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Improving the design and operation of an integrated emergency post via simulation

NJ Borgman*, MRK Mes, IMH Vliegen and EW Hans

University of Twente, Enschede, The Netherlands

In the Netherlands, patients with an acute care demand after office hours often wrongly choose to visit the emergency department (ED), while they could have visited the general practitioners' post (GPP). This may lead to overcrowding and increased costs. In this paper, we focus on an Integrated Emergency Post (IEP) at a Dutch hospital, where the ED and the GPP have been merged into a single point of access for patients. To find the optimal process design for this new IEP, we use computer simulation incorporating patient preferences. We define many potential interventions, and compare these by categorizing and grouping them, and sequentially withdrawing ineffective interventions, while accounting for possible interaction effects. Results show a sustainable solution for all stakeholders involved, reducing patients' length of stay up to 17%. Based on these results, an intervention has been trialled in practice, showing a decrease in patient LOS.

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1. Introduction

The delivery of acute care to patients is highly complex and constrained by limited resources. In addition, many of the involved processes are stochastic and there are interactions both within and external to the acute care providers. Consequently, the effects of organizational changes tend to be unpredictable. Therefore, operations research methods, such as computer simulation, are suitable for prospectively evaluating changes such as alternative resource allocations. Indeed, simulation is used often in emergency department modelling (Gunal and Pidd, 2010). In this paper we focus on the delivery of acute care outside office hours, when general practitioners' practices are closed. In the Netherlands, when people are confronted with an acute care demand outside normal office hours, they choose whether to go to an Emergency Department (ED) or go to a General Practitioners Post (GPP). In the Netherlands, as well as in several other countries, the organization of primary care delivery is shifting towards an increasing integration of triage and advice by phone, as well as larger care provider cooperatives (Grol *et al*, 2006). The self-referring patients—or 'walk-ins'—who arrive at the ED could often have been seen and treated by a general practitioner (GP), at a GPP, with significant cost savings (Hoot and Aronsky, 2008).

A new concept in the delivering of acute care after office hours is the integrated emergency post (IEP). Similarly to the earlier creation of GPPs, an IEP organizes the provision of after-hours care in a larger cooperative grouping of health-care providers by integrating an ED with a GPP. The main intention of the IEP is to alleviate ED overcrowding by shifting primary care demands from the secondary care provider to the primary care provider, while providing the necessary treatment for patients with an acute care need. The IEP thus offers a sustainable solution to ED overcrowding, resulting in cost savings for the hospital, increased quality of care for the patients and better usage of resources. In this way, the IEP not only has economic benefits, but also on a social and environmental level, and as such contributes to all three pillars of the Triple Bottom Line (TBL). The integration into the IEP gives patients more clarity on where to go with their acute care need, avoids travel times between the GPP and the ED, and provides more opportunities to treat high urgency patients at the ED. In addition, as the IEP is a new concept for health-care providers, this integration of acute health care offers new opportunities for efficiency and efficacy gains.

The objective of this study is to prospectively evaluate organizational interventions and design improvements for an IEP. To this end, we utilize insights from both the screening and the optimization literature as well as domain knowledge of the emergency care environment. A case study is carried out at the IEP in Almelo, the Netherlands, where the ED of the hospital ZiekenhuisGroep Twente merged with the GPP Centrale Huisartsen Post Almelo.

Sustainable development can be defined as the 'development that meets the needs of the present without compromising the ability of future generations to meet their own needs' (WCED, 1987). Similarly, sustainable health care ensures that in the future, resources are available to address possible future needs. This study contributes to this in two different ways. First, we study an IEP, a new concept that in itself is sustainable, since it uses fewer resources to provide better care to urgent patients. Second, we describe a method, consisting of simulation modelling and a

*Correspondence: NJ Borgman, Industrial Engineering and Business Information Systems, University of Twente, PO Box 217, Oversijssel, Enschede 7500 AE, The Netherlands.
E-mail: n.j.borgman@utwente.nl

systematic approach, that even leads to better usage of the resources within the IEP. In this way, we contribute to all three pillars of the TBL: people, planet and profit. In this study we explicitly consider the effects of interventions on both people (patients as well as health-care professionals) and profit (cost savings for both the ED and GPP). Efficiently organizing the provision of acute care within an IEP allows for an equitable distribution of care, where patients receive care appropriate to their care needs. Within this study, patient preferences are used to define appropriate performance indicators, accounting for the people aspect in sustainability. Besides effectiveness, the costs of interventions are evaluated such that (in total) a cost effective organization of the IEP is designed (profit). This allows for an increased delivery in care while maintaining current costs. As such, the future ability to offer care to potential future needs is ensured. Implicitly, a better use of resources, for example, through a reduction of diagnostic equipment (previously placed at both GPP and ED), as well as less travel time between organizations for both patients and health-care providers may have a positive environmental impact.

The theoretical contribution of our work is twofold. First, we put forward a method to systematically evaluate a large number of interventions simultaneously, using discrete event simulation, to improve the processes in an acute care chain. Second, we validate and apply this approach to the IEP in Almelo, incorporating patient preferences, and provide insights into the efficient organization of an IEP in general, based on this case study. The practical contribution of our work is the delivery of a sustainable design of the new IEP, taking into account patient preferences and hospital costs, as well as the implementation of a flexible simulation model at the hospital. This implementation includes training of IEP staff in using the model, enabling them to adapt the model when necessary and to evaluate new interventions in the future.

The remainder of this paper is organized as follows. In Section 2, we review the screening and the optimization literature and applications of the reported findings in health care. In addition, we position the IEP concept in literature. Next, we describe the problem and the simulation model (Section 3). In Section 4, we present the approach used to define and evaluate interventions. Following this, we give the results from this approach as well as describe the implementation in practice based on the results (Section 5). We end this paper with the conclusions drawn from this study (Section 6).

2. Literature

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 *et al*, 1995; Kulu-Glasgow *et al*, 1998). However, the cooperation between acute care providers is limited (Thijssen *et al*, 2012), and the effects of creating an IEP, and its potential efficiency gains are uncertain (Kool *et al*, 2008). Within the IEP evaluated in this paper, the collaboration between a GPP and an ED is investigated with regards to the effect of sharing resources, expertise, and organizational strengths, and the efficiency gains these may contain.

Computer simulation is an often used tool in health-care studies, with several comprehensive literature reviews detailing its uses (Jun *et al*, 1999; Fone *et al*, 2003; Brailsford *et al*, 2009; Gunal and Pidd, 2010; Mielczarek and Uziałko-Mydlikowska, 2012). Within the health-care domain, much attention has been given to the modelling of EDs, which are compared with other departments (Gunal and Pidd, 2010). Much of the simulation of EDs is focused on developing and creating valid models. For example, Sinreich and Marmor (2005) detail a basic approach to creating and using a simulation model, focusing on creating a flexible and easy-to-use model, as well as stakeholder involvement. Similarly, Jurishica (2005) discusses proven practices used in developing ED simulation models.

Following model building and validation, usually several interventions are evaluated. For example, Duguay and Chetouane (2007) present a detailed simulation model to evaluate different interventions focusing on staff and room availability with the aim to reduce ED waiting times, and Komashie and Mousavi (2005) evaluate the change in bed availability in an ED. Paul *et al* (2010) conducted a literature review on the use of simulation to investigate overcrowding of EDs and detailed the different evaluated changes. The interventions evaluated were divided over resource-related, process-related, and environmental-related scenarios. Most of the reported articles focus on the reduction of waiting times for patients (Paul *et al*, 2010).

Our goal is to prospectively evaluate many different interventions, using a simulation model, and to find a close to optimal process design of the IEP. Related methodologies to support this are factor screening and simulation optimization. Factor screening is used to screen for influential factors, and aims to reduce model complexity and computation time, while still achieving good outcomes (Kelton, 2000; Kleijnen, 2008). Simulation optimization attempts to find the combination of controllable factor settings that lead to the best outcome (April *et al*, 2003). However, it must also deal with noise, as simulation outcomes are approximations of true performance indicators.

A straightforward screening method is a full factorial or 2^k design, such that both main effects and interactions may be evaluated (Law, 2007). A downside of this method is that, as the number of factors increase, many runs are required. To overcome this, fractional factorial designs may be used, which require fewer runs, with a loss of some interaction effects (Law, 2007). However, care should be taken not to combine potentially important effects (Montgomery, 2008). Other screening approaches for a large number of factors are two-stage group screening (Mauro, 1984; Ivanova *et al*, 1999; Trocine and Malone, 2001), sequential bifurcation (Bettonvil and Kleijnen, 1997; Cheng, 1997; Yaesoubi *et al*, 2010), iterated fractional factorial designs and supersaturated designs. We see that among the different screening techniques, many are specific in regard to the assumptions made, the maximum number of factors, applicability regarding qualitative and (continuous) quantitative factors, and the use of information already known before screening, such as the signs of interaction.

Different approaches to simulation optimization are ranking & selection (Boesel *et al*, 2003; Fu *et al*, 2005), response surface methodology (Fu *et al*, 2005), gradient-based procedures (Fu *et al*, 2005), random search (Andradóttir, 2006), and sample path optimization and metaheuristics (April *et al*, 2003). An example of simulation optimization applied to an ED is given by Ahmed and Alkhamis (2009), who determine the number of staff required to optimize patient throughput and waiting times. Similar to the screening methods, the application of optimization techniques relies on characteristics of the underlying simulation model. Depending on input variables and constraints, certain optimization methods are more applicable than others. For more details we refer to Andradottir (1998) and Barton and Meckesheimer (2006). An additional challenge with optimization is that the methods may propose a solution which requires many organizational changes within the ED, which might prevent a successful implementation. Much of the literature on simulation in health care focuses on model construction and validation, with less emphasis on defining and evaluating possible interventions and their interaction effects. This has motivated us (i) to propose a way to evaluate and improve over a large number of interventions using a discrete event simulation model and (ii) to consider the optimal organization of a new innovative concept in health care, that is, the IEP.

Since it is unlikely that the management of the IEP will accept drastic organizational changes in which many interventions are combined, we put forward a structured approach in which we identify only the most effective interventions for an area of change (eg, rostering alternatives). This results in a smaller set of interventions that increase the effectiveness of the IEP without making drastic organizational changes.

3. Problem description

In this section, we give a general description of an IEP and describe the implemented IEP in Almelo. Following this, we briefly address the simulation model that is used to evaluate the IEP and the way in which we incorporate patient and community preferences in formulating performance indicators. For a complete description of this simulation model, we refer to Mes and Bruens (2012).

3.1. Integrated emergency post design

In an IEP, the GPP and ED work together to provide acute care to patients outside of office hours. The largest change with the introduction of the IEP is that self-referring patients, or walk-ins, are now first seen at the GPP, instead of possibly going to the ED. 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 IEP 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 either 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 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 GPP. In most cases, this treatment is sufficient after which a patient goes home. Possibly, the patient may require an X-ray, 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 GPP, or require additional treatment, are further referred to the ED.

Patients that enter the ED are first triaged again, as the triage system differs from the one used at the GPP, 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. Additionally, some patients require multiple diagnostic tests with treatment after each test. Figure 1 shows a conceptual view of the care pathways defined of the IEP in Almelo.

As the IEP is a new concept, many organizational changes may improve the IEP's efficiency, for example, by pooling resources between the GPP and the ED, which can be prospectively evaluated using simulation. The IEP in Almelo has been modelled and validated in a detailed simulation model.

3.2. Simulation model of the integrated emergency post

The simulation model is characterized by patients, resources, and processes. Patients move through the IEP and require resources in the form of health-care professionals, diagnostic test equipment, and beds/rooms. Patients and resources are characterized by various attributes, such as urgency, diagnostics needed, availability, and capacity. The processes define the care path—the sequence of steps—that a patient must undergo.

Within the simulation model, a task list contains all the treatment steps that are to be taken next for all patients in the system. When a patient is created, a module is triggered that, depending on patient attributes and care pathway, adds the first task (treatment step) for that patient to the task list, and checks and prioritizes all open tasks. If a task is started, patient and resource handling is started, which involves updating resource availability, performance registration and animation. When a task ends, patients and resources are handled (ie, released), the next task in the care pathway is added to the task list, and the module again checks all open tasks. Besides the arrival of patients and the ending of a task, the passing of time triggers the module. For example, when a shift ends, there is a change in staff availability, requiring resource handling.

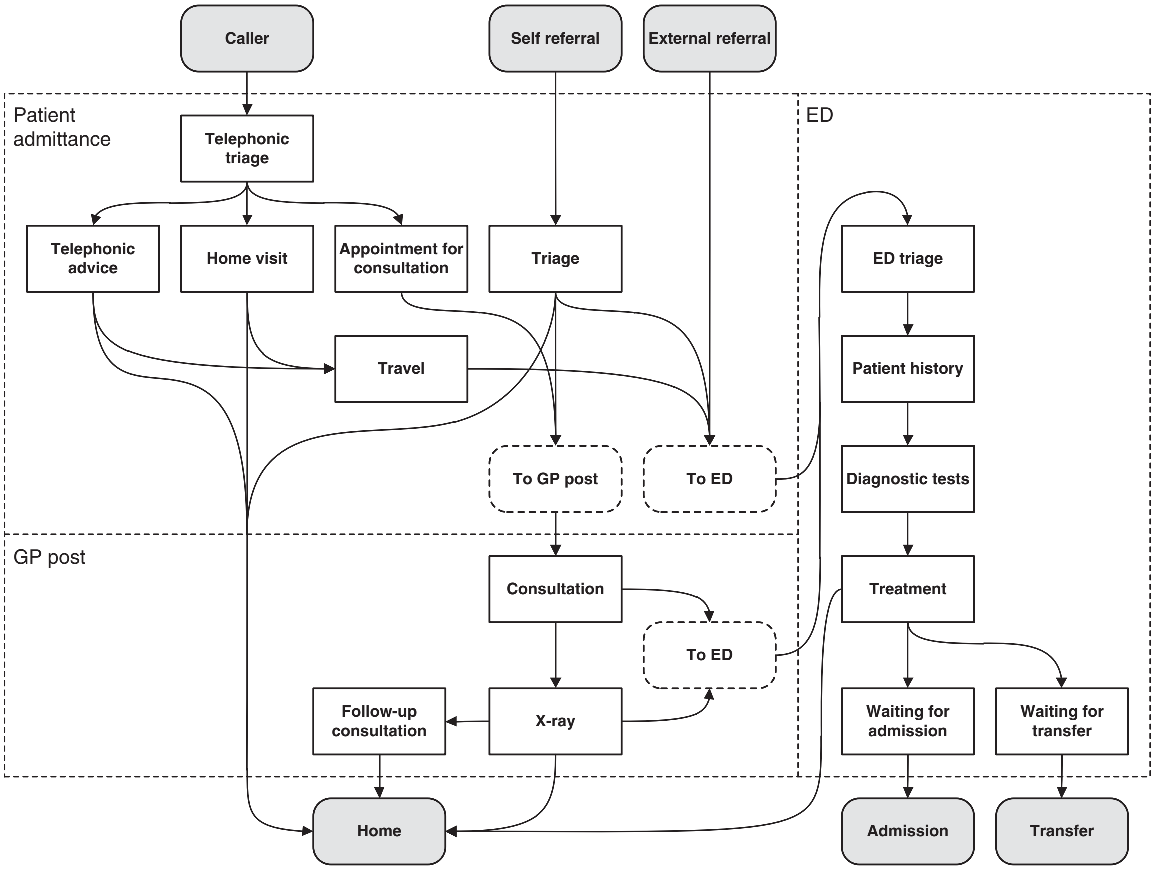

Figure 1 Patient flow and processes at the IEP Almelo (Mes and Bruens, 2012).

Three different types of processes (tasks) are modelled, being regular tasks, parallel tasks, and delay tasks. Regular tasks are the treatment steps required by patients. These are mostly processes where a patient and staff member come together in a room, and potentially require additional resources such as diagnostic equipment (eg, ultrasound). Parallel tasks are those where a patient need not be present, such as the reviewing of diagnostic tests. As such, this task may also be carried out while a patient undergoes another regular task. The delay tasks are processes that must be carried out before a regular task may start, causing waiting time. For example, when a patient requires treatment from a specialist, this staff type is called in from elsewhere in the hospital. This waiting time for the specialist to finish his current job and travel to the ED is modelled as a delay task. Within the simulation model, the arrival of patients, as well as the occurrence of treatments and diagnostic tests is modelled using probability distributions based on four years of historical data, as well as on expert opinion.

Arrivals of patients entering the IEP are described using a non-stationary Poisson process, depending on the time of day, day of the week, and week of the year. As input we have 24 arrival rates (one per hour) for weekdays (Monday till Friday) and 24 arrival rates for days in the weekend. In addition, we have 7 day factors and 52 week factors that we multiply with the arrival rate to determine the arrival rate within a given hour at a specific day. These factor distributions are determined using multiple years of historic data and represent the daily and weekly fluctuations in patient arrivals. For the non-stationary Poisson process, we generate arrivals based on the highest arrival rate per hour in combination with the thinning procedure (Law, 2007).

The resources in the model are distinguished as staff, equipment and rooms. The following staff is included: GP, GP assistant, triage assistant, ED nurse, nurse practitioner, physician assistant, medical resident and surgical resident. In addition, medical specialists and diagnostic nurses are included as external staff, who may be called to the ED when needed for treatment and diagnostic tests respectively. Since these staff types are not usually present at the ED, but requested frequently, we take into account the waiting time for their availability, and travel time to the ED. Regarding equipment and rooms, we include one triage room, six GP rooms, eight ED rooms, a CT room, two plaster rooms, and two X-ray rooms. In addition there is portable ECG and ultrasound equipment which are used in combination with an ED room. For more details on the components and the construction of the simulation model, we refer to Mes and Bruens (2012).

3.3. Modelling for sustainability

Organizations place an increasing focus not only on cost-related performance indicators, but also on social and environmental factors. These factors, and especially the social factors, are crucially important to health-care organizations. This paper is part of a research project studying the optimal process design of an IEP, such that patients are seen by the right care provider, without unnecessary delays, while accounting for patient preferences (Doggen *et al*, 2010). This research scope accounts not only for production measures, but for social and environmental measures as well. In addition to a simulation study and advice aimed to improve the current situation, the simulation model is designed flexibly, to enable health-care professionals (policy advisors) to adapt the model to the changing environment and to evaluate further improvements in the future.

To account for patient preferences, and to construct social and equitable performance indicators for this study, Fransman (2011) conducted a patient and community preference analysis using best-worst scaling. These outcomes showed that patients primarily value (lower) waiting times, followed by direct access to care provider (self-referral over appointment based), and type of care provider (physician over nurse practitioner). These indicators are incorporated in the simulation model, which is now used by the IEP. To keep our presentation concise, we focus on the key performance indicator (KPI), that is, the patient length of stay (LOS).

To improve the IEP, we aim to evaluate the effects of all potential interventions, and also account for the interaction that can take place between interventions. However, as the number of potential interventions increases, an evaluation of all combinations becomes intractable. Therefore we want to improve the IEP without evaluating every intervention alternative. The next section formulates the approach to first identify potentially effective interventions and then further evaluate these interventions.

4. Approach

In this section, we formulate the approach used to identify and evaluate potential organizational interventions. As many interventions are identified, we first formulate and categorize the interventions into several categories and eliminate ineffective interventions. Following this, we evaluate the remaining interventions and combine these into several combinations.

Given the simulation run time, a full factorial design involving many interventions quickly becomes intractable. In addition, some interventions can have many variations, such as changing staff numbers, creating many potential staffing schedules. We, therefore, first assess for which of the interventions further evaluation seems promising. We do this by evaluating interventions in groups, which reduces the number of possible alternatives. Furthermore, it is unlikely that the management of the IEP will accept drastic organizational changes in which many interventions are combined. We use a structured approach in which up to three influential interventions per group are included. This increases the effectiveness of the IEP without drastically changing its organization. Therefore, we use the approach given below.

1. List interventions
2. Categorize interventions based on type and specificity
    a. Evaluate (interaction) effects per group
    b. Select the most effective interventions per group
3. Formulate intervention sets
4. Compare intervention sets
    a. Evaluate absolute intervention outcomes
    b. Scenario analysis

Paul *et al* (2010) give an overview of interventions evaluated in health-care simulation, and make the distinction between process, resource, and environmental (eg, increasing patient arrivals) changes. Following this approach, we group interventions into process and resource changes. In addition, we further divide the resource interventions into subgroups consisting of interventions of similar nature, namely staff, diagnostics, allocation, and a roster options group.

Each 'roster options' intervention is a combination of several smaller interventions. For example, an earlier or later start of the main shifts gives insights into the fit between patient arrivals and number of staff, which is a combination of varying several staffing levels and starting times.

The environmental changes are similar to simulations carried out in a scenario analysis, evaluating the effect future demographic changes may have.

Based on the patient and community preferences we compare interventions using the patient LOS as KPI, which incorporates both treatment and waiting times (cf use in Sinreich *et al* (2012) and Ashour and Kremer (2013)). We use total LOS as a KPI, because potential interventions may affect waiting times as well as treatment times (eg, due to the intervention to use a single triage system). Some interventions target the ED or GPP specifically, so we split the LOS into GPP LOS and ED LOS. However, some interventions may target specific patient groups (eg, high urgency patients). Therefore, in the second part of our analysis, we also study the impact of the interventions for urgent and non-urgent patient groups. Also, we make a distinction between the impact on week and weekend days.

New interventions are formulated from the groups, combining the effective interventions. This is done not only based on simulation outcomes, but also based on expert opinion about the feasibility of the interventions (eg, staff availability and costs). Ideally, an equitable distribution of health care places more emphasis of those patients that need more care (ie, high urgency patients); therefore, the intervention set alternatives are compared by evaluating LOS for both high and low urgency patients individually. The categorization of high and low urgency patients is based on the triage systems used at the GPP and ED. The GPP uses the Dutch GP society (NHG) triage system (Giesen *et al*,

Table 1 Identified and categorized interventions

Category	*Group*	*Intervention*
Process		Use a single triage system (1) Change triage protocol to let ED nurse order diagnostics (2) Give priority only to high urgency patients (3) Assign physician assistants to patients before physicians (4) Initiate request of hospital admission earlier (5)
Resource	Staff	Vary the number of ED nurses (6) Vary the number of surgical residents (7) Vary the number of internal medicine residents (8) Vary the number of physician assistants (9) Vary the number of general practitioners (10) Vary the number of ED specialists (11)
Resource	Diagnostics	Vary the number of X-ray rooms (12) Vary the number of CT scan rooms (13) Vary the number of ECG equipment (14) Vary the number of Ultrasound equipment (15)
Resource	Allocation	Treat (low urgency) ED patients in GPP rooms (16) Let physician assistants treat both ED and GPP patients (17) Let ED nurse treat GPP patients (18) Let ED specialists/residents treat GPP patients (19)
Resource	Roster options	Use medical specialists at IEP at all times (20) Use future hospital roster (21) Replace internal medicine resident with ED specialist (22) Earlier main shift (GP/GP assistant/ED nurse) (23) Later main shift (GP/GP assistant/ED nurse) (24)

2006), and the ED uses the Manchester Triage System (Mackway-Jones *et al*, 2006). At the GPP, a patient's urgency ranks from U4 (not urgent), to U1 (very urgent), and at the ED, a patient's urgency is ranked blue (not urgent), green, yellow, orange, or red (very urgent). We categorized U1 and U2 patients, as well as red and orange patients as high urgency patients, and all remaining patients as low urgency patients.

5. Results

In this section, we conduct the approach described before and evaluate the (interaction) effects within each of the intervention groups. Following this, we select the interventions that show significant improvements, and use these to formulate intervention sets, which we then compare using the simulation model. Finally, a detailed evaluation and scenario analysis is carried out on the most promising intervention sets.

5.1. List interventions

To come up with interventions to evaluate, we use both simulation literature and interviews with stakeholder from the GPP and ED to define as many interventions as seem feasible to simulate and implement. In total 24 interventions are defined. For example, a stakeholder at the intervention hospital noted the possibility of utilizing a single triage system, such that patients that are referred from the GPP to the ED no longer have to be triaged a second time. Another example is the allocation of staff to patients. Currently, when a patient arrives, first ED specialists or residents are assigned to that patient, and if none of them is available, a physician assistant is assigned. As an intervention this prioritization is reversed, so that lower urgency patients are treated first by a physician assistant, keeping ED specialists and residents available for higher urgency patients that may arrive. A third example is the staffing of medical specialists at the ED. Currently, specialists are called when needed at the ED; by having specialists placed at the ED, the waiting time once a specialist is called is removed. An overview of all defined interventions is given in Table 1, the numbers in parenthesis indicate the intervention number.

5.2. Categorize interventions

Following the listing of interventions, a categorization is made based on the type of intervention as well as on the resulting number of interventions per category. Table 1 lists the division of interventions over the possible categories. The interventions in the category 'process' and in the group 'allocation' are all binary (on/off), while the diagnostics and staff changes may have several alternatives created by adding or subtracting more than one resource. In addition, staffing changes can also be temporal in nature by changing the starting times. To evaluate the potential of staff interventions, we first only add an additional staff member during the busiest hours of the IEP. We use the outcomes and insights of the staff interventions in the next step, where the intervention sets are created, by further specifying feasible staffing alternatives (ie, staff allocations). Similarly for diagnostics, an additional diagnostics machine is added in the simulation model. The roster options group consists of larger organizational interventions, which are a combination of smaller interventions.

For the first four groups, the insights into the main effects as well as interaction effects between interventions are evaluated per group using full factorial designs, and used to define the (up to) three most promising interventions per group. As the interventions in the roster options group are mutually exclusive staffing alternatives, these are evaluated individually.

During the categorical evaluation, we set the run length such that the specified precision of the most variable intervention has at most a relative error of 5% with a confidence level of 95% (Law, 2007). Using this method, the simulation run length is 32 weeks per experiment for the process, staff, and diagnostics designs; 48 weeks for the pooling and allocation design; and 31 weeks for the roster design. Table 2 lists the number of experiments per factorial design that are evaluated initially, as well as the number of simulation runs carried out per experiment.

In total, 24 different interventions are evaluated, of which the first 19 (Table 1) are evaluated using four full factorial designs. The last five interventions are evaluated individually. This results in 133 different intervention combinations that are evaluated, with a total number of 4507 runs. Based on the outcomes of these experimental designs and individual comparisons, we select the interventions that both have a significant (positive) effect on the IEP, and are deemed feasible based on expert opinion.

5.3. Category outcomes

Of the 19 interventions evaluated with full factorial designs, 12 are found to have a significant main effect within their respective groups (ie, full factorial design), with an additional five significant interaction effects. Figure 2 lists all the main and two-way interactions that are found to be significant ($\alpha = 0.05$).

Table 2 Experiments per intervention category

Experimental design	*#interventions*	*#experiments*	*#runs (#exp x #repl)*
Process interventions	5	32 (=2^5)	1024 (32 × 32)
Staff interventions	6	64 (=2^6)	2048 (64 × 32)
Diagnostics	4	16 (=2^4)	512 (16 × 32)
Pooling and allocation	4	16 (=2^4)	768 (16 × 48)
roster interventions	5	5 (=5^1)	155 (5 × 31)
Total	24	133	4507

Several process changes show an improvement at the ED. Both a single triage system (1), as well as a direct ordering of more diagnostic tests (2) reduce the ED LOS by approximately 300 seconds (5%). Furthermore, the direct admission requests (5) of specific patient groups reduce ED LOS by approximately 120 s (2%). Reprioritizing patients (3) reduces average GPP LOS by 20 s (1.3%); however, from results not shown here, low urgency (U4) LOS decreases by 10%, while LOS increases by 4 and 18% for U2 and U3 patients, respectively, redistributing the time spent at the GPP over the different patient types.

From the interaction effect in Figure 2, it is apparent that the biggest influence on reducing the GPP LOS is achieved by adding a physician assistant (9), followed by adding a GP (10). 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 on the reduction of the LOS. For the ED, we see that the biggest influence is achieved by adding an ED specialist (11), followed by adding a surgical resident (7) and adding a physician assistant (9). By adding these staff types, the average LOS is reduced by 115 (11), 60 (7) and 36 (9) seconds, respectively. Looking at the interaction effects on the GPP and ED LOS, we see that the biggest reduction on GPP LOS is achieved by allowing ED staff to treat GPP patients (18 and 19).

Additionally, there is a substitution effect where the combined interventions have a dampening effect on each other. By letting ED staff treat GPP patients, the bottleneck of staff being unavailable decreases, and shifts to another resource type. In this situation, while staff may be available, treatment room shortages may occur. The roster alternatives show a large reduction in ED LOS when medical specialists instead of residents are scheduled at the IEP. By staffing the ED with medical specialists, they no longer need to be called from within the hospital, removing the waiting- and travel time when requested for consultation. This staffing of medical specialists results in a LOS reduction of over 10 min (10%). However, this would also be a costly intervention, as specialist salaries are considerably higher than those of the residents'.

Based on these outcomes, combined with insights on associated costs and feasibility, we identify the following effective interventions.

1. Use a single triage system (1)
2. Change triage protocol to let ED nurse order diagnostics (2)
3. Initiate request of hospital admission earlier (5)
4. Vary the number of surgical residents (7)
5. Vary the number of physician assistants (9)
6. Vary the number of ED specialists (11)
7. Treat (low urgency) ED patients in GPP rooms (16)
8. Let physician assistants treat both ED and GPP patients (17)

5.4. Formulate intervention sets

As the variations of staff allow for many different schedules, we further specify interventions which are not of a binary nature, and

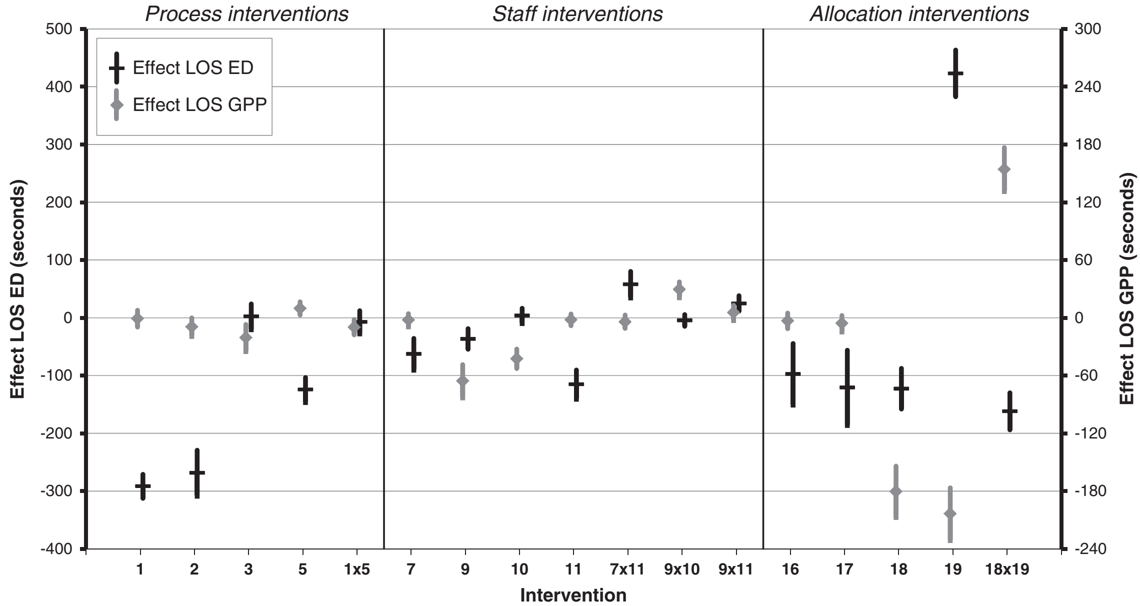

Figure 2 Significant ED and GPP main and two-way interaction effect confidence intervals (α = 0.05) (A × B denotes the interaction effect between interventions A and B).

formulate several cost equivalent alternatives. These alternatives combined with the binary process and pooling interventions result in the interventions shown below. In total, we define 10 interventions, which we combine into five sets (combinations of interventions).

1. Use a single triage system
2. Change triage protocol to let ED nurse order diagnostics
3. Initiate request of hospital admission earlier
4. Treat (low urgency) ED patients in GPP rooms
5. Let physician assistants treat both ED and GPP patients
6. Roster alternatives

    a. Replace surgical resident with ED specialist and add a physician assistant during the weekends busy hours (similar to intervention 21, future hospital staffing schedule)
    b. Schedule two physician assistants during the Saturday and Sunday busy hours instead of a GP
    c. Schedule a surgical and internal medicine resident instead of the ED specialist during the Saturday and Sunday busy hours
    d. Schedule a physician assistant instead of an ED nurse during the Saturday and Sunday busy hours
    e. Schedule a physician assistant instead of an ED nurse during the first opening hours of the IEP (5 pm–8 pm)

The different process and pooling interventions can be combined with each other to form different intervention sets. However, none of the five process and pooling interventions showed interaction within their respective groups, and it seems likely that there will be little interaction between these interventions. Therefore, we expect that a combination of these interventions, together with a roster alternative, will show the greatest LOS reduction for the IEP. To evaluate the effect of the roster alternatives, we combine each of them with the selected process and pooling interventions as shown in Table 3. Specifically, from the listed interventions we create five intervention sets. In each set interventions 1–5 are evaluated. In addition, each of the five sets also incorporates one of the mutually exclusive roster alternatives (6a–6e). Note that intervention 6e only affects the weekday evening schedule, instead of the weekend days.

Table 3 Intervention sets

Set\Intervention	1	2	3	4	5	6a	6b	6c	6d	6e
Set 1	x	x	x	x	x	x				
Set 2	x	x	x	x	x		x			
Set 3	x	x	x	x	x			x		
Set 4	x	x	x	x	x				x	
Set 5	x	x	x	x	x					x

5.5. Compare intervention sets

To evaluate the effect of the intervention sets, we make a distinction between LOS at the ED and GPP, as well as in LOS during weekend and weekdays. Additionally, we look at the LOS for high (U1 and U2 at the GPP, and red and orange at the ED) and low (U3 and U4 at the GPP, and yellow-blue at the ED) urgency patients. Figure 3 shows the effect of the various intervention sets with 95% confidence intervals. We set the run length of the experiments such that the specified precision of the most variable intervention and LOS measurement has at

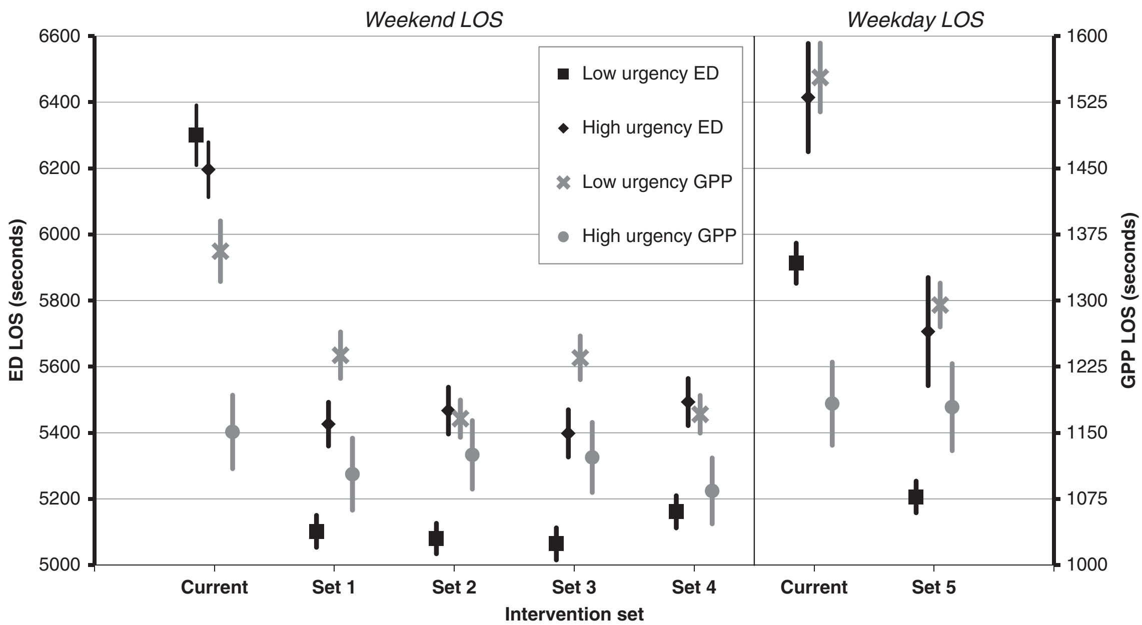

Figure 3 Average LOS outcome confidence intervals (95%) per intervention set.

most a relative error of 5% with a confidence level of 95% (Law, 2007). This results in a run length of 222 weeks per experiment.

All intervention sets improve the ED LOS compared with the original situation, as not only the procedural interventions are implemented, there is also an additional staff member working during the busy hours. The results between intervention sets in Figure 3 are significantly different ($\alpha = 0.05$) for all comparisons except the weekday LOS for High urgency GPP patients, and set 2 and 3 regarding weekend high urgency GPP LOS. The highest decrease is shown when two residents are scheduled instead of an ED specialist (set 3). However, for the cases where the differences are not significant, the differences are small compared with the total LOS times.

Similarly, we see a decrease in GPP LOS. However, the effect on high urgency patients is remarkably lower, with the confidence intervals overlapping with those of the current situation. Replacing a GP with two physician assistants (set 2) has the greatest effect on lowering the low urgency patient LOS. However, the differences between combinations are all minor. The differences in ED LOS between the best and worst intervention set differ approximately 100 s, and at the GPP the differences are around 60 s.

As no alternative intervention set decreases LOS significantly more than any other intervention set, the most promising weekend alternative seems to be 6a (set 1), given that this set contains a roster alternative preferred by the IEP stakeholders. In addition, the weekday replacement of an ED nurse with a physician assistant (6e) that treats both GPP and ED patients shows a decrease for all low urgency patients, making this a promising alternative as well.

We simulate the interventions individually to assess the absolute effects of each individual intervention on the IEP, and compare them with each other. Table 4 shows the LOS for both the GPP and the ED over both type of day (weekend or weekday) as well as high or low urgency patients. The bolded outcomes are found to be significant ($\alpha = 0.05$).

Overall, all selected interventions show a significant improvement over the current situation. Of these, the roster alternatives show the greatest effect on GPP LOS, and process interventions on ED LOS. In addition, the pooling of resources, such as staff, shows that both the GPP and ED can benefit, while the overall staffing costs remain virtually unchanged. In addition, the interventions have no significant negative effects on any subset of patients. This is especially important for the interventions that target the low urgency patient groups, as an (overall) decrease in LOS may still allow for an unequal distribution of care over patient groups.

With a sensitivity analysis we evaluate the effects of potential environmental changes (cf Paul *et al*, 2010). By varying the number of patient arrivals, as well as the urgency of patients, the LOS is measured for both the current organization of the IEP, and all interventions from Table 4 combined. The sensitivity analysis results show that with the selected interventions, both ED and GPP are able to treat both more patient arrivals and more acute patients. For example, when patient arrivals increase, the difference in average GPP LOS between selected interventions and the current organization of the IEP increases. At a 20% patient increase, the average GPP LOS increases by approximately 65% in the current situation, and 40% with the selected interventions. At a 50% patient increase, the average GPP LOS with the selected interventions increases with 80%, while the GPP LOS

Table 4 Absolute outcomes (seconds) per intervention with significant outcomes ($\alpha = 0.05$) made bold

	Weekday high urgency	*Weekday low urgency*	*Weekend high urgency*	*Weekend low urgency*
GPP performance				
Current situation	1186	1557	1151	1356
1	+4 (+0.4%)	+9 (+0.6%)	−28 (−2.5%)	−16 (−1.2%)
2	+11 (+0.9%)	+14 (+0.9%)	−32 (−2.8%)	−5 (−0.4%)
3	+33 (+2.8%)	+19 (+1.2%)	−28 (−2.5%)	−14 (−1%)
4	+29 (+2.4%)	+3 (+0.2%)	−8 (−0.7%)	+4 (+0.3%)
5	+8 (+0.7%)	−38 (−2.4%)	−32 (−2.8%)	+12 (+0.9%)
6a	+19 (+1.6%)	−34 (−2.2%)	−21 (−1.8%)	***−122 (−9%)***
6e	−8 (−0.7%)	**−274 (−17.6%)**	−7 (−0.6%)	−7 (−0.5%)
ED performance				
Current situation	6421	5901	6201	6299
1	−193 (−3%)	**−287 (−4.9%)**	**−183 (−2.9%)**	**−349 (−5.5%)**
2	**−366 (−5.7%)**	**−203 (−3.4%)**	**−381 (−6.1%)**	**−290 (−4.6%)**
3	−215 (−3.3%)	**−126 (−2.1%)**	**−141 (−2.3%)**	−109 (−1.7%)
4	+36 (+0.6%)	**−119 (−2%)**	−18 (−0.3%)	−108 (−1.7%)
5	+5 (+0.1%)	−15 (−0.3%)	−71 (−1.2%)	**−236 (−3.7%)**
6a	+17 (+0.3%)	−46 (−0.8%)	**−238 (−3.8%)**	**−476 (−7.5%)**
6e	+26 (+0.4%)	−11 (−0.2%)	−28 (0.4%)	−7 (−0.1%)

in the current situation increases with 250%, showing that an optimized IEP is better equipped to treat an increasing number of patients.

5.6. Implementation

Based on the simulation study outcomes, a physician assistant that treats both GPP and ED patients during the starting hours of the IEP has been trialled in a 3-week pilot study. The aim of this study was to investigate the effects of adding a physician assistant in the actual situation, treating both ED and GPP patients. During a 3-week measurement period (January 2013), every week day from 5 pm until 8 pm, a physician assistant consulted and treated both low urgency GPP patients, as well as low urgency ED patients. During this pilot study, in addition to other performance indicators, GPP waiting times ($n = 273$) were measured and compared with measurements carried out before the pilot ($n = 237$). This pilot study showed a positive effect for GPP patients, reducing the average waiting time with 124 s while having no effect on ED patient LOS. These outcomes are similar to those of the simulation model, where no significant effect on the ED LOS is visible and the GPP LOS is reduced by the same order of magnitude. This similarity has been recognized by the IEP staff. From this we conclude that the simulation model is a valid representation of the actual situation.

5.7. Sustainability

By using community and patient preferences in the KPIs, we evaluated both economic and social effects of the interventions. From our results, we see that all patients benefit from using the IEP, and those patients that need the most care, receive the most benefit (ie, ED patients). An additional side effect of the integration into an IEP is environmental in nature. With the repositioning of care providers such that they are placed at a single location, both travel time and costs that patients would have incurred when travelling between the GPP and the ED are removed. Furthermore, resources in the IEP are better used thanks to the integration, also leading a more sustainable solution.

The end product of this research is twofold: first we give advice to the health-care providers on an improved process design for the IEP in the current situation, and second we developed a reusable simulation tool and systematic approach the IEP can use to evaluate potential interventions that arise in future situations. To this end, simulation tutorials have been given to the IEP stakeholders, including physicians, ED managers, and the GPP director. During these tutorials, simple health-care processes have been modelled to gain understanding and acceptance of simulation modelling, and by using the simulation model of the IEP, the participants could evaluate various interventions by themselves. In addition, the hospital appointed one employee, responsible for process improvements in the hospital, to keep the simulation model up to date, and use it to both help and evaluate the IEP in continuous and sustainable process improvements.

6. Conclusion

We used a systematic approach in defining and evaluating many organizational interventions for an IEP. We did this by first grouping interventions and selecting the most effective interventions per group. Following this, we formulated intervention sets which were compared and further evaluated. Using this approach, we evaluated both the effects of potential interventions, as well as the interaction between these interventions. This enabled us to compare and evaluate many changes while keeping the required simulation time feasible. The use of the simulation model, as well as the structured approach was essential to evaluate the IEP in Almelo, without intervening in the actual processes of the IEP.

We identified various interventions, divided by process interventions, staffing interventions, and resource allocation interventions, showing a reduction in patient LOS at both the GPP and ED. Process and allocation interventions show a decrease of 2–6% in ED LOS, and staffing alternatives reduce GPP and ED LOS with 3–17%, depending on the patient group. The IEP offers a sustainable solution to the problem of ED overcrowding, where all stakeholders benefit: better care is provided to patients by increasing clarity (ie, for patients to decide where to go) and effectiveness, at reduced costs. By accounting for patient and community preferences, various interventions have been identified resulting in positive effects on both social and environmental factors without causing drastic changes to the organization and without introducing additional costs for the ED or the GPP. In addition, a reusable simulation tool is embedded within the hospital with staff trained to use this, allowing for continuous improvements of the IEP.

Finally, based on the results of this study, a pilot project of one of the interventions, letting physician assistants treat patients at both the GPP and ED, has been trialled in practice, showing an improvement that closely matches the prediction resulting from our simulation model. Future work will involve modelling the interaction between the IEP and other departments in the hospital, such that the entire care pathway chain can be optimized. In addition, a follow-up study would be of interest evaluating the implementation and continued use of the simulation model and approach, as well as the hospital's experiences using this model. This would help to further understand the barriers found in practice when using simulation models, and indicate how such problems may be overcome.

References

Ahmed MA and Alkhamis TM (2009). Simulation optimization for an emergency department healthcare unit in Kuwait. *European Journal of Operational Research* **198**(3): 936–942.

Andradottir S (1998). A review of simulation optimization techniques. In: *Proceedings of the 30th conference on Winter simulation*, Washington, DC, USA, IEEE Computer Society Press, pp 151–158.

Andradóttir S (2006). Chapter 20 An overview of simulation optimization via random search. In: Henderson SG and Nelson BL (eds). *Handbooks in Operations Research and Management Science*. Vol. 13, Elsevier: Amsterdam, pp 617–631.

April J, Glover F, Kelly JP and Laguna M (2003). Simulation-based optimization: practical introduction to simulation optimization. In: *Proceedings of the 35th conference on Winter simulation: driving innovation*, New Orleans, Louisiana, Winter Simulation Conference, pp 71–78.

Ashour OM and Kremer GEO (2013). A simulation analysis of the impact of FAHP-MAUT triage algorithm on the emergency department performance measures. *Expert Systems with Applications* **40**(1): 177–187.

Barton RR and Meckesheimer M (2006). Chapter 18: Metamodel-based simulation optimization. In: Henderson SG and Nelson BL (eds). *Handbooks in Operations Research and Management Science*. Vol. 13, Elsevier: Amsterdam, pp 535–574.

Bettonvil B and Kleijnen JPC (1997). Searching for important factors in simulation models with many factors: Sequential bifurcation. *European Journal of Operational Research* **96**(1): 180–194.

Boesel J, Nelson BL and Kim S-H (2003). Using ranking and selection to "clean up" after simulation optimization. *Operations Research* **51**(5): 814–825.

Brailsford SC, Harper PR, Patel B and Pitt M (2009). An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation* **3**(3): 130–140.

Cheng RCH (1997). Searching for important factors: Sequential bifurcation under uncertainty. In: *Proceedings of the 29th conference on Winter simulation*, Atlanta, Georgia, USA, IEEE Computer Society, pp 275–280.

Dale J, Green J, Reid F and Glucksman E (1995). Primary care in the accident and emergency department: I. Prospective identification of patients. *Bmj* **311**(7002): 423–426.

Doggen CJM, Hans EW, Snel JE, Velde DV and Verheij HJW (2010). *Subsidieaanvraag: "Optimale logistiek en patienten voorkeuren in de acute zorgketen; de huisartsenpost en spoedeisende hulpin een geintegreerde spoedpost."* Research Proposal, University of Twente.

Duguay C and Chetouane F (2007). Modeling and improving emergency department systems using discrete event simulation. *Simulation* **83**(4): 311–320.

Fone D *et al* (2003). Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *Journal of Public Health* **25**(4): 325–335.

Fransman C. (2011). *Patient and community preferences for out-of-hours emergency care using best-worst scaling*. MSc thesis, University of Twente.

Fu MC, Glover FW and April J (2005). Simulation optimization: a review, new developments, and applications. In: *Proceedings of the 37th conference on Winter simulation*, Orlando, Florida, Winter Simulation Conference, pp 83–95.

Giesen P, Franssen E, Mokkink H, Bosch W, van Vugt A and Grol R (2006). Patients either contacting a general practice cooperative or accident and emergency department out of hours: A comparison. *Emergency Medical Journal* **23**(9): 731–734.

Grol R, Giesen P and van Uden C (2006). After-hours care in the United Kingdom, Denmark, and the Netherlands: New models. *Health Affairs* 25(6): 1733–1737.

Gunal MM and Pidd M (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation* **4**(1): 42–51.

Hoot NR and Aronsky D (2008). Systematic review of emergency department crowding: Causes, effects, and solutions. *Annals of Emergency Medicine* **52**(2): 126–136.

Ivanova T, Malone L and Mollaghasemi M (1999). Comparison of a two-stage group-screening design to a standard 2k-p design for a whole-line semiconductor manufacturing simulation model. In: *Proceedings of the 31st conference on Winter simulation: Simulation—a bridge to the future—Volume 1*, Phoenix, Arizona, USA, ACM, pp 640–646.

Jun JB, Jacobson SH and Swisher JR (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society* **50**(2): 109–123.

Jurishica CJ (2005). Emergency department simulations: medicine for building effective models. In: *Proceedings of the 37th conference on Winter simulation*, Orlando, Florida, Winter Simulation Conference, pp 2674–2680.

Kelton WD (2000). Design of experiments: experimental design for simulation. In: *Proceedings of the 32nd conference on Winter simulation*, Orlando, Florida, Society for Computer Simulation International, pp 32–38.

Kleijnen JPC (2008). Design of experiments: overview. In: *Proceedings of the 40th Conference on Winter Simulation*, Miami, Florida, Winter Simulation Conference, pp 479–488.

Komashie A and Mousavi A (2005). Modeling emergency departments using discrete event simulation techniques. In: *Proceedings of the*

37th conference on Winter simulation, Orlando, Florida, Winter Simulation Conference, pp 2681–2685.
Kool R, Homberg D and Kamphuis H (2008). Towards integration of general practitioner posts and accident and emergency departments: A case study of two integrated emergency posts in the Netherlands. *BMC Health Services Research* **8**(1): 225.
Kulu-Glasgow I, Delnoij D and de Bakker D (1998). Self-referral in a gatekeeping system: Patients' reasons for skipping the general-practitioner. *Health Policy* **45**(3): 221–238.
Law AM (2007). *Simulation Modeling and Analysis*. McGraw-Hill: Boston, MA.
Mackway-Jones K, Marsden J and Windle J Machester Triage Group (2006). *Emergency Triage*. Wiley: New York.
Mauro CA (1984). On the performance of two-stage group screening experiments. *Technometrics* **26**(3): 255–264.
Mes M and Bruens M (2012). A generalized simulation model of an integrated emergency post. In: *Proceedings of the Winter Simulation Conference*, Berlin, Germany, Winter Simulation Conference, pp 1–11.
Mielczarek B and Uziałko-Mydlikowska J (2012). Application of computer simulation modeling in the health care sector: A survey. *Simulation* **88**(2): 197–216.
Montgomery DC (2008). *Design and Analysis of Experiments*. Wiley: New York.
Paul SA, Reddy MC and DeFlitch CJ (2010). A systematic review of simulation studies investigating emergency department overcrowding. *Simulation-Transactions of the Society for Modeling and Simulation International* **86**(8–9): 559–571.
Sinreich D, Jabali O and Dellaert NP (2012). Reducing emergency department waiting times by adjusting work shifts considering patient visits to multiple care providers. *IIE Transactions (Institute of Industrial Engineers)* **44**(3): 163–180.
Sinreich D and Marmor Y (2005). Emergency department operations: The basis for developing a simulation tool. *IIE Transactions (Institute of Industrial Engineers)* **37**(3): 233–245.
Thijssen WA, Giesen PH and Wensing M (2012). Emergency departments in the Netherlands. *Emergency Medicine Journal* **29**(1): 6–9.
Trocine L and Malone LC (2001). Experimental design and analysis: An overview of newer, advanced screening methods for the initial phase in an experimental design. In: *Proceedings of the 33rd conference on Winter simulation*, Arlington, Virginia, IEEE Computer Society, pp 169–178.
WCED (1987). *Our Common Future*. Oxfourd University Press: New York.
Yaesoubi R, Roberts SD and Klein RW (2010). Modification of cheng's method: An alternative factor screening method for stochastic simulation models. In: *Proceedings of the Winter Simulation Conference*, Baltimore, Maryland, Winter Simulation Conference, pp 1034–1047.

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