HEALTH SYSTEMS
2019, VOL. 8, NO. 3, 162–183
https://doi.org/10.1080/20476965.2018.1561160

ORIGINAL ARTICLE

Improving patient timeliness of care through efficient outpatient clinic layout design using data-driven simulation and optimisation

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ABSTRACT
With greater demand for outpatient services, the importance of patient-centric clinic layout design that improves timeliness of patient care has become more elucidated. In this paper, a novel simulation-optimisation (SO) framework is proposed focusing on the physical and process flows of patients in the design of a paediatric orthopaedic outpatient clinic. A discrete-event simulation model is used to estimate the frequency of movements between clinic units. The resulting information is utilised as input to a mixed integer programming (MIP) model, optimising the clinic layout design. In order to solve the MIP model, Particle Swarm Optimisation (PSO), a metaheuristic approach enhanced with several heuristics is utilised. Finally, the optimisation model outputs are evaluated with the simulation model. The results demonstrate that improvements to the quality of the patient experience can be achieved through incorporating SO methods into the clinic layout design process.

ARTICLE HISTORY
Received 4 September 2018
Accepted 15 December 2018

KEYWORDS
Outpatient clinic layout design; patient quality of care; discrete-event simulation; mixed-integer programming; composition/decomposition heuristics; simulation-optimisation

1. Introduction

According to the United States National Ambulatory Medical Care Survey (NAMCS), the number of hospital outpatient visits exceeded 125 million in 2011, demonstrating a 24% increase compared to 2010 (National Center for Health Statistics, 2016). With the trend of increasing demand for ambulatory care services, the need for development of new healthcare facilities and redesign of current healthcare clinics has heightened. Correspondingly, the United States (US) capital expenditures for constructing and equipping outpatient care centres and physician offices reached $14.5 billion dollars in 2016, accounting for 15% of total US capital healthcare expenditures (United States Census Bureau, 2018). Meanwhile, the ongoing trend of consolidation of different outpatient clinics, in order to improve the quality and coordination of care (Brown Jr, Werling, Walker, Burgdorfer, & Shields, 2012), also has resulted in the expansion of the size of outpatient clinics.

Construction of new or renovation of existing outpatient clinics is an expensive and long-term endeavour. Therefore, it is critical that the layout designs are developed strategically to account for the effect of the design on the patient experience and the quality of care delivered in the clinic. In the past few years, in order to provide more patient-centric designs, multiple methods for planning physical spaces have been introduced and widely utilised. For instance, "co-creation" designs refer to the process during which patients, staff, and physicians have active roles during the layout design process (Prahalad & Ramaswamy, 2004) which has been shown to enhance the engagement of employees (Hatch & Schultz, 2010). "Design thinking" stimulates out-of-the-box thinking for the designer by emphasising and encouraging patients and staff to be involved in all major steps of the design process (Goldschmidt, 1994). However, from empirical data analysis, design thinking has not been shown to have a direct relation with performance (Wattanasupachoke, 2012). "Evidence-Based Design" (EBD) has been widely utilised to improve healthcare outcomes by using best practices from research (Zengul & O'Connor, 2013). Through EBD, healthcare organisations focus on the role of the physical environment, such as light and noise, to improve the outcomes for both patients and staff (Berry & Bendapudi, 2003; Nelson, West, & Goodman, 2005). Despite this, EBD rarely considers the relationship between the design of facilities and physical flows of patients or providers and its ultimate effects on the patient experience and quality of care (Reiling et al., 2004).

Health centre facilities are commonly planned by architecture firms and hospital administration with more focus on design aspects, safety codes, and building standards, and less focus on patient timeliness of care and efficiency (Arnolds & Nickel, 2015). Without proper examination of the work and patient flows, current strategies for the design of clinics can

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overlook some of the critical components to healthcare quality as defined by the Institute of Medicine, which include timeliness, efficiency, and patient-centred care (Institute of Medicine, 2001).

In addressing these needs, this work presents new mathematical methods for supporting the layout design of healthcare clinics with a focus on improving quality and patient satisfaction by minimising patient walking distances during their visits. As most outpatient clinics are currently designed in a physician-centric manner (Ferenc, 2016), accounting for the patient experience in this process can ultimately lead to the delivery of more timely and efficient care. Further, a focus on walking distances is particularly critical for patients with mobility restrictions and senior patients, who accounted for nearly 20% of outpatient visits in 2011 (Rui & Okeyode, 2015).

Beyond the consideration of the adverse events and patient dissatisfaction that may occur with poor layout designs (Joseph & Rashid, 2007), the problem of designing an effective clinic layout is complex. In addition to architectural requirements, an outpatient clinic layout must be designed in accordance with healthcare-focused safety recommendations such as the location of elevator spaces or staircases, the location of diagnostic rooms (e.g., x-rays) relative to waiting areas, and the standardisation of clinic units (Reiling et al., 2004), such as exam rooms, which must follow a predetermined length and width standards. At the same time, there are units such as waiting areas which have flexibility in their dimensions as long as ratio restrictions between length and width are met. Hence, effective clinic layout solution approaches must be designed to account for the unique characteristics of each clinic while addressing these architectural constraints. For example, while patients may only see one provider during their visit in some clinics, patients may need to visit a sequence of providers or have multiple diagnostic services in other clinics. Thus, the design of the layout must consider and accommodate for the features of patient flows within the clinic.

This work focuses on the design of a paediatric orthopaedic outpatient clinic and expands upon the current literature of outpatient clinic layout design, proposing a data-driven simulation-optimisation (SO) approach via utilisation of mathematical modelling to solve the problem. By integrating Particle Swarm Optimisation (PSO), a metaheuristic (MH) algorithm, and a discrete-event simulation (DES) model, this framework provides a set of promising solutions for a large-scale complex outpatient clinic layout design problem. Correspondingly, this paper presents a novel generic SO framework which:

- Incorporates complexities of outpatient clinic layout design in accordance with healthcare-focused architectural recommendations including (i) the presence of both standard-sized and variable-sized units, (ii) fixed-position spaces, and (iii) minimum distances between units.
- Integrates a simulation environment to (i) accurately estimate patient flows and (ii) assess the performance of the generated layout solutions to determine the best layout that best benefits patients.

A review of related research focusing on layout design problems and solution algorithms in healthcare systems is presented in Section 2. In Section 3, a summary of the paediatric orthopaedic clinic underlying this research and a comprehensive review of the constructed DES model, input data acquisition, and model validation are presented. Combining the simulation with a layout optimisation model, a SO solution procedure is proposed to identify a layout which minimises walking distances for patients in Section 4. The results pertaining to layout of the studied paediatric orthopaedic clinic are presented in Section 5, demonstrating the applicability of the proposed framework in a real case study of an outpatient clinic. Finally, a discussion of the results and future research directions are included in Section 6.

2. Literature review

Layout planning involves the arrangement of units in the best possible way within a facility space to minimise distances and associated handling costs between units. Research on layout problems originally focused on organising manufacturing units to improve performance of workers by reducing walking distances. However, in the last two decades, research on layout problems has been extended to include the design of spaces in service sectors such as airport terminals (Edwards, 2004; Manataki & Zografos, 2009), train and railway stations (Li, 2000), shipyards and ports (Bruzzone & Signorile, 1998), retail stores (Levy, Weitz, & Grewal, 2012), online web services (Wu, Lee, Fu, & Wang, 2013), and healthcare facilities (Arnolds & Gartner, 2018; Chraibi, Osman, & Kharraja, 2018).

In general, layout design in healthcare has been characterised by the scale of the design problem, either “macro-level design” or “micro-level design” (Arnolds & Nickel, 2015). In macro-level design, primary functional departments such as wards, outpatient clinics, and emergency departments are assigned to locations inside the hospital building, accounting for exclusions on the permissible assignment locations for different departments. On the other hand, in micro-level hospital layout planning, units inside a single functional department need to be located. The layout design of an outpatient clinic is an example of a micro-level planning problem, in which units such as exam rooms, waiting areas, physician work areas, nurse stations, and patient/staff hallways should be located. This paper focuses on the micro-level layout design of a paediatric orthopaedic outpatient clinic and proposes a data-driven SO approach to solve the problem.

In the following section, a review of facility layout optimisation modelling and solution methodologies is presented. First, two common facility layout mathematical model approaches, discrete and continuous modelling, are explored in Section 2.1. Then, existing solution methods including exact algorithms for small-sized problems, along with heuristic and MH approaches for large-scale problems, are reviewed in Section 2.2. The literature review concludes with a discussion of the benefits of hybrid simulation optimisation approaches to solve large-scale facility layout problems (FLP).

2.1. Facility layout problems

FLP is a class of Operations Research (OR) problems that address determining the placement and the relative positions of facilities in a layout area with the objective of minimising the travelling or handling costs (Drira, Pierreval, & Hajri-Gabouj, 2007). Several formulations exist to define layout problems based on the limitations and restrictions that exist in the studied industry. The formulation that most closely addresses the outpatient clinic layout problem was first introduced by Meller, Narayanan, and Vance (1998). In this formulation, layout problem is defined as a process of finding a non-overlapping planar orthogonal arrangement of n rectangular facilities within a given rectangular plane to minimise the overall travel distance.

Drira et al. (2007) classified layout problems into two main formulation categories: discrete and continuous formulations. Discrete formulations of the FLP are mostly explored by Quadratic Assignment Problem (QAP) modelling. QAP models for layout problems were first introduced by Koopmans and Beckmann (1957) and are shown to be NP-complete (Sahni & Gonzalez, 1976). In a discrete formulation, each unit can only be assigned to a set of certain and pre-defined discrete locations in the facility. In the early layout models with discrete formulations, all units are assumed to have the same size and shape (Fruggiero, Lambiase, & Negri, 2006). QAP models in the design of healthcare facilities were first used in 1972. A German university hospital, Klinikum Regensburg, was interested in positioning 30 departments within the hospital in a macro-level design problem (Krarup & Pruzan, 1978). Similarly, Elshafei (1977) used a QAP model in hospital planning to model a hospital with 19 equally sized clinics to be located within the hospital.

The QAP formulation has been extended to cover unequal area units that can occupy different blocks (Wang, Hu, & Ku, 2005). The discrete representation can also facilitate modelling dynamic layout problems where the layout changes over time (Samarghandi, Taabayan, & Behroozi, 2013). However, this approach is incapable of representing models with other assumptions such as unit orientations (vertically or horizontally), pick up and drop off points, and consideration of required distances among units (Drira et al., 2007).

In the continuous representation of FLP, the planar site is not divided into discrete locations. Instead, all units, with unequal sizes and shapes, can be located at any place in the planar site as long as units do not overlap (Das, 1993). Montreuil (1991) proposed one of the first Mixed Integer Programming (MIP) formulations for the continuous representation of the FLP, using binary variables to avoid overlapping. Further, Meller et al. (1998) introduced another MIP formulation of the FLP that was enhanced by Sherali and Smith (2001). In the latter formulation, two sets of binary variables are used to locate the relative positions of two units, horizontally or vertically. Further enhancements to the MIP formulation by Meller, Chen, and Sherali (2007) led to the sequence-pair formulation with additional valid inequalities that optimally solved instances up to 11 units, the largest such results to date. Often heuristic solution methods have been used to solve MIP models of the FLP, as discussed in the following section.

2.2. Solution methodologies for facility layout problems

While layout problems are known to be complex and NP-hard (Gary & Johnson, 1979), the last two decades have shown the use of both exact and approximation methods to find the best solution. Branch-and-bound algorithms (Kohara, Yamamoto, & Suzuki, 2008) and dynamic programming (Dunker, Radons, & Westkmper, 2005) are examples of exact algorithms that are used in layout problems. Xie and Sahinidis (2008) developed a branch-and-bound algorithm that systematically prunes the inferior region in the sequence-pair space. They proved that facility layout sequence-pair modelling can be accomplished by solving minimum-cost network flow problems for a restricted version of the layout problems where the planar space has no limitations. Castillo and Westerlund (2005) developed a solution method for unequal block areas in a facility which satisfies the area requirements using cutting planes.

Since most real applications of layout designs involve large-scale problem instances, heuristic algorithms have been developed to find near optimal solutions. Heuristic solutions can be divided into two main categories. Construction algorithms make up one class of heuristic approaches in which placement of facilities are made sequentially, thus progressively building until a complete layout is achieved (Hassan, Hogg, & Smith, 1986). As opposed to construction algorithms, improvement algorithms start with an initial feasible solution and examine other similar solutions by exchanging positions of facilities (Armour & Buffa, 1963). Heuristics that combine construction and improvement algorithms have also been introduced and studied in recent years (Tasadduq, Imam, & Ahmad, 2015).

By early 2000, as computational capabilities increased substantially, MH algorithms were widely employed to solve layout optimisation problems. These algorithms are not guaranteed to give the optimal solution; however, the algorithms are shown to find relatively good results (Holst, 2015). Tabu Search (Liang & Chao, 2008; Samarghandi & Eshghi, 2010; Scholz, Jaehn, & Junker, 2010), Simulated Annealing (SA) (Chwif, Barretto, & Moscato, 1998; de Alvarenga, Negreiros-Gomes, & Mestria, 2000; Moslemipour & Lee, 2012; Tasadduq et al., 2015; Tuzkaya, Gülsün, Tuzkaya, Onut, & Bildik, 2013), Genetic Algorithms (GAs) (Al-Hakim, 2000; Azadivar & Wang, 2000; El-Baz, 2004; Enea, Galante, & Panascia, 2005; Sadrzadeh, 2012), PSO (Asl & Wong, 2017), and Firefly Algorithms (FA) (Ingole & Singh, 2017) are examples of metaheuristics being used to solve FLP.

Metaheuristics are able to solve large-scale combinatorial optimisation problems, yet most of these methods assume that inputs and the underlying objective function of the problem are deterministic (Juan, Faulin, Grasman, Rabe, & Figueira, 2015). This oversimplified assumption does not account for the stochastic nature of complex systems. As Kulturel-Konak (2007) stated, there is a growing need for designing flexible and robust layouts that consider uncertainty in service industries. Two of the most common methods for modelling uncertainties are fuzzy theory and computer simulation. Lin, Liu, Wang, and Liu (2015) used systematic layout planning and fuzzy constraint theory to design and optimise the facility layout of an operating theatre in Shanghai East Hospital. Arnolds, Nickel, Shashaani, and Wernz (2012) proposed a robust optimisation via simulation framework, by hybridising mathematical optimisation and DES, to address hospital layout planning. However, the authors did not elaborate on the details and efficiency of the proposed algorithm. Another example of hybridisation was presented by Azadivar and Wang (2000) in which simulation and a GA were combined to solve an FLP in a manufacturing setting for a relatively small problem. The authors used GA to optimise the layout design of a manufacturing system while the simulation served as a system performance evaluation tool.

In this research, the outpatient clinic layout problem is formulated by a MIP model and is solved with PSO, a suitable MH algorithm for continuous space problems. To accelerate the PSO performance, a composition/decomposition heuristic is proposed and used. In addition, a DES model of the outpatient clinic is constructed to define the flows among units and evaluate the performance of layouts provided by PSO. The combination of simulation and optimisation, as presented in this work, provides benefits from both methods as MH algorithms are capable of finding promising solutions to large-scale combinatorial optimisation problems, while simulation is capable of modelling and evaluating complex systems.

3. Orthopaedic clinic overview

This work has been performed in collaboration with an outpatient orthopaedic department located in the north-east region of the United States. The orthopaedic outpatient department, which is part of a major paediatric hospital, receives more than 40,000 patient visits per year across 3 different locations. The department leadership sought to explore the redesign of one of the clinics, with interest in identifying a creative design that would benefit patient quality of care. Since the clinic serves paediatric orthopaedic patients, the design needs to account for patients with mobility restrictions and to provide a layout that minimises patients' walking distances. Analysis of the potential for the redesign of the current clinic is intended to give insights to the department leadership team for design of a new outpatient centre, planned for construction in the future.

Orthopaedic clinics are among complex outpatient clinics with regard to patient flow paths, since patients often require services from ancillary departments such as cast and radiology. A variety of patient paths that can occur in the studied orthopaedic outpatient clinic are depicted in Figure 1. For example, a patient path can involve arriving to the clinic, checking-in, having a cast taken off, getting an x-ray, meeting with a medical provider, getting a cast put on, checking-out, and finally leaving the clinic. Each patient may experience a different subset of these activities during a visit and the order may also vary.

Since a patient visit may include several services being provided in different locations, and the patient path is not analogous for all patients, it is critical that the design of the clinic layout accounts for the variety and uncertainty associated with each of the possible patient paths. The current layout of the clinic is a rectangular space of 6528 cm in length and 2529 cm in width, containing 24 exam rooms and 8 physician work areas as shown in Figure 2. The current layout follows a pod-based layout, where each sets of three exam rooms are paired with one physician work area. The pod-based layout is designed to maximise accessibility of rooms for providers. Generally, each pod is

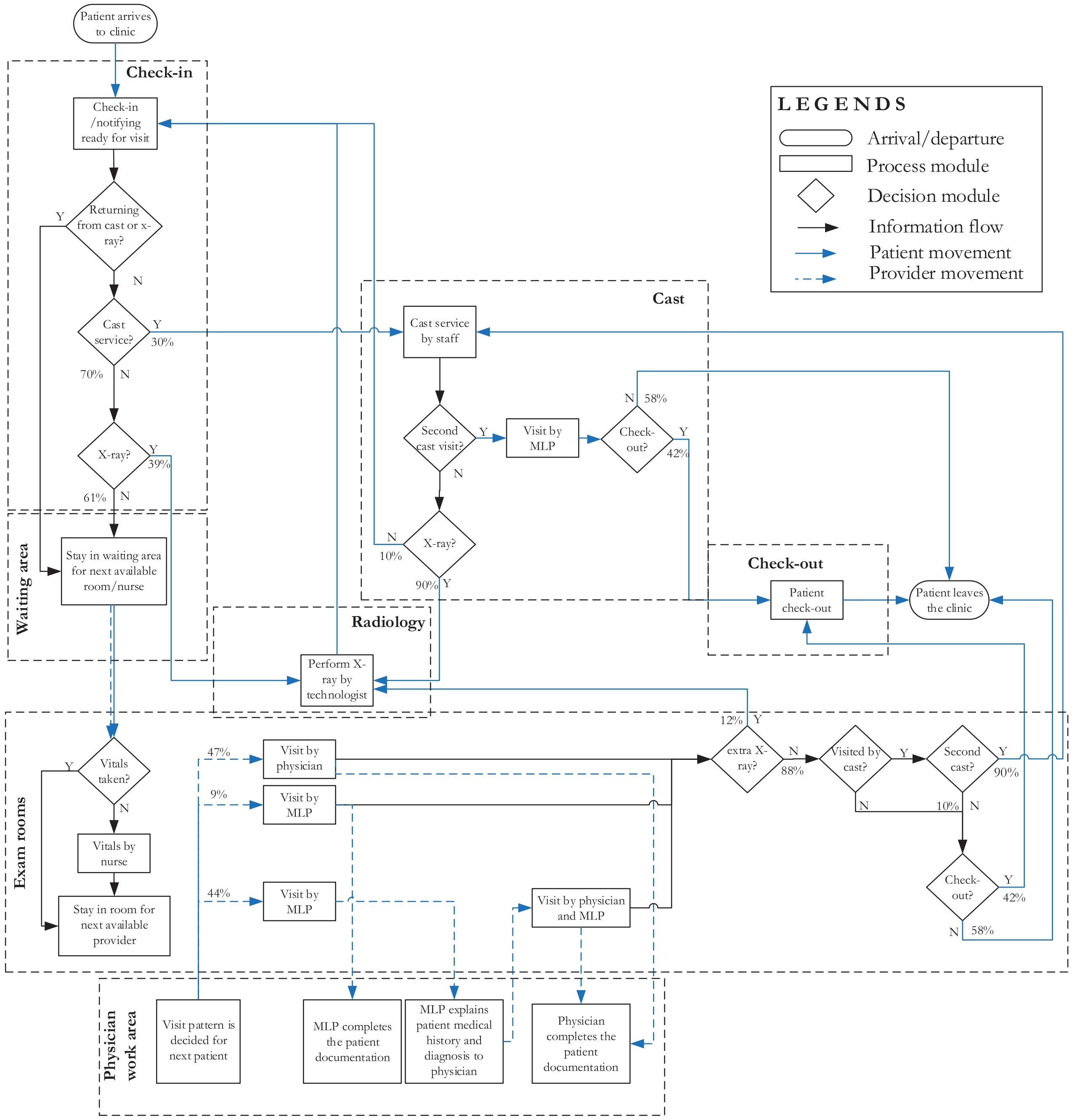

Figure 1. Variety of complex patient paths in an orthopaedic outpatient clinic. Blue arrows indicate patient movements inside the clinic and dashed blue arrows represent providers (i.e., physicians, nurses, and mid-level providers) movements.

assigned to one provider, minimising the distance between exam rooms and the physician work area.

The current layout parameters, including the size and the number of units, are provided in Table 1. These parameters are used to analyse the clinic redesigning process by comparing the performance of the current with the proposed layouts. Each of the units in the layout can be characterised as either (i) standard sized, (ii) variable sized, or (iii) fixed-position. Standard-sized units have a predefined length and width derived from provided standards (e.g., exam rooms, physician work areas). Variable-sized units have flexible lengths and widths which are constrained to be within an allowable range to satisfy total required area (e.g., waiting area and check-in). Fixed-position units are not allowed to be relocated through redesign of the clinic, based on the safety codes and architecture limitations. For the studied clinic, the only units that have a fixed-position and size are the elevator and the staircase.

3.1. Discrete-event simulation model

A data-driven DES model is developed using the Anylogic 7.2 simulation modelling software to understand the impact of the layout design on patient timeliness of care while considering uncertainties

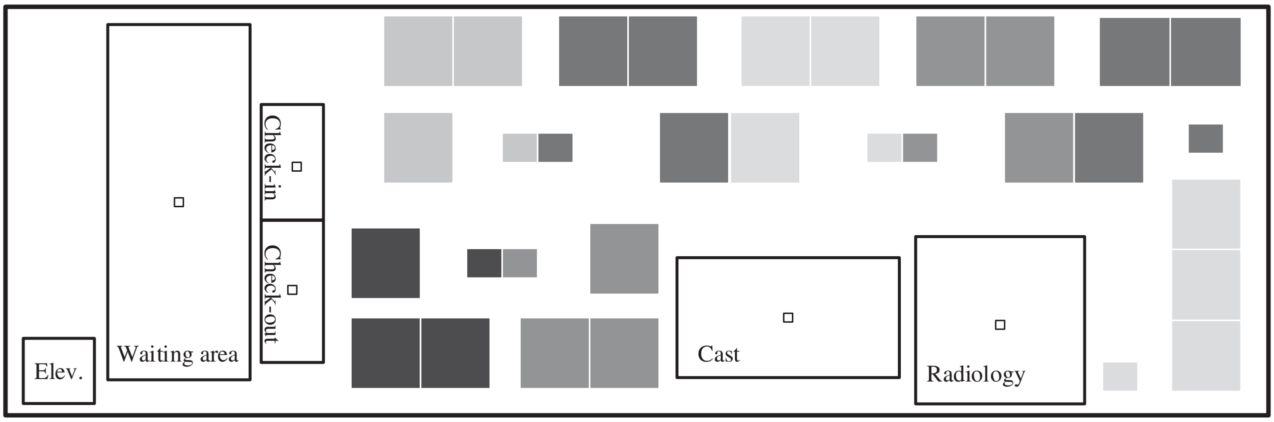

Figure 2. The current layout of the existing orthopaedic outpatient clinic. Each of the four units with similar colour defines a pod with three exam rooms and one physician work area.

Table 1. Parameters of the current layout of orthopaedic outpatient centre including Unit type, length, and width (in centimetres).

Units	Unit count	Width(l_i^x)	Length(l_i^y)	Standard-sized	Variable-sized	Fixed-position
Exam room	24	376	366	✓		
Waiting area	1	1857	676		✓	
Cast room	1	925	475		✓	
X-ray room	1	472	671		✓	
Check-in	1	384	564		✓	
Check-out	1	192	282		✓	
Physician work area	8	188	183	✓		
Elevator space and staircase	1	470	439	✓		✓
Facility dimensions	–	6,528 (L^x)	2,529 (L^y)	✓		

and stochastic patient paths in the clinic as outlined above (Borshchev & Filippov, 2004).

DES models are capable of representing the dynamic behaviours of a real-world system while also accounting for high levels of uncertainty. In turn, DES models applied in the healthcare sector are often used to evaluate resource and staff utilisation and forecast patient-related metrics (e.g., average length of stay and wait time [WT]) under a variety of operational and physical constraints (Jun, Jacobson, & Swisher, 1999). All simulation models are built with stochastic input parameters that are embedded into the model using probability distribution functions. The inputs of the constructed DES model are gathered from both analysis of existing data sets retrieved from clinic databases and observations of the clinic operations.

3.1.1. Data analysis and observation

A comprehensive data analysis was performed on a data set containing information about more than 120,000 patient appointments between August 2013 and August 2015. The average number of physicians per day, the average number of patients visited by each physician, the no-show rate, and the hourly patient arrival pattern are examples of information that are derived from this data set and used as inputs to the DES model.

The patient arrival pattern is modelled as a non-stationary Poisson process that varies based on hour of the day. Additionally, patient–provider interactions including the number and pattern of encounters with orthopaedic providers over the course of the patient visit is extracted from the database. A patient may be seen only by one provider (Type 1 and 2) or a team of providers (Type 3). Based on the historical data analysis, 47% of the patients had one encounter with the physician and 9% of patients only met with a mid-level provider (MLP). Alternatively, 44% of patients had their first encounter with an MLP and a second encounter jointly with the MLP and physician. Other model inputs derived from clinic data sets are presented in Table 2.

In addition to the information captured from the clinic databases, clinic operations were observed to capture information about the patient flow. The clinic was observed in March and April of 2016, accounting for 600 patient visits. The collected data provided considerable insight into the patient experience and resource utilisation. The data were transformed into data-driven probability distribution functions to be used as input into the simulation model. Accordingly,

Table 2. Resource, staffing, and scheduling parameters in the studied orthopaedic outpatient clinic, retrieved from clinic databases.

Simulation model inputs from clinic data set analysis	Daily patient and staff levels
Average number of patients per physician per day	25
Average number of patients per day	200
No-show rate	10%
Number of physicians	8
Number of mid-level providers (MLP)	8
Cast services staff	2
Clinical assistant staff (i.e., nurse)	3
Check-in and check-out staff	3 and 2

a triangular distribution was fitted for each process as shown in Table 3. Some of these clinical processes may or may not be required for each patient during their time in the clinic. The completion of these probabilistic processes is modelled with uniform probability distributions (see Table 3). For example, the probability of visiting cast services after a provider visit is based on a random number generated from a uniform distribution ($\sim uniform(0, 85, 0.95)$) taking into consideration which patients have been in cast services prior to the orthopaedic appointment.

3.1.2. Model verification and validation

The simulation model was verified by testing extreme conditions to ensure that the model performed as intended. In order to verify the constructed simulation model, an animation of a simulated clinic day with respect to the current layout was presented to clinic managers and staff. The management team confirmed the dynamics of the simulation model including the number of patients in the waiting area during each hour of a day, the utilisation of resources, and the patterns of patient flow.

After verifying the model's accuracy, outputs of the simulation model were validated against the collected data to ensure that the simulation model was an accurate representation of the studied clinic. To evaluate the performance and validate the model, the following key metrics were examined: (i) patient wait time in waiting area (WTWA), referring to the time that a patient waits for the next available exam room, (ii) patient wait time in the exam room (WTR) denoting the aggregate time that the patient is in the exam room waiting for a provider, and (iii) patient length of stay in the exam room (LOSR) accounting for the total time a patient spends in the exam room with or without the providers. Analysis of these performance metrics provide a reliable framework to verify a comprehensive patient experience through patient length of stay (LOS) or the period of time between the arrival and departure of patient from outpatient clinic.

A two-sample t-test was used to statistically compare the mean values of interest. As shown in Table 4, there is no significant evidence to conclude that the underlying means are statistically different at a 95% confidence interval level for average WTWA, WTR, and LOSR. As a result, it has been concluded that the simulation model is an accurate representation of the clinic and can be used to analyse the impact of different layouts on patients' experiences.

3.1.3. Results pertaining to efficiency of the current layout

While many system features contribute to the patient experience, the focus of our analysis is the timeliness of care driven by patient walking distances which are impacted by the layout. Precise measurement of patient walking distances was not possible, as it would have significantly interfered with the patients' visit; therefore, walking distances for each simulated patient is instead captured with the DES model. The simulation model is run for a 3-month period resulting in more than 10,000 simulated patients. The walking distances resulting from the current layout are shown in Table 5. On average, each patient walks 261.44 m during a visit, but the maximum walking distance is more than 610 m.

The impact of walking distances on LOS is highly dependent on patient walking speed. Previous studies have shown that a comfortable walking speed for adults

Table 3. Probability distributions for occurrence and duration of clinical processes. A uniform distribution, defined by minimum and maximum is fitted to likelihood of occurring a process. A non-symmetric triangular distribution, defined by the minimum, mode, and maximum is fitted for the duration of all patient processes.

Probabilistic process	Probability distribution of likelihood of process occurring	Process duration (in minutes)
Check-in	100%	$\sim$Triangular(1, 2, 8)
X-ray before orthopaedic appointment	$\sim$Uniform(0.58, 0.65)	$\sim$Triangular(5, 10, 20)
First cast service before orthopaedic appointment	$\sim$Uniform(0.20, 0.40)	$\sim$Triangular(3, 15, 20)
X-ray after cast service	$\sim$Uniform(0.85, 0.95)	$\sim$Triangular(5, 10, 20)
Vitals and patient preparation	100%	$\sim$Triangular(1, 1, 5.5)
Encounter with provider-Type 1	47%	$\sim$Triangular(9, 12, 33)
Encounter with provider-Type 2	9%	$\sim$Triangular(3, 9, 27)
Encounter with provider-Type 3	44%	$\sim$Triangular(2, 7.5, 25)
X-ray during orthopaedic appointment	$\sim$Uniform(0.07, 0.17)	$\sim$Triangular(5, 10, 20)
Patient leaves the room	100%	$\sim$Triangular(1, 1, 3)
Second cast service after orthopaedic appointment	$\sim$Uniform(0.85, 0.95)	$\sim$Triangular(0, 15, 30)
Check-out	$\sim$Uniform(0.36, 0.48)	$\sim$Triangular(2, 5, 10)

Table 4. Simulation model validation. 95% confidence intervals (CI) show no statistically significant differences between observed and simulated outputs.

	Simulated		Actual	
Metric	Mean	95% CI	Mean	95% CI
WTWA	11.31	[10.86, 11.76]	12.90	[7.04, 18.76]
WTR	16.02	[15.63, 16.41]	16.93	[15.00, 18.86]
LOSR	36.21	[35.80, 36.62]	37.23	[32.00, 42.46]

Table 5. Patient walking distance analysis (in metres) based on simulation of the current layout.

	Patient walking distance performance metrics (in metres)							
	Mean	Median	Standard Deviation	Range	Minimum	First quartile	Third quartile	Maximum
Current layout	261.44	262.75	94.36	523.69	87.28	183.51	322.04	610.98

is between 1.26 and 1.46 meters per second (m/s) (Bohannon, 1997). However, in-hospital walking speeds for older adults can be as low as 0.43 m/s (Graham, Fisher, Bergés, Kuo, & Ostir, 2010). As there are no published studies of the walking speed of patients in an orthopaedic clinic, especially patients with crutches or other walking aids, the patient walking speed is approximated to follow a uniform distribution spanning between 0.50 and 1.10 m/s ($\sim uniform(0.5, 1.10)$). Correspondingly, on average, 5.4 min of patient LOS is associated with walking inside the clinic. In the worst case scenario, a patient may need to walk for as long as 13 min before leaving the clinic. Although walking only takes up a small portion of the total visit length, it contributes greatly to the patient experiences.

The simulation model provides insights regarding the impact of clinic layouts on patient walking distances and quality of care, yet it is not possible to extract insights or guidelines for redesigning the layout to improve the average walking distance. In the following section, a hybrid SO framework is proposed to utilise both simulation and layout optimisation models concurrently to recommend a design that can improve the quality of the patient experience.

4. Proposed solution framework

Optimisation and simulation methods have been traditionally used as independent approaches for solving complex problems. However, the rise in computational power promoted the possibility of combining these methods to simultaneously explore the details of a system by simulation and identify optimal solutions using optimisation methods (Amaran, Sahinidis, Sharda, & Bury, 2016; Figueira & Almada-Lobo, 2014). SO methods can be classified into four categories based on the interactions between the simulation and optimisation modules (Figueira & Almada-Lobo, 2014). In Sequential Simulation-Optimisation (SSO), one of the categories of SO research, the simulation and optimisation modules are run sequentially. For example, either a simulation or optimisation module is run in the first stage independently. In the next stage, results of the first stage are used by the other module.

In this research, a multi-phase SSO approach is proposed to solve the facility layout design problem for the outpatient clinic. A summary of this approach is presented in Figure 3. In Phase I, the constructed DES model is used to obtain the frequency of patient movements between units (f_{ij})

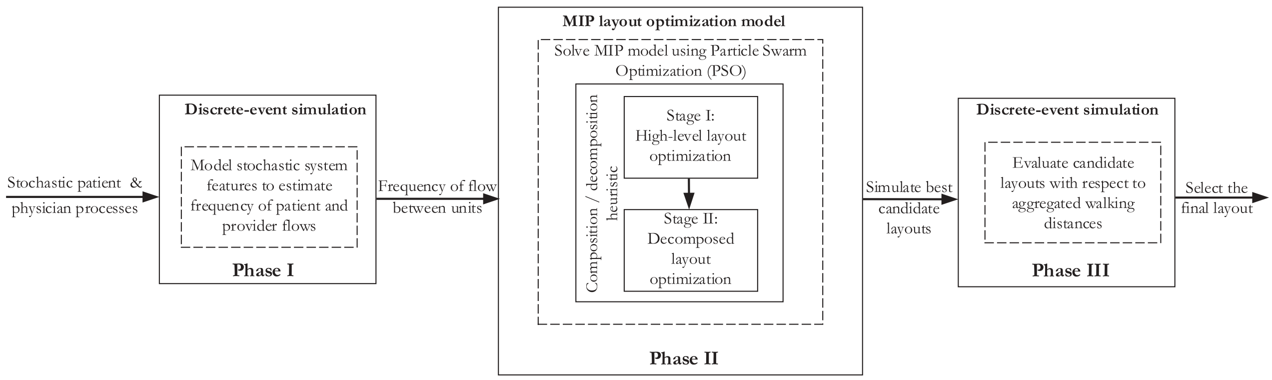

Figure 3. The proposed simulation-optimisation platform to solve the outpatient clinic layout design problem.

inside the orthopaedic clinic. The obtained frequency is one of the key inputs to Phase II, a MIP layout optimisation model. An enhanced PSO is applied to solve the proposed mathematical model and to identify candidate layouts. Finally, in Phase III, outputs of the optimisation algorithm are evaluated via the simulation model. The best layout is defined as the one with the minimum average patient walking distance in response to different patient paths. The details of these three phases and the interactions among the phases are provided in Section 4.1, 4.2, and 4.3.

4.1. Phase I: parameter estimation using the discrete-event simulation model

One of the key considerations in designing an efficient outpatient layout is understanding the frequency of flows between each pair of units. This information is difficult to collect through clinical observations due to the wide variety of patient paths that can occur. To estimate the frequency of physical flows between units, the DES model, as presented in Section 3.1, is simulated under 500 independent and identically distributed replications. Each replication is run to simulate 3 months or 10,000 patients, or whichever is achieved first. The results are then aggregated to provide a unique frequency of flows between each pair of units.

4.2. Phase II: mathematical modelling of the outpatient clinic

Driven by the clinic leadership's interest in designing a clinic which focuses on the patient experience, and correspondingly improves the quality of care by increasing efficiencies in the visit, the outpatient clinic FLP is formulated as an MIP model. This model minimises the average patients' walking distances in the clinic by defining the positions of non-overlapping units in a continuous planar space. The corresponding FLP, builds upon the model developed by Sherali, Fraticelli, and Meller (2003), and enhances the optimal facility layout model to account for the placement of variable-sized and fixed-position units and the rotation of standard-sized units, as presented below.

The model assumes that there are n number of units that need to be located within a facility. In this formulation, the superscript $s \in \{x, y\}$ denotes the dimension along the x-axis or the y-axis, in a two-dimensional coordinate system. Let the overall facility be a rectangle of size $(L^x \times L^y)$. Accordingly, for each unit i, (l_i^x, l_i^y) denotes the length and width of the unit. The objective of the mathematical model is to minimise the average travelling distance which is calculated as a weighted sum of the travel distance between each pair of units i and j where the weights pertain to the frequency of travel among units denoted by $f_{i,j}$. These frequencies are calculated based on the output from the simulation in Phase I.

The decisions within the FLP include the placement of each unit i, as defined by the coordinates of the centroid of the unit, (c_i^x, c_i^y), along the x-axis and y-axis. Using centroid information of each unit, the Manhattan (ℓ_1-norm) distance between unit i and j can be calculated as $d_{ij} = \left|(c_i^x - c_j^x) + (c_i^y - c_j^y)\right|$.

For standard-sized units, an additional decision of placing the unit horizontally $(r_i = 1)$ or vertically $(r_i = 0)$ must be made. For variable-sized units, two additional decision variables must be defined. These are the length and the width of each variable-sized unit i, denoted as (l_i^x, l_i^y). A detailed list of parameters, sets, decision variables, the objective function, and constraints of the mixed-integer linear mathematical model are included in Appendix A.

4.2.1. Particle Swarm Optimisation (PSO)

FLP are often hard and intractable to be solved by exact methods. To address the complexities, heuristic and MH approaches are often employed, which achieve near-optimal solutions, when exact algorithms are computationally expensive (Jourdan, Basseur, & Talbi, 2009; Pacheco, Alvarez, Casado, & Alegre, 2008). PSO is an evolutionary computational MH technique developed by Eberhart and Kennedy (1995) that is capable of solving mathematical models in a continuous solution space. The concept of PSO originates from the social behaviour of flying birds and their methods of information exchange (Dehghanimohammadabadi & Keyser, 2017).

In a PSO algorithm, a candidate layout, hereafter referred to as a candidate solution, is represented as a particle. The algorithm is initiated with a population of particles where each particle has a fitness value and velocity. The particle's fitness value is defined as the value of the optimisation objective function based on the candidate solution. The velocity indicates the direction that the particle should fly in the next iteration. Using the fitness value and velocity, particles fly through the problem solution space following the current optimum particles (Shi, 2001). The algorithm searches for the "best local solution", generally called exploitation in the MH context, and the "best global solution", denoted as exploration (Kang, Lu, & He, 2013). This process repeats until the best conditions in the solution space are discovered. The PSO pseudo-code pertaining to the problem of optimising the layout of an outpatient clinic is presented in Figure 4.

(1) **Particles initialization**
   (a) Initiate 500 empty particles. In this study, each particle is a layout consisting a list of centroid locations for each unit i, or (c_i^x, c_i^y), that is located inside the outpatient clinic.
   (b) For each particle
      (i) Initialize the particle's placement $O_p(t=0)$ by assigning a uniform random position $\sim U(0, L^s)$ to the centroid of each unit(c_i^x, c_i^y))
      (ii) Evaluate the particle's fitness $(f_p(t=0))$ by calculating the layout problem's objective function. Additionally, a large penalty proportional to amount of overlaps between units are added to the particle's fitness value to evaluate particles' goodness and improvements.
      (iii) Set the initial position and fitness value as the particle's best personal reached position $(O_p^{best}(t=0))$ and the best fitness value$(f_p^{best}(t=0))$
   (c) Set the global best particle
      (i) Among all particles, find the particle with the best fitness value and select it as the global best particle
      (ii) Set the global best position $(O_g^{best}(t=0))$ and the fitness $(f_g^{best}(t=0))$ according to the global best particle values

(2) **Main PSO algorithm:** Repeat until stopping criteria is met.
   For each particle p at iteration t
   {
   (a) Calculate and update the velocity of the particle for time $t+1$:
   $V_p(t+1) = wV_p(t) + c_1r_1\big(O_p^{best}(t) - O_p(t)\big) + c_2r_2\big(O_g^{best}(t) - O_p(t)\big)$
   w denotes inertia weight coefficient that is between 0.4 to 0.9; c_1 and c_2 are acceleration coefficients that define the ratio of exploration versus exploitation and should be between 0 and 2; and r_1, r_2 are uniform random variables between 0 and 1.
   (b) Apply the velocity and fly to find the new position of the particle $O_p(t+1)$
   (c) Evaluate the particles fitness $f_p(t+1)$ and update individual and global best solutions
   (i) If $\big(f_p(t+1) < f_p^{best}(t)\big)$, then:
   $O_p^{best}(t) \Leftarrow O_p(t+1)$
   $f_p^{best}(t) \Leftarrow f_p(t+1)$
   (ii) If $\big(f_p(t+1) < f_g^{best}(t)\big)$, then:
   $O_g^{best}(t+1) \Leftarrow O_p(t+1)$
   $f_g^{best}(t) \Leftarrow f_p(t+1)$
   }

(3) **Return the best solution**

Figure 4. Revised Particle Swarm Optimisation (PSO) pseudo-code for layout optimisation problem.

4.2.2. Enhancement methods for metaheuristic procedure

Through exploitation of local and exploration of global solutions, MH algorithms perform as an extensive search engines on large set of feasible solutions. However, there is still no guarantee that MH can find a suitable solution in a reasonable time frame for NP-hard problems such as FLP. Enhancement on the search procedure must be made specifically towards the problem of interest so that MH can find near optimal solution with lower computational time and memory.

As part of the improvement in the MH algorithms, the solution quality can be enhanced by optimising the MH parameters, such as c_1 and c_2 in Figure 4. At the same time, in the effort of finding good solutions, many researchers have successfully integrated multiple heuristics within the MH algorithms. The integration of multiple heuristics accelerates the process of finding acceptable solutions to large-scale optimisation problems.

In order to accelerate the PSO algorithm for solving the layout problem from the studied outpatient clinic, the integration of three heuristic approaches is investigated. In the first approach, rather than starting from an empty set, an initial feasible solution is given to the PSO algorithm. By providing an initial solution, the required time to find a feasible solution by PSO is minimised.

In the second approach, a neighbourhood search is embedded into the PSO algorithm to examine adjacent solutions which are defined by minimally moving and rotating the location of overlapping units in the layout. Neighbourhood search increases the possibility of finding a feasible solution only by considering local movements.

In the last approach, a composition/decomposition heuristic is introduced and applied. In this heuristic, the problem size is first reduced by grouping units together to form pods and the reduced problem is solved. Once the positions of pods in the layout are obtained, pods are decomposed to their constitutive units to form the final layout design. In the following sections, the second and third approaches, neighbourhood search and composition/decomposition heuristics are further discussed. Results of using each of the accelerated PSO techniques, either individually or in combination, are compared with the standard PSO approach.

4.2.3. Neighborhood search

The MIP model for the layout optimisation problem considers a continuous planar space. Thus, any continuous value can be assigned to a unit's centroid coordinates as long as the unit lengths do not exceed the facility boundary. This model may result in solutions with units that are minimally overlapping, making the solution infeasible. An example of an infeasible layout is shown in Figure 5(a) where (i) the waiting area overlaps with four exam rooms and (ii) one exam room (shaded square unit) overlaps with another unit. A feasible layout solution can be found by neighbourhood search where the waiting area is rotated and the exam room is moved slightly, as shown in Figure 5(b).

However, checking every neighbour solution for all units in each iteration is not computationally efficient. Therefore, a limited neighbourhood search is performed on the best global solution every 200 iterations to a subset of overlapping units. The neighbourhood search examines neighbour solutions created by ϵ-moving all overlapping units in eight possible directions and rotating the standard-sized units. The value of ϵ is set to 5 cm for this problem.

While the feasibility of the solution may change with the neighbourhood search procedure, the objective function value will not be impacted substantially. This is due to the fact that (i) distances between units do not change significantly with limited movements of the units and (ii) all units are rectangular and the distance between units are measured between centroids, thus rotation of the units will not impact the objective function.

The neighbourhood search procedure is computationally expensive. Therefore, applying it to only a few solutions accelerates the run-time of the PSO by finding feasible solutions, but limits the adverse impacts on run-time that would result from regular use of the procedure.

4.2.4. Heuristic algorithm: two-stage composition/decomposition for layout problem

Another method often integrated into MH algorithms involves adding problem-centric heuristics or modifying the problem representation space. Due to the large number of units needing to be located in the continuous layout space, finding feasible solutions for PSO is time-expensive and does not necessarily result in high-quality solutions. In order to improve the solution procedure, a two-stage composition/decomposition approach is used. In the first stage, each group of three exam rooms are paired with one physician work area unit, composing a pod. As a result, instead of optimising the position of every single unit in the layout, the position of pods in relation to other main units (i.e., waiting area, cast, X-ray, check-in, check-out, and elevator) are optimised. In the second stage, the pods are decomposed into the original units and the problem of finding the best layout for each pod is solved in a limited discrete space. A detailed explanation of the proposed heuristic can be found in Appendix B.

4.2.5. Evaluation of heuristics' efficiencies

To verify the efficiency and effectiveness of the proposed decomposition heuristic and the implemented neighbourhood search, results are compared to the original PSO approach with and without the definition of an initial feasible solution. The solution algorithm is implemented in MATLAB 2017b and all experiments are run with an Intel Core i7@ 2.5 GHz CPU machine with 16 GB RAM and a Microsoft Windows 7 operating system. The stopping

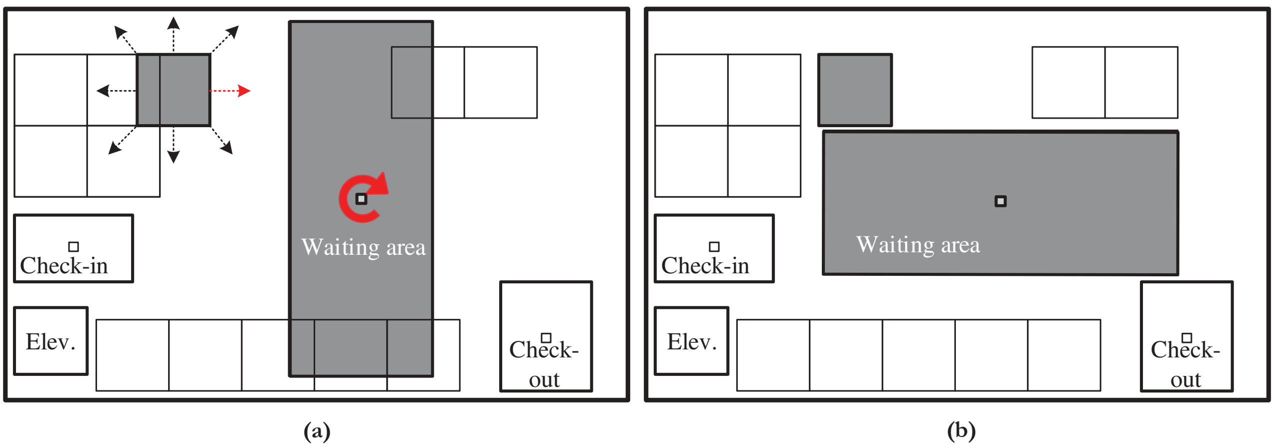

Figure 5. Neighbourhood search heuristic example. The layout in (a) is not a feasible layout. A neighbourhood search algorithm explores local solutions created by moving units in one of the eight possible directions and rotating units to create a feasible solution as shown in (b). Note that the red arrows in (a) show the selected movement directions.

Table 6. Comparison of proposed heuristics effectiveness for solving the outpatient clinic layout problem.

	PSO algorithm				
	With initial feasible solution	With neighbourhood search	With two-stage decomposition heuristic	Time to first feasible solution (seconds)	Objective function value of the best solution and improvement over the original PSO approach
Case 1	–	–	–	742.74	1.324e + 18(0.0%)
Case 2	✓	–	–	–	1.234e + 18(6.5%)
Case 3	–	✓	–	336.1596	1.318e + 18(0.15%)
Case 4	–	–	✓	56.2767	8.953e + 17(32%)
Case 5	✓	✓	–	–	1.173e + 18(11%)
Case 6	✓	–	✓	–	8.066e + 17(38%)
Case 7	–	✓	✓	29.2574	7.527e + 17(42%)
Case 8	✓	✓	✓	–	7.037e + 17(46%)

criteria used to terminate the PSO procedure, as shown in PSO pseudo-code in Figure 4, are the limit of a maximum number of iterations (10,000 times), or achieving less than a 1% solution improvement in 1000 runs.

A variety of PSO algorithms are tested, each defined by inclusion of a different set of heuristics. As shown in Table 6, the heuristic approaches not only improve the value of the objective function, but also accelerate the algorithm in finding the first feasible solution. The objective function values are significantly improved when the two-stage composition/decomposition heuristic is applied to the PSO algorithm. This heuristic also reduces the time to find the first feasible solution when an initial feasible solution is not provided. Overall, the best candidate layouts for the outpatient clinic are found when all three heuristics are applied to PSO. Therefore, in order to obtain the best candidate layout designs, the PSO algorithm with an initial feasible solution, neighbourhood search, and composition/decomposition heuristic (Case 8 in Table 6) is selected and executed 50 times. Out of 50 candidate layouts, the best 3 layouts with the minimum objective function values which are distinctly different are selected as final layout candidates.

4.3. Phase III: discrete-event simulation for evaluation

To evaluate the candidate layouts identified with the PSO algorithm, the DES model is again utilised. Even when different layouts have similar objective function values, the performances of the layouts differ, if the effectiveness of layouts is compared in terms of the aggregate patient walking distances rather than frequency of flows. The optimisation model only minimises the frequency-weighted pair-wise cost of flows between units, however a patient may move between multiple units to receive services during a visit. Therefore, it is important to compare the candidate layouts corresponding to the full patient flows, which cannot be achieved through the use of the optimisation model. Instead, the DES model is utilised in Phase III to evaluate the actual walking distances.

For the simulation model, no warm-up period is utilised and each candidate layout is run for a 3-month period. This results in more than 10,000 simulated patients which account for the stochastic nature of patient flows. All other parameters of the simulation model remained unchanged for each candidate layout.

5. Results

Using the PSO approach and all of the introduced heuristics (case 8 in Table 6), three candidate layouts were selected. These three layouts, in addition to the current layout, are presented in Figure 6. The layouts are verified and minimally edited by an architect, to form layouts in alignment with architectural best practices.

As mentioned earlier, two different performance metrics are evaluated through simulation and optimisation. In the optimisation model, pair-wise walking distances between units are minimised. While in the simulation phase, layouts are evaluated with respect to the aggregate patient walking distances, which account for both the layout and the full patient flow paths during a visit. Correspondingly, the candidate layouts in Figure 6 have relatively insignificant differences in terms of the pair-wise walking distances (i.e., less than 8% difference in the objective function value). However, the aggregate patient walking distances vary between the four layouts, as shown in the box plots in Figure 7.

According to the results, the second layout performs better in terms of the average aggregate patient walking distances compared to other layouts. Moreover, the median and variance of patient walking distances between the units are lower for the second layout. The major differences between the second candidate layout and the other layouts are:

(1) The waiting area is located in the centre of the layout. This configuration results in the

Figure 6. Final candidate layouts for the studied outpatient clinic from optimisation model. Note that each of the four units with similar colour defines a pod and the smaller room in the pod is the physician work area.

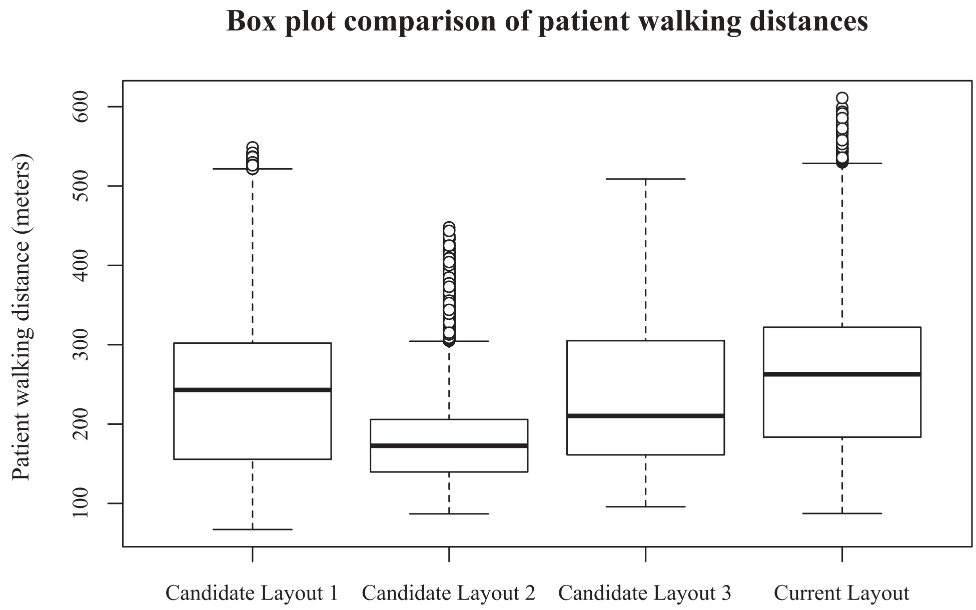

Figure 7. Box plot of simulated patient walking distances for the three candidate and the current layouts.

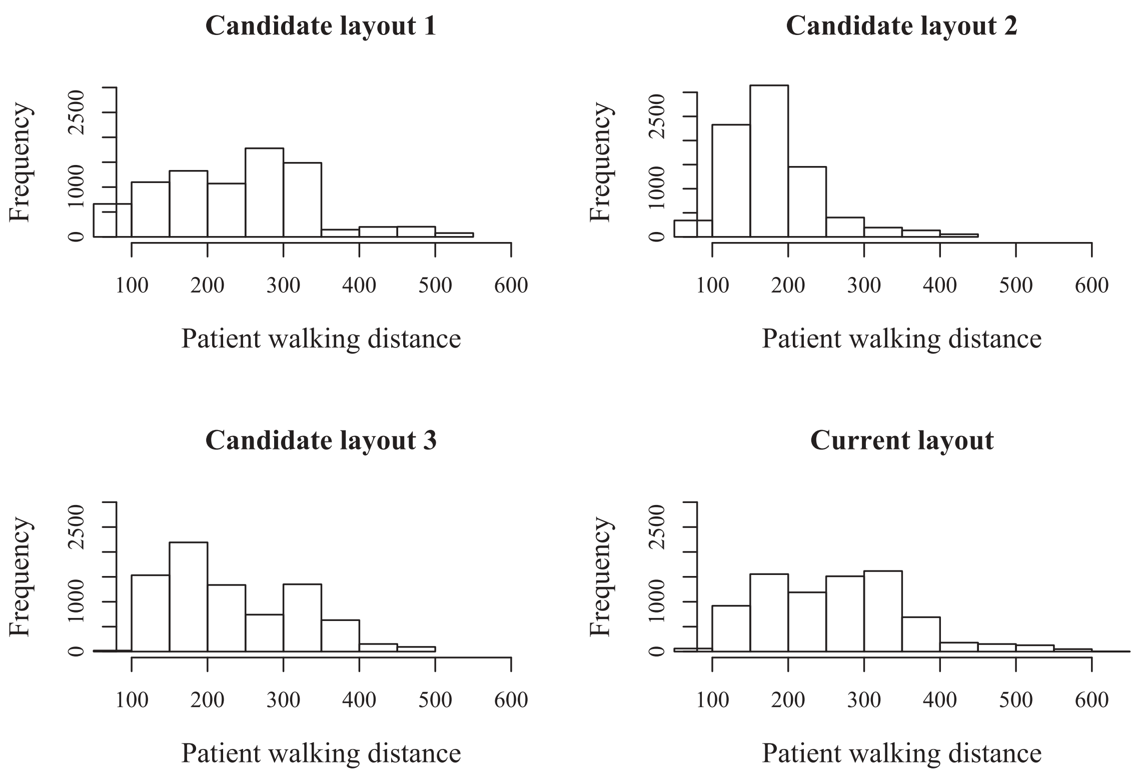

Figure 8. Histograms of aggregate patient walking distances for the candidate layouts (in metres). Candidate Layout 2 outperforms other layouts, with a lower mean, median, and maximum walking distance for patients during the visit.

distance between exam rooms and the waiting area being similar for all patients.

(2) The location of the ancillary services (main units) are towards the entrance, near the elevator. In the case that a patient needs radiology or cast services before the visit, the small distances between the elevator, check-in, radiology, and cast room would prohibit patients from walking long distances for such services. Also, patients can check-in or check-out easily on their way in and out of the clinic.

The histograms of patient walking distances for each of the candidate layouts are also shown in Figure 8. The histogram provides a more in-depth analysis of the distribution of walking distances among patients. The histogram of candidate Layout 2 is highly right-skewed and the majority of the patients walk less than 200 m during their visits. Candidate Layout 3 outperforms candidate Layout 1 and the current layout in terms of the minimum and maximum walking distances a patient may experience during a visit. However, in candidate Layout 1, the majority of patients walk less than 350 m, lower than the other two layouts. Candidate Layout 2 outperforms other layouts, with a lower mean, median, and maximum aggregate walking distances for patients during a visit.

Finally, layouts are compared with respect to patients' LOS or the period of time between arrival and departure of patients from the outpatient clinic. The average LOS is considered to be a good proxy for efficiency and quality of care in health centres, since it includes both service and WTs for patients (McDermott & Stock, 2007). Further, LOS has been shown to have a strong impact on patient satisfaction (Quintana et al., 2006; Tokunaga & Imanaka, 2002). In turn, reducing LOS has been a main focus of reforms intended to promote efficiency (García-Lacalle & Bachiller, 2011; Perelman & Closon, 2007). The mean, 95% confidence interval, median, and mode of LOS, as calculated in the simulation, are computed for each layout and presented in Table 7. The average LOS for patients are statistically significantly different based on the Analysis of Variance (ANOVA) and Fisher individual comparison tests with regard to the current layout ($P - value < 0.05$). The average LOS decreases from 73.27 min in the current layout to 68.88 min in candidate Layout 2. The most significant impacts are found for patients that need several services from different units during their visit. Regarding the maximum patient LOS, candidate Layout 2 improves LOS by 71 min (21%), compared to the current layout. Similar analyses are performed for patient WT or the aggregate of the times that the patient is waiting for a service in any location. Results of an ANOVA test show that the WT mean is not significantly different between the layouts ($P - value = 0.77$). The underlying reason is that while the layout design can improve the patient walking distances within the clinic, it is not necessarily impacting the patient WT. The latter is more dependent on the number, assignment, and availability of resource such as physicians, exam rooms, and ancillary services. Therefore, the major reduction in LOS is a result of lower patient walking distances, demonstrating the impact of layout design in patient timeliness of care and satisfaction.

6. Conclusion

Key to improving quality of care in healthcare clinics is the need to account for the impact of design and operational decisions on the patient experience, including the timeliness of care and efficiency of the system. One of the main elements effecting timeliness and efficiency of clinics is the physical design of the space and the way in which this design supports the physical work flows and patient flows within the clinic. Despite this, traditionally, ambulatory care centres have been designed primarily with a physician-centric perspective.

To address this, the presented work examines developing new methods for designing outpatient clinics with a focus on improving the quality of the patient experience and improving efficiencies. Specifically, in order to account for the patient flow behaviours during a visit, a simulation model of the clinic dynamics is created and integrated with facility optimisation methods. As shown in the results, assessing a facility design only with respect to optimising the objective function would not fully capture the effects of the design on quality of patients' experience. Therefore, integration of simulation with the optimisation methods is critical for achieving the best layout.

In addition to the novelty of incorporating the simulation model for developing a patient-centric clinic design, the research includes the development of a heuristic approach paired with a PSO algorithm. As the demand for outpatient services and clinics continues to grow in size, exact optimisation methods are no longer computationally efficient. Instead MH methods are critical. In this work, a composition/decomposition heuristic and a neighbourhood search heuristic are introduced to accelerate the PSO solution time and to identify better solutions. Through analysis of the resulting layouts with the DES, the findings verify that the candidate layouts outperform the current layout in terms of both the average and variation among patient walking distances in the system. These results support the value of integrating the presented SO method in the

Table 7. Patient length of stay (LOS) analysis (in minutes) based on simulation of the candidate and the current layouts.

	Patient length of stay (in min)						
	Mean (95%CI)	Median	Mode	Standard deviation	Range	Minimum	Maximum
Candidate Layout 1	71.06 ($\pm$ 1.21)	62.32	48.00	36.47	265.79	14.88	280.67
Candidate Layout 2	68.88 ($\pm$ 1.19)	59.32	42.00	34.83	241.82	14.49	256.31
Candidate Layout 3	70.66 ($\pm$ 1.22)	61.41	46.00	36.49	250.35	15.76	266.11
Current Layout	73.27 ($\pm$ 1.26)	64.52	48.00	37.57	312.96	14.60	327.56

design process of health clinics to improve quality of care and patient satisfaction.

While the primary emphasis of this research is designing the layout of an outpatient clinic based on patient flows, work flows of other care providers such as physicians, nurses, and mid-level providers can be incorporated in future models by extending the presented approach. Further, even with a patient-focused design process, there may be unintended consequences for the providers in the system. In future work, the evaluation process can be further extended to assess features that directly impact these critical members of the healthcare system. This additional focus on providers would be expected to be more significant when patients are seen by care teams which may consist of many healthcare members (e.g., residents, medical assistants, counsellors, etc.) who see the patients sequentially and/or concurrently. In such a circumstance, minimising patient walking distances could lead to increased walking by members of the care team. To build a layout that integrates the decisions regarding patient walking distances and the healthcare members, the PSO approach would benefit from being updated to account for multiple objectives, through a weighted objective function, and additional heuristic approaches could be examined to appropriately balance trade-offs in performance for the different members. Fortunately, with the integration of simulation, the various perspectives would be able to be assessed. Additionally, since layout design is a one-time strategic decision, efforts to integrate the role of tactical (e.g., patient scheduling) and operational (e.g., physician room assignment) decision-making in the facility layout process is recommended for future research. Similar to the approach in this study, capturing the complexities of these decision processes in simulation and integrating with optimisation methods as part of the design process is suggested. This would support the mission of accounting for the role of the physical clinic features and operational characteristics on quality metrics during the design process for new healthcare facilities.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendices

Appendix A. Mathematical model for outpatient layout optimisation

Sets:	
N	Set of units to be located in the clinic layout.
N_v	Set of variable-sized units with variable length and width. $N_v \subset N$
N_f	Set of standard-sized units with fixed locations. $N_f \subset N$
N_s	Set of standard-sized units with invariable length and width. $N_s \subset N, N_f \cup N_v \cup N_s = N, N_f \cap N_v \cap N_s = \emptyset$
S	Set of directions denoting distance along x-axis and y-axis in a Cartesian coordinate system. $s = \{x, y\}$
Parameters, constants, and coefficients:	
L^s	The facility length in direction s It is equivalent to maximum length of each units in direction s. $s \in S$
l_i^s	Unit length in direction s for standard-sized units. For each unit i, (l_i^x, l_i^y) denotes the length (along x-axis) and width (along y-axis), respectively. $i \in N \backslash N_v, s \in S$
ub_i^s	Upper bound of variable-sized unit i length in direction s. $i \in N_v, s \in S$
lb_i^s	Lower bound of variable-sized unit i length in direction s. $i \in N_v, s \in S$
a_i	Required area of variable-sized unit i. $i \in N_v$
α_i	Maximum permissible ratio between the longest and shortest side of variable-sized unit i. $i \in N_v$
Δ	Number of discrete points as tangential supports for area approximation
f_{ij}	Frequency of flows of providers and patients from unit i to unit j. $i, j \in N, \mathrm{f}_{ij} \geq 0$
δ_{ij}^s	Required distance between the unit i and unit j in direction s. $i, j \in N, s \in S$

In this Appendix, the Mixed Integer Linear Programming (MIP) model to optimise the outpatient clinic layout design problem is explained. The MIP model is based on a continuous representation of facility layout problems where each unit can be located in any place in the planar site as long as units are not overlapping and units remain inside the borders of the planar site. The parameters related to the introduced MIP model include the features of the units to be located (see Table 1), minimum distances required between units in x and y directions (δ_{ij}^s), and frequency of flows between pairs of units (f_{ij}), estimated with the discrete-event simulation model.

The main decision within the facility layout problem is the placement of each unit i, as defined by the centroid coordinates (c_i^x, c_i^y), along the x-axis and y-axis. But there are additional decisions for each category of units. For standard-sized units, an additional decision of placing the unit horizontally $(r_i = 1)$ or vertically $(r_i = 0)$ must be made. For variable-sized units, two additional decision variables of interest are the length and the width of each unit i, denoted as (l_i^x, l_i^y).

c_i^s and l_i^s can be used for obtaining the borders of each unit i and verifying overlap of the units. For instance the lower right corner of the unit i can be calculated as $(c_i^x + l_i^x/2, c_i^y - l_i^y/2)$. Correspondingly, the distances between the centroids, for all pairs of units (i, j) are defined as d_{ij}. A binary decision variable Z_{ij}^s denotes the relative location of units i and j with respect to the x-axis and the y-axis to prevent the overlap between the units. The variable is equal to 1 if unit i must precede unit j in the direction s.

Decision variables:	
Continuous decision variables:	
c_i^s	Coordinate of unit i centroid location in direction s. $i \in N \backslash N_f, s \in S$
l_i^s	Length of variable-sized unit i in direction s. $i \in N_v, s \in S$
d_{ij}^s	Rectilinear distance between centroids of units i and j in direction s. $i \in N, s \in S$ d_{ij} is expressed as the sum of the rectilinear distances in x and y-directions. $d_{ij} = d_{ij}^x + d_{ij}^y$
Binary decision variables:	
Z_{ij}^s	Binary variable indicating if unit i precedes unit j in direction s or not. $i, j \in N, s \in S$
r_i	Binary variable indicating if unit i is located horizontally or not. $i \in N \backslash (N_v \cup N_f)$

The objective is to minimise the average distance travelled by patients within the clinic, as a function of the location of the units. Thus, the objective function is calculated as the sum of the product of the frequency of the patient flows and the rectilinear (Manhattan) distance between the centroids for all pairs of units i and j.

$$\min_s \sum_i^N \sum_j^N \mathrm{f}_{ij} \left(d_{ij}^s \right) \tag{A1}$$

$$d_{ij}^s \geq c_i^s - c_j^s \qquad \forall s \in S, \forall i \in N, j \in N \tag{A2}$$

$$d_{ij}^s \leq c_i^s - c_j^s \qquad \forall s \in S, \forall i \in N, j \in N \tag{A3}$$

$$\frac{a_i l_i^x}{2} + 2\left(lb_i^x + \frac{\lambda}{\Delta - 1}\left(ub_i^x - lb_i^x\right)\right)^2 l_i^y \geq 2a_i\left(lb_i^x + \frac{\lambda}{\Delta - 1}\left(ub_i^x - lb_i^x\right)\right) \tag{A4}$$

$$\begin{aligned} &\forall \lambda \in \{0, 1, .., \Delta\}, 2 \leq \Delta \leq 50, \forall i \in N_v \\ &lb_i^s \leq l_i^s \leq ub_i^s \qquad \forall s \in S, \forall i \in N_v \end{aligned} \tag{A5}$$

$$\frac{l_i^s}{2} \leq c_i^s \leq L^s - \frac{l_i^s}{2} \qquad \forall s \in S, \forall i \in N_v \tag{A6}$$

$$\frac{l_i^x}{2}(1 - r_i) + \frac{l_i^y}{2}(r_i) \leq c_i^x \leq L^x - \left(\frac{l_i^x}{2}(1 - r_i) + \frac{l_i^y}{2}(r_i)\right) \quad \forall i \in n\backslash(N_v \cup N_f) \tag{A7}$$

$$\frac{l_i^x}{2}(r_i) + \frac{l_i^y}{2}(1 - r_i) \leq c_i^y \leq L^y - \left(\frac{l_i^x}{2}(r_i) + \frac{l_i^y}{2}(1 - r_i)\right) \quad \forall i \in n\backslash(N_v \cup N_f) \tag{A8}$$

$$\begin{aligned} &c_i^x - c_j^x + c_i^y - c_j^y \geq \left(\tfrac{l_i^x}{2}(1 - r_i) + \tfrac{l_i^y}{2}(r_i) + \tfrac{l_j^x}{2}(1 - r_j) + \tfrac{l_j^y}{2}(r_j)\right) + \\ &\left(\tfrac{l_i^x}{2}(r_i) + \tfrac{l_i^y}{2}(1 - r_i) + \tfrac{l_j^x}{2}(r_j) + \tfrac{l_j^y}{2}(1 - r_j)\right) \qquad \forall i \in n\backslash(N_v \cup N_f) \end{aligned} \tag{A9}$$

$$\begin{aligned} &c_i^x - c_j^x + c_i^y - c_j^y \leq \left(\tfrac{l_i^x}{2}(1 - r_i) + \tfrac{l_i^y}{2}(r_i) + \tfrac{l_j^x}{2}(1 - r_j) + \tfrac{l_j^y}{2}(r_j)\right) + \\ &\left(\tfrac{l_i^x}{2}(r_i) + \tfrac{l_i^y}{2}(1 - r_i) + \tfrac{l_j^x}{2}(r_j) + \tfrac{l_j^y}{2}(1 - r_j)\right) \qquad \forall i \in n\backslash(N_v \cup N_f) \end{aligned} \tag{A10}$$

$$c_i^s + \frac{l_i^s}{2} \leq c_j^s - \frac{l_j^s}{2} + d_{ij}^s + L^s(1 - Z_{ij}^s) \qquad \forall s \in S, \forall i, j \in N, i \neq j \tag{A11}$$

$$\sum_s^S (Z_{ij}^s + Z_{ji}^s) = 1 \qquad \forall i, j \in N i \leq j \tag{A12}$$

$$c_i^s - c_j^s < (1 - Z_{ji}^s) \times M \qquad \forall s \in S, \forall i, j \in N_f, i \neq j \tag{A13}$$

$$c_i^s - c_j^s \geq Z_{ji}^s \times -M \qquad \forall s \in S, \forall i, j \in N_f, i \neq j \tag{A14}$$

$$l_i^s + l_j^s < L^s + M \times (1 - (Z_{ji}^s + Z_{ij}^s)) \qquad \forall s \in S, \forall i, j \in N\backslash N_v, i < j \tag{A15}$$

$$l_i^s + l_j^s \geq L^s - M \times (Z_{ji}^s + Z_{ij}^s) \qquad \forall s \in S, \forall i, j \in N\backslash N_v, i < j \tag{A16}$$

$$Z_{ij}^s \in \{0, 1\} \qquad \forall s \in S, \forall i, j \in N, i \neq j \tag{A17}$$

$$r_i \in \{0, 1\} \qquad \forall i \in n\backslash(N_v \cup N_f) \tag{A18}$$

$$l_i^s \text{ fixed} \qquad \forall s \in S, \forall i \in N\backslash N_v \tag{A19}$$

$$c_i^s \text{ fixed} \qquad \forall s \in S, \forall i \in N_f \tag{A20}$$

$$(Z_{ij}^s, Z_{ji}^s) \text{ fixed} \qquad \forall s \in S, \forall i, j \in (n\backslash N_v) \cap N_f, i < j \tag{A21}$$

Constraints (A2) and (A3) impose the linearisation of the absolute value of the rectilinear distance between the centroids of units i and j in both directions, or $d_{ij}^s = \left|c_i^s - c_j^s\right|$. The linearisation is valid since the flows between units are non-negative or $f_{ij} \geq 0$. Constraint (A4) incorporates the linear segmentation of the hyperbolic curve, developed by Sherali et al. (2003) and used by Meller et al. (2007), for the lengths of variable-sized units. Instead of using a nonlinear (nonconvex and hyperbolic) area constraint, $a_i = l_i^x \times l_i^y$, the discretised polyhedral outer-approximation of the area constraint is used, as shown in constraint (A4). Unlike Lacksonen (1994), constraint (A4) provides a purely linear approximation of the area constraint without involving binary variables. The Δ tangential supports to the curve $l_i^y = \frac{a_i}{l_i^x}$ limit the width and length of each unit in each direction. As shown in previous studies, the number of tangential supports can be limited to 50, ($\Delta < = 50$), while obtaining an accurate approximation (Sherali et al., 2003).

For the variable-sized units, the upper and lower bounds on the lengths are calculated based on the permissible aspect ratio and required area of the units. Specifically, the upper bound can be calculated as $(ub_i^s = \min\left\{\sqrt{a_i \alpha_i}, L^s\right\})$ and the lower bound can be defined with the following equation $\left(lb_i^s = \frac{a_i}{2ub_i^s}\right)$. Constraint (A5) confirms that the lengths of the variable-sized units remain between the permissible lower and upper bounds in both directions.

Constraint (A6) ensures that all the variable-sized units remain inside the rectangular bounds defining the outpatient clinic facility (L^s). Despite the initial definition of length and width for standard-sized units, these units can be placed in two different configurations, as defined or rotated 90°. The concept of rotation of the departments inside the facility is incorporated in constraints (A7)–(A10). With the use of a binary decision variable r_i, the rotation should keep the standard-sized units inside the rectangular bound of the outpatient facility represented in constraints (A7)–(A8) and decrease the absolute distance between units shown in constraints (A9)–(A10). Since all the units are rectangular, considering two rotational options (horizontal and vertical) covers all the possible configurations for each unit.

Constraints (A11) and (A12) ensure that separation restrictions are satisfied and prevent the overlap of units, using the relative locations, Z_{ij}^s. δ_{ij}^s is added to ensure a specified distance, if required, between any two units i and j in direction s. More specifically, constraint (A12) assures that either unit i proceeds unit j in one of the directions s, or unit j proceeds unit i.

Additional logical constraints that tighten the feasible polyhedron for fixed-location units and standard-sized units are added to the formulation. Constraints (13)–(14) verify the sequence of two fixed location units. If the centroid location of unit i proceeds the centroid location of unit j, unit j cannot proceed unit i or $Z^s_{ji} = 0$. Constraints (15)–(16) regulates that if the summation of any two standard-sized units' lengths are greater than the length of the facility (L^s) in either direction, they cannot precede each other in that direction.

Constraints (17) and (18) are binary constraints for two decision variables of the model. Constraints (19) and (20) are trivial constraints for standard-sized and fixed-location units. Constraint (21) ensures that for standard-sized units that have fixed locations, the precedence of units (Z^s_{ij} and Z^s_{ji}) do not change over the optimisation process.

Appendix B. Two-stage composition/decomposition heuristic

As shown in Figure B1, in the first stage, each group of three exam rooms are paired with one physician work area unit, constructing a pod. As a result, instead of optimising the position of every single unit in the layout, the positions of pods in relation to other main units (i.e., waiting area, cast, X-ray, check-in, check-out, and elevator) are optimised. With this change, the problem size is reduced significantly leading to the problem being solved more efficiently.

The intuition of creating pods is derived from the fact that in many outpatient clinics, a set of exam rooms are associated with a physician work area, or office, for the purpose of minimising the walking distances for providers. In fact, layouts are designed in a way such that each physician has access to a number of dedicated rooms. Depending on the clinic type, a physician may be assigned to one or more exam rooms. In the studied clinic, each physician has access to a maximum of three exam rooms. Since the only flow that couples the exam rooms to each other is the flow of the provider between exam rooms, when the rooms are aggregated to create pods, the flow frequency can be summed without misrepresenting the system. An example of a first-stage layout solution, in which pod locations are defined, is shown in Figure B1(a).

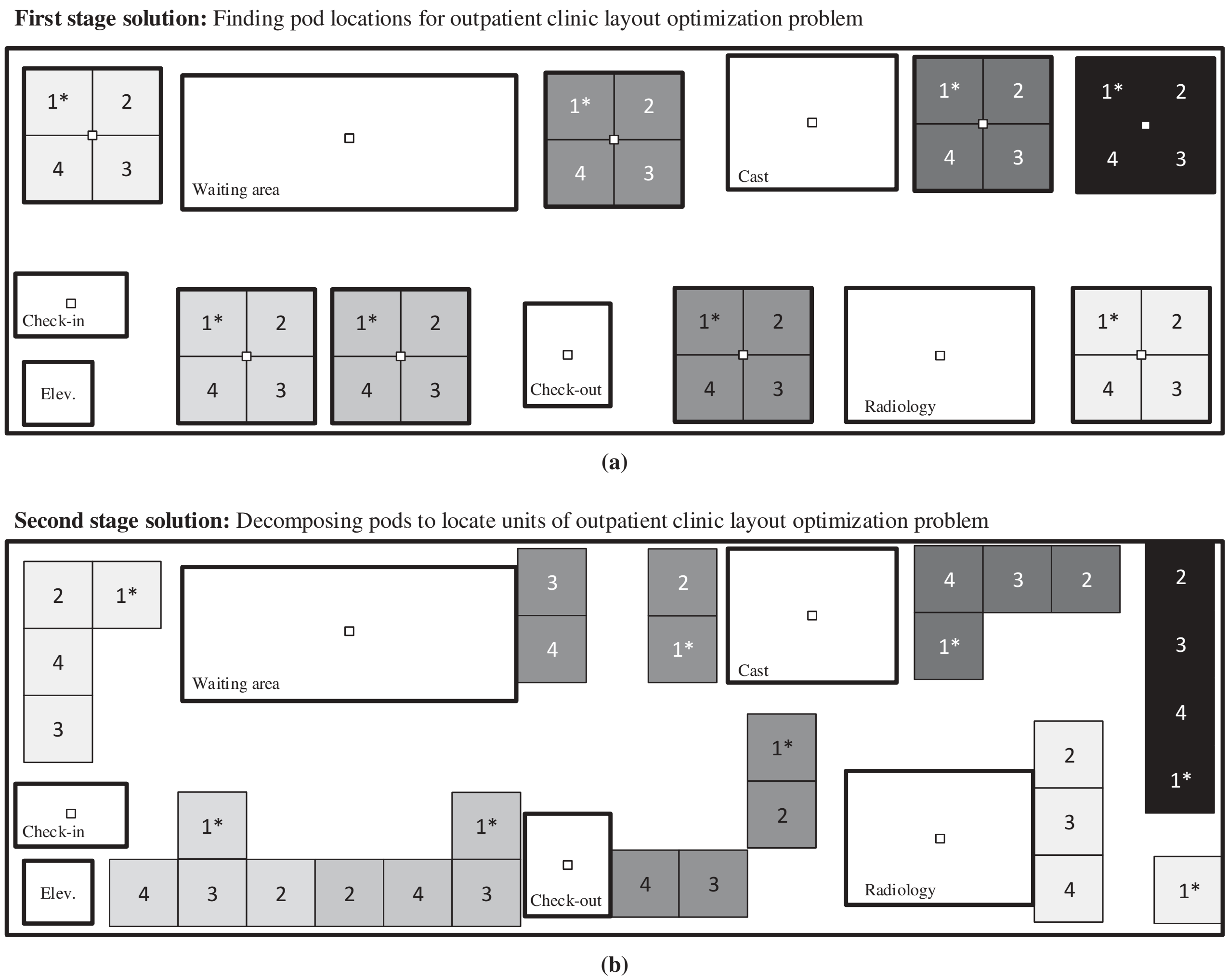

Figure B1. Example of the two-stage composition/decomposition heuristic for the outpatient clinic layout problem. Note that the units with (*) represent physician work areas.

After the location of the pods and the main units are determined in the first stage, next the pods are decomposed and the problem of finding the best layout for each pod is solved in the second stage, as shown in Figure B1(b). The pods are decomposed in such a way that the final layout remains feasible, with no overlapping units, and the total cost of flows between the units is minimised.

To build different layouts for the units inside the pod, without significantly altering the solution from that found in the first stage, a locally expanded space that extends beyond the initial location of the pods is defined. More specifically, the expanded space is defined to be the area that would result from adding an additional exam room on any side of the pod (see Figure B2). The MH solution procedure examines different layouts of the three exam rooms and one work area that can occur in this expanded space. These solutions are only deemed to be permissible if units do not overlap with main units (i.e., cast, waiting area, radiology, check-in and check-out) or units from other pods and are not located outside of the facility boundary. Examples of solutions for the layout of these units in the feasible space such that no units overlap with the check-in space are presented in Figure B2. Since the search space, defined by the different pod layouts, is discrete and independent for each pod, the solution to this stage can be obtained efficiently.

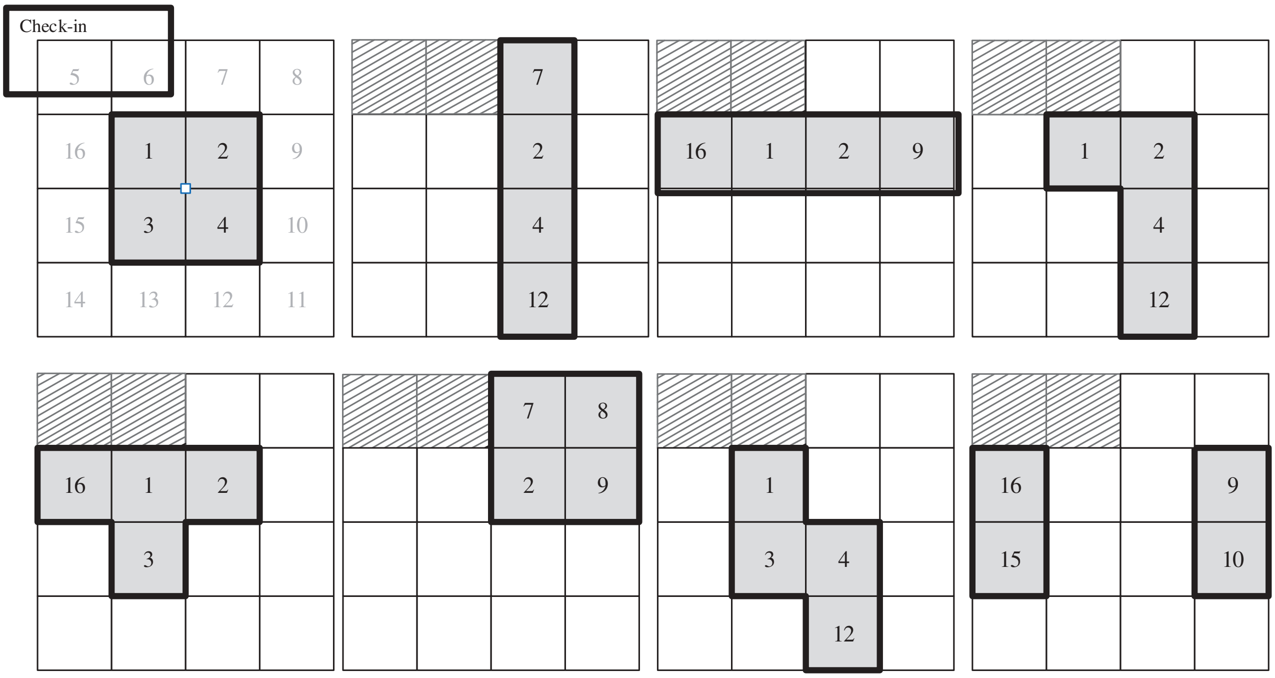

Figure B2. Pod decomposition examples. In the top-left corner, the initial pod prior to decomposition is shown. In the decomposition phase, units can be located in any of the 12 adjacent locations in the expanded space (see squares 5–16 at top-left corner) as long as no units overlap with the main units. In this example, the check-in location prohibits the pod units to be located in positions 5 and 6.