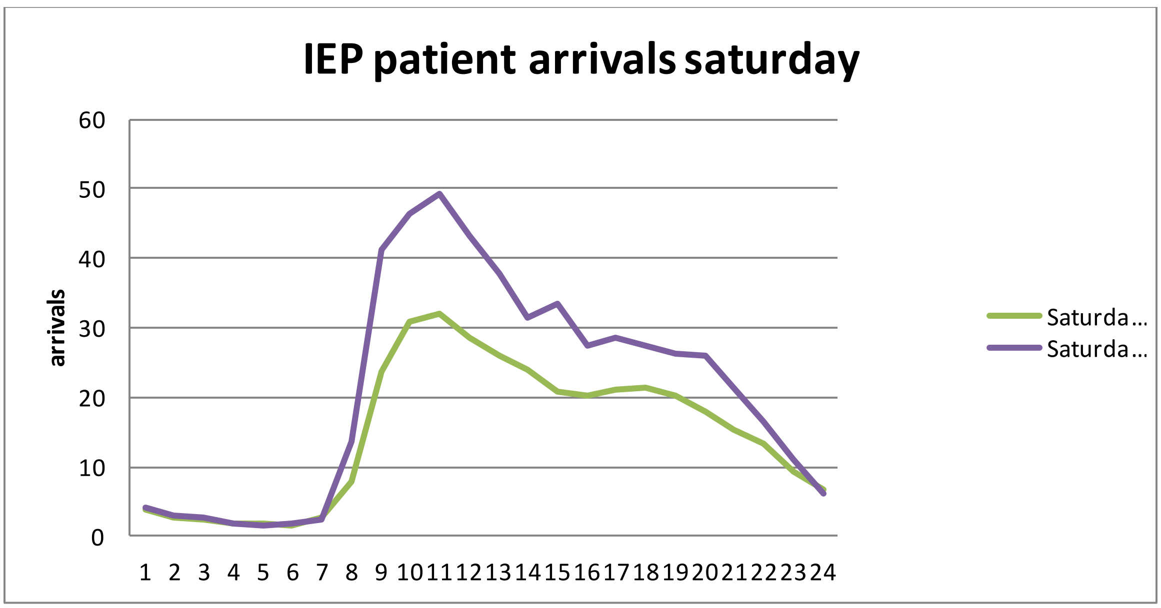
Appendix 5

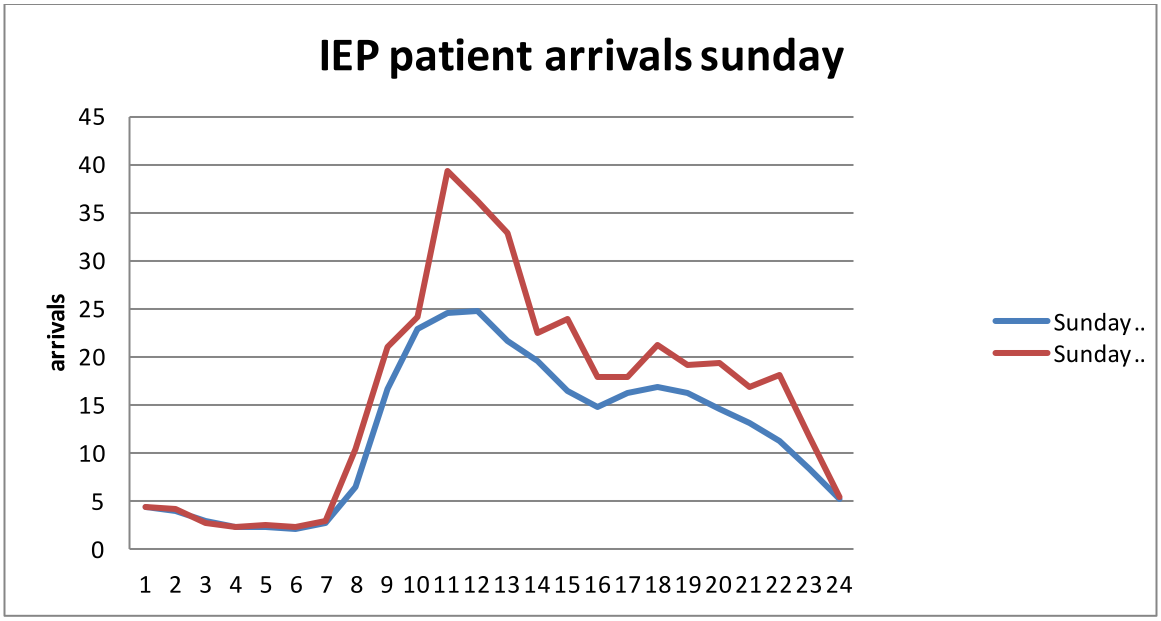
The figures below show the average arrival and variance per hour for external arrivals during weekdays, Sundays, as well as IEP arrivals for weekdays, Saturdays and Sundays.






IEP patient arrivals weekdays
arrivals
20
18
16
14
12
10
8
6
4
2
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
w..
va...


IEP patient arrivals saturday
arrivals
60
50
40
30
20
10
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Saturda...
Saturda...


IEP patient arrivals sunday
arrivals
45
40
35
30
25
20
15
10
5
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Sunday..
Sunday..

APPENDIX 6

The tables below give an overview of the verification and comparison of model input and outputs, for pathways, and urgency types.

Care path A per GP post urgency comparison

	Output				Input				Difference			
Pad1	U1	U2	U3	U4	U1	U2	U3	U4	U1	U2	U3	U4
A1	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	-0.13	-0.72	-0.30	-0.28
A2	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	-0.03	-0.58	0.23	-0.05
A3	0.02	0.08	0.07	0.04	0.01	0.07	0.07	0.04	0.72	0.10	0.01	0.00
A4	0.44	0.05	0.08	0.56	0.39	0.05	0.08	0.55	0.13	-0.03	0.02	0.01
A5	0.31	0.02	0.01	0.01	0.36	0.02	0.01	0.01	-0.14	-0.01	0.08	-0.04
A6	0.17	0.40	0.19	0.03	0.18	0.40	0.18	0.03	-0.07	0.00	0.02	0.00
A7	0.01	0.02	0.00	0.00	0.01	0.02	0.01	0.00	-0.12	0.03	-0.10	0.15
A8	0.03	0.43	0.65	0.35	0.03	0.43	0.65	0.36	0.19	-0.01	-0.01	-0.01

Care path B comparison

Pad2	Output	Input	Difference
B1	0.77	0.77	0.00
B2	0.09	0.09	-0.01
B3	0.06	0.06	-0.01
B4	0.09	0.09	0.00

Care path 3 comparison

Pad3	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
C1	0.00	0.01	0.00	-0.02	-0.03	-0.07	0.01	0.01	-0.03	-0.01
C2	0.17	-0.06	0.06	0.09	0.36	0.07	0.22	0.26	0.59	-0.02
C3	-0.02	-0.03	0.00	0.02	0.03	0.00	0.00	-0.01	0.04	0.01

APPENDIX 7

The tables below show the experimental design formats as they are used in the computer simulation model, and the interventions evaluated.

List of evaluated interventions

Process interventions	Resource interventions
1. Single triage system 2. Extra tests during pretreatment diagnostic round 3. Reprioritization of low urgency patients 4. Changed staff allocation to patients 5. Direct admission requests	1. Added ED nurse 2. Added resident AC 3. Added resident AI 4. Added physician assistant 5. Added general practitioner 6. Added ED specialist 7. Added X-ray 8. Added CT-scan 9. Added ECG 10. Added ultrasound 11. Using GP rooms for ED patients 12. Letting physician assistants perform ED tasks during out-of-office hours 13. Letting ED nurses treat U4 patients 14. Letting ED specialist/resident treat GP patients 15. Using dedicated medical specialists 16. Using desired ZGT roster 17. Replacing resident AI with ED specialist 18. Early shift change 19. Late shift change

Process experimental design (Process interventions 1-5)

Exp	Prediag	Urgencies	Taskprio	DirectAdmission	SEHtriage
1	0	0	0	0	0
2	0	0	0	0	1

3	1	0	0	0	0
4	1	0	0	0	1
5	0	1	0	0	0
6	0	1	0	0	1
7	1	1	0	0	0
8	1	1	0	0	1
9	0	0	1	0	0
10	0	0	1	0	1
11	1	0	1	0	0
12	1	0	1	0	1
13	0	1	1	0	0
14	0	1	1	0	1
15	1	1	1	0	0
16	1	1	1	0	1
17	0	0	0	1	0
18	0	0	0	1	1
19	1	0	0	1	0
20	1	0	0	1	1
21	0	1	0	1	0
22	0	1	0	1	1
23	1	1	0	1	0
24	1	1	0	1	1
25	0	0	1	1	0
26	0	0	1	1	1
27	1	0	1	1	0
28	1	0	1	1	1
29	0	1	1	1	0
30	0	1	1	1	1
31	1	1	1	1	0
32	1	1	1	1	1

Resource experimental design A (resource interventions 1-6)

Exp	SV	AC	AI	PA	HA	SA	Exp	SV	AC	AI	PA	HA	SA
1	0	0	0	0	0	0	33	0	0	0	0	0	3
2	3	0	0	0	0	0	34	3	0	0	0	0	3
3	0	3	0	0	0	0	35	0	3	0	0	0	3
4	3	3	0	0	0	0	36	3	3	0	0	0	3
5	0	0	3	0	0	0	37	0	0	3	0	0	3

6	3	0	3	0	0	0	38	3	0	3	0	0	3
7	0	3	3	0	0	0	39	0	3	3	0	0	3
8	3	3	3	0	0	0	40	3	3	3	0	0	3
9	0	0	0	3	0	0	41	0	0	0	3	0	3
10	3	0	0	3	0	0	42	3	0	0	3	0	3
11	0	3	0	3	0	0	43	0	3	0	3	0	3
12	3	3	0	3	0	0	44	3	3	0	3	0	3
13	0	0	3	3	0	0	45	0	0	3	3	0	3
14	3	0	3	3	0	0	46	3	0	3	3	0	3
15	0	3	3	3	0	0	47	0	3	3	3	0	3
16	3	3	3	3	0	0	48	3	3	3	3	0	3
17	0	0	0	0	3	0	49	0	0	0	0	3	3
18	3	0	0	0	3	0	50	3	0	0	0	3	3
19	0	3	0	0	3	0	51	0	3	0	0	3	3
20	3	3	0	0	3	0	52	3	3	0	0	3	3
21	0	0	3	0	3	0	53	0	0	3	0	3	3
22	3	0	3	0	3	0	54	3	0	3	0	3	3
23	0	3	3	0	3	0	55	0	3	3	0	3	3
24	3	3	3	0	3	0	56	3	3	3	0	3	3
25	0	0	0	3	3	0	57	0	0	0	3	3	3
26	3	0	0	3	3	0	58	3	0	0	3	3	3
27	0	3	0	3	3	0	59	0	3	0	3	3	3
28	3	3	0	3	3	0	60	3	3	0	3	3	3
29	0	0	3	3	3	0	61	0	0	3	3	3	3
30	3	0	3	3	3	0	62	3	0	3	3	3	3
31	0	3	3	3	3	0	63	0	3	3	3	3	3
32	3	3	3	3	3	0	64	3	3	3	3	3	3

Resource experimental design B (resource interventions 7-10)

Exp	Nonintegrated	Extrarooms	Resources
1	0	0	0
2	0	1	0
3	0	2	0
4	0	3	0
5	0	0	1
6	0	1	1
7	0	2	1
8	0	3	1
9	0	0	2

10	0	1	2
11	0	2	2
12	0	3	2
13	0	0	3
14	0	1	3
15	0	2	3
16	0	3	3

Resource experimental design C (resource interventions 11-14)

Exp	Nonintegrated	Roomdivision	PA	NP	Taakverd
1	0	0	0	0	0
2	0	1	0	0	0
3	0	0	4	4	0
4	0	1	4	4	0
5	0	0	0	0	1
6	0	1	0	0	1
7	0	0	4	4	1
8	0	1	4	4	1
9	0	0	0	0	2
10	0	1	0	0	2
11	0	0	4	4	2
12	0	1	4	4	2
13	0	0	0	0	3
14	0	1	0	0	3
15	0	0	4	4	3
16	0	1	4	4	3

Resource experimental design D (Resource interventions 15-19)

Exp	SV	AC	AI	PA	DA	HA	SA	StaffSpecialist
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	1
3	0	1	1	1	0	0	1	0
4	0	0	2	0	0	0	2	0
5	1	0	0	0	1	1	0	0
6	2	0	0	0	2	2	0	0

Appendix 8

To determine the minimum number of simulation runs while simultaneously maintaining a specified precision we use (per experimental design) the following parameters and sequence of procedures.

For a specified precision we use the relative error γ (γ=0.05) and α (α = 0.05) percent confidence interval. The formula to the right details the formulation of the relative error.

$$\frac{t_{n-1,1-\alpha/2}\sqrt{s^2/n}}{\bar{X}} < \gamma'$$

Given that there are multiple performance indicators (each with their own variance) and experiments we wish to run as many simulations such that the most variable performance indicator for the most variable experiment has a relative error < 0.05. To do this we use the following steps:

- Perform 10 simulation runs per experiment
- Determine the variance per KPI per experiment
- Estimate the minimum required runs per KPI of the most variable experiment using:

$$n^* = \min\left\{ i \geq n : \frac{1.96\sqrt{S_n^2/i}}{\bar{X}} \leq \gamma' \right\}$$

- Perform the estimated number of runs per KPI
- Determine if the relative error requirement is met, and at which number of runs.

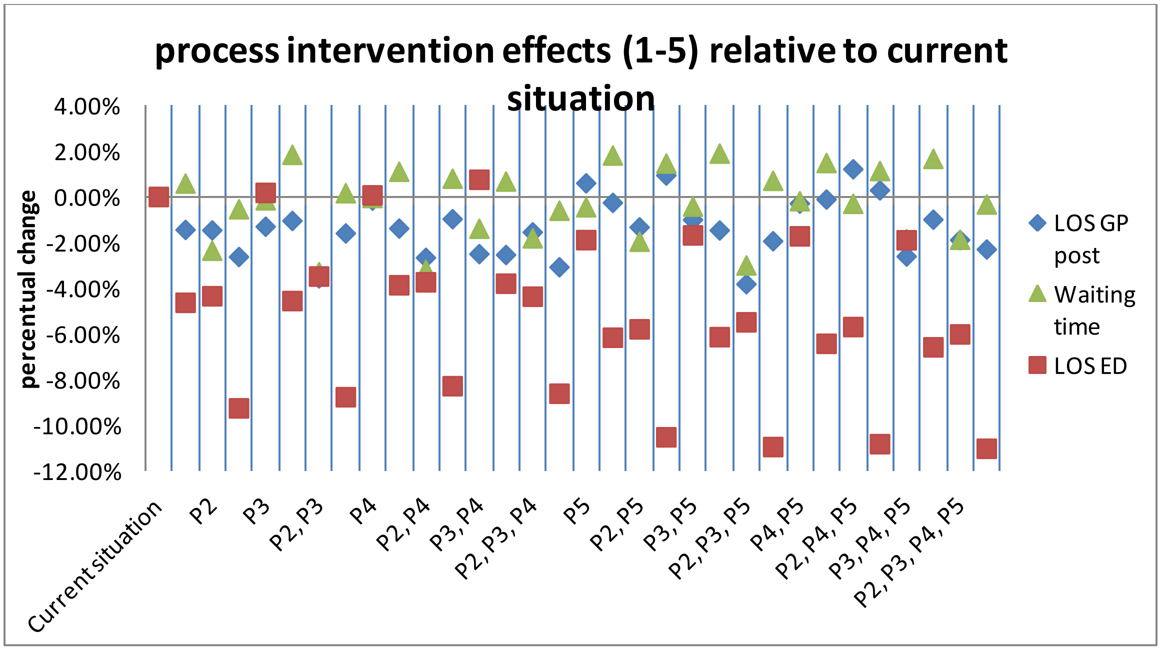
The following table details the number of runs (simulated weeks) conducted per experimental design:

Experimental design	Number of runs
Processes	32
Resource ED1	32
Resource ED2	33
Resource ED3	48
Resource ED4	31
Phase 2 experiments	222
Promising interventions comparison	222

APPENDIX 9

Process ED outcomes

The figure and table below give the relative, as well as the absolute average outcomes per experiment in the process experimental design.

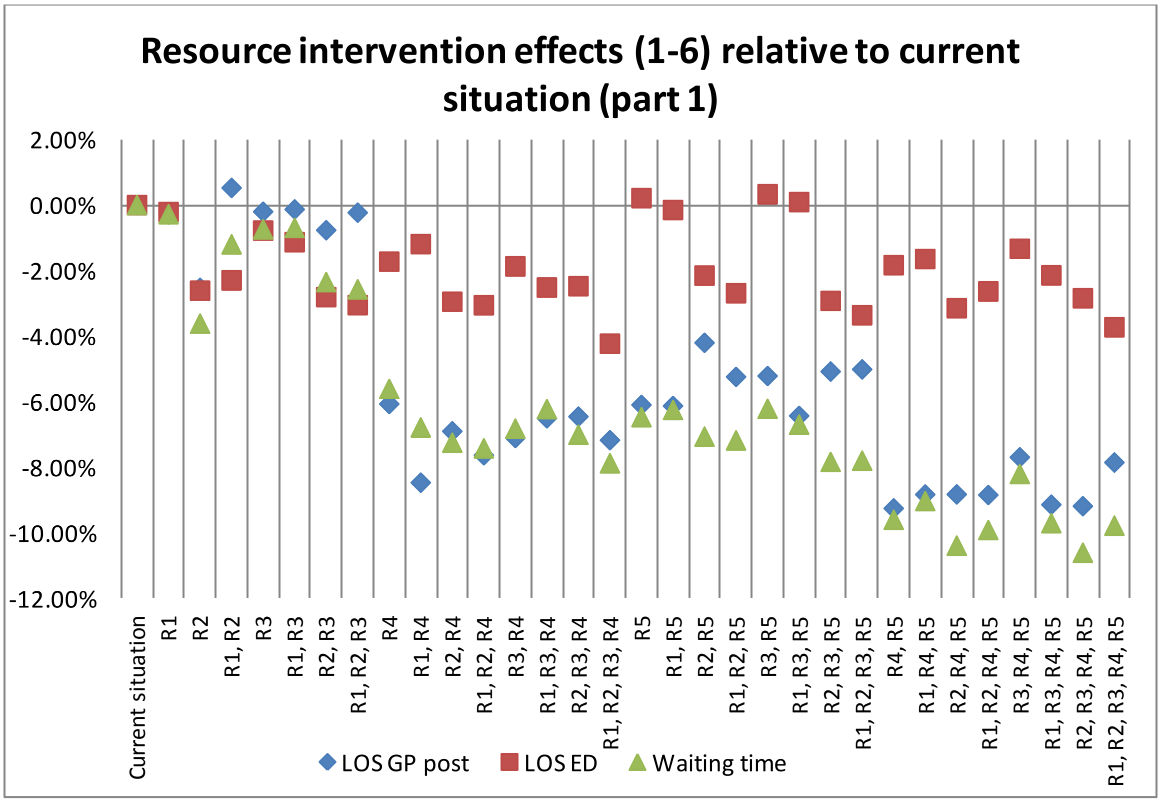


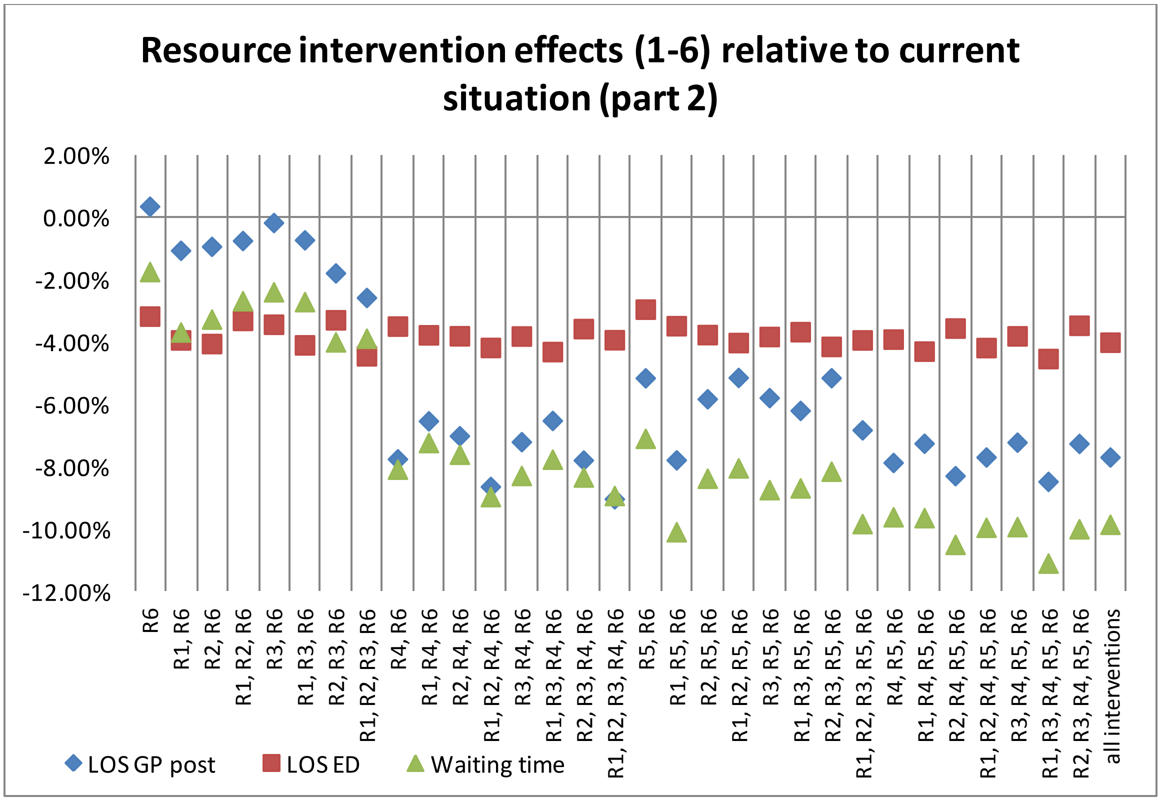
	Avg LOS	Avg LOSENTR	Avg LOSHAP	Avg LOSSEH	Avg Process	Avg Waiting	Avg Occupancy	Perc Helped
Current situation	2543	1198	1440	6197	490	414	0.39	0.99
P1	2486	1186	1419	5909	495	416	0.39	0.99
P2	2486	1184	1418	5927	496	404	0.39	0.99
P1, P2	2443	1190	1402	5623	501	411	0.38	0.99
P3	2537	1200	1421	6208	490	413	0.39	0.99
P1, P3	2500	1199	1424	5914	495	421	0.39	0.99
P2, P3	2479	1185	1388	5981	498	400	0.39	0.99
P1, P2, P3	2459	1195	1417	5653	503	414	0.39	0.99
P4	2537	1193	1437	6201	488	413	0.39	0.99
P1, P4	2496	1190	1420	5957	496	418	0.39	0.99
P2, P4	2480	1181	1401	5965	498	400	0.39	0.99
P1, P2, P4	2466	1195	1426	5683	503	417	0.39	0.99
P3, P4	2528	1195	1404	6243	492	408	0.40	0.99
P1, P, P4	2486	1188	1403	5961	495	416	0.39	0.99
P2, P3, P4	2492	1193	1417	5926	498	406	0.40	0.99

P1, P2, P3, P4	2446	1190	1395	5663	503	411	0.39	0.99
P5	2525	1192	1448	6080	486	412	0.39	0.99
P1, P5	2488	1194	1436	5815	490	421	0.39	0.99
P2, P5	2481	1189	1420	5837	492	406	0.39	0.99
P1, P2, P5	2463	1195	1453	5544	497	420	0.39	0.99
P3, P5	2523	1198	1425	6092	484	412	0.39	0.99
P1, P3, P5	2483	1197	1418	5816	488	421	0.39	0.99
P2, P3, P5	2468	1192	1385	5856	492	401	0.39	0.99
P1, P2, P3, P5	2447	1202	1412	5518	497	417	0.39	0.99
P4, P5	2518	1188	1435	6090	483	413	0.40	0.99
P1, P4, P5	2481	1188	1438	5798	488	420	0.39	0.99
P2, P4, P5	2503	1196	1457	5844	493	412	0.40	0.99
P1, P2, P4, P5	2457	1196	1444	5526	497	418	0.39	0.99
P3, P4, P5	2506	1192	1402	6079	484	406	0.40	0.99
P1, P3, P4, P5	2484	1198	1425	5788	489	421	0.39	0.99
P2, P3, P4, P5	2483	1198	1412	5824	492	406	0.40	1.00
All interventions	2432	1190	1406	5513	496	412	0.39	0.99

Staff resource ED outcomes

The figures and table below give the relative, as well as the absolute average outcomes per experiment in the staff resource experimental design.





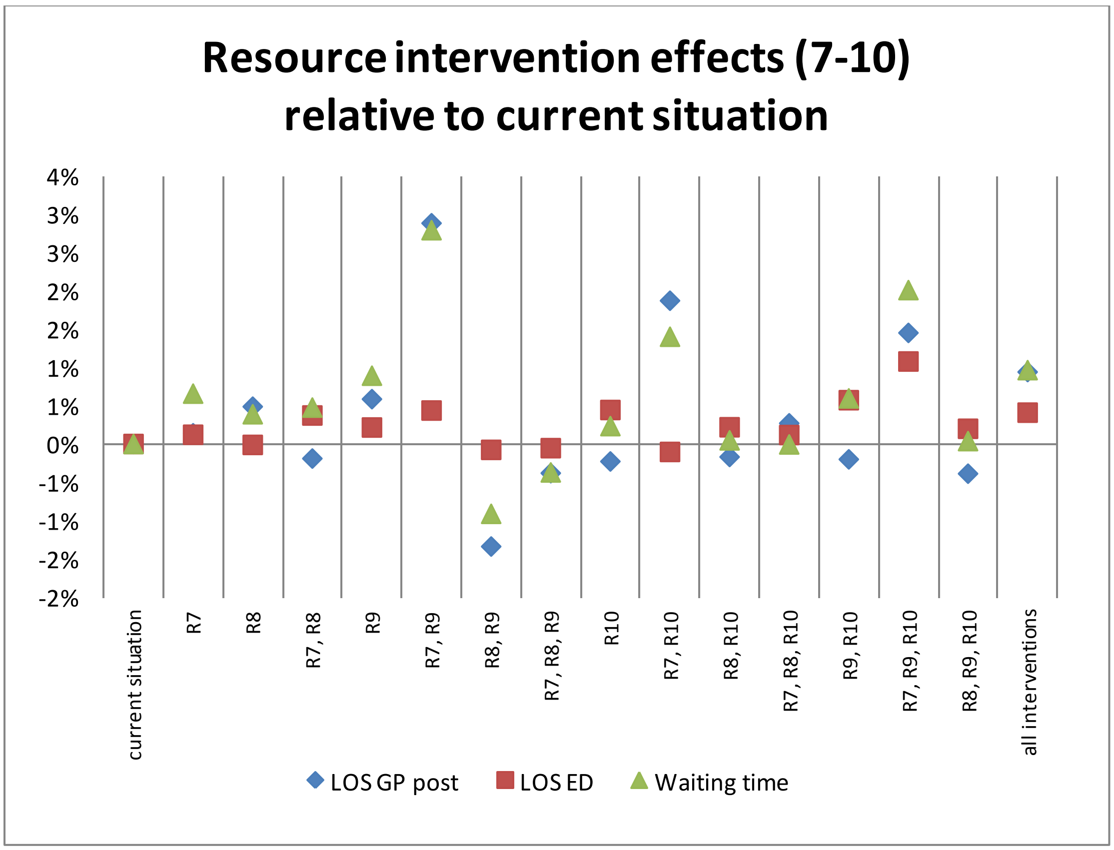
	Avg LOS	Avg LOSENTR	Avg LOSHAP	Avg LOSSEH	Avg Process	Avg Waiting	Avg Occupancy	Perc Helped
Current situation	2542	1197	1441	6205	490	413	0.39	1.00
R1	2534	1192	1437	6192	490	412	0.39	0.99
R2	2494	1185	1405	6043	490	398	0.39	0.99
R1, R2	2527	1197	1449	6063	490	408	0.38	0.99
R3	2532	1195	1438	6157	491	410	0.38	0.99
R1, R3	2530	1194	1439	6135	490	411	0.38	0.99
R2, R3	2513	1195	1430	6031	491	404	0.38	0.99
R1, R2, R3	2505	1185	1438	6016	490	403	0.37	0.99
R4	2465	1171	1354	6098	489	390	0.39	0.99
R1, R4	2452	1169	1319	6131	490	385	0.38	0.99
R2, R4	2447	1169	1342	6022	490	383	0.38	0.99
R1, R2, R4	2440	1167	1331	6016	489	383	0.37	0.99
R3, R4	2455	1170	1339	6089	490	385	0.38	0.99
R1, R3, R4	2456	1172	1348	6049	490	388	0.37	0.99
R2, R3, R4	2458	1172	1348	6052	492	384	0.37	0.99
R1, R2, R3, R4	2432	1165	1338	5943	489	381	0.37	0.99
R5	2463	1152	1353	6218	491	387	0.38	0.99
R1, R5	2462	1155	1353	6196	491	388	0.38	0.99
R2, R5	2456	1152	1381	6072	491	384	0.38	0.99
R1, R2, R5	2446	1153	1366	6038	490	384	0.37	0.99

R3, R5	2470	1152	1366	6226	492	388	0.37	0.99
R1, R3, R5	2454	1147	1349	6211	491	386	0.37	0.99
R2, R3, R5	2443	1151	1368	6024	490	381	0.37	0.99
R1, R2, R3, R5	2443	1153	1369	5997	490	381	0.36	0.99
R4, R5	2417	1142	1308	6091	489	374	0.37	0.99
R1, R4, R5	2427	1149	1314	6103	491	376	0.37	0.99
R2, R4, R5	2409	1141	1314	6010	489	370	0.37	0.99
R1, R2, R4, R5	2413	1142	1314	6042	490	372	0.36	0.99
R3, R4, R5	2441	1153	1330	6122	491	380	0.37	0.99
R1, R3, R4, R5	2419	1146	1310	6072	491	373	0.36	0.99
R2, R3, R4, R5	2415	1147	1309	6029	492	370	0.36	0.99
R1, R2, R3, R4, R5	2417	1148	1328	5974	491	373	0.36	0.99
R6	2520	1199	1446	6008	492	406	0.39	0.99
R1, R6	2498	1190	1426	5961	491	398	0.38	1.00
R2, R6	2498	1191	1428	5954	491	400	0.38	0.99
R1, R2, R6	2508	1194	1430	6000	491	402	0.37	0.99
R3, R6	2513	1196	1439	5992	491	404	0.38	0.99
R1, R3, R6	2504	1197	1431	5951	491	402	0.37	0.99
R2, R3, R6	2494	1185	1416	6001	490	397	0.37	0.99
R1, R2, R3, R6	2481	1187	1404	5929	488	397	0.36	0.99
R4, R6	2432	1162	1330	5988	488	380	0.38	0.99
R1, R4, R6	2446	1172	1347	5971	490	384	0.37	0.99
R2, R4, R6	2447	1176	1340	5969	491	382	0.37	0.99
R1, R2, R4, R6	2424	1166	1317	5946	489	376	0.37	0.99
R3, R4, R6	2441	1172	1338	5969	491	379	0.37	0.99
R1, R3, R4, R6	2442	1172	1347	5938	490	381	0.36	0.99
R2, R3, R4, R6	2438	1170	1329	5983	490	379	0.36	0.99
R1, R2, R3, R4, R6	2429	1174	1311	5961	491	377	0.36	0.99
R5, R6	2455	1164	1367	6022	491	384	0.38	0.99
R1, R5, R6	2414	1141	1329	5989	490	372	0.37	0.99
R2, R5, R6	2432	1152	1357	5971	489	379	0.37	0.99
R1, R2, R5, R6	2438	1155	1367	5956	491	380	0.36	0.99
R3, R5, R6	2434	1153	1358	5968	490	377	0.37	0.99
R1, R3, R5, R6	2427	1147	1352	5977	490	378	0.36	0.99
R2, R3, R5, R6	2438	1156	1367	5948	491	380	0.36	0.99
R1, R2, R3, R5, R6	2420	1147	1343	5961	491	373	0.36	0.99
R4, R5, R6	2418	1151	1328	5962	490	374	0.37	0.99
R1, R4, R5, R6	2419	1151	1337	5939	490	374	0.36	0.99
R2, R4, R5, R6	2413	1147	1322	5984	492	370	0.36	0.99
R1, R2, R4, R5, R6	2416	1151	1330	5946	491	372	0.36	0.99
R3, R4, R5, R6	2420	1147	1337	5969	490	372	0.36	0.99

R1, R3, R4, R5, R6	2403	1145	1319	5924	490	368	0.35	0.99
R2, R3, R4, R5, R6	2422	1147	1337	5990	492	372	0.36	0.99
all interventions	2415	1148	1330	5956	491	373	0.35	0.99

Diagnostic equipment interventions

The figure and table below give the relative, as well as the absolute average outcomes per experiment in the diagnostic resource experimental design.

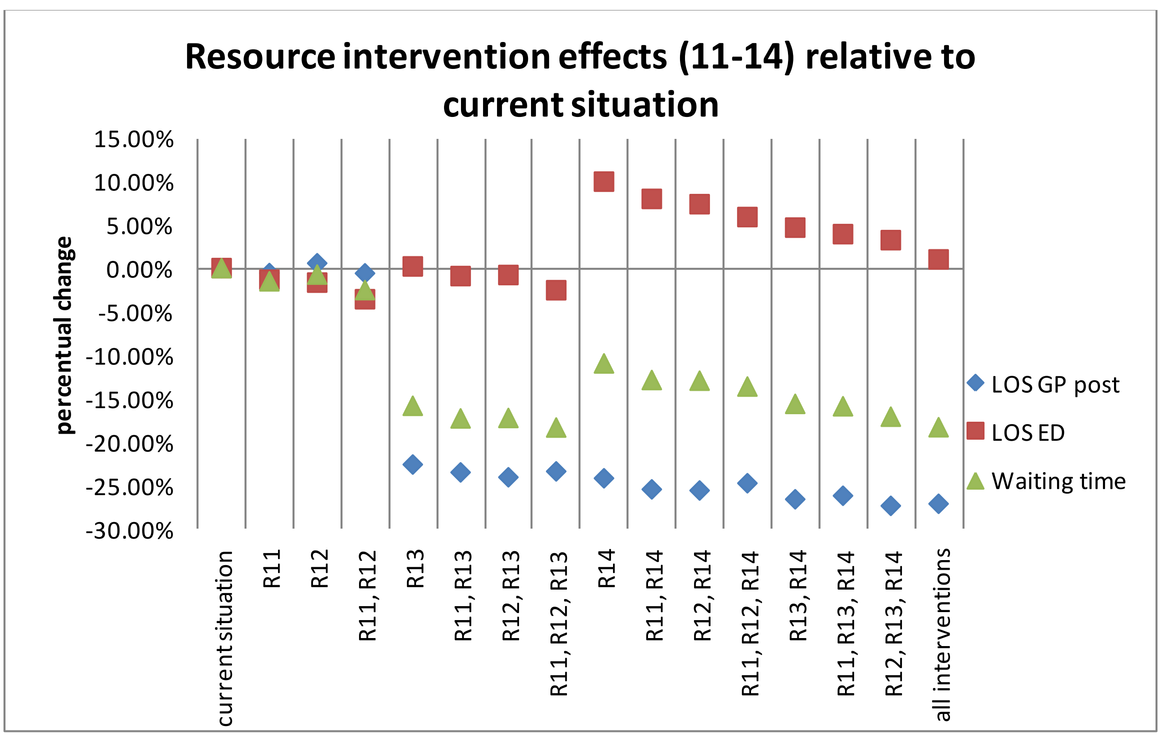


	Avg LOS	Avg LOSENTR	Avg LOSHAP	Avg LOSSEH	Avg Process	Avg Waiting	Avg Occupancy	Perc Helped
current situation	2517	1187	1423	6191	490	409	0.39	0.99
R7	2525	1193	1425	6199	490	411	0.39	0.99
R8	2521	1187	1430	6190	490	410	0.39	1.00
R7, R8	2520	1188	1420	6214	490	411	0.39	0.99
R9	2523	1188	1431	6205	490	412	0.39	0.99
R7, R9	2557	1206	1464	6218	493	420	0.39	0.99

R8, R9	2503	1182	1404	6186	490	405	0.39	0.99
R7, R8, R9	2510	1183	1417	6188	490	407	0.39	0.99
R10	2519	1187	1419	6219	491	410	0.39	0.99
R7, R10	2533	1192	1449	6185	490	414	0.39	0.99
R8, R10	2518	1187	1420	6205	490	409	0.39	0.99
R7, R8, R10	2517	1184	1427	6198	490	409	0.39	0.99
R9, R10	2518	1184	1420	6227	489	411	0.39	0.99
R7, R9, R10	2541	1192	1443	6258	491	417	0.39	0.99
R8, R9, R10	2516	1186	1417	6203	490	409	0.39	0.99
all interventions	2528	1188	1436	6217	490	413	0.39	0.99

Resource allocation interventions

The figure and table below give the relative, as well as the absolute average outcomes per experiment in the resource allocation experimental design.



	Avg LOS	Avg LOSENTR	Avg LOSHAP	Avg LOSSEH	Avg Process	Avg Waiting	Avg Occupancy	Perc Helped

current situation	2544	1199	1441	6203	490	415	0.39	0.99
R11	2525	1194	1433	6120	490	408	0.39	0.99
R12	2530	1194	1449	6100	489	412	0.39	0.99
R11, R12	2511	1199	1432	5981	491	404	0.40	0.99
R13	2345	1144	1115	6215	490	349	0.39	0.99
R11, R13	2327	1140	1102	6146	490	343	0.38	0.99
R12, R13	2325	1140	1094	6154	489	343	0.39	0.99
R11, R12, R13	2321	1145	1104	6045	492	339	0.39	0.99
R14	2411	1141	1093	6820	492	369	0.39	0.99
R11, R14	2381	1138	1074	6697	491	361	0.38	0.99
R12, R14	2379	1140	1072	6659	490	361	0.39	0.99
R11, R12, R14	2375	1143	1084	6567	492	358	0.39	0.99
R13, R14	2349	1138	1058	6492	490	350	0.38	0.99
R11, R13, R14	2347	1140	1064	6446	491	349	0.38	0.99
R12, R13, R14	2328	1133	1047	6403	489	344	0.38	0.99
all interventions	2313	1135	1050	6265	489	339	0.39	0.99

APPENDIX 10

The tables and list below give the length of stay outcomes (seconds) for the most promising interventions, both absolute as well as relative to the current situation, and the two sample t-test (α=0.05) results for every intervention-performance indicator combination.

1. Current situation.
2. Weekend NP replacement with PA.
3. Treating low urgency ED patients in GP post rooms.
4. Ordering pre-diagnostic tests for ED patients that likely need them.
5. Direct bed admission requests for ED patients that are likely to be admitted.
6. Using a single triage system.
7. Using the ZGT roster.
8. Adding a PA during the weekend.
9. Replacing an ED nurse with a PA during weekdays (5pm-8pm).

Average outcomes	GP post weekday high urgency	GP post weekday low urgency	GP post weekend high urgency	GP post weekend low urgency
current	1185.922	1557.131	1151.116	1355.752
2	1193.815	1519.433	1119.444	1367.295
3	1214.459	1559.977	1143.136	1359.864
4	1196.98	1571.452	1118.649	1350.742
5	1219.083	1576.382	1122.773	1341.547
6	1190.21	1566.035	1123.425	1339.998
7	1204.543	1522.673	1130.502	1233.567
8	1233.512	1564.474	1101.164	1195.157
9	1177.832	1282.862	1144.48	1349.13
	ED weekday high urgency	ED weekday low urgency	ED weekend high urgency	ED weekend low urgency
current	6421.009	5901.223	6201.318	6298.65
2	6426.42	5885.775	6129.989	6062.955
3	6456.62	5781.747	6183.08	6190.307
4	6055.086	5697.889	5820.507	6008.199
5	6206.478	5774.82	6060.017	6189.311
6	6227.85	5614.083	6018.461	5950.059
7	6438.044	5855.56	5963.522	5823.149
8	6388.995	5909.325	6161.48	6057.35
9	6447.434	5890.235	6173.542	6292.036

Relative outcomes	GP post weekday high urgency	GP post weekday low urgency	GP post weekend high urgency	GP post weekend low urgency
current	1185.922	1557.131	1151.116	1355.752
2	7.893429	-37.6986	-31.6716	11.54234
3	28.53668	2.845179	-7.98013	4.11136
4	11.05853	14.32072	-32.4663	-5.01046
5	33.16157	19.25094	-28.3428	-14.2053
6	4.287928	8.903153	-27.6913	-15.7538
7	18.62132	-34.4582	-20.6134	-122.185
8	47.59017	7.34239	-49.9516	-160.595
9	-8.09013	-274.269	-6.63554	-6.62244
Relative outcomes	ED weekday high urgency	ED weekday low urgency	ED weekend high urgency	ED weekend low urgency
current	6421.009	5901.223	6201.318	6298.65
2	5.411109	-15.4481	-71.3287	-235.695
3	35.61118	-119.477	-18.238	-108.342
4	-365.923	-203.334	-380.811	-290.45
5	-214.531	-126.403	-141.302	-109.338
6	-193.159	-287.14	-182.858	-348.591
7	17.03534	-45.6629	-237.796	-475.501
8	-32.0142	8.101474	-39.8383	-241.299
9	26.42465	-10.9881	-27.7763	-6.61358

p-values	GP post weekday high urgency	GP post weekday low urgency	GP post weekend high urgency	GP post weekend low urgency
current	0.00	0.00	0.00	0.00
2	0.82	0.17	0.26	0.64
3	0.43	0.92	0.78	0.87
4	0.75	0.61	0.26	0.84
5	0.35	0.49	0.34	0.55
6	0.90	0.75	0.35	0.50
7	0.61	0.22	0.49	0.00
8	0.19	0.79	0.08	0.00
9	0.81	0.00	0.82	0.79
p-values	ED weekday high urgency	ED weekday low urgency	ED weekend high urgency	ED weekend low urgency
current	0.00	0.00	0.00	0.00
2	0.96	0.70	0.23	0.00

3	0.77	0.00	0.75	0.09
4	0.00	0.00	0.00	0.00
5	0.05	0.00	0.02	0.09
6	0.09	0.00	0.00	0.00
7	0.88	0.29	0.00	0.00
8	0.77	0.84	0.48	0.00
9	0.82	0.79	0.64	0.92