Computers & Operations Research 79 (2017) 223–263

Contents lists available at ScienceDirect

Computers & Operations Research

journal homepage: www.elsevier.com/locate/caor

A survey of healthcare facility location

Amir Ahmadi-Javid [a,*], Pardis Seyedi [a], Siddhartha S. Syam [b]

[a] Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran
[b] Department of Management, Marquette University, Milwaukee, WI, USA

ARTICLE INFO

Article history:
Received 12 March 2015
Received in revised form
2 April 2016
Accepted 30 May 2016
Available online 15 October 2016

Keywords:
Healthcare facility location
Health systems
Emergency medical services
Optimization methods
Operations research
Discrete location problems

ABSTRACT

Healthcare facility (HCF) location has attracted considerable attention from the operations research community over nearly four decades as one of the most important strategic issues in healthcare systems, disaster management, and humanitarian logistics. However, the lack of a comprehensive review in the last decade is a serious shortcoming in the literature of HCF location. This survey presents a framework to classify different types of non-emergency and emergency HCFs in terms of location management, and reviews the literature based on the framework. The papers on HCF location problems are classified in detailed tables along ten descriptive dimensions, which are consideration of uncertainty, multi-period setting, particular input/setting, objective function, decision variable, constraint, basic discrete location problem, mathematical modeling approach, solution method, and case study inclusion. For each HCF type, research gaps and possible future directions are identified. Moreover, the literature and future research possibilities are analyzed in terms of modeling approach and solution method.

Contents

* Corresponding author.
E-mail address: ahmadi_javid@aut.ac.ir (A. Ahmadi-Javid).

http://dx.doi.org/10.1016/j.cor.2016.05.018
0305-0548/

1. Introduction

Facility location decisions play a critical role in the strategic design of systems for a wide range of private and public organizations (e.g., retail facilities, warehouses, airline hubs, police stations, hospitals, etc.). This is because poorly located facilities or an improper number of facilities can greatly increase capital and inventory costs and degrade customer services. The first theoretical study on the location of facilities began in 1909 when Alfred Weber [1] introduced a warehouse location problem to minimize the total distance between a warehouse and a set of customers. Thereafter, location theory and its applications were developed in different research areas along with a variety of models.

In healthcare, incorrect facility location decisions have a serious impact on the community beyond simple cost and service metrics; for instance, hard-to-access healthcare facilities are likely to be associated with increased morbidity and mortality. From this perspective, facility location modeling for healthcare is more critical than similar modeling for other areas. In addition, because of globally pervasive trends, such as decreasing birth rates, higher longevity and associated growth in elderly population, and increasing environmental problems (e.g., sound and air pollution), healthcare and the associated healthcare facility (HCF) location problems have become noticeably more critical and important to society. Due to this, HCF location modeling continues to attract keen interest from the operations research (OR) community.

Perhaps the earliest location-allocation study in the field of healthcare facilities (HCFs) was presented by Gould and Lienbach [2]. In this study, the problem of locating hospitals and determining their capacities was considered as a p-median problem in the western part of Guatemala. The transportation algorithm was used to solve the problem. From 2000 onwards, researchers reviewed different parts of the literature of HCF location from various perspectives (see [3–11]). The scopes of these review papers are summarized in Table 1 and explained in more detail subsequently.

The use of location-allocation models in development planning of health services in developing nations was reviewed by Rahman and Smith [3]. They classified studies into four categories: (i) finding a set of optimal sites, (ii) locating optimal sites in a new area, (iii) measuring the effectiveness of past location decisions, and (iv) improving existing location patterns. Brotcorne et al. [4] investigated the evolution of ambulance location and relocation models over the course of thirty years. For this purpose, they classified models into deterministic and probabilistic categories, and summarized the literature in two corresponding tables. Furthermore, they noted the introduction of dynamic models in ambulance location.

Daskin and Dean [5] classified the location models used in healthcare literature into three categories: accessibility,

Table 1
Review papers related to HCF location from 2000 onwards.

Reference	Year	The scope of review
[3]	2000	Location-allocation models for health service development
[4]	2003	Ambulance location and relocation models
[5]	2004	Location of HCFs from modeling perspective
[6]	2011	Emergency response facility location
[7]	2011	An overview of several applications of OR in healthcare
[8]	2012	Methodological advancements in healthcare accessibility
[9]	2013	Home healthcare logistics
[10]	2013	An overview on planning and management of EMSs
[11]	2015	An introduction and a short review of three types of HCFs

adaptability, and availability models. In their view, accessibility models are extensions of location models whose goals were predominantly to maximize coverage or to minimize average distance. Adaptability models attempt to find solutions that perform properly across a range of possible scenarios and conditions. Availability models are divided into deterministic, queuing-based and probabilistic models. These models address very short-term changes that result from facilities being busy.

The literature of covering models and optimization techniques for locating emergency response facilities was studied by Li et al. [6]. Rais and Vianna [7] briefly surveyed several applications of operations research in healthcare planning (e.g., demand forecasting, location selection, and capacity planning), healthcare management and logistics (e.g., resource and staff scheduling), and other applications (e.g., disease diagnosis and treatment planning). Wang [8] presented a literature review regarding three issues related to inequality in healthcare accessibility: measurement, optimization, and impact, with emphasis on methodological advancements and implications for public policy.

Gutiérrez and Vidal [9] reviewed the literature of home healthcare logistics in terms of a three-dimension framework. In the first dimension, home healthcare planning levels were distinguished according to the time horizon, namely strategic, tactical, and operational levels. In the second dimension, logistics management decisions were divided into four groups: network design, transportation management, staff management, and inventory management. In the third dimension, service processes were defined as the set of steps performed in the delivery of home healthcare services. These service processes include medical prescription, patient admission, appointment scheduling, visiting patients, and medical discharge. Ingolfsson [10] briefly reviewed research on the planning and management of emergency medical services (EMSs) with emphasis on four topics: performance measurement; location of ambulance stations; allocation of ambulances to stations; and forecasting of demand, response times, and workload. Recently, Gunes and Nickel [11] provided an overview of facility location problems in health systems with a focus on three main areas in the healthcare context: public facility location, ambulance planning, and hospital layout.

By considering the scope of the recent review papers (given in Table 1), one finds that each paper covers a part of the healthcare services. Thus, the field of OR continues to lack a comprehensive review of facility location in healthcare. In this regard, we decided to provide a thorough classification of HCF location models and survey the literature on HCF location in the last decade. The review considers 18 types of facilities in three main categories (see Section 3.1) along 10 descriptive dimensions (see Section 3.2). For this purpose, we identified approximately 150 articles that have been published since 2004. Note that almost all earlier papers on HCF location published before 2004 have been reviewed in surveys [3–11].

Furthermore, the scope of this paper is to review only those papers that consider a specific type of HCFs, not a generic type of service facility. Actually, there are papers that study typical (mobile or immobile) service facilities with specific properties, which are not reviewed in this paper unless they provided a case study on a healthcare location problem. For a review of such papers, the reader may refer to the recent survey [12] and references therein. The models developed in such papers can be potentially adapted for different types of HCFs, depending on the assumptions underlying each model.

One should pay careful attention to the point that HCFs are widely considered in many different interrelated research fields. These fields along with related survey papers are listed as follows: healthcare operations management ([13,14]), healthcare services supply chains ([15,16]), services supply chains ([17]), pharmaceutical supply chains ([18–20]), healthcare waste management ([21]), disaster operations management ([22–24]), emergency logistics ([25]), relief distribution ([26]), humanitarian logistics ([25,27–29]), homeland security ([30,31]), emergency response ([5,32,33]), emergency services stations ([34]), emergency services vehicles ([35]), and supply chain with disruptions ([36]). This indicates that HCFs have various types and widespread usages in different fields, which made our survey process more challenging.

The remainder of the paper is organized as follows: Section 2 presents an overview of discrete location problems. Section 3 provides a framework for the classification of HCFs from a location analysis perspective and describes the structure of this review paper. Section 4 and Section 5 are devoted to review and scrutiny of non-emergency and emergency HCF location papers, respectively, based on the framework proposed in Section 3. Section 6 analyzes the literature from different perspectives. Section 7 presents directions for possible future research. Section 8 concludes the review. Appendix A provides definitions and details on different types of HCFs.

2. An overview of discrete location problems

Facility location theory refers to the modeling, formulation, and solution methods of a class of problems that deal with locating facilities in some given space. Since facility location is a critical subject at the strategic planning level, location theory and its applications have received increasing attention from the OR community. The study of facility location models has its roots in the pioneering work of Weber in 1909. Thereafter, numerous papers and books have dealt with facility location problems (see, e.g., [37–39] and references therein).

Over the years, the broad spectrum of location problems has been divided in several ways. For instance, Revelle et al. [40] proposed a taxonomy for location problems based on the space in which the problems are modeled. They divided these location problems into four broad basic classes: analytic, continuous, network, and discrete. Among these classes, discrete location problems have been used in numerous practical contexts including, in particular, health systems.

Facility location problems can be extended by specializing them in various ways; for example, stochastic location problems, hierarchical location problems, multi-criteria location problems, hub location problems, dynamic and online location problems, competitive location problems, etc. (see, the recent book [41] for a review of different types of location problems). In addition, the integration of location decisions with other important logistical decisions or other related decisions became an increasingly important topic in the literature. Instances of this integration include location-inventory problems (see, e.g., [42,43]), location-routing problems (see, e.g., [44,45]), location-routing-inventory problems (see, e.g., [46,47]), location-pricing problems (see, e.g., [48–50]), and location-inventory-pricing problems (see, e.g., [51,52]).

In general, location problems may be either continuous (in which facilities may be located anywhere in the feasible region) or discrete (in which they can be established only at candidate locations that can include the demand points) [38]. We focus on discrete location problems since they comprise one of the best known categories of location problems and frequently arise in healthcare settings. Daskin [53] classified discrete location problems into three broad categories: covering-based problems, median-based problems, and other problems. This classification, with slight changes, is shown in Fig. 1.

Discrete location problems comprise an important set of applications of location modeling and theory. Thus, it is not surprising that many extensions to basic discrete problems have been proposed and studied in the literature of health system problems. Given our focus on healthcare facility location, we will consider and discuss many of these extensions in the rest of this paper.

On the one hand, covering-based and median-based problems are well-known facility location problems for modeling real-world situations. On the other hand, important problems, such as p-center and p-median location problems on a general network or in the plane are NP-hard for $p>1$ [53–55]. These are problems with no known polynomial-time exact solution algorithms. It means that the time required to exactly solve an instance of these problems may increase very rapidly as the size of the problem instance grows, often well beyond any reasonable time frame. As a consequence, a variety of algorithms have been developed in the literature to solve these problems both optimally and heuristically.

In the rest of this section, we study the three broad categories given in Fig. 1 and mathematical programming models of basic discrete location problems in these categories. The analysis of HFC literature based on different types of discrete location problems will be presented in Section 6.1.

2.1. Covering-based problems

Covering-based problems assume that demand locations need to be within a specific coverage distance (or time) from facilities which service them, in order to be covered by the service, or satisfactorily served. This class of problems includes three basic types: set covering problems, maximal covering problems, and p-center problems. In particular, we note that covering-based problems are typically appropriate for determining the location of emergency service facilities.

2.1.1. Set covering location problems

In a set covering location problem, the goal is minimizing the number of established facilities or the total location cost, given a specified level of demand coverage which must be achieved. These problems find the number and location of facilities such that all demand points are within a specified travel distance (or time) of the facilities that serve them. In formulating a basic set covering location problem, the following notation is used:

Sets:

I	The set of demand points.
J	The set of candidate locations.
N_i	The set of all candidate locations which can cover demand point $i{\in}I$, $N_i{=}\{j{\in}J{:}\ d_{ij}{\le}D_i\}$.

Input parameters:

d_{ij}	The travel distance (or time) from demand point $i{\in}I$ to candidate location $j{\in}J$.
f_j	The fixed cost of locating at candidate location $j{\in}J$.
D_i	The maximum acceptable travel distance or time from demand point $i{\in}I$ (the cover distance or time).

Decision variables:

x_j	1, if a facility is established (located or opened) at candidate location $j\in J$; 0 otherwise.

Formulation:

$$\min \sum_{j\in J} f_j x_j \tag{1}$$

subject to

$$\sum_{j\in N_i} x_j \ge 1,\ i\in I \tag{2}$$

$$x_j\in\{0,1\},\ j\in J. \tag{3}$$

In this model, the objective function (1) minimizes the location cost of the facilities which are needed to cover all demand points. Constraints (2) ensure that each demand point must be covered and Constraints (3) are integrality constraints.

2.1.2. Maximal covering location problems

Maximal covering location problems (MCLPs) determine the location of p facilities in order to maximize the demand covered within a pre-specified maximum coverage distance. These

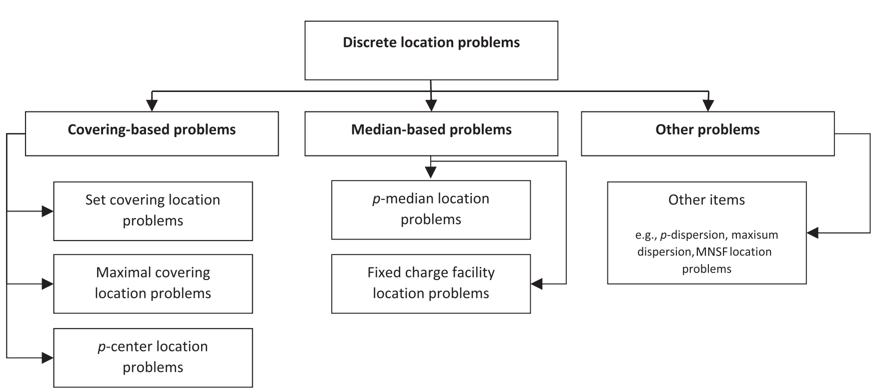

Fig. 1. A classification of discrete location problems.

problems differentiate between points with large and small demand, by taking into account the level of demand at each point. A basic MCLP can be formulated with the following notation:

Sets:

I The set of demand points.
J The set of candidate locations.
N_i The set of all candidate locations which can cover demand point $i \in I$, $N_i = \{ j \in J : d_{ij} \le D_i \}$.

Input parameters:

d_{ij} The travel distance (or time) from demand point $i \in I$ to candidate location $j \in J$.
w_i The demand at point $i \in I$.
D_i The maximum acceptable travel distance or time from demand point $i \in I$ (the cover distance or time).
p The number of candidate locations to be established.

Decision variables:

x_j 1, if a facility is established at candidate location $j \in J$; 0 otherwise.
z_i 1, if demand point $i \in I$ is covered; 0 otherwise.

Formulation:

$$\max \sum_{i \in I} w_i z_i \tag{4}$$

subject to

$$\sum_{j \in J} x_j = p \tag{5}$$

$$z_i \le \sum_{j \in N_i} x_j, \ i \in I \tag{6}$$

$$z_i \in \{0, 1\}, \ i \in I \tag{7}$$

$$x_j \in \{0, 1\}, \ j \in J. \tag{8}$$

The objective (4) maximizes the total covered demand. Constraint (5) states that p facilities are to be located. Constraints (6) require that demand points are only covered by open facilities. Constraints (7) and (8) are integrality constraints.

2.1.3. *p*-center location problems

p-center location problems (PCLPs) are the third classical type of covering-based problems, which minimize the maximum travel distance (or time) among all demand points and the allocated facilities, considering that every demand point is covered. When the facilities are uncapacitated, the demand points are assigned to the closet open facilities. These covering-based location problems are a type of minmax problem and may be also referred to as location-allocation problems since they require simultaneous facility location and allocation of the demand points to the open facilities. To formulate the canonical form of a basic PCLP, the following notation is used:

Sets:

I The set of demand points.
J The set of candidate locations.
N_i The set of all candidate locations which can cover demand point $i \in I$, $N_i = \{ j \in J : d_{ij} \le D_i \}$.

Input parameters:

d_{ij} The travel distance (or time) from demand point $i \in I$ to candidate location $j \in J$.
w_i The demand at point $i \in I$.
D_i The maximum acceptable travel distance or time from demand point $i \in I$ (the cover distance or time).
p The number of candidate locations to be established.

Decision variables:

x_j 1, if a facility is established at candidate location $j \in J$; 0 otherwise.
y_{ij} 1, if demand point i is assigned to a facility at candidate location $j \in N_i$; 0 otherwise.

Formulation:

$$\min L \tag{9}$$

subject to

$$\sum_{j \in N_i} y_{ij} = 1, \ i \in I \tag{10}$$

$$\sum_{j \in J} x_j = p \tag{11}$$

$$\sum_{j \in N_i} d_{ij} y_{ij} \le L, \ i \in I \tag{12}$$

$$y_{ij} \le x_j, \ i \in I, \ j \in N_i \tag{13}$$

$$y_{ij} \in \{0, 1\}, \ i \in I, \ j \in N_i \tag{14}$$

$$x_j \in \{0, 1\}, \ j \in J \tag{15}$$

$$L \ge 0. \tag{16}$$

The objective (9) minimizes the maximum demand-weighted distance (or time) between a demand point and the (nearest) facility allocated to it. Constraints (10) guarantee that each demand point is covered by only one facility. Constraint (11) specifies the total number of facilities to be established. Constraints (12) determine the maximum demand-weighted distance (or time). Note that L is an auxiliary variable (not a decision variable) that is used to compute the maximum distance. Constraints (13) show that demand points are only covered by open facilities. Finally, Constraints (14)-(16) are domain constraints.

2.2. Median-based problems

Median-based problems locate facilities at candidate points so as to minimize the weighted average distance costs between demand points and the facilities to which they are assigned. These locations are the medians of the network. This class of problems may be referred to as location-allocation problems as they determine both location and allocation decisions. p-median and the fixed charge location problems are important problems in this class.

2.2.1. p-median location problems

p-median location problems (PMLPs) are among the most popular problems in facility location. These problems aim to locate p facilities in a network. The sets, parameters, and decision variables used in the formulation of a basic PMLP are as follows:

Sets:

I	The set of demand points.
J	The set of candidate locations.

Input parameters:

d_{ij}	The travel distance (or time) from demand point $i \in I$ to candidate location $j \in J$.
w_i	The demand at point $i \in I$.
p	The number of candidate locations to be established.

Decision variables:

x_j	1, if a facility is established at candidate location $j \in J$; 0 otherwise.
y_{ij}	1, if demand point $i \in I$ is assigned to a facility at candidate location $j \in J$; 0 otherwise.

Formulation:

$$\min \sum_{i \in I} \sum_{j \in J} w_i d_{ij} y_{ij} \tag{17}$$

subject to

$$\sum_{j \in J} y_{ij} = 1, \; i \in I \tag{18}$$

$$\sum_{j \in J} x_j = p \tag{19}$$

$$y_{ij} \le x_j, \; i \in I, \; j \in J \tag{20}$$

$$y_{ij} \in \{0, 1\}, \; i \in I, \; j \in J \tag{21}$$

$$x_j \in \{0, 1\}, \; j \in J. \tag{22}$$

In this model, the objective (17) minimizes the total demand-weighted travel distance (or time). Constraints (18) show that each demand point is assigned to only one facility. Constraint (19) specifies the total number of facilities to be established. Constraints (20) limit assignments to open facilities. Constraints (21) and (22) are integrality constraints.

2.2.2. Fixed charge facility location problems

Fixed charge facility location problems (FCLPs) are closely related to PMLPs. While PMLPs disregard the differences in the facility establishing costs at different candidate locations, FCLPs attempt to minimize the total cost of facility opening and traveling. The notation and formulation of a basic uncapacitated FCLP are described below:

Sets:

I	The set of demand points.
J	The set of candidate locations.

Input parameters:

d_{ij}	The travel distance (or time) from demand point $i \in I$ to candidate location $j \in J$.
w_i	The demand at point $i \in I$.
f_j	The fixed charge of establishing a facility at candidate location j.
v	The transportation cost per item per distance unit (the variable transportation cost).

Decision variables:

x_j	1, if a facility is established at candidate location $j \in J$; 0 otherwise.
y_{ij}	1, if demand point $i \in I$ is assigned to a facility at candidate location $j \in J$; 0 otherwise.

Formulation:

$$\min \sum_{j \in J} f_j x_j + v \sum_{i \in I} \sum_{j \in J} w_i d_{ij} y_{ij} \tag{23}$$

subject to

$$\sum_{j \in J} y_{ij} = 1, \; i \in I \tag{24}$$

$$y_{ij} \le x_j, \; i \in I, \; j \in J \tag{25}$$

$$y_{ij} \in \{0, 1\}, \; i \in I, \; j \in J \tag{26}$$

$$x_j \in \{0, 1\}, \; j \in J. \tag{27}$$

The objective (23) minimizes the total cost which includes the facility-opening and transportation costs. Constraints (24) ensure that each demand node is assigned to an open facility, while Constraints (25) restrict assignments to open facilities. Constraints (26) and (27) are integrality constraints.

In a capacitated FCLP, a new parameter U_j is defined as the maximum capacity of each facility j. The formulation of a basic capacitated FCLP is similar to the one given above with the following additional capacity constraints:

$$\sum_{i \in I} w_i y_{ij} \le U_j, \; j \in J.$$

2.3. Other problems

Finally, the problems which are not in either of the above two broad categories (covering-based and median-based problems) belong to the last category. For example, in the p-dispersion problem, p facilities are located on a network in order to maximize the minimum separation distance between any pair of open facilities, which can be applied to facilities with a threat to each other, or to systems of retail or service franchises [56]. The maxisum dispersion problem is a similar problem, which maximizes the average separation distance between open facilities [56]. Another example is the maximum-number-of-sustainable-facilities (MNSF) location problem that maximizes the number of bases for healthcare workers (HCW), which can work sustainably in an area. An open HCW basis works sustainably if a sufficient number of self-help groups (SHGs), within a certain travel distance, are allocated to it, where SHGs are located on a given network [57]. One may add other problems to this category.

3. Scope of literature survey

This section includes two subsections. The first presents the framework that is used to classify the different types of HCFs, and the second introduces the descriptive dimensions considered to analyze each research paper.

3.1. A framework for classification of HCFs

In most societies, the healthcare industry has grown over time, leading to high levels of aggregation and integration of various sectors in order to provide healthcare products and services efficiently and effectively to the society members. The five major players of the healthcare industry are producers, distributors, providers, waste management actors, and fiscal intermediaries (Fig. 2). Producers include all health suppliers, such as pharmaceutical companies, medical-surgical product companies, and medical equipment manufacturers. Distributors who comprise links between producers and providers include different types of wholesalers and distributors in the field of health products. The main body of a healthcare system is made up of providers that are responsible for provision of a variety of healthcare services to the people of a country or an area. The last, but not least, components in a health supply chain are healthcare waste management (HCWM) facilities which are responsible for the collection, distribution, recycling, and disposal of medical waste and used medical equipment. Finally, the health systems also involve the participation of fiscal intermediaries, such as insurance agencies and health maintenance organizations. The objective of this paper is to present a survey of the location literature that applies to health systems from an OR perspective.

Our review of the literature indicated that on the one hand supply chains for health services have been addressed by many researchers (see survey papers [15,16]); on the other hand, determination of the optimal location of medical producers, distributors, and fiscal intermediaries has not received much attention from the OR community even though that is crucially important in the timely delivery of medical products and services. Actually, we could find only two papers studying the location of medical distributors in disaster situations [58,59] (Mete and Zabinsky [58] modeled the location of stockpiles, i.e., medical supplies warehouses, in disaster situations using a two-stage stochastic program; and Paul and Hariharan [59] developed a deterministic stockpile location model which includes disaster specific casualty characteristics, such as the severity and type of medical condition, and the unique nature of each type of disaster). The main reason perhaps is that these areas are covered by the extensive literature of supply chain location management (see [60,61] and references therein). Despite the fact that producers are keenly interested in improving products and ensuring quality and safety, they often have insufficient expertize in logistics and distribution. Moreover, reducing those expenses is not a priority for producers or distributors because in most cases the transportation cost is ultimately passed on to the healthcare providers. Therefore, logistics and distribution are promising future areas for cost-cutting in health systems [62].

Medical waste comprises a wide range of waste materials generated by the broad variety of facilities related to health systems, including infectious and non-infectious waste; anatomical and pathological waste; pharmaceutical waste; genotoxic waste; chemical waste; heavy-metal waste; hazardous and non-hazardous materials, and used medical devices. Nowadays, the tremendous rise in the amount of medical waste poses grave challenges to all of the facilities related to health systems [21]. Components of an HCWM system are responsible for collection, distribution, recycling, and disposal of medical waste (see [21,63] for further study of HCWM). In this regard, determining the best location and optimal number of the related facilities is a pivotal strategic decision in health systems in order to avoid the transmission of infections as well as toxic effects, injuries, and pollution of the environment. Given the importance of strategic planning in HCWM, a corresponding investigation of this area from an operations research perspective has not been seen in the literature. Nevertheless, we believe that proper location of the facilities for collection, distribution, recycling, and disposal of medical waste will receive considerable attention from government and society in the future, and that the OR community can significantly contribute to this emerging important need (see [64] for a review of OR models for solid waste management).

Healthcare providers, by virtue of forming the main body of health systems, are the key players of these systems. These facilities provide a variety of healthcare services to the people of society. Accordingly, developing location models for healthcare providers has received attention from the OR community in general and specialists in location management in particular. The rest of this paper is dedicated to the literature on location of healthcare providers. Hence, healthcare facilities (HCFs) refer to healthcare provider facilities in the remainder of this paper.

As was mentioned, there are a wide range of services related to the improvement of human health. Nowadays, many types of HCFs are required to perform these services with each providing different features and applications. High or optimal performance of a health system depends on determining the optimal number of facilities, their optimal locations, and a system of communication between these HCFs. Considering the wide range of healthcare and medical activities, a framework must be developed based on a systematic way in order to classify all types of HCFs based on their locational properties. Using such a framework, the healthcare location literature can be comprehensively reviewed, and gaps and

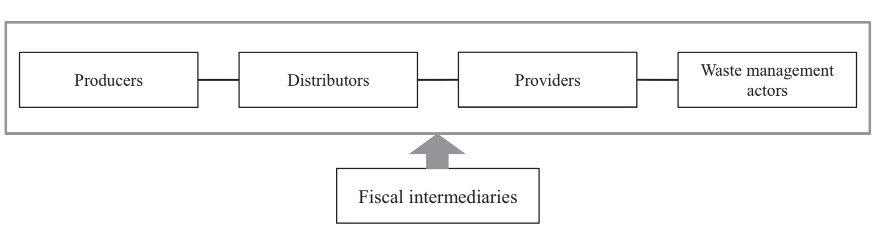

Fig. 2. The major players in health systems.

deficiencies can be identified.

To develop the framework used in this paper, all activities associated with human health were first considered based on the last edition of the international standard industrial classification (ISIC), introduced in 2008. Then, all types of HCFs performing these activities were collected through two sources: Iran's ministry of health and medical education and the north American industry classification system (NAICS). In Fig. 3, these HCFs are classified with regard to the location management purposes. This framework is quite comprehensive in the scene that it considers all types of known HCFs for all types of known heath activities. This will also serve to make researchers aware that the “story” is significantly different for each type of HCF found in the literature.

As shown in Fig. 3, the HCFs are classified into two main categories: (1) non-emergency facilities and (2) emergency facilities. Emergency facilities are also divided into permanent and temporary groups. In addition, each category includes several subcategories which are described in detail in Appendix A.

Almost all of the published literature over the last decade is classified in Table 2 according to the proposed framework. Table 2 aids in both the concise representation of non-emergency and emergency HCFs considered in the literature in an accessible fashion, and in the identification of gaps in the literature.

It is also possible to draw some conclusions based on Table 2. Almost 50% of the surveyed papers refer to non-emergency HCF location. Among these, about half of the papers (52%) address the location of primary care facilities (hospitals, clinics, etc.). Emergency HCF location makes up almost 50% of the papers. Further, about 16% of these examined the HCF location in disaster situations (temporary emergency facilities). Fig. 4 shows the share of each HCF type in the literature of location management.

3.2. Descriptive dimensions

Various methods are used in the search for solutions of HCF location problems; however, optimization methods are widely used. Other methods include GIS (e.g., see [178]) and simulation (e.g., see [179,180]) are sparsely considered in the literature, and therefore not discussed in this review paper. However, those papers using these methods to visualize or validate input and/or output data are considered in this paper (e.g., [174]). Furthermore, HCF layout problems, as a special class of HCF planning problems, are not considered in this review. An overview of these problems can be found in Section 21.4 of [11].

The following sections elaborate on optimization methods used in each HCF category of Fig. 3. In order to analyze the literature, we propose a review that is structured using ten main descriptive dimensions. These are consideration of uncertainty, multi-period setting, particular input/setting, objective function, decision variable, constraint, basic location problem, mathematical modeling approach, solution method, and case study inclusion. These dimensions, which are described in Tables 3 and 4, investigate the papers from two different perspectives: location theory and computation, respectively. The last three columns in Table 3 indicate the general HCF types for which each row-item is applicable.

Note that a decision problem can be modeled using various approaches, and each resulting model can be solved by different solution methods (see Table 4). Moreover, the classification regarding solution methods in Table 4 could be presented in more detail, but this level of detail is sufficient for our survey. Some of the subclasses may have overlaps and interconnections which are not detailed here. It should also be noted that solution methods are here divided into two main classes: A and B. A method in Class A finds, in a given time, either an optimal (exact) solution or a perturbed (or near-optimal) solution with a known deterministic error bound on the (relative or absolute) optimality gap of the resulting solution. However, a method in Class B does not provide an error bound and basically cannot determine the quality of its resulting solution. Borrowing from terminology used in the literature of metrology, methods in Classes A and B may be simply referred to as accurate and inaccurate, respectively [181].

Any non-exact method is sometimes called heuristic. This definition is much broader than the definition of heuristic methods in this paper. Based on our definition, heuristic methods are non-exact methods in Class B which do not fall in the other two subclasses: metaheuristic and approximate stochastic optimization. One should also note that polynomial time algorithms with bounded relative errors are referred to as approximation

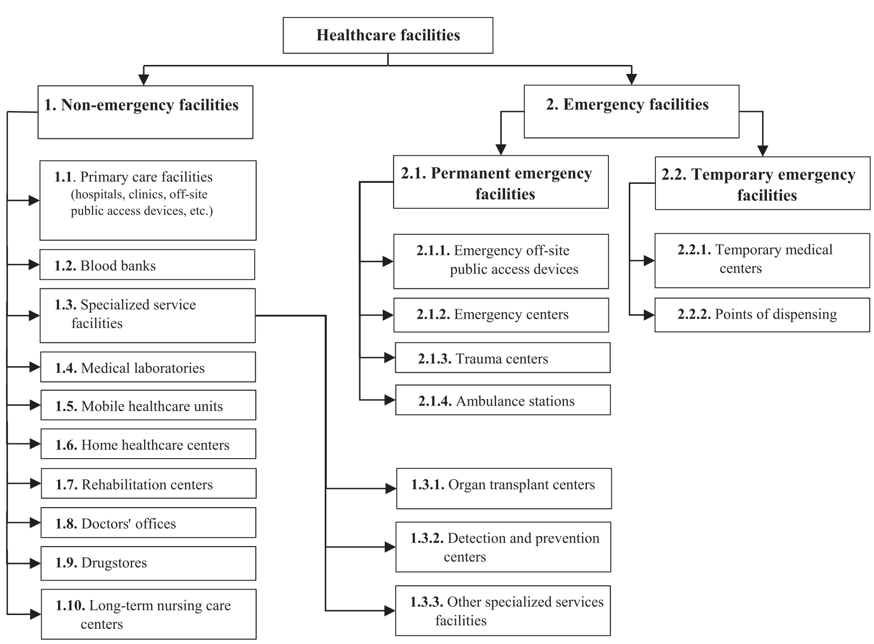

Fig. 3. The proposed framework for the classification of healthcare provider facilities.

Table 2
The breakdown of the HCF location literature into HCF types given in the framework (Fig. 3).

Non-emergency facilities	Primary care facilities (hospitals, clinics, off-site public access devices, etc.)		[65–91]
	Blood banks		[92–97]
	Organ transplant centers		[98–101]
	Detection and prevention centers		[102–110]
	Other specialized services facilities		[111–114]
	Medical laboratories		[115]
	Mobile healthcare units		[116]
	Long-term nursing care centers		[117,118]
Emergency facilities	Permanent emergency facilities	Emergency off-site public access devices	[119–124]
		Emergency centers	[125]
		Trauma centers	[126–131]
		Ambulance stations	[132–165]
	Temporary emergency facilities	Temporary medical centers	[57,166–170]
		Points of dispensing	[171–174]
Combination of several types of HCFs	Combination of 1.1 and 1.3.3*		[175,176]
	Combination of 1.1 and 1.6 *		[177]

* See Fig. 3 for HCF type codes.

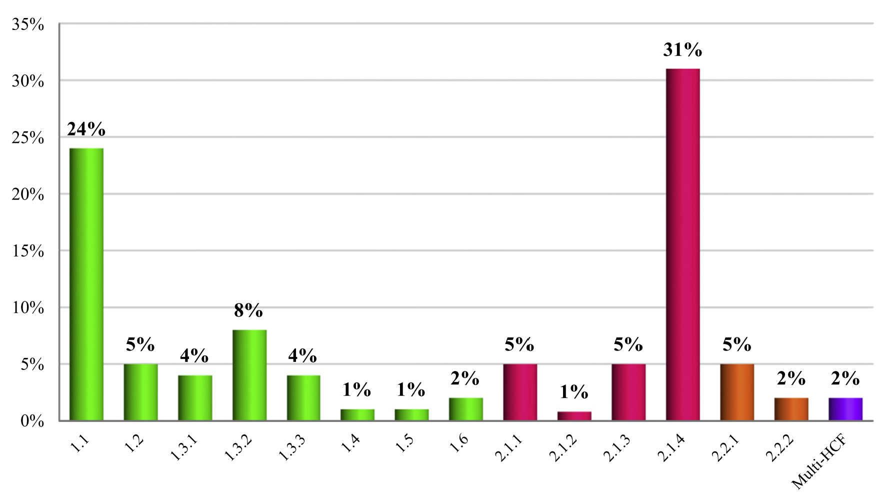

Fig. 4. The frequencies of papers on HCF types in the HCF location literature (see Fig. 3 for HCF type codes).

algorithms in the combinatorial optimization literature. These are rarely used in the location literature because most bounded-error methods used in the location literature, such as branch-and-bound and Lagrangian relaxation, do not result in polynomial-time solution algorithms. Moreover, under specific conditions, it is possible to present some convergence analysis or probabilistic error analysis for methods in Class B (which are randomized in nature). However, these are not elaborated here for the sake of brevity.

4. Non-emergency HCF location

Following the classification of HCFs illustrated in Fig. 3, content within the non-emergency literature can be classified into several categories. In the following, the reviewed papers in each category are analyzed according to Tables 3 and 4.

4.1. Primary care facilities (hospitals, clinics, off-site public access devices, etc.)

All the facilities in this class of HCFs provide primary care, i.e., first-contact care, which is early diagnosis, and timely and effective treatment. Primary care is usually performed by a general practitioner and has great potential for referral to specialty services, which are secondary, tertiary, or quaternary care; or non-medical services ([182]). Primary care, which is also referred to as primary medical care ([183]), differs from a broader concept of primary health care that includes primary care services, health promotion and disease prevention, and population-level public health functions ([184,185]).

Ease of access for all sections of society is an important goal for primary care facilities (PCFs). Almost all of these facilities are open 24 hours a day and clients refer to the nearest one. Attention must be paid to PCFs because the optimal location of these facilities is currently, as in the past, the subject of ongoing debate among researchers, as reflected in the fact that about half of this section's papers are dated from 2012 and onward.

It should be mentioned that hospitals and most clinics provide, beside primary care, specialty services, which are secondary, tertiary, or quaternary care. Therefore, if the main task of HCFs is the provision of primary care to the public, they will be considered as PCFs which are always available for all sections of society. However, if the main task of a hospital, such as specialty, super-specialty, or multi-specialty hospitals, is to provide specialty care

Table 3
Survey descriptive dimensions from location-theory perspective: consideration of uncertainty, multi-period setting, particular input/setting, objective function, decision variable, constraint, and basic location problem.

Survey dimension	Code	Descriptive dimension		Non-emergency facilities	Permanent emergency facilities	Temporary emergency facilities
Consideration of uncertainty	Y	Considering uncertainties		✓	✓	✓
	N	Not considering uncertainties		✓	✓	✓
Multi-period setting	S	Static		✓	✓	✓
	D-1	Dynamic	Multi-period short-term decisions (e.g., ambulance deployment or shift resource allocation)	✓	✓	✓
	D-2		Multi-period long-term decisions (e.g., location)	✓	✓	✓
Particular input/ setting	P1	Demand		✓	✓	✓
	P2	Travel time		✓	✓	✓
	P3	Travel distance		✓	✓	✓
	P4	Facility capacity		✓	✓	✓
	P5-1	Cost	Fixed cost	✓	✓	✓
	P5-2		Variable cost	✓	✓	✓
	P5-3		Penalty for lost demand	✓	✓	✓
	P6	Waiting time		✓	✓	✓
	P7	Multiple servers: Considering several servers at each facility		✓	✓	✓
	P8	Multiple services/Multi-type demand		✓	✓	✓
	P9	Elastic demand: Demand depends on distance, waiting time, etc.		✓		✓
	P10	Busy fraction: Probability of an ambulance being busy			✓	
	P11	Hierarchical system		✓	✓	✓
	P12	Other items, e.g., number of periods and different coefficients		✓	✓	✓
Objective function	O1	Minimize total number of facilities		✓	✓	✓
	O2	Minimize total number of ambulances			✓	
	O3	Minimize total travel distance (or time)		✓	✓	✓
	O4	Minimize sum of costs		✓	✓	✓
	O5	Minimize maximum travel distance (or time)		✓	✓	✓
	O6	Maximize participation		✓		
	O7	Maximize demand coverage		✓	✓	✓
	O8	Maximize multiple coverage			✓	
	O9	Minimize number of uncovered demand		✓	✓	
	O10	Other objectives, e.g., maximize number of voluntary facilities, minimize number of ambulance relocations, and minimize maximum transfer time between stations		✓	✓	✓
Decision variable	D1	Location of facilities		✓	✓	✓
	D2	Allocation of resources		✓		✓
	D3	Deployment (location or relocation) of ambulances in stations			✓	
	D4	Allocation of HCFs to demand points		✓	✓	✓
	D5-1	Demand coverage	Once	✓	✓	✓
	D5-2		More than once		✓	✓
	D6	Dispatch (assignment) of ambulances to demand points			✓	
	D7	Number of required resources		✓		✓
	D8	Other items, e.g., demand flow and number of required facilities		✓	✓	✓
Constraint	C1	Full coverage		✓	✓	✓
	C2	Partial coverage			✓	
	C3	Multiple coverage			✓	
	C4	Maximum number of required facilities		✓	✓	✓
	C5	Maximum travel distance (or time)		✓	✓	✓
	C6	Ambulance reliability/service level (probabilistic coverage)		✓	✓	✓
	C7	Maximum number of ambulances at each station			✓	
	C8	Maximum available resources		✓	✓	✓
	C9-1	Service capacity	Maximum capacity for demand response	✓	✓	✓
	C9-2		Minimum capacity for demand response	✓		
	C10	Budget		✓	✓	✓
	C11	Other items: e.g., no-vacant and flow constraints		✓	✓	✓

Table 3 (*continued*)

Survey dimension	Code	Descriptive dimension	Non-emergency facilities	Permanent emergency facilities	Temporary emergency facilities
Basic location problem	SCL	Set covering location problem	✓	✓	✓
	MCL	Maximal covering location problem	✓	✓	✓
	PCL	*p*-center location problem	✓	✓	✓
	PML	*p*-median location problem	✓	✓	✓
	FCL	Fixed charge facility location problem	✓	✓	✓
	O	Other items, e.g., *p*-dispersion, maxisum dispersion, and MNSF location problems	✓	✓	✓

rather than primary care, it should not be classified as a pure PCF. For such facilities one may use multi-objective optimization models to compromise between different location criteria (e.g., see [75,84]). Finally, it is worth noting that off-site public access devices, which are a new type of HCF (see Section 5.1.1 and Appendix A), can be possibly used as PCFs in the near future.

PCFs can be classified into different levels. For such facilities, hierarchical extensions of PMLPs can be useful (see [186] for a review of hierarchical location problems). In this regard, we formulate a p-median single-flow hierarchical problem for locating a set of PCFs with two levels, in which the total travel distance (or time) for patients is minimized. The sets, parameters and decision variables used in the formulation of this problem are as follows:

Sets:

I	The set of demand points.
K	The set of candidate locations for a level-1 PCF (e.g., clinics).
J	The set of candidate locations for a level-2 PCF (e.g., hospitals).

Input parameters:

d_{ik}	The travel distance (or time) between demand point $i\in I$ and a level-1 PCF in candidate location $k\in K$.
d_{kj}	The travel distance (or time) between a level-1 PCF in candidate location $k\in K$ and a level-2 PCF in candidate location $j\in J$.
w_i	The population size at demand point $i\in I$.
C_k^1	The capacity of a level-1 PCF in candidate location $k\in K$.
C_j^2	The capacity of a level-2 PCF in candidate location $j\in J$.
p	The number of alevel-1 PCFs to be established.
q	The number of level-2 PCFs to be established.
θ_k	The proportion of patients in a level-1 PCF at candidate location $k\in K$ referred to a level-2 PCF.

Decision variables:

x_k^1	1, if a level-1 PCF is established at candidate location $k\in K$; 0 otherwise.
x_j^2	1, if a level-2 PCF is established at candidate location $j\in J$; 0 otherwise.
u_{ik}	The flow of patients between demand point $i\in I$ and a level-1 PCF at candidate location $k\in K$.
v_{kj}	The flow of patients referred form a level-1 PCF at candidate location $k\in K$ to a level-2 PCF at candidate location $j\in J$.

Formulation:

$$\min \sum_{i\in I}\sum_{k\in K} d_{ik}u_{ik}+\sum_{k\in K}\sum_{j\in J} d_{kj}v_{kj} \tag{28}$$

subject to

$$\sum_{k\in K} u_{ik}=w_i,\ i\in I \tag{29}$$

$$\sum_{j\in J} v_{kj}=\theta_k\sum_{i\in I} u_{ik},\ k\in K \tag{30}$$

$$\sum_{i\in I} u_{ik}\le C_k^1 x_k^1,\ k\in K \tag{31}$$

$$\sum_{k\in K} v_{kj}\le C_j^2 x_j^2,\ j\in J \tag{32}$$

$$\sum_{k\in K} x_k^1=p \tag{33}$$

$$\sum_{j\in J} x_j^2=q \tag{34}$$

$$u_{ik}\ge 0,\ i\in I,\ k\in K \tag{35}$$

$$v_{kj}\ge 0,\ k\in K,\ j\in J \tag{36}$$

$$x_k^1\in\{0,1\},\ k\in K \tag{37}$$

$$x_j^2\in\{0,1\},\ j\in J. \tag{38}$$

In this model, the objective (28) minimizes the total demand-weighted travel distance (or time). Constraints (29) show that the entire population of patients at each demand point must be assigned to level-1 PCFs. Constraints (30) stipulate that θ_k proportion of patients in a level-1 PCF are referred to open level-2 PCFs. Constraints (31) and (32) control the capacities of open level-1 and level-2 PCFs. Constraints (33) and (34) specify the total number of level-1 and level-2 PCFs to be established. Constraints (35)–(38) are domain constraints.

Table 5 provides a breakdown of the optimization studies on the location of PCFs. It should be noted that Burkey et al. [65] and Fo and Mota [66] also addressed this class of HCFs, but their work has not been summarized in Table 5 since they limited themselves to comparing the performance of different existing discrete location models in health systems.

It can be seen from "Consideration of uncertainty" column of Table 5 that almost all of the papers deal with deterministic models. The exceptions are the papers [69,70,83,84,88]. Oliveira and Bevan [70] developed a utilization-based model which used behavioral

Table 4
The survey descriptive dimensions from computational perspective: modeling approach, solution method, and case study inclusion.

Survey dimension	Code			
Modeling approach	ILP	Integer linear programming		
	INLP	Integer nonlinear programming		
	MILP	Mixed-integer linear programming		
	MINLP	Mixed-integer nonlinear programming		
	GP	Goal programming		
	NLP	Nonlinear programming		
	FP	Fuzzy programming		
	PSP	Stochastic programming	Probabilistic (or chance-constraint) programming	
	1-SSP		Single-stage stochastic programming	
	2-SSP		Two-stage stochastic programming	
	M-SSP		Multi-stage stochastic programming	
	SP-O		Other	
	DP	Dynamic programming		
	SDP	Stochastic dynamic programming		
	RO	Robust optimization		
	MLP	Multi-level programming		
	CP	Constraint programming		
	MCDM	Multi-criteria decision making		
	MPDM	Multi-person decision making (Game Theory)		
	O	Other items, such as queueing theory (QT), graph theory (GT), and network theory (NT)		
Solution method	SL	Class A (accurate methods: exact or bounded-error methods)	Solving by a general-purpose optimization software package	Lingo
	SC			CPLEX
	SX			Xpress
	SG			Gams
	SO			Other items
	BB		Branch and bound	
	BC		Branch and cut	
	BP		Branch and price	
	BCP		Branch and cut and price	
	CP		Cutting plane	
	LR		Lagrangian relaxation	
	BD		Benders decomposition	
	DP		Dynamic programming	
	O		Other items, such as combinatorial and randomized algorithms	
	H	Class B (inaccurate methods: methods without any error analyses)	Heuristic	
	MH-TS		Metaheuristic	Tabu Search
	MH-GA			Genetic algorithm
	MH-SA			Simulated Annealing
	MH-AC			Ant Colony
	MH-O			Other items
	S-SBO		Approximate stochastic optimization	Simulation-based optimization
	S-SA			Stochastic approximation
	S-SAA			Sample average approximation
	S-SO			Scenario optimization
	S-O			Other items
Case study inclusion	Y	With case study		
	N	Without case study		

information generated by gravity models in order to improve geographic equity. Mitropoulos et al. [79] presented a probabilistic extension of the p-median model which combines data envelopment analysis (DEA) and location analysis. The uncertainty in the model was associated with the number of the treatment population which they estimated in exponential form using SPSS. In [83], a scenario-based location-allocation model was presented, which aimed to balance hospitals' usage, minimize congestion at the hospitals, and increase accessibility to the hospitals. Mestre et al. [84] developed two location models to address the planning of hospital networks over a planning horizon under uncertainty. They did this using a set of discrete scenarios. Shishebori and Babadi [88] proposed a robust and reliable model which simultaneously takes uncertainty in demand and transfer cost, and system disruptions into account.

Another important conclusion that can be drawn from Table 5 refers to the large number of static (i.e., single-period) models when compared with dynamic (i.e., multi-period) models (approximately 83% against 17%). A short-term dynamic model for seasonally moving populations was introduced in [71], and long-term dynamic location-allocation models were considered in [81,84,85].

The papers on location of PCFs emphasized the need for primary care of various sectors of society. While different sectors of society are multi-type demand and require different services, a few papers consider multiple services (see [72,75]) and multi-type demand (see [80,89]). In addition, health systems are generally hierarchical in nature leading to several types of services which may differ in cost and complexity. In this context, facilities tend to specialize in the sophistication of services they provide – consider, for example, services provided by hospitals compared to those

Table 5
Non-emergency healthcare facilities: primary care facilities (hospitals, clinics, off-site public access devices, etc.).

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[67] (2000)	N	S	P1, P12	O10	D1, D2	C1, C4, C9-1, C9-2, C11	SCL	MILP, GP, MCDM	SL	Y
[90] (2001)	N	S	P1, P3, P5-1, P5-2	O7	D1, D4	C4, C5, C10, C11	MCL	ILP	SC, H	Y
[68] (2002)	N	S	P1, P3, P8, P11, P12	O3	D1, D8	C1, C4, C9-1, C10	PML	MILP	SC, LR	Y
[89] (2004)	Y	S	P1, P3, P5-1, P5-2, P8, P12	O7	D1, D4	C4, C5, C10, C11	MCL	ILP, O(QT)	SC	N
[85] (2004)	N	D-2	P3, P4, P5-2, P7, P12	O3, O4, O9, O10	D7, D8	C9-1	FCL	MILP, MCDM	MH-TS	Y
[69] (2006)	N	S	P1, P3, P4	O3, O5	D1, D4	C1, C4, C5, C8, C9-1	PML	MILP, MCDM	SX	Y
[70] (2006)	Y	S	P1, P3, P4	O10	D4, D8	C4, C9-1, C9-2, C11	O	PSP, MINLP	SO	Y
[71] (2008)	N	D-1	P1, P5-1, P5-2	O4	D1, D4, D8	C1, C4, C9-2	FCL	ILP	SL	Y
[72] (2008)	N	S	P1, P4, P5-1, P5-2, P8	O7	D1, D4, D8	C5, C9-1, C10, C11	MCL	MILP	–	Y
[73] (2009)	N	S	P1, P3, P5-1, P5-2, P11	O9	D1, D4, D8	C4, C5, C10	MCL	MILP	SO	Y
[74] (2009)	N	S	P1, P3, P11, P12	O10	D1, D4	C4, C5, C11	O	ILP	SX	Y
[75] (2012)	N	S	P1, P2, P4, P8, P11, P12	O3	D1, D4, D7, D8	C1, C5, C9-1, C9-2, C11	PML	MILP	SG	Y
[76] (2012)	N	S	P1, P3, P4	O7	D1, D4	C1, C4, C5, C9-1	MCL	ILP	SC, MH-GA	Y
[77] (2012)	N	S	P1, P3, P4, P7, P9	O3/O6/O7	D1, D4, D7	C1, C4, C8, C9-1, C9-2, C11	MCL	ILP	–	Y
[78] (2012)	N	S	P1, P3, P5-1, P5-2	O3	D1, D4, D8	C1, C10, C11	FCL	MILP	SC	Y
[86] (2012)	N	S	P1, P3, P8, P11, P12	O3, O10	D1, D4	C1, C4, C5, C11	PML	ILP, MCDM	SX	Y
	N	S	P1, P3, P8, P11, P12	O7, O10	D1, D4, D5-1	C4, C5, C11	MCL	MILP, GP, MCDM	SX	Y
[79] (2013)	Y	S	P1, P3, P8, P12	O3, O10	D1, D4, D8	C1, C5, C9-2	PML	MILP, PSP, MCDM	SX	Y
[80] (2013)	N	S	P1, P3, P5-1, P8, P12	O7	D1, D4	C5, C9-1, C10, C11	MCL	ILP	SC, LR	Y
[81] (2013)	N	D-2	P1, P3, P5-1, P5-2, P12	O4	D1, D4, D8	C1, C10, C11	FCL	MINLP	SC, MH-SA, H	Y
[82] (2014)	N	S	P1, P3, P5-1, P12	O3/O4/O10	D1, D4, D8	C1, C4, C9-1, C9-2	PML	MILP, MCDM	MH-GA	Y
[83] (2014)	Y	S	P1, P2, P4, P5-1, P5-2	O4, O10	D1, D4	C1, C4	FCL	INLP, 2-SSP, MCDM	SG, MH-O	Y
[87] (2014)	N	S	P1, P3, P5-1, P5-2, P8, P12	O3, O4, O10	D1, D4	C1, C5, C9-2	FCL	MILP	SC	Y
[84] (2015)	Y	D-2	P1, P2, P5-1, P5-2, P5-3, P8, P11, P12	O3, O4, O9	D1, D7, D8	C4, C5, C9-1, C9-2	FCL, MCL	MILP, 2-SSP, MCDM	SG	Y
[88] (2015)	Y	S	P1, P3, P4, P5-1, P5-2, P12	O4	D1, D4, D8	C4, C9-1, C10, C11	FCL	MILP, RO	SG	Y
[91] (2016)	N	S	P1, P2, P12	O10	D1, D8	C4, C11	O	MILP	O	Y

provided by health centers. Furthermore, there are many links between the different levels of PCFs which makes it impossible to solve the location problems for each level independently [187]. Nevertheless, the small number of P11s in "Particular input/setting" column of Table 5 (see [68,73–75,84,86]) shows that hierarchical location models have not received much attention. As seen from the lack of P6 in the "Particular input/setting" column and O(QT) in the "Modeling approach" column, waiting time and queuing theory considerations are rarely included in the literature.

Efficiency and effectiveness, equity, and demand coverage are three major criteria to evaluate accessibility to non-emergency HCFs. Cost minimization is another major objective that is used in HCF location problems. Table 5 depicts the types of objective functions that measure the locational performance of PCFs. A major policy issue for a national health system in particular is the efficiency and effectiveness of the public HCFs with respect to their locations in local communities [69]. Distance (or time) minimization is a key factor in enhancing the efficiency and effectiveness of these facilities (see [68,69,75,77–79,82,84–87]). The most frequent service goal which is used to improve the equity and fairness of services is minimizing the maximum distance to the nearest facility (see [69]). However, Beheshtifar and Alimohammadi [82] proposed a new definition for equity by minimizing the variability of access distance to healthcare services. It should be noted that cost minimization has recently gained particular attention for these PCFs (see [71,81,83–85,87,88]). As seen in Table 5, more than half of the papers (approximately 53%) utilized median-based location problems and about 38% used covering-based location problems.

The considerable number of D1s and D4s in the "Decision variable" column of Table 5 clearly indicates that location decisions are frequently combined with allocation of demand (see [69–77,79,80,82,86–90]) and rarely with allocation of resources (see [67,75]). However, incorporating transportation modes (e.g., air, truck, and rail) and routing decisions have not attracted attention from researchers.

Another important conclusion from the "Modeling approach" column of Table 5 is the large number of ILP and MILP models (see [68,69,71–80,82,84,89–91]), compared to the number of stochastic (see [70,79,83,84]), dynamic, fuzzy, nonlinear (see [81,83]), and goal programming (see [67]) models.

In addition, Table 5 gives an overview of the types of solution methods that have been used to solve location problems in this class of HCFs. As is evident from the table, these problems have been solved frequently by general-purpose software packages (see [67,69–71,73–75,78,79,84,86–89]), Lagrangian relaxation method (see [68,80]), heuristic methods (see [81,90]), and genetic algorithms (see [76,82]). It can be concluded that approximately 72% of the papers used Class A methods and 28% used Class B methods to solve their models.

The papers that deal with PCFs can be divided into subcategories, such as hospitals, clinics, ambulatory healthcare centers, and off-site public access devices (see Appendix A). Nevertheless, we deliberately chose to avoid more detailed classification since papers do not determine any specific subcategory (it seems there is no clear difference among these subcategories from a location analysis perspective). Special types of PCFs are, however, studied in some papers. For instance, Ndiaye and Alfares [71] considered primary health units that are seasonally operated for nomadic population groups. Griffin et al. [72] determined the best location and number of new community health centers (CHCs) as well as the services each CHC should offer using publicly available data with the goal of maximizing the coverage of the weighted demand given budget and capacity constraints.

The combination of departments' layout and hospitals' location is less considered in the literature. For instance, Stummer et al. [85] developed a multi-objective model to determine the size and location of departments in facilities within a given network of hospitals.

Thus, given the detailed analysis provided above, future research could be conducted in the following fields:

- Proposing dynamic PCF location models (i.e., multi-period location models) that take into account changes in the problem setting over time, such as population migration, significant changes in management objectives, transportation and facility capacities, patient population, etc.
- Designing a hospital network with different types of PCFs (hospitals, clinics, ambulatory healthcare centers, and off-site public access devices).
- Developing location models by considering PCFs with different payment systems (e.g., with or without insurance).
- Incorporating transportation modes (e.g., air, truck, and rail) and routing decisions into PCF location models.
- Developing statistical methods to estimate the input parameters of the existing models.
- Incorporating logistics and distribution considerations into the existing PCF location models.
- Integrating PCF location with related healthcare planning decisions.
- Extending the existing PCF location models in a competitive environment for private primary care providers (see, e.g., [89]).
- Developing models for centralizing locational decisions for a set of (dependent or independent) primary care providers to improve the service quality and the utilization of the common resources.

4.2. Blood banks

The use of blood and blood products on a daily basis is extensive worldwide for accident victims, cancer patients, and other patients undergoing various surgeries, organ and marrow transplants, inherited blood disorders, etc. The literature on blood stockpile management focuses on the complexity of effective and efficient inventory management of blood [92]. For instance, Prastacos [188] reviewed the studies that incorporates OR techniques into blood inventory management theory and practice, and Beliën and Forcé [189] surveyed the literature on inventory and supply chain management of blood products.

Extreme shortage of blood occurs in over 80% of the countries in the world [93]. In addition, the world health organization has stated that many patients requiring transfusion do not have timely access to safe blood. The median blood donation rate in high-income countries is 36.8 donations per 1000 population, 11.7 in middle-income countries, and 3.9 in low-income countries (note that the blood donation rate is an indicator of the general availability of blood in a country). Consequently, the lack of availability and accessibility of blood can be attributed to the inefficient allocation of resources (i.e., blood collection methods) that may be the result of poor geographic location of the blood supply sources.

Hence, access to different types of blood banks (e.g., blood transfusion providers, blood centers, blood stations and mobile units) is highly important in health systems. A major problem for blood banks is that human blood is a perishable, scarce, and valuable product with a life time of only 21 days. Moreover, both demand and supply of blood are stochastic. The extension of covering-based problems for blood stations and mobile units as well as median-based problems for the blood centers and transfusion organization can be considered as an effective location method in order to increase people's participation in blood donation and timely access to safe blood. In addition, applying a hierarchical approach is also suggested (see [92]).

Table 6
Non-emergency healthcare facilities: blood banks.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[92] (2007)	N	S	P1, P3, P11, P12	O1/O3/O7	D1, D2, D4	C1, C4, C8, C11	PML/SCL	ILP/MILP	SC	Y
[93] (2009)	N	S	P1, P3, P4, P5-1, P12	O4	D1, D4	C1, C4, C9-1, C11	FCL	MINLP, GP	SO	N
[97] (2014)	Y	D-1	P1, P3, P4, P5-1, P5-2, P12	O4	D1, D2, D7, D8	C5, C8, C9-1, C11	FCL	MILP, RO	SL	Y
[96] (2015)	Y	D-1	P1, P2, P3, P4, P5-1, P5-2, P12	O3, O4	D1, D2, D4, D8	C1, C4, C5, C8, C9-1, C11	FCL	MILP, 2-SSP, MCDM	LR, SG	N
[95] (2015)	Y	D-1	P1, P3, P4, P5-1, P5-2, P12	O4	D1, D2, D4, D8	C2, C4, C5, C8, C9-1, C11	FCL	MINLP, PSP, RO, FP	SG	Y
[94] (2015)	N	S	P1, P5-1, P5-2, P12	O4	D1, D4	C10	PML	MINLP	SG, DP, O	Y

Table 7
Non-emergency healthcare facilities: organ transplant centers.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[98] (2006)	N	S	P1, P2, P3	O3, O10	D1, D2, D4, D8	C1, C4, C5	PML	MILP,MCDM	SL	Y
[99] (2013)	Y	S	P1, P2, P5-1, P8, P12	O3	D1, D2, D4, D8	C1, C4, C5, C8, C10, C11	PML	MILP	SC	Y
[100] (2014)	Y	D-1	P1, P2, P5-1, P5-2, P5-3, P8, P12	O4	D1, D2, D7, D8	C1, C5, C6, C8, C9-1, C11	FCL, MCL	MINLP, PSP, FP, RO	SG	Y
[101] (2014)	Y	D-1	P1, P2, P5-1, P5-2, P7, P8, P12	O3, O4	D1, D2, D8	C2, C4, C5, C6, C8, C11	FCL	MINLP, FP, PSP, MCDM, O(QT)	SG, MH-SA, MH-O	Y

Given the importance of blood bank locations in a health system, only a few papers [92–97] studied the location of blood banks. Şahin et al. [92] considered a blood bank location problem in a hierarchical system in which the regional blood centers (RBCs) are defined as the upper level; and blood centers, blood stations, and mobile units are defined as the lower level. They decomposed the problem into three sub-problems. The first sub-problem solves a hierarchical PMLP, called the *pq*-median location problem, to determine the locations of q RBCs (regional blood centers) which provide services to p blood centers located at the demand points. In the second sub-problem, location of blood stations–as supporting facilities–are determined to improve the accessibility at the demand points by set covering models. Finally, the third sub-problem is formulated as an IP model to reduce inefficiency in the use of mobile units and ensure a homogenous distribution of mobile units among the service regions. Cetin and Sarul [93] developed a model which determines a set of independent blood banks that should be established and the assignment of hospitals to the open blood banks. In their model, the locations of blood banks are determined based on the center of gravity method.

The location of fixed and temporary blood facilities, and the design of distribution networks over a multi-period horizon with uncertainty in the input parameters were addressed by Zahiri et al. [95]. Elalouf et al. [94] focused on the determination of centrifuge centers in a three-echelon blood sample collection chain composed of clinics, centrifuge centers, and testing laboratories under the assumption that centrifugation services can be performed in clinics and centrifuge centers.

Jabbarzadeh et al. [97] and Fahimnia et al. [96] addressed the location of permanent and/or temporary blood facilities in disasters. Jabbarzadeh et al. [97] proposed an FCLP-based robust model to determine the number and location of permanent and temporary blood facilities as well as to periodically determine blood inventory levels by coordinating supply and demand during and after disasters. Fahimnia et al. [96] also presented a two-stage bi-objective model to determine location and relocation planning of mobile blood facilities; and to specify blood collection and transportation quantities, and inventory levels for efficient and timely supply of blood in disasters. In addition to the brief description provided above, the papers are listed in Table 6.

In this regard, some possible future directions are as follows:

- Extending location models for handling both independent blood banks and dependent blood bank units (inside hospitals or clinics).
- Developing models that consider stochastic and dynamic conditions (see, e.g., [95]).
- Considering new settings, such as budget constraints or multi-ple-server blood banks.
- Taking into account the different levels of the blood supply's life time(s) when locating blood banks; in particular, considering the fact that some specialized treatments require the use of only fresh blood.
- Developing a model for optimal location/relocation of components of a blood supply chain.
- Proposing online location models for mobile blood units in order to effectively increase voluntary blood donation rate and enrich blood banks (see, e.g., [92,97]).
- Incorporating the average age, sex, and blood groups of people who can donate blood in each region in blood station location models.
- Addressing emergency conditions arising at times of disasters, or other similar events, in locating blood banks (see, e.g., [96]).

4.3. Specialized services facilities

There are two important considerations in the location of specialized services facilities. On the one hand, proper location is related to availability of specialized and experienced resources. On the other hand, their role in enhancing the quality of healthcare, satisfaction of demand, and social welfare, is important to governments, the private sector, and individuals alike. The literature on the location of specialized services facilities is examined in the following three subsections.

4.3.1. Organ transplant centers

Organ transplant centers (OTCs) are the main components of organ transplantation programs in healthcare systems, which have three distinctive features that should be considered in their location:

1. As the demand for organs continues to exceed the supply, organ transplants suffer from long waiting lists.
2. The time that elapses between donor notification and transplantation is vital and very important in the process of organ donation.
3. Organ transplantation involves both a donor (a person who donates an organ intended for transplant) and a recipient (a person who receives an organ).

Hence, the strategic planning of the organ transplantation programs requires a different location decision approach. For this purpose, we present a PMLP-based model which takes into consideration the above three features. The following MILP model is a generalization of the one given in [98], with the notation:

Sets:

I	The set of donor hospitals.
J	The set of candidate OTC locations.
K	The set of potential organ recipient points.
T_k	The set of all candidate OTCs which are within an acceptable travel time (or distance) of organ recipient point $k\in K$, $T_k=\{j: t_{kj}\le T\}$.

Input parameters:

t_{kj}	The travel time (or distance) for transferring patients from organ recipient point $k\in K$ to an OTC at candidate location $j\in J$.
a_{ij}	The travel time (or distance) for transferring organs from donor hospital $i\in I$ to candidate OTC $j\in J$.
w_k	The demand size at organ recipient point $k\in K$.
T	The maximum acceptable travel time (or distance) from an organ recipient point (the cover distance or time).
p	The number of candidate OTCs to be established.

Decision variables:

z_j	1, if an OTC is active at candidate location $j\in J$; 0 otherwise.
y_{kj}	1, if recipient point $k\in K$ is served by an OTC at candidate location $j\in J$; 0 otherwise.
x_{ij}	1, if donor hospital $i\in I$ serves an OTC at candidate location $j\in J$; 0 otherwise.

Formulation:

$$\min \sum_{j\in J}\sum_{i\in I} a_{ij}x_{ij}+\sum_{k\in K}\sum_{j\in T_k} w_k t_{kj} y_{kj}+E \tag{39}$$

subject to

$$\sum_{j\in J} x_{ij}=1,\ i\in I \tag{40}$$

$$\sum_{j\in T_k} y_{kj}=1,\ k\in K \tag{41}$$

$$\sum_{j\in J} z_j=p \tag{42}$$

$$y_{kj}\le z_j,\ k\in K,\ j\in J \tag{43}$$

$$x_{ij}\le z_j,\ i\in I,\ j\in J \tag{44}$$

$$E\ge \sum_{k\in K} w_k y_{kj},\ \ j\in J \tag{45}$$

$$y_{kj}\in\{0,\ 1\},\ k\in K,\ j\in J \tag{46}$$

$$x_{ij}\in\{0,\ 1\},\ i\in I,\ j\in J \tag{47}$$

$$z_j\in\{0,\ 1\},\ j\in J \tag{48}$$

$$E\ge 0. \tag{49}$$

In this model, the objective (39) minimizes the sum of the total demand-weighted travel time (or distance) from donor hospitals and organ recipient points to active OTCs, and the maximum size of waiting list among all active OTCs. Constraints (40) and (41) stipulate that each recipient point and donor hospital is only assigned to one active OTC. Constraint (42) specifies the total number of OTCs to be established. Constraints (43) and (44) limit assignments to active OTCs. Constraints (45) determine the maximum size of the waiting lists of active OTCs. Note that E is an auxiliary variable (not a decision variable), used to compute the maximum size. Constraints (46)-(49) are domain constraints.

Both Bruni et al. [98] and Belien et al. [99] formulated an OTC location problem based on a PMLP to minimize the time components of transplant, with the difference that the latter work considers both the donors and the recipients in the problem. Furthermore, the former work considers three situations that all have different paths and travel times. Zahiri et al. [100] also investigated an OTC location problem, but slightly differently from the previous papers. They presented a fuzzy programming model for a long-term dynamic location-allocation problem to minimize the total costs including fixed, variable, and unsatisfied demand costs. Thereafter, this model was extended by Zahiri et al. [101]. They considered alternative transportation mode as well as uncertainty in demand and supply of organs in a multi-objective location-queuing model.

Although most research studies on OTC planning focused primarily on topics, such as transplant waiting list and allocation policies (see, e.g., [190–193]), it can be seen from Table 7 that only a few papers addressed the location of OTCs. Indeed, proper location of OTCs plays a vital role in successful transplants (in terms of saving time and optimizing links with other required units).

Based on Table 7, locating OTCs in terms of both modeling and solution methods, appears to have many opportunities for improvement, such as

- Integrating location of OTCs with other related components

(hospitals and emergency departments) in a health system.
- Developing multi-stage stochastic programming models to incorporate other relevant OTC planning aspects in the determination of OTC locations.
- Centralizing decision making on locating/relocating OTCs.
- Extending the existing models to take dynamic and online aspects of transplant procedures into account.
- Considering more realistic transportation features (e.g., stochastic travel times and ambulance busy fractions) in OTC location problems.

4.3.2. Detection and prevention centers

Detection and prevention centers (DPCs) provide healthcare services which are different from other healthcare services (e.g., healthcare services for acute diseases). These services are usually defined based on (local or national) detection and prevention programs. DPCs have the following two key characteristics:

1. Each center needs to have a minimum number of clients in order to retain accreditation.
2. People have more flexibility as to when or where to receive services, and might not refer to the closest DPC; therefore, participation in detection and prevention programs depends on the accessibly as well as quality of services provided by DPCs.

As a result, DPCs require a different location decision approach to incorporate these characteristics. The first characteristic can be satisfied by adding constraints in which each center has at least a minimum number of clients. The second can be managed by considering distance or waiting-time elasticity of demands. In this regard, by using the model proposed in [102], a DPC location problem can be formulated as follows:

Sets:

I	The set of client points.
J	The set of candidate DPC locations.

Input parameters:

d_{ij}	The travel distance (or time) from client point $i\in I$ to candidate DPC location $j\in J$.
w_i	The population size at client point i.
σ_{ij}	The expected number of clients at client point $i\in I$ who take services from a DPC at candidate location $j\in J$, which is a function of w_i and d_{ij}, e.g., $\sigma_{ij}=w_i f(\min\{d_{ij}, D_i\}/D_i)$ with f a decreasing function.
D_i	The maximum acceptable travel distance or time (the cover distance or time) from client point $i\in I$.
p	The number of DPCs to be established.
W_{min}	The minimum required clients at an open DPC.

Decision variables:

x_j	1, if a DPC is established at candidate location $j\in J$; 0 otherwise.
y_{ij}	1, if client point $i\in I$ is assigned to an open DPC at candidate location $j\in J$; 0 otherwise.

Formulation:

$$\max \sum_{j\in J}\sum_{i\in I}\sigma_{ij}y_{ij} \tag{50}$$

subject to

$$\sum_{j\in J} x_j=p \tag{51}$$

$$\sum_{j\in J} y_{ij}\le 1,\ i\in I \tag{52}$$

$$\sum_{i\in I}\sigma_{ij}y_{ij}\ge W_{min}x_j,\ \ j\in J \tag{53}$$

$$y_{ij}\le x_j,\ i\in I,\ j\in J \tag{54}$$

$$y_{ij}\in\{0,1\},\ i\in I,\ j\in J \tag{55}$$

$$x_j\in\{0,1\},\ j\in J. \tag{56}$$

The objective (50) maximizes the total expected number of clients who take services from open DPCs. This is a relevant measure for participation in detection and prevention programs operated by open DPCs. Constraint (51) states that p DPCs are to be established. Constraints (52) specify that each client point is served by at most one open DPC. Constraints (53) ensure that each open DPC has the minimum number of clients. Constraints (54) show that demand points are only covered by open DPCs. Constraints (55) and (56) are integrality constraints.

Table 8 represents the papers dealing with DPC location problems. Because one of the purposes of detection and prevention programs is to maximize participation, the majority of the papers in this category considered participation maximization objectives (see [102–105,107,108,110]). Moreover, some papers (see [106,109]) used travel distance (or time) minimization objectives, which implicitly results in higher accessibility, and thus, in increased participation.

Almost all of the papers in this section considered uncertainty in the problem (see, [103,104,106–110]). In contrast, dynamic conditions have not received attention from researchers. Another conclusion from Table 8 is that the basic location problem for approximately all of the papers, excepting [106,109], is the MCLP. From the O(QT)s in the "Modeling approach" column, it is also seen that papers [103,104,106,108–110] used queuing theory to consider service quality, which depends on the expected total time in the system, to increase participation in detection and prevention programs. Moreover, all of the papers presented case studies demonstrating the importance of this approach in the real-world.

Breaking down the literature into the smaller parts identified in Table 8 leads us to propose specific future research suggestions. These include the following:

- Developing dynamic DPC location models.
- Applying other unconsidered settings such as multiple services.
- Considering various types of costs related to the health system and clients, and budget constraints.
- Incorporating non-spatial factors, such as demographic and socioeconomic variables into the existing models to increase participation in detection and participation programs.

4.3.3. Other specialized services facilities

Other specialized services facilities, which are discussed in this

Table 8
Non-emergency healthcare facilities: detection and prevention centers.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[102] (2002)	N	S	P1, P3, P4, P9	O6	D1, D4	C5, C9-2	MCL	ILP	O, BB	Y
[103] (2009)	Y	S	P1, P2, P4, P6, P9	O6	D1, D4	C1, C5, C9-2, C11	MCL	INLP, O(QT)	H, MH-O	Y
[104] (2010)	Y	S	P1, P2, P4, P6, P9	O6	D1, D4, D7	C5, C8, C9-2, C11	MCL	MINLP, O(QT)	MH-TS, H	Y
[105] (2010)	N	S	P1, P3, P4, P9	O6, O10	D1	C4, C5, C9-2	MCL	ILP, MCDM	H	Y
[110] (2012)	Y	S	P1, P2, P6, P7, P9, P12	O6	D1, D4, D8	C8, C9-1, C9-2, C11	MCL	MILP, PSP, O(QT)	SC, H, MH-GA	Y
[109] (2012)	Y	S	P1, P3, P5-1, P5-2, P6, P7, P9, P12	O4	D1, D4, D8	C9-1, C9-2, C11	FCL	MINLP, O(QT)	O, H	Y
[106] (2014)	Y	S	P1, P2, P5-1, P6	O3, O10	D2, D4	C1, C9-2, C10, C11	PML	MINLP, O(QT)	CP	Y
[107] (2014)	Y	S	P1, P3, P5-1, P5-2, P9	O6, O10	D4, D7	C1, C10, C11	MCL	INLP, GP, PSP, FP, MCDM	S-SBO	Y
[108] (2015)	Y	S	P1, P2, P4, P6, P9	O6	D1, D4, D7	C9-1, C9-2, C11	MCL	MINLP, O(QT)	O, SC	Y

section, were not included in the above two sections. These provide services, such as exercise stress test, radiation therapy, EEG, ECG, etc., which are not related to detection and prevention programs or organ transplants. These are typically units with two characteristics:

1. They can be located either as independent units, or embedded in hospitals and other healthcare centers.
2. If they are embedded, they should support their host facilities while also providing service to their own clients. In this case, two types of demand are considered: flexible demand (coming from their own clients) and non-flexible demand (coming from the hosting facility).

As it can be seen from Table 9, the location of these units has received considerable attention from OR/MS researchers in recent years, after 2011 (see [111–114]). The two types of demand were addressed by [111,114]. Moreover, Syam and Côté [113] defined several acuity levels for patients. In addition, the majority of papers located specialized services facilities within hospital networks as dependent units (see [111–113]).

Although establishment of these facilities enhance the quality of healthcare, satisfaction of demand, and social welfare; they are generally very expensive. Hence, the main objective sought in the literature is related to minimization of the various costs involved as evident in Table 9 (see [111–114]). For instance, Guo et al. [114] embraced a multi-objective approach by considering optimizing both cost and efficiency. They extended the basic FCLP and used the non-inferior set estimation method (see [194]) to evaluate the tradeoffs between cost and service. Furthermore, all papers in this section have capacity constraints in their models. In contrast, none of them takes budget constraints, multiple servers, or multiple services into account. Moreover, only one paper considered uncertainty or dynamic setting. All studies used the MCDM modeling approach and applied software packages to solve the models.

Future studies on locating other specialized services facilities can be conducted to cover the following gaps:

- Extending the existing location models for other specialized services facilities to handle uncertainties.
- Studying the location of other specialized services facilities with multiple servers, budget constraints, or multiple services.
- Developing dynamic location models for other specialized services facilities.
- Using accurate methods to solve large-sized instances of the resulting location models for other specialized services facilities.
- Integrating location of other specialized services facilities with other related HCFs with both flexible demand and non-flexible demand.

4.4. Medical laboratories

Medical laboratories provide services in testing and diagnosing diseases (especially infection and contagious diseases). Though the location of medical laboratories is critical for disease management, infection control, and public health; research on location of these HCFs is lacking. Considering various types of laboratories (see Appendix A), a different location decision approach seems to be needed. In this regard, only Shemshaki et al. [115] presented a PMLP-based model to design a network of tuberculosis (TB) testing laboratories where there are two possibilities: opening new laboratories or equipping existing ones. Their model minimizes the total time required for transportation of samples that are collected daily in new or existing laboratories by considering laboratory capacities, budgets, and maximum transportation times (between origins and laboratories) as constraints. They applied their model to the TB reference laboratory in the Canadian province of British Columbia.

4.5. Mobile healthcare units

Mobile healthcare units often provide primary care services in areas where there is no fixed primary HCF (i.e., hospital or clinic). While this situation tends to be relatively rare in developed countries, it can still be found in some developing countries. The main task of the mobile healthcare units is to enable governments to provide essential public health programs. This includes preventing the spread of dangerous diseases (e.g., polio, diphtheria, tetanus, and hepatitis) often through specific vaccination program for children and adults. The dynamic nature of location/relocation decisions is an essential aspect of location modeling of mobile healthcare units.

Doerner et al. [116] proposed a model for locating mobile HCFs. They considered a closed tour with selected stops and formulated a multi-objective location-routing model to determine the optimal number and location of these stops. As a result, they evaluated tours according to three criteria, namely efficiency, average distances, and coverage.

4.6. Home healthcare centers

Home healthcare (HHC) services emerged around 1950 as a way to reduce costs of health systems and improve patients' quality of life [9]. In recent years, the number of HHC service providers and demand for these services have grown rapidly. For instance, the number of HHC companies in France increased 137% from 2005 to 2010 (in just five years). Hence, the OR/MS literature investigated different challenges of the HHC services, such as routing, scheduling nurses and patients, and various resource allocation issues. However, our literature review reveals that no paper studies the location of HHC centers. This shows that more emphasis is required on location management and the strategic planning level of these HCFs (see [9]).

4.7. Rehabilitation centers, doctors' offices, and drugstores

Rehabilitation centers, doctors' offices, and drugstores are identified in Appendix A as constituting crucial components of health systems. Nevertheless, research on location management of these HCFs is lacking in the literature. It should be noted that most HCFs which are discussed in this section are private and easy to construct. Since they also make up the conduit for widely used services to reach patients, determination of the optimal number and proper location of them is very effective in increasing system profitability (by cost reduction and revenue increase). Thus, given that this shortage is identified, we hope that research on the location of these HCFs will be included in the OR/MS research literature in the future.

4.8. Long-term nursing care centers

Due to decrease in both birth rates and mortality rates, many developed and developing countries are experiencing significant aging of the population. Aging societies require specific social and medical services that have to be provided in healthcare centers, such as long-term nursing care centers. Undoubtedly, governments (and private providers) need to plan for the ideal location of these centers in order to provide the best possible services to aged people. According to Appendix A, long-term nursing centers have some features that should be considered in terms of location modeling:

Table 9
Non-emergency healthcare facilities: other specialized services facilities.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[111] (2011)	Y	S	P1, P3, P4, P5-1, P5-2, P5-3	O4,O9	D1, D2 D4	C1, C6, C9-1, C9-2	FCL, MCL	MINLP, PSP, MCDM	SL, SO, SG	N
[112] (2012)	N	S/D-1	P1, P3, P4, P5-1, P5-2, P5-3, P12	O4, O7, O10	D1, D4, D7	C4, C5, C9-1, C11	FCL, MCL	ILP, MCDM	SL	Y
[113] (2012)	N	S	P1, P3, P4, P5-1, P5-2, P5-3, P7, P8, P9	O4, O7	D1, D2, D4	C1, C4, C5, C6, C8, C9-1, C9-2, C11	FCL, MCL	INLP, MCDM	SC	N
[114] (2013)	N	S	P1, P3, P5-1, P5-2	O4, O7	D1, D2, D4	C5, C8, C9-1, C9-2	FCL, MCL	MILP, MCDM	SC	Y

Table 10
Non-emergency healthcare facilities: long-term nursing care centers.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[117](2010)	N	S	P1, P3, P4	O10	D1, D4	C1, C4, C5	PCL	MILP	SC, BB	N
[118](2015)	Y	D-2	P1, P2, P4, P5-1, P5-2, P7, P8, P12	O4	D1, D2, D4, D7, D8	C4, C5, C6, C9-1, C9-2, C11	FCL	MILP, 2-SSP	SG	Y

1. Long-term nursing centers provide medical (including nursing care) and social services to inpatients, and therefore the concurrent determination of optimal capacity levels (in terms of the number of beds), inventory levels, and locations is essential.
2. The clients of long-term care often do not require emergency services and can wait until beds become available.

The location of this category of HCFs was studied by Kim and Kim [117] and Cardoso et al. [118]. Kim and Kim [117] formulated this problem as a p-center location model to minimize the maximum load of open facilities for load balancing. Moreover, they suggested a branch and bound algorithm for the location problem as well as a heuristic method to find an initial feasible solution. Cardoso et al. [118] developed an FCLP-based model by taking into consideration demand uncertainty, multiple services, and various forms of equity (access, utilization, socioeconomic, and geographical equities). Table 10 describes these papers in detail.

According to what was mentioned above, we believe that the long-term nursing centers will receive considerable attention from government and society in the future. There is a great need to address the proper location of these centers, and the OR community could greatly contribute to this area; and thereby improve the quality of healthcare and social welfare in general, and the quality of life of the elderly in particular. In this regard, future research could be directed towards:

- Improving the current models by taking other related HCFs into account.
- Extending the models by considering multiple services and service quality.
- Clustering demand points based on non-spatial factors, such as various emergency categories, social classes, age, race, etc.
- Developing competitive location models to represent situations where private long-term nursing care centers compete for clients.
- Incorporating logistics considerations into locating long-term nursing care centers.

4.9. Combinations of several types of HCFs

In this section, the papers that considered the combination of several types of HCFs are reviewed. These papers are listed in Table 11. In the literature, Galvao et al. [176], as well as Baray and Cliquet [175], studied the combination of primary care facilities (hospitals, clinics, off-site public access devices, etc.) and other specialized services facilities. Since the paper by Baray and Cliquet [175] used the models of the basic MCLP and PMLP without any extension to locate maternity hospitals, it is not included in Table 11. Galvao et al. [176] presented a p-median capacitated three-level hierarchical model to assign the prenatal HCFs to three levels in a hierarchy and developed a Lagrangian heuristic to solve it. Kim et al. [177] studied the problem of determining locations of public HCFs which provide both hospital services and homecare services. Though there are many interrelations among different types of non-emergency or emergency HCFs, the above review shows that a few studies have addressed the combination of multiple HCF types. This represents a promising future research opportunity area.

5. Emergency HCF location

We classify the emergency HCFs according to whether HCFs perform under permanent or temporary emergency situations. Permanent emergency HCFs include emergency centers, emergency off-site public access devices, trauma centers, and ambulance stations which provide emergency services all the time. On the other hand, temporary emergency HCFs include temporary medical centers and points of dispensing, which deal with healthcare services in disaster situations.

It should be recalled that emergency HCFs, especially temporary emergency HCFs, are considered by many different fields, for example: disaster operations management, emergency logistics, relief distribution, humanitarian logistics, homeland security, emergency response, emergency departments, and emergency service stations and vehicles. In the introduction, we have provided appropriate survey papers on each topic for those readers who are interested in more exploration.

5.1. Permanent emergency HCFs

Permanent emergency facilities provide wide range of emergency healthcare services. According to Fig. 3, these facilities can be classified into four main categories in order to identify research gaps. These categories are studied in the sequel. Since the nature of emergency and non-emergency HCFs are very different, descriptive fields, such as particular input/setting, objective function, decision variable, and constraint are examined from a somewhat different perspective than those considered in Section 4 (see Table 3).

5.1.1. Emergency off-site public access devices

Off-site public access devices (OPADs) are non-interactive and interactive facilities for providing a variety of healthcare services in out-of-HCF environments (see Appendix A). OPADs have some features that should be considered in terms of location modeling:

1. OPADs are public access devices, which mean that they empower individuals or bystanders to receive healthcare services without the presence of any trained medical personnel.
2. Priority locations for OPADs placement are typically public and non-residential buildings (e.g., schools, transportation buildings, commercial, civic and industrial sites, and recreational areas), and spaces containing high foot-traffic.

Hence, the strategic planning of OPAD placement programs requires a location decision approach with regard to maximizing coverage and ensuring timely access for the public. For this purpose, extensions of covering-based problems seem appropriate. In addition, applying the MCDM modeling approach is also suggested in order to improve the quality of service, reduce response time, and consider both emergency and non-emergency situations.

Recently, the investigation into locating automated external defibrillators (AEDs) as non-interactive emergency OPADs has been widely considered in the literature with different approaches (see, e.g., [195–201]). For instance, Folke et al. [198] used simple geospatial techniques to evaluate and compare the effectiveness of alternative AED placement strategies. Lerner et al. [199] and Warden et al. [200] used GIS to locate AEDs. Dao et al. [196] developed stochastic multi-time window MCLP and PMLP, and also presented visualization techniques for 3D AEDs layout in a multi-story academic building. Brooks et al. [201] presented a way to quantify the demand in AED location models which may be important when a funding agency evaluates the deployment of AEDs in practice. For this purpose, they sought to identify types of locations (e.g., race track/casino, jail, hotel/motel, hostel/shelter, and rail station) with higher per-site risk for cardiac arrest.

Since 2009, several papers have studied the emerging problem of locating AEDs in different environments (schools, university, urban, etc.) with regard to the mentioned features [119–124]. Myers and Mohite [122] and Chan et al. [121] located AEDs optimally based on the criterion that a person should be covered by an AED which is located no further than a particular travel time threshold to ensure effective service delivery. Siddiq et al. [123] developed this problem further by considering an effective range for each AED, which is affected by storage in a low-visibility and limited-access location, and lack of registration with local EMS authorities as potential barriers to AED usage. Multi-responder and gradual coverage by a probabilistic extension of the basic MCLP were studied by Chan et al. [120]. Bonnet et al. [119] also presented a multi-objective optimization along with simulation to test the optimization output for the AEDs performance in terms of time-to-retrieve. Furthermore, they displayed the results in an interactive decision-making web-based user interface to visualize potential deployment configurations. These papers are listed in Table 12. Since papers [121–124] used the basic MCLP without any extension to locate AEDs, they are not included in Table 12.

Based on the discussion above, we believe that OPADs, particularly interactive and web-based devices, will receive considerable attention by governments, private sectors, and societies in the future due to their countless benefits in ways similar to what happened with automated teller machine (ATMs) in financial systems. There is a great need to address the appropriate OPAD placement locations. In this regard, future research could be directed towards:

- Extending models to determine locations for placing OPADs by considering more realistic factors, such as uncertainty in demands; the weight of each building (e.g., based on its population); traffic patterns; and building accessibility influenced by locked doors, multiple floors, hours of operation, etc.
- Developing location models for OPADs, especially for interactive and web-based ones, which can be covered by other related HCFs, such as emergency centers and trauma centers if required.
- Proposing integrated models for locating/relocating OPADs and other related HCFs.

5.1.2. Emergency centers

Emergency centers (or emergency departments) are permanent emergency facilities which provide medical care to both walk-ins (unscheduled patients) and emergency patients transported by an ambulance, who require immediate and urgent medical treatment. In the OR literature, locating these facilities has not received much attention, despite the fact that many papers studied location problems on other related emergency facilities, such as ambulance stations (see Section 5.1.4). In this regard, only Silva and Serra [125] studied the location of emergency centers. They presented a priority queuing-based covering location problem to consider different service priority levels and applied a greedy randomized adaptive search procedure to solve randomly-generated problem instances. Thus, location of emergency centers, particularly those associated with hospitals and clinics or ambulance stations is a gap in the literature and needs to receive attention.

5.1.3. Trauma centers

Trauma centers are hospitals that provide specialized medical and nursing care to patients with traumatic injuries, and typically have helicopter platforms to transfer patients. Although trauma patients require immediate transfer to trauma centers, the establishment of helicopter platforms and using air transport are expensive.

Extensions of the maximal backup coverage problem (BACOP) can be deployed to address the modeling of location problems for trauma centers. The BACOP, which was introduced by Hogan and Revelle [202], is based on an MCLP. In this regard, an extension of the BACOP is presented to model a joint location problem of trauma centers and helicopters with a budget constraint. In this problem, we assume that the helicopters are not initially sent to any demand point, and that they only provide backup coverage for

Table 11
Combinations of several types of HCFs.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[176] (2006)	N	S	P1, P3, P4, P8, P11, P12	O3	D1, D4	C1, C4, C9-1	PML	MILP, MCDM	SC, LR	Y
[177] (2012)	N	S	P1, P3, P4, P5-1, P9, P12	O1	D1, D4	C1, C5, C9-1, C9-2	SCL	ILP	SC, H	N

Table 12
Emergency healthcare facilities: emergency off-site public access devices.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[120] (2015)	Y	S	P1, P3, P7, P9	O7	D1, D5-1	C2, C4, C11	MCL	MILP, MINLP, PSP	O, SO	Y
[119] (2015)	N	S	P1, P3, P5-1	O1, O7, O10	D1, D5-1	C11	MCL, SCL	ILP, MCDM	MH-GA, SO	Y

Table 13
Emergency healthcare facilities: trauma centers.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[126] (2000)	N	S	P1, P2, P12	O7	D1, D5-1	C4, C5	MCL	MILP	SC	Y
[127] (2001)	N	S	P1, P2, P12	O7	D1, D5-1	C4, C5	MCL	MILP	SC, H	Y
[128] (2007)	N	S	P1, P3, P4, P5-2, P5-3, P8, P9	O4, O9	D1, D4, D8	C1, C5, C6, C9-1, C11	FCL, MCL	MILP, MCDM	SL	Y
[129] (2010)	N	S	P1, P3, P4, P5-1, P5-2, P5-3, P9, P12	O4, O9	D1, D4	C1, C5, C9-1, C9-2, C11	FCL, MCL	ILP, MCDM	SL, MH-SA	N
[130] (2010)	N	S	P1, P2, P5-1, P7, P12	O1, O2, O7	D1, D3, D5-1, D8	C1, C3, C5, C11	SCL	ILP	SC, H	Y
	N	S	P1, P2, P5-1, P7, P12	O7, O8	D1, D3, D5-1, D5-2, D8	C3, C5, C10, C11	MCL	ILP	SC, H	Y
[131] (2013)	N	S	P1, P3, P4, P7, P10	O7	D1, D3, D4	C4, C5, C7, C9-1, C11	MCL	MINLP	SC, BD, H	Y

ambulances that are dispatched to crash locations. To formulate this problem, the following notation is used:

Sets:

I	The set of demand points (trauma patients' locations).
J	The set of candidate locations for trauma centers.
K	The set of candidate locations for helicopter platforms.
N_i	The set of all candidate locations which can cover demand point i by ambulances, $N_i=\left\{j: t_{ij}^A\le T_i\right\}$.
S_i	The set of all pairs of candidate locations of trauma centers and helicopter platforms, which can provide backup coverage for demand point i by helicopters, $S_i=\left\{(j,k): (t_{ij}^H+t_{ki}^H)\le T_i\right\}$.

Input parameters:

w_i	The population size at demand point $i\in I$.
t_{ij}^A	The driving time from demand point $i\in I$ to a trauma center at candidate location $j\in J$.
t_{ij}^H	The flying time from demand point $i\in I$ to a trauma center at candidate location $j\in J$.
t_{ki}^H	The flying time from a helicopter platform at candidate location $k\in K$ to demand point $i\in I$.
p^{TC}	The number of trauma centers to be established.
p^{HP}	The number of helicopter platforms to be established.
c_j^{TC}	The fixed cost to establish a trauma center at candidate location $j\in J$.
c_k^{HP}	The fixed cost to establish a helicopter platform at candidate location $k\in K$.
α_1	The weight parameter, between 0 and 1, representing the importance of the total population with primary coverage.
α_2	The weight parameter, between 0 and 1, representing the importance of the total population with backup coverage ($\alpha_2=1-\alpha_1$).
T_i	The maximum acceptable travel time (the cover time) from demand point $i\in I$.
B	The maximum budget that can be allocated for establishing trauma centers and helicopter platforms.

Decision variables:

x_j^{TC}	1, if a trauma center is established at candidate location $j\in J$; 0 otherwise.
x_k^{HP}	1, if a helicopter platform is established at candidate location $k\in K$; 0 otherwise.
y_{kj}	1, if a helicopter platform is established at candidate location $k\in K$ and a trauma center is established at candidate location $j\in J$; 0 otherwise.
z_i^A	1, if demand point $i\in I$ is covered by ambulance; 0 otherwise.
z_i^H	1, if demand point $i\in I$ is covered by helicopter; 0 otherwise.

Formulation:

$$\max\ \alpha_1\sum_{i\in I} w_i z_i^A+\alpha_2\sum_{i\in I} w_i z_i^H \tag{57}$$

subject to

$$\sum_{j\in J} c_j^{TC} x_j^{TC} + \sum_{k\in K} c_k^{HP} x_k^{HP} \le B \tag{58}$$

$$\sum_{j\in J} x_j^{TC} = p^{TC} \tag{59}$$

$$\sum_{k\in K} x_k^{HP} = p^{HP} \tag{60}$$

$$z_i^A - z_i^H \ge 0,\ i\in I \tag{61}$$

$$\sum_{j\in N_i} x_j^{TC} - z_i^A \ge 0,\ i\in I \tag{62}$$

$$\sum_{(j,k)\in S_i} y_{kj} - z_i^H \ge 0,\ i\in I \tag{63}$$

$$y_{kj} \le 0.\ 5(x_j^{TC} + x_k^{HP}),\ j\in J,\ k\in K \tag{64}$$

$$x_j^{TC} + x_k^{HP} - 1 \le y_{kj},\ j\in J,\ k\in K \tag{65}$$

$$y_{kj} \in \{0,\ 1\},\ k\in K,\ j\in J \tag{66}$$

$$x_j^{TC} \in \{0,\ 1\},\ j\in J \tag{67}$$

$$x_k^{HP} \in \{0,\ 1\},\ k\in K \tag{68}$$

$$z_i^A,\ z_i^H \in \{0,\ 1\},\ i\in I. \tag{69}$$

The objective function (57) maximizes the weighted combination of primary and backup coverage given to demand points. Constraint (58) is the budget constraint to establish and equip the selected trauma centers and helicopter platforms. Constraints (59) and (60) specify the total number of facilities to be established. Constraints (61) ensure that backup coverage is credited in the proper order. Constraints (62) assure that demand points are only covered by open trauma centers, and Constraints (63) show that demand point i is covered by helicopters when at least one pair of trauma center and helicopter platform within the set S_i services it. Constraints (64) and (65) provide the logical links between the binary variables. Finally, Constraints (66)-(69) are integrality constraints.

Papers that studied the location of trauma centers have been listed in Table 13. Examination of this table allows us to draw some conclusions. Despite random variation (especially in demand) being the main characteristic of these centers, none of the papers has incorporated uncertainty. In addition, dynamic models (either long-term or short-term) have not been applied to problems of trauma center location.

Another deficiency observed from Table 13 is the lack of hierarchical facility location models when injuries can be classified at different therapeutic levels depending on predetermined factors (e.g., the intensity and time of the event, resource availability at each level of hierarchy, and the type of injury). These different therapeutic classes could subsequently be treated at different levels of a facility hierarchy. Moreover, the inclusion of multiple servers and/or busy fractions of ambulances can assist in the proper handling of traumatic events, but this is not seen in the literature.

Furthermore, since equipping these centers is expensive, the inclusion of cost factors in objective functions and/or constraints is needed. In general, the objective is either cost minimization (see [128,129]) or demand coverage maximization (see [126,127,130,131]) in almost all the papers cited in Table 13, and other objectives have not received attention.

Branas et al. [126] and Cho et al. [131] studied integrated location of trauma centers, and associated helicopter platforms and helicopter depots. Erdemir et al. [130] considered the possibility of using hybrid transportation modes in which both ambulances and helicopters (i.e. air ambulances) are used to transfer trauma patients to trauma centers when the scene of an incident does not have a suitable nearby area where a helicopter can safely land. Future studies can address combinations of ambulance stations and trauma centers with hybrid transportation modes.

Concluding the above discussion, suggestions for future research directions are as follows:

- Extending the existing models to capture more realistic assumptions, such as uncertainty of demand, multi-type demand, and multiple server settings.
- Developing location models for trauma centers in multi-period settings.
- Presenting hierarchical facility location models for trauma centers.
- Combining ambulance stations, helicopter depots, and trauma centers with hybrid transportation modes.
- Developing integrated models for simultaneously locating/relocating trauma centers, and other related permanent and temporary emergency HCFs, such as emergency departments, OPADs, temporary medical centers, etc.
- Incorporating scenarios that may occur in disasters into the location of trauma centers.

5.1.4. Ambulance stations

EMSs (emergency medical services) play a pivotal role in health systems, which are generally concerned with providing out-of-hospital acute medical care and transferring patients to emergence centers, emergency departments within hospitals, or trauma centers for definitive care [10]. Each EMS is typically a service process including the following four main steps: (i) receiving an emergency call and evaluating the situation, (ii) dispatching an ambulance(s) to the scene, if required, (iii) serving on-scene emergency services, and (iv) transferring a patient(s) to a related HCF, if required, and coming back to a station or other emergency sites.

Ingolfsson [10] surveyed EMS planning and management from four perspectives: forecasting of demand, response times, and workload; performance measurement; choosing station locations; and allocation of ambulances to stations. Moreover, Chaiken [203] provided key lessons for implementing OR studies in EMS cases. Li et al. [6] reviewed the covering models and optimization methods for emergency response facility location and planning. In this paper, several effective research directions are presented at the conclusion. Other related review papers on emergency response are [33,204,205].

Ambulances are a major resource for EMSs. Ambulances must be located at appropriate points in order to provide adequate coverage and minimize the response time. Hence, a great deal of attention has been paid to the location of ambulance stations, the deployment (location or relocation) of ambulances in the stations, and the dispatch (assignment) of ambulances to the demand points (emergency sites). One should also note that there are two types of location decisions related to ambulances: locating ambulance stations and locating ambulances in stations (also known as ambulance deployment or ambulance relocation). When ambulances are homogeneous, the ambulance deployment is equivalent to determine the number of ambulances at each station.

Brotcorne et al. [4] provided a detailed review of the literature with further focus on relocation and dispatching, up to 2003, and

Jeffrey and Goldberg [35] surveyed the research done on emergency vehicles, including ambulances, up to 2004. Location of emergency services stations before 2012 are reviewed in [34].

One should note that ambulance stations differ from emergency centers (or emergency departments). Emergency centers are units equipped and staffed to provide immediate and urgent medical care to unscheduled patients, who show up or are transported by an ambulance. However, ambulance stations are responsible for dispatching ambulances which provide EMSs on scene or during transport to an emergency center, an emergency department, a trauma center, etc.; and return to a predetermined station to await another call.

We assert that extensions of the basic MCLP can be useful for locating ambulance stations or deploying ambulances. An example of such extensions is the maximum expected coverage location problem (MEXCLP), developed by Daskin [206]. This formulation seeks to maximize the expected covered demand. It models each ambulance as being busy with probability p and operating independently from other ambulances. In the sequel, we formulate a multi-period version of MEXCLP in order to consider the redeployment of ambulances as well as changes in the quantity of available ambulances in the candidate stations. The dynamic MEXCLP can be formulated with the following notation:

Sets:

I	The set of demand points.
J	The set of candidate locations for ambulance stations.
K	The set of ambulances.
T	The set of time intervals.

Input parameters:

D_i	The maximum acceptable travel distance or time (the cover distance or time) from demand point $i \in I$.
$a_{ij,t}$	1, if an ambulance at candidate location $j\in J$ covers demand point $i\in I$ in cover distance D_i at time interval $t\in T$; 0 otherwise.
$w_{i,t}$	The population size at demand point $i\in I$ at time interval $t\in T$.
M_t	The maximum number of ambulances to be stationed at time interval $t\in T$.
p_t	The probability that an ambulance is not working at time interval $t\in T$.
c_t	The minimum expected coverage requirement at time interval $t\in T$.

Decision variables:

$u_{j,t}$	The number of ambulances stationed at candidate location $j\in J$ at time interval $t\in T$.
$y_{ik,t}$	1, if demand point $i\in I$ is covered by at least $k\in K$ ambulances at time interval $t\in T$; 0 otherwise.

Formulation:

$$\max \sum_{t\in T}\sum_{i\in I} w_{i,t}\left(\sum_{k\in K}(1-p_t)p_t^{k-1}y_{ik,t}\right) \tag{70}$$

subject to

$$\sum_{j\in J} u_{j,t}\le M_t,\ t\in T \tag{71}$$

$$\sum_{k\in K} y_{ik,t}\le \sum_{j\in J} a_{ij,t}u_{j,t},\ i\in I,\ t\in T \tag{72}$$

$$y_{ik,t}\in\{0,1\},\ i\in I,\ k\in K,\ t\in T \tag{73}$$

$$u_{j,t}\ge 0\ \&\ integer,\ j\in J,\ t\in T. \tag{74}$$

The objective function (70) maximizes the expected coverage of total demand by the ambulances over multiple periods. Constraints (71) state that in each time interval up to M_t ambulances can be deployed. Constraints (72) show that demand points in each time interval are only covered by the stationed ambulances. Constraints (73) and (74) are integrality constraints.

One can alternatively minimize the number of stationed ambulances:

$$\min \sum_{t\in T}\sum_{j\in J} u_{j,t}$$

by assuring that the expected coverage of total demand is larger than a predetermined constant c_t in each time period,

$$\sum_{i\in I} w_{i,t}\left(\sum_{k\in K}(1-p_t)p_t^{k-1}y_{ik,t}\right)\ge c_t,\ t\in T.$$

Batta et al. [207] introduced the adjusted MEXCLP (AMEXCLP) in order to relax the assumption that ambulances are independent by using the hypercube queuing model, which is a spatial queuing-theoretic model that tracks the status of mobile servers in order to compute performance measures, such as the mean user response times, fraction of time that the system is in each state, fraction of dispatches of each server to each region, server workloads, etc. [204,208–210].

This section covers location models that addressed ambulance stations and deployment from the past decade and breaks them down into categories. Results are given in Table 14. In fact, around 31% of the total number of papers which are reviewed in this paper and also approximately 61% of the papers that discussed emergency HCF location are included in Table 14, highlighting the importance of these location models.

It can be seen from Table 14 that about 75% of the surveyed papers deal with stochastic problems. This is because location management of ambulance stations involves the inherent uncertainty of EMS systems. The busy fraction of ambulances and uncertainty in service requests (i.e., the number of emergency calls) are considered in [134,141,147,154], which can be managed in different ways including queuing theory, chance constraints ([134,147]), two-stage stochastic programming ([141]), and robust optimization ([154]). C6s in the “Constraint” column represent that ambulance reliability (also known as service level) are frequently considered by many papers using chance constraints or queuing theory ([133, 134, 136–141, 143, 145, 147, 151, 152, 159, 164, 165]). An EMS system is called reliable if there is at least one ambulance available to provide service whenever a service demand arises. Unfortunately, based on the “Solution method” column in Table 14, it can be seen that there are a few papers that developed exact or bounded-error algorithms.

Another important conclusion that can be drawn from Table 14 refers to dynamic (i.e., multi-period) models which have emerged in the literature as a significant development. Several papers considered short-term dynamic settings (see [132,138,140,144, 146,150,152,158,159]). This is sometimes motivated by the

Table 14
Emergency healthcare facilities: ambulance stations.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/ setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[132] (2001)	N	D-1	P1, P2, P4, P5-2, P7, P12	O8, O10	D3, D5-2, D6	C1, C3, C7, C11	MCL	ILP	SC, MH-TS	Y
[133] (2002)	Y	S	P1, P2, P5-2, P10	O4, O8	D1, D5-2, D6	C4, C6	MCL	MILP, MCDM, O (QT)	SL, SBO	Y
[134] (2004)	Y	S	P1, P3, P4, P5-1, P5-2, P7	O4	D1, D3	C1, C5, C6, C7	FCL	ILP, PSP	SC	N
[135] (2004)	Y	S	P1, P3, P4, P7, P10	O9	D1, D3, D5-2	C2, C4, C7	MCL	ILP	–	Y
[136] (2005)	N	S	P1, P2, P4, P7, P12	O8, O9, O10	D3, D5-2, D6	C3, C5, C6, C7	MCL	ILP	MH-TS, MH-AC	Y
[137] (2006)	Y	S	P1, P2, P4, P7, P10	O2, O7	D1, D6	C2, C5, C6, C7	MCL	ILP, GP, MCDM, O (QT)	O	Y
[162] (2006)	Y	S	P1, P2, P10, P12	O7	D3, D6, D8	C11	MCL	ILP	SC	Y
[138] (2007)	N	D-1	P1, P2, P7, P8	O5	D3, D6	C5, C6, C11	PCL	MILP	H	N
[139] (2008)	Y	S	P1, P2, P7, P8, P10, P12	O7	D3, D8	C5, C6	MCL	INLP, PSP, O(QT)	SO, H	Y
[140] (2008)	Y	D-1	P1, P3, P7, P10	O2	D3, D5-2	C2, C5, C6, C11	SCL	INLP, PSP, O(QT)	MH-TS	N
[141] (2009)	Y	S	P1, P3, P4, P5-1, P5-2, P7	O4	D1, D3, D6	C2, C5, C6, C7, C11	FCL	ILP, PSP, 2-SSP	SC, BB, H	N
[142] (2009)	Y	S	P1, P2, P4, P7, P8, P10	O8	D3, D5-2	C5, C7	MCL	ILP, O(QT)	SC	Y
[143] (2009)	Y	S	P1, P2, P10	O3	D3, D6	C1, C2, C5, C6	PML	INLP, PSP, O(QT)	MH-TS	Y
[144] (2010)	N	D-2	P1, P2, P5-1, P5-2, P7, P8, P12	O4	D1, D3, D5-2, D6	C1, C3, C5, C9-1, C9-2, C11	FCL	ILP	SL	Y
[145] (2010)	Y	S	P1, P2, P10, P12	O8	D3, D5-2	C5, C6	MCL	ILP	SC	Y
[146] (2010)	N	D-1	P1, P2, P4, P5-2, P7, P12	O7, O8, O10	D3, D5-2	C3, C5, C7, C9-1, C11	MCL	ILP, MCDM	MH-O	Y
[147] (2010)	Y	S	P1, P3, P4, P5-1, P5-2, P7	O4	D1, D3	C5, C6, C7, C11	FCL	MILP, PSP, 2-SSP	H	N
[148] (2011)	N	S	P1, P2, P12	O7	D3, D5-2	C2, C5, C9-1	MCL	ILP	S-SBO	N
[149] (2011)	Y	S	P1, P3, P4, P7, P10, P12	O5, O7, O9	D3, D5-2	C5, C7, C11	MCL	ILP, MCDM, O(QT)	SO	Y
[159] (2011)	Y	D-1	P1, P2, P10, P12	O2	D3, D6	C6, C11	SCL	ILP/INLP, O(QT)	H, MH-TS	Y
[150] (2012)	Y	D-1	P1, P2, P7, P10, P12	O3	D3, D6	C5, C11	PML	SDP	S–O	Y
[151] (2012)	Y	S	P1, P2, P5-1, P5-2, P7, P10, P12	O1, O2/O3	D1, D3, D8, D5-2	C2, C3, C5, C6, C11	SCL	ILP	SG	Y
[152] (2013)	Y	D-1	P1, P2, P10	O2, O10	D3, D5-2	C2, C5, C6, C11	SCL	MILP, MCDM, O (QT)	MH-TS, H	Y
[153] (2013)	Y	S	P1, P2, P10, P12	O3	D3, D6	C11	PML	MINLP, O(QT)	MH-GA	Y
[163] (2013)	Y	D-1	P1, P2, P4, P5-2, P5-3, P8, P12	O9, O10	D3, D6	C2, C7, C11	MCL	ILP, 2-SSP	SC	Y
[154] (2014)	Y	S	P1, P3, P4, P5-1, P5-2, P5-3	O4	D1, D3, D6	C1, C7, C11	FCL	MILP, MCDM, RO	SC	Y
[158] (2015)	Y	D-1	P1, P2, P5-1, P10, P12	O1, O7, O10	D1, D3, D5-2	C11	MCL, SCL	MILP, MCDM	SC	Y
[165] (2015)	N	D-1	P1, P2, P4, P5-2, P5-3, P12	O4, O10	D3, D6	C6, C7, C11	PML	MILP, MCDM	SC	N
[164] (2015)	Y	S	P1, P3, P5-1, P5-2	O2, O4	D1, D3, D6	C1, C6, C9-1	FCL	MINLP, PSP	SC	Y
[160] (2016)	N	D-1	P1, P2, P4, P8	O2	D3, D6	C1, C2, C5, C9-1, C11	SCL	MILP	S-SBO	Y

application of these location models to update ambulance positions during a specific time period. Furthermore, Table 14 shows that stochastic settings are only used in half of dynamic models (see [140,150,152,158,159]). This is because combining a stochastic approach with a multi-period setting can result in very complex models that are difficult to solve. As a consequence, the papers developing stochastic multi-period models presented metaheuristic algorithms (often Tabu Search) to solve their models (see [140,159]).

From the "Objective function" column in Table 14 one can conclude that most of the papers aim for lower cost (see O4) and better responsiveness, and often deal with the tradeoff between these objectives. In the literature, better responsiveness is evaluated through the use of objectives, such as minimizing travel distance (or time) of ambulances, minimizing unmet demand, and maximizing demand coverage (single and multiple) (see O9, O7, and O8). Some objectives, such as minimizing the relocation and coverage costs (included in O10) can also implicitly reduces the response time (see, e.g., [152,158]). Furthermore, minimizing the maximum response time and the number of ambulances are rarely considered as objectives (see O2 and O10).

In addition, according to the "Modeling approach" column in Table 14, ILP and MILP are the basis of almost all the models for locating ambulances and their stations while nonlinear programming (see [153,159]), goal programming (see [137]), robust optimization (see [154]), and dynamic programming (see [150]) are rarely found in the literature. Further, fuzzy programming, hierarchical programming, and multi-stage stochastic programming have not been considered in the literature at all.

There are a few papers that could not be listed in Table 14 ([155–157, 161]). Paper [155] compared the performance of existing discrete location models for locating ambulances. The method proposed in [156] is based on embedding a hypercube model into a hybrid genetic algorithm to find the optimal location and coverage areas of ambulances in order to minimize the response time. Paper [161] presented two greedy algorithms using genetic algorithm which can be embedded with either an exact or approximate hypercube model.

Erkut et al. [157] introduced a new covering location problem for EMS stations which is called the maximal survival location problem (MSLP) where the objective is to maximize the expected number of patients who survive. For this purpose, they incorporated a decreasing function of the response time into existing covering models. Their empirical comparison of the MSLP with the corresponding MCLP and PMLP showed that the MSLP was more appropriate for the EMS location.

Bélanger et al. [211] empirically investigated the location and relocation strategies in ambulance fleet management. First, they briefly reviewed the literature, and then proposed four management strategies, ranging from simple to sophisticated strategies. Finally, they designed a simulation tool to analyze each of these strategies with extensive simulation experiments. Aringhieri et al. [160] also combined optimization and simulation for ambulance location.

It should be mentioned that there are other techniques that can be used to improve optimization modeling in the ambulance location literature. For instance, Alanis et al. [212] proposed a stochastic queuing model that could be used to evaluate the performance of a repositioning plan for ambulances. This model can, in principle, be incorporated into an optimization model for ambulance repositioning. Moreover, Budge et al. [213] provided a statistical model that can be used to estimate input parameters associated with travel times for ambulance location models.

Review of the literature indicates that many ambulance location problems have been addressed by integrated models which incorporated deployment strategies and/or dispatching decisions into ambulance station location (see, e.g., [141,154,164]). Deployment decisions, which are indispensable for fleet management, are concerned with the modification of ambulance location in particular stations and the determination of where to send ambulances when their missions are complete. Dispatching decisions focus on proper procedures for assigning ambulances to demand points which are assumed to be based on a priority list, which is a list of ambulances sorted with regard to their priority of dispatch based on call severity (see, e.g., [142]). In this section, D3, D6 and D5-2 in the "Decision variable" column represent the ambulance deployment, dispatching, and multiple coverage decisions, respectively, which can be integrated with the ambulance station location decision (D1). Note that in Table 14 there are papers which take ambulance stations as given, and subsequently optimize both deployment and dispatching decisions (see, e.g., [138,150,163,165]) or a combination of other decisions including deployment decisions (see, e.g., [132,162]).

In conclusion, based on Table 14, we can suggest some future research directions:

- Considering more realistic assumptions in locating ambulances and their stations, such as ambulance capacity, interruptions, dynamic setting, real-time setting, and general travel and service probability distributions.
- Extending the hierarchical location models for ambulance stations and other related HCFs, such as trauma centers, OPADs, emergency centers, etc.
- Integrating ambulance station and deployment decisions with other EMS strategic and tactical decisions, such as fleet size, staff number, crew planning, standby sites, etc.
- Extending location models for ambulance stations with considering their role in disasters.
- Integrating ambulance station decisions with most related operational decisions, i.e., deployment and dispatching decisions.
- Incorporating real-time (online) relocating or dispatching strategies into locating ambulance stations ([214]).
- Developing multi-stage stochastic programming to more accurately determine ambulance station locations under a set of stochastic scenarios.
- Proposing exact or bounded-error algorithms for solving existing ambulance location models.

5.2. Temporary emergency HCFs

Temporary emergency events occur suddenly and infrequently, but lead to great demand for a wide range of emergency services. As a result, a variety of medical, social, and relief services are needed. Temporary emergency HCFs are crucially important to rescue large number of people facing a catastrophic disaster or major emergency situations. The optimal location of these HCFs in pre-disaster planning leads to risk mitigation and reduction in response time.

According to Fig. 3, temporary medical centers and points of dispensing are two major types of temporary emergency HCFs, which are studied in the following subsections.

5.2.1. Temporary medical centers

Temporary medical centers (TMCs) are providers of healthcare services to people who are affected by disasters or large-scale emergencies, which may be of a catastrophic nature. This class contains field hospitals, Red Crescent and/or Red Cross tents, casualty collection points (CCPs), and any existing hospitals and clinics, that are pre-planned to play short-term roles in disasters. TMCs have some distinctive features that should be considered in terms of location modeling:

1. Pre-planned TMCs may be completely disrupted or their service capacities may be significantly reduced in disasters, and thus they cannot be operationalized in some disaster scenarios.

Table 15
Temporary emergency healthcare facilities: temporary medical centers.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/ setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[170] (2006)	N	S	P1, P3, P12	O10	D1, D4	C4, C5	O	MCDM	H, MH-TS	N
[167] (2008)	N	S	P1, P3, P4	O3	D1, D4	C1, C4, C9-1, C11	PML	MILP	SC, MH-SA	Y
	N	S	P1, P3, P4, P5	O4	D1, D4	C1, C9-1, C11	PML	MILP	SC, MH-SA	Y
[57] (2010)	N	S	P1, P3	O5	D1, D4	C1, C5, C11	PCL	ILP, DP	SC, DP, O	N
[168] (2014)	N	D-1	P1, P2, P4, P7, P8, P9, P12	O7/O3	D1, D2, D3, D4, D8	C1, C4, C8, C9-1, C9-2, C11	MCL/PML	MILP	SG	Y

Table 16
Temporary emergency healthcare facilities: points of dispensing.

Reference (year)	Consideration of uncertainty	Multi-period setting	Particular input/setting	Objective function	Decision variable	Constraint	Basic location model	Modeling approach	Solution method	Case study
[171] (2009)	N	S	P1, P3, P4	O1/O3	D1, D4	C1, C4, C5, C9-1	SCL/PML	ILP	SC, MH-GA	Y
[172] (2012)	Y	S	P1, P3, P4, P9, P12	O7	D1, D2, D7	C4, C8, C9-1	MCL	ILP, PSP	H	Y
[174] (2015)	Y	S	P1, P2, P3, P4, P6, P7, P8, P12	O3	D1, D4, D7, D8	C1, C4, C8, C11	PML	MINLP, PSP, O(QT)	MH-GA	Y

2. In disaster events, the medical services provided by operationalized TMCs may be cut off from emergency sites because of the destruction of the area's civil infrastructure (freeways, roads, communications, emergency medical services, etc.).
3. The demand for emergency cares stochastically varies under different scenarios associated with disasters.
4. It is possible to use helicopters for air transportation of medical supplies or of people in need of further care to other HCFs inside or outside the affected area.
5. Pre-planned TMCs are not required to be operational in all disaster scenarios.

CCPs are mass collection TMCs which are used for provision of first aid in some public or private facilities, such as colleges, schools, and public parks, which are large enough to accommodate a large number of people, and are relatively free from falling debris ([168–170]). CCPs are basically pre-determined units that are operationalized and staffed after a disaster occurrence by medical teams who have been preassigned. People in need of medical attention have to get to these CCPs on their own by foot or off-road vehicles, and subsequently transferred to more equipped HCFs or shelters if needed.

Below, a two-stage stochastic programming model is proposed based on an MCLP. In this model, a set of candidate TMCs is determined in the pre-disaster planning phase, considered as the first stage. All pre-planned TCMs will be established when a disaster happens. The assignment of open TMCs to demand points is decided in the post-disaster planning phase, considered as the second stage. The capacities of TCMs and the populations seeking urgent care at demand points vary with the disaster scenarios.

Sets:

I	The set of demand points.
J	The set of candidate locations.
K	The set of possible disaster (large-scale emergency) scenarios.

Input parameters:

p_k	The probability of occurring disaster scenario $k \in K$.
w_{ik}	The population at demand point $i \in I$ who need emergency care under disaster scenario $k \in K$.
c_{jk}	The service capacity of a TMC at candidate location $j \in J$ under disaster scenario $k \in K$.
p	The maximum number of candidate TMCs to be established.

Decision variables:

x_j	1, if a TMC is established at candidate location $j \in J$; 0 otherwise (first-stage decision variable).
y_{ijk}	The fraction of the demand of demand point $i \in I$ served by a TMC at candidate location $j \in J$ under disaster scenario $k \in K$; 0 otherwise (second-stage decision variable).
z_{ik}	1, if demand point $i \in I$ is covered under disaster scenario $k \in K$; 0 otherwise (second-stage decision variable).

Formulation:

$$\max \sum_{k \in K} p_k \left(\sum_{i \in I} w_{ik} z_{ik} \right) \tag{75}$$

subject to

$$\sum_{j\in J} x_j \le p \tag{76}$$

$$\sum_{j\in J} y_{ijk} = z_{ik},\ i\in I,\ k\in K \tag{77}$$

$$\sum_{i\in I} w_{ik} y_{ijk} \le c_{jk} x_j,\ j\in J,\ k\in K \tag{78}$$

$$x_j \in \{0,1\},\ j\in J \tag{79}$$

$$0 \le y_{ijk} \le 1,\ i\in I,\ j\in J,\ k\in K \tag{80}$$

$$z_{ik} \in \{0,1\},\ i\in I,\ k\in K. \tag{81}$$

The objective (75) maximizes the expected coverage by open TMCs. Constraint (76) specifies the maximum number of TMCs to be established. Constraints (77) specify which TMCs meet the demand of a covered demand point. Constraints (78) specify the maximum capacities of open TMCs. Finally, Constraints (79)–(81) are domain constraints.

Papers that studied the location of TMCs are listed in Table 15. Paper [169] on CCP location and paper [166] on location of medical services facilities for large-scale emergencies are not included in this table since they compared different existing location models.

As mentioned above, important characteristics of such situations are the possibility of facilities being destroyed, changes in the capacities of facilities, changes in the capacities of roads, and uncertainty in the size and location of demand. Nevertheless, we are surprised to see in Table 15 that all papers investigate problems under deterministic conditions.

Moreover, another main characteristic of these facilities, CCPs in particular, is the possibility of accommodating helicopter platforms for air transportation, which has not received attention in the literature. In addition, based on Table 15, we believe that more attention should be paid to hierarchical models, required resources, and multiple services in order to make the models more realistic.

As indicated by Larson [205], traditional facility location problems may be highly inappropriate in disasters or major emergencies where one must consider the destruction of facilities and infrastructure. In such cases, to increase the probability of survivability of the drug and supplies distribution system, one may want to position more than the usual number of facilities, each containing fewer medications and supplies than usual, resulting in a problem that has some similarity to the *p*-dispersion location problem (see Section 2.3). One may use the location models with disruptions, which have been extensively studied over the last decade by several authors (see the survey paper by Synder et al. [36]). Moreover, incorporating priorities can be another feature of such models. For example, Oran et al. [215] developed a location-routing problem where demand points have different priorities in getting service in emergency response planning.

The above observations can be used to suggest studies to cover the following research gaps:

- Incorporating uncertainty of demand and service capacities into existing TMC location models.
- Developing multi-stage stochastic programming models to adequately model disaster operations management under different scenarios.
- Presenting models for simultaneously locating different types of TMCs, such as field hospitals and CCPs simultaneously.
- Integrating the location of helipads with TMCs.
- Adapting existing location models with disruptions to locate TMCs, whose service capacities fluctuate in disasters.
- Considering concerns of disaster management and humanitarian logistics in the location of non-emergency HCFs which can play a temporary role in large-scale emergencies.
- Developing location models for TMCs with disruptions impacting both TMCs and links, under different disaster scenarios (see e.g., [88,167]).

5.2.2. *Points of dispensing*

A point of dispensing (POD) is a mass medication dispensing site that is capable of providing medicine and medical supplies (e.g., vaccines, drugs, and therapeutics) to protect the general population in infectious disease disasters (e.g., epidemics, pandemics, or an outbreak of an emerging infectious disease). PODs are one type of the temporary emergency HCFs used in disaster situations, but differ from HCFs given in the previous subsection. They are more similar to typical public service facilities where reduction of congestion costs is critical and where all people should be able to access them with no trouble.

In this regard, the OR community has concentrated on bioterrorist attacks as a kind of infectious disease disaster (see [216]) with reference to this HCF type ([171–174,217–219]) and has addressed the various challenges in mass dispensing: medical supply distribution, locations of dispensing facilities, optimal facility staffing and resource allocation, routing of the population, and dispensing methods. For this purpose, interactive tools have recently received attention to help decision makers in mapping out real-time dynamic optimization, and analyzing the economic and potential benefits. Moreover, the integration of simulation tools is growing, since simulation is typically a much more realistic evaluator of system performance and is useful for validating the results returned from optimization models. For instance, Lee et al. [171] focused on the problem of selecting an adequate number of

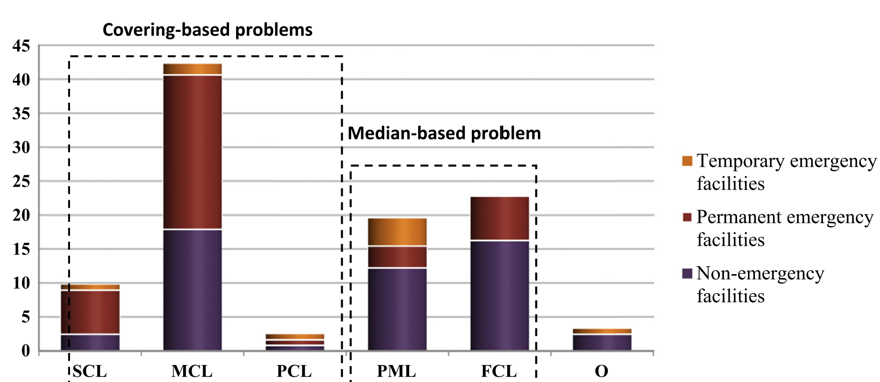

Fig. 5. The frequencies of basic discrete location problems used in the HCF location literature.

Table 17
The basic corresponding discrete location problems which are used in the literature.

→The Types of HCFs ↓The basic corresponding discrete location problems		Non-emergency HCFs: A-NE-HCF	Non-emergency HCFs: B-NE-HCF	Emergency HCFs, Permanent emergency facilities: Emergency OPADs	Emergency HCFs, Permanent emergency facilities: Emergency centers	Emergency HCFs, Permanent emergency facilities: Trauma centers	Emergency HCFs, Permanent emergency facilities: Ambulance stations	Emergency HCFs, Temporary emergency facilities: Points of dispensing	Emergency HCFs, Temporary emergency facilities: Temporary medical centers
Covering-based problems	SCLP	[67,177]	[92]	[119]	–	[130]	[140,151,152,158–160]	[171]	–
	MCLP	[72,73,76,77,80,84,86,89,90,100]	[92,102–105,107,108,110–113]	[119–124]	[125]	[126–131]	[132,133,135–137,139,142,145,146,148,149,157,158,162,163]	[172]	[168]
	PCLP	–	[117]	–	–	–	[138]	–	[57]
Median-based problems	PMLP	[68,69,75,79,82,86,98,99,176]	[92,94,106,115,116]	–	–	–	[143,150,153,165]	[171,174]	[167,168]
	FCLP	[71,78,81,83–85,87,88,100,101]	[93,95–97,109,111–114,118]	–	–	[128,129]	[134,141,144,147,154,164]	–	–

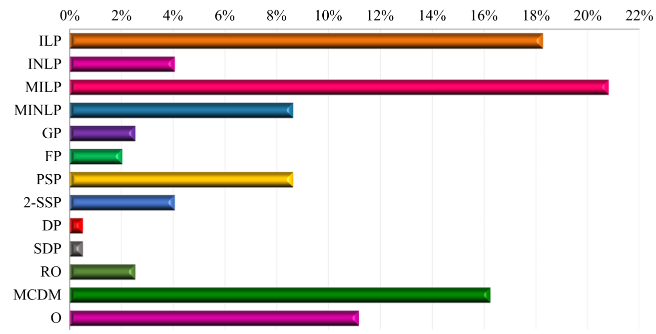

Fig. 6. The frequencies of modeling approaches used in the HCF location literature.

well-placed PODs where established PODs are dynamically designed and staffed in a stochastic environment. For this purpose, they integrated simulation and optimization into a decision support system (Real opt-POD) that can perform optimization of strategic and operational planning over each simulation iteration. The papers ([171,172,174]) which proposed location models for PODs are analyzed in Table 16.

The following directions can be suggested for future studies on POD location:

- Integrating related humanitarian logistics decisions with POD location decisions.
- Applying the MCDM approach to locate PODs.
- Developing accurate methods for solving the resulting POD location models.
- Studying POD location when different disasters (e.g., bioterrorist attacks during an earthquake) can happen simultaneously.

6. Analyses of literature from different perspectives

We complete our review of the literature on facility location models in health systems by presenting additional information regarding the surveyed papers. For this purpose, we analyze the types of basic discrete location problems corresponding to these papers, specify the modeling approaches and solution methods used to solve the problems, and determine whether a case study is considered or not. Finally, we break down the papers with respect to the subcategories of the survey's descriptive dimensions.

6.1. Basic discrete location problems

Fig. 5 and Table 17 provide an overview of the basic discrete location problems that have been used in modeling HCF location problems (i.e., the strategic planning level of health systems). As can be seen from Fig. 5, the basic MCLP (41.9%), PMLP (19.4%), and FCLP (22.6%) are three popular basic location problems used to study healthcare location problems. Furthermore, approximately 54% of the basic location problems are covering-based problems; about 43% are median-based problems, and about 4% of the problems are not in either of the above two broad classes.

Table 17 indicates the basic discrete location problems which are used in the surveyed papers. In this table, the non-emergency HCFs have been divided into two main classes, namely, A-NE-HCF and B-NE-HCF. The HCFs in Class A-NE-HCF provide mainly healthcare services that directly affect clients' experience of health treatment while those in Class B-NE-HCF mainly provide supportive services that are used in other healthcare services, such as radiology, CT scan, blood provision, etc. Class A-NE-HCF can include hospitals and clinics (general or specialized), organ transplant centers, and home healthcare centers.

The median-based location problems find the median locations

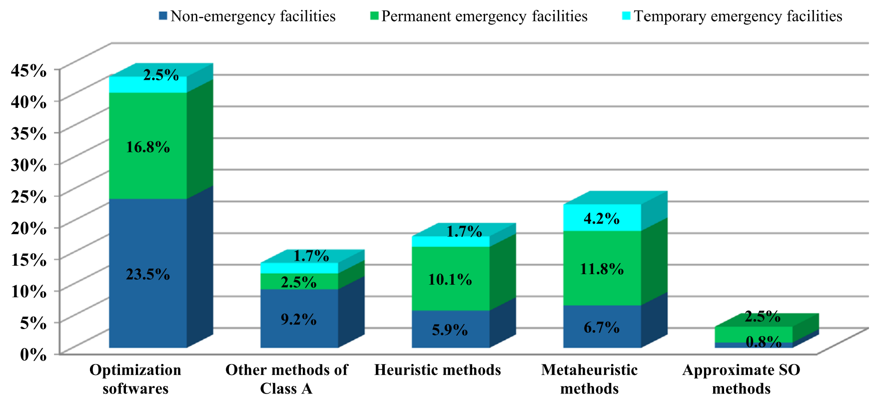

Fig. 7. The frequencies of solution methods used in the HCF location literature.

With case study	**NEF**	[67-70, 72-84, 85-88, 90-95, 97-110, 112, 114-116, 118, 175, 176]
	PEF	[119, 120, 124-128, 131, 133, 135-137, 139, 142-146, 149-164]
	TEF	[58, 166-168, 171, 172, 174]
Without case study	**NEF**	[89, 93, 96, 111, 113, 117, 177]
	PEF	[121, 129, 130, 132, 134, 138, 140, 141, 147, 148, 165]
	TEF	[57, 170]

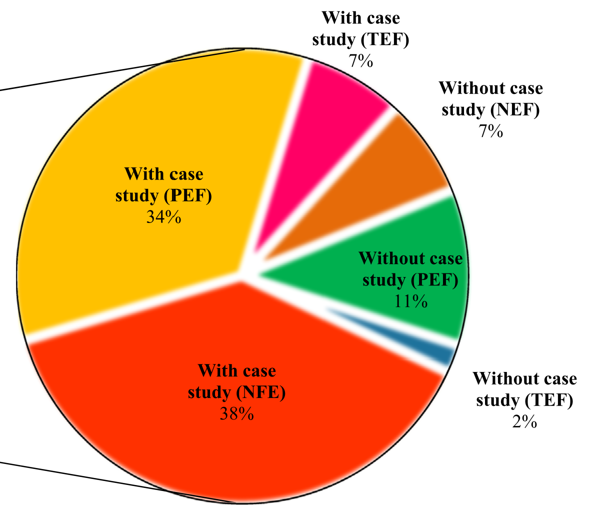

Fig. 8. The classification of papers on HCF location problems based on whether or not they present a case study (NEF, PEF and TEF stand for non-emergency, permanent emergency, temporary emergency facilities, respectively).

among the candidate locations of facilities in order to minimize the demand-weighted average travel distance (or time) while the covering-based location problems emphasize the demand coverage within a specified travel distance. As a consequence, the proposed non-emergency HCF location problems were generally median-based problems and the emergency HCF location problems were generally covering-based, as can be seen from Fig. 5 and Table 17. However, studies on temporary emergency HCF location problems tended to apply both median-based and covering-based problems.

6.2. Modeling approaches

Fig. 6 depicts the frequencies of the modeling approaches used to formulate the HCF location problems. Over 50% of the papers used integer programming, including ILP, INLP, MILP and MINLP, with ILP and MLIP as the most popular modeling approaches. MCDM is also widely used to deal with HCF location problems which naturally involve several performance measures. Unfortunately, only a few studies incorporated an uncertain optimization approach, such as fuzzy programming, stochastic programming, stochastic dynamic programming, and robust optimization, despite the fact that uncertainty is an important modeling factor which should not be simplified. Moreover, multi-stage stochastic programming and stochastic dynamic programming are rarely used though many decisions in HCF location problems are made in different stages. It seems that the HCF literature has mostly tended to use a modeling approach that results in simple models, which can be optimally solved using existing optimization solvers within reasonable times (see also the next subsection), but sacrifices or dilutes the validity of the models. This shows that there is much room for OR experts to use more advanced modeling approaches.

6.3. Solution methods

Fig. 7 summarizes the different types of solution methods that have been used to solve HCF location problems. From this figure, one can see that a variety of solution methods in both Classes A and B (accurate and inaccurate) have been developed to solve these problems. Approximately half of the papers used general-purpose optimization software (43%); and, among these, non-emergency problems comprise the majority.

Moreover, approximately 45% of the papers solve the problems heuristically using methods in Class B. Among metaheuristic methods, Tabu Search (32%) and Genetic (32%) methods are more popular compared to Simulated Annealing (14%) and Ant Colony (4%) methods. In addition, among the methods in Class A, branch and bound and Lagrangian relaxation methods have been used more than dynamic programming, decomposition, and cutting plane methods (see Table 18). Note that the branch and cut, branch and price, and column generation methods have not been applied

Table 18
The categorization of the literature with respect to the survey descriptive dimensions.

Dimension	Codes	Papers
Consideration of uncertainty	Y	[58,70,79,83,84,88,89,95–97,99–101,103,104,106–111,118,120,121,133–135,137,139–143,145,147,149–154,158,159,162–164,172,174]
	N	[57,67–69,71–78,80–82,85–87,90–94,98,102,105,112–114,117,119,125–132,136,138,144,146,148,160,165,167,168,170,171,176,177]
Multi-period setting	S	[57,58,67–70,72–80,82,83,86–94,98,99,102–114,117,119–121,125–131,133–137,139,141–143,145,147–149,151,153,154,162,164,167,170–172,174,176,177]
	D-1	[71,95–97,100,101,112,132,138,140,146,150,152,158–160,163,165,168]
	D-2	[81,84,85,118,144]
Particular input/setting	P1	[57,58,67–84,86–114,117–121,125–154,158–160,162–165,167,168,170–172,174,176,177]
	P2	[58,75,83,84,91,96,98–101,103,104,106,108,110,118,121,126,127,130,132,133,136–139,142–146,148,150–153,158–160,162,163,165,168,174]
	P3	[57,58,68–70,73,74,76–82,85–90,92,93,95–98,102,105,107,109,111–114,117,119–121,125,128,129,131,134,135,140,141,147,149,154,164,167,170–172,174,176,177]
	P4	[58,69,70,72,75–77,83,85,88,93,95–97,102–105,108,111–113,117,118,128,129,131,132,134–137,141,142,146,147,149,160,163,165,167,168,171,172,174,176,177]
	P5-1	[71–73,78,80–84,87–90,93–97,99–101,106,107,109,111–114,118,119,129,130,134,141,144,147,151,154,164,177]
	P5-2	[58,71–73,78,81,83–85,87–90,94–97,100,101,107,109,111–114,118,128,129,132–134,141,144,146,147,151,154,158,163–165]
	P5-3	[58,84,100,111–113,128,129,163,165]
	P6	[103,104,106,108–110,174]
	P7	[77,85,101,109,113,118,120,130–132,134–142,144,146,147,149–151,168,174]
	P8	[58,68,72,75,79,80,84,86,87,89,99–101,113,118,128,138,139,142,144,160,163,168,174]
	P9	[77,102–105,107–110,113,120,128,129,168,172,177]
	P10	[131,133,135,137,139,140,142,143,145,149–153,158,159,162]
	P11	[68,73–75,84,86,92,176]
	P12	[67,68,74,75,79–82,84–89,91–97,99–101,109,110,112,118,126,127,129,130,132,136,139,144–146,148–151,153,158,159,162,163,165,168,170,172,174,176,177]
Objective function	O1	[92,119,130,151,158,171,177]
	O2	[130,137,140,151,152,159,160,164]
	O3	[58,68,69,75,77–79,82,84–87,92,96,98,99,101,106,143,150,151,153,167,168,171,174,176]
	O4	[58,71,81–85,87,88,93–97,100,101,109,111–114,118,129,133,134,141,144,147,154,164,165,167]
	O5	[57,69,138,149]
	O6	[77,102–105,107,108,110]
	O7	[72,76,77,80,86,89,90,92,112–114,119–121,125–127,131,137,139,146,148,149,158,162,168,172]
	O8	[130,132,133,136,142,145,146]
	O9	[73,84,85,111,128,129,135,136,149,163]
	O10	[58,67,70,74,79,82,83,85–87,91,98,105–107,112,117,119,132,136,146,152,158,163,165,170]
Decision variable	D1	[57,58,67–69,71–84,86–105,108–114,117–121,125–131,133–135,137,141,144,147,151,154,158,164,167,168,170–172,174,176,177]
	D2	[58,67,75,92,95–97,99–101,106,111,113,114,118,168,172]
	D3	[130–132,134–136,138–154,158–160,162–165,168]
	D4	[57,69–83,86–90,92–96,98,99,102–104,106–114,117,118,121,125,128,129,131,167,168,170,171,174,176,177]
	D5-1	[86,119,120,126,127,130]
	D5-2	[130,132,133,135,136,140,142,144–146,148,149,151,152,158]
	D6	[132,133,136–138,141,143,144,150,153,154,159,160,162–165]
	D7	[58,75,77,84,97,100,104,107,108,112,118,172,174]
	D8	[58,68,70–73,75,78,79,81,82,84,85,88,91,95–101,109,110,118,121,128,130,139,151,158,162,168,174]
Constraint	C1	[57,58,67–69,71,75–79,81–83,86,92,93,96,98–100,103,106,107,111,113,117,129,132,134,143,144,154,160,164,167,168,171,174,176,177]
	C2	[95,101,120,135,137,140,141,143,148,151,152,160,163]
	C3	[130,132,136,144,146,151]
	C4	[67–71,73,74,76,77,82–84,86,88–93,95,96,98,99,101,105,112,113,117,118,120,121,125–127,131,133,135,167,168,170–172,174,176]
	C5	[57,69,72–76,79,80,84,86,87,89,90,95–105,112–114,117,118,121,125–131,134,136–143,145–152,160,170,171,177]
	C6	[100,101,111,113,128,133,134,136–141,143,145,147,151,152,159,164,165]
	C7	[132,134–137,141,142,146,147,149,154,163,165]
	C8	[58,95–97,100,101,172,174]
	C9-1	[58,67–70,72,75–77,80,82–85,88,93,95–97,100,106,108–114,118,128,129,131,144,146,148,149,160,164,167,168,171,172,176,177]
	C9-2	[67,70,71,75,77,79,82–84,87,102–106,108–111,113,114,118,129,144,168,177]
	C10	[68,72,73,78,80,81,88–90,94,99,106,107,130,176]
	C11	[57,58,67,70,72,74,75,77,78,80,81,86–93,95–97,99–101,103,104,106–110,112,113,118–121,128,129,131,132,138,139,141,144,146,149–154,158–160,162,163,165,167,168,174]

Table 18 (*continued*)

Dimension	Codes	Papers
Basic location problem	SCL	[67,92,93,119,130,140,151,152,158–160,171,177]
	MCL	[72,73,76,77,80,84,86,89,90,92,100,102–105,107,108,110–113,119–121,124–133,135–137,139,142,145,146,148,149,158,162,163,168,172]
	PCL	[57,117,138]
	PML	[68,69,75,79,82,86,92,94,96,98,99,106,115,143,150,153,165,167,168,171,174,176]
	FCL	[58,71,78,81,83–85,87,88,93,95–97,100,101,109,111–114,118,128,129,134,141,144,147,154,164]
	O	[70,74,91,170]
Modeling approach	ILP	[57,71,74,76,77,80,86,89,90,92,102,105,112,119,125,129,130,132,134–137,141,142,144–146,148,149,151,159,162,163,171,172,177]
	INLP	[83,103,107,113,139,140,143,159]
	MILP	[58,67–69,72,73,75,78,79,82,84–88,91,92,96–99,110,114,117,118,120,121,126–128,133,138,147,152,154,158,160,165,167,168,176]
	MINLP	[70,81,93–95,100,101,104,106,108,109,111,120,131,153,164,174]
	GP	[67,86,93,107,137]
	FP	[95,100,101,107]
	PSP	[70,79,95,100,101,107,111,120,134,139–141,143,147,164,172,174]
	2-SSP	[58,83,84,96,118,141,147,163]
	DP	[57]
	SDP	[150]
	RO	[88,95,97,100,154]
	MCDM	[58,67,69,77,79,82–86,96,98,101,105,107,111–114,119,128,129,133,137,146,149,152,154,158,165,170,176]
	O	[89,101,103,104,106,108–110,121,133,137,139,140,142,143,149,152,153,156,159,161,174]
	NLP, 1-SSP, M-SSP, SP-O, CP, MPDM	-
Solution method	SL	[67,71,97,98,111,112,128,129,133,144]
	SC	[57,68,76,78,80,81,87,89,90,92,99,108,110,113,114,117,125–127,130–132,134,141,142,145,154,158,162–165,167,171,176,177]
	SX	[69,74,79,86]
	SG	[58,75,83,84,88,94–96,100,101,111,118,151,168]
	SO	[70,73,93,111,119,120,139,149]
	BB	[102,117,141]
	CP	[106]
	LR	[68,80,96,176]
	BD	[131]
	DP	[57,94]
	O	[57,91,94,102,108,109,120,137]
	BC, BP, BCP	-
	H	[81,90,103–105,109,110,127,130,131,138,139,141,147,152,159,170,172,177]
	MH-TS	[85,104,132,136,140,143,152,159,170]
	MH-GA	[76,82,110,119,153,156,161,171,174]
	MH-SA	[81,101,129,167]
	MH-AC	[136]
	MH-O	[83,101,103,121,146]
	S-SBO	[107,133,148,160]
	S-O	[150]
	S-SA, S-SAA, S-SO	-
Case study inclusion	Y	[58,67–88,90–95,97–110,112,114,115,118–120,125–128,130–133,135–137,139,142–146,149–154,156–164,167,168,171,172,174,176]
	N	[57,89,93,96,113,121,129,134,138,140,141,147,148,165,170,177]

to solve the HCF location problems.

6.4. Case studies

Generally, researchers provide evidence of the applicability of their research through the process of validation. Some research studies apply their results to a case study, which refers to a real-life example using historical data or implementation in practice to demonstrate the importance of their results in the real world. Fig. 8 classifies the surveyed literature according to whether they used a case study or not. As shown in Fig. 6, 80% of the papers presented case studies while the remaining 20% only tested their results using test problems, which are randomly generated.

It may be noted that data collection for testing HCF location models in disaster situations is very difficult. Indeed, in such situations data may not be available or may not be easy to communicate. However, we are pleased to have found that 77% of the papers dealing with temporary emergency HCF location problems tested their results using real-life case examples.

6.5. Categorization of literature with respect to all descriptive dimensions

The papers related to each type of HCFs were analyzed in detail in the previous sections. Nevertheless, if the readers are interested in reviewing the literature corresponding to each subcategory of the descriptive dimensions, they have to check each section. Therefore, we presented an inverse categorization in Table 18 which helps the readers to find the papers belonging to each subcategory of these dimensions.

7. Future research directions

In general, we have provided most of our suggestions for future research in each section. However, in this section we summarize related discussions and potential future research directions that are drawn from the overall review. We do this with respect to (i) the computational perspective (mathematical modeling approach and solution method) and (ii) different types of location problems in health systems.

7.1. Future research directions from computational perspective

We divided the computational future research directions into two separate subsections in terms of modeling approach and solution method.

7.1.1. Future research directions: modeling approaches

Considering the analysis presented in Section 6.2, we can suggest the following future guidelines:

- Incorporating stochastic or robust optimization into the HCF location models in static and dynamic settings.
- Using multi-stage uncertain programming, such as multi-stage stochastic programming, stochastic dynamic programming, or adjustable robust optimization approaches to address more realistic real-world applications in an uncertain dynamic setting.
- Applying game theory to model HCF location problems in competitive environments.
- Taking advantage of queuing theory when developing HCF location models in order to capture congestion and related service quality metrics. (e.g., papers [106, 174] incorporated congestion terms into their objective functions and papers [103, 104, 108–110] considered constraints on waiting times).
- Modeling complex HCF location problems using constraint programming which simplifies the statement of constraints.
- Developing models with equilibrium constraints or multi-level programming models to address HCF location problems where health system actors can decide independently after learning the decisions made by upper-level decision makers.
- Using the simulation approach for modeling HCF location problems which cannot be mathematically modeled or their mathematical models cannot be solved efficiently.

7.1.2. Future research directions: solution methods

As shown in Fig. 6, approximately half of the papers used general-purpose optimization software packages (43%), corresponding to the first subclass of Class A methods (i.e., accurate methods: exact or bounded-error methods). There is relatively little work on the other subclasses of Class A methods in the literature. Furthermore, about 45% of the papers used Class B methods (i.e., inaccurate methods: heuristic, metaheuristic, and approximate stochastic optimization methods) for solving their models. Thus, based on detailed analyses of various tables provided previously in this review, other conclusions in terms of solution methods are summarized below:

- Using accurate solution methods (exact or bounded-error methods) to solve the existing models which are basically solved by software packages and cannot be solved in large scale by the commercial solvers within reasonable times.
- Applying advanced IP methods (e.g., branch and cut, Lagrangian relaxation, and Benders decomposition) to solve existing ILP or MILP models.
- Solving those HCF problems tackled by inaccurate solution methods (e.g., heuristics or meta-heuristics) using accurate solution methods.
- Applying simulation-based methods to solve location problems in complex health systems, for which other solution methods cannot be used.
- Developing software packages or web-based programs which can be used for free by all health systems worldwide.
- Organizing a data base which systematically collects benchmark test problems for HCF location problems.

7.2. Future research directions in terms of HCF type

The health systems require various types of HCFs to perform a wide range of services related to human health. Each type of HCF has different characteristics and applications. Naturally, these characteristics and applications interact with the optimal locations of HCFs. Therefore, relevant characteristics should be considered in location modeling in order to make location models more efficient and closer to reality. With respect to this aspect, the literature can be scrutinized to identify the distinctive features of different types of HCFs that should be considered in location modeling of health systems.

Thus, there are many research directions which are useful for addressing more realistic HCF location problems. With regard to this, Table 19 summarizes some suggestions for identifying potentially fertile areas in real-world HCF location modeling.

7.3. General future research directions

In addition to the categorized suggestions in Table 19, some future research directions could also be suggested for all HCFs:

- Combining related types of HCFs in location models.
- Integrating location decisions with other strategic, tactical, or operational decisions in HCF location models.
- Extending the existing HCF location models to multi-period

Table 19
The future research directions in terms of HCF type.

The types of HCFs	The future research directions in terms of the HCF type
Primary care facilities (hospitals, clinics, off-site public access devices, etc.)	• Proposing dynamic PCF location models (i.e., multi-period location models) that take into account changes in the problem setting over time, such as population migration, significant changes in management objectives, transportation and facility capacities, patient population, etc. • Designing a hospital network with different types of PCFs (hospitals, clinics, ambulatory healthcare centers, and off-site public access devices). • Developing location models by considering PCFs with different payment systems (e.g., with or without insurance). • Incorporating transportation modes (e.g., air, truck, and rail) and routing decisions into PCF location models. • Developing statistical methods to estimate the input parameters of the existing models. • Incorporating logistics and distribution considerations into the existing PCF location models. • Integrating PCF location with related healthcare planning decisions. • Extending the existing PCF location models in a competitive environment for private primary care providers. • Developing models for centralizing locational decisions for a set of (dependent or independent) primary care providers to improve the service quality and the utilization of the common resources.
Blood banks	• Extending location models for handling both independent blood banks and dependent blood bank units (inside hospitals or clinics). • Developing models that consider stochastic and dynamic conditions. • Considering new settings, such as budget constraints or multiple-server blood banks. • Taking into account the different levels of the blood supply's life time(s) when locating blood banks; in particular, considering the fact that some specialized treatments require the use of only fresh blood. • Developing a model for optimal location/relocation of components of a blood supply chain. • Proposing online location models for mobile blood units in order to effectively increase voluntary blood donation rate and enrich blood banks. • Incorporating the average age, sex and blood groups of people who can donate blood in each region in blood station location models. • Addressing emergency conditions arising at times of disasters, or other similar events, in locating blood banks.
Organ transplant centers	• Integrating location of OTCs with other related components (hospitals and emergency departments) in a health system. • Developing multi-stage stochastic programming models to incorporate other relevant OTC planning aspects in the determination of OTC locations. • Centralizing decision making on locating/relocating OTCs. • Extending the existing models to take dynamic and online aspects of transplant procedures into account. • Considering more realistic transportation features (e.g., stochastic travel times and ambulance busy fractions) in OTC location problems.
Detection and prevention centers	• Developing dynamic DPC location models. • Applying other unconsidered settings, such as multiple servers and multiple services. • Considering various types of costs related to the health system and clients, and budget constraints. • Incorporating non-spatial factors, such as demographic and socioeconomic variables into the existing models to increase participation in detection and participation programs.
Other specialized services facilities	• Extending the existing location models for other specialized services facilities to handle uncertainties. • Studying the location of other specialized services facilities with multiple servers, budget constraints, or multiple services. • Developing dynamic location models for other specialized services facilities. • Using accurate methods to solve large-sized instances of the resulting location models for other specialized services facilities. • Integrating location of other specialized services facilities with other related HCFs with both flexible demand and non-flexible demand.
Long-term nursing care centers	• Improving the current models by taking other related HCFs into account. • Extending the models by considering multiple services and service quality. • Clustering demand points based on non-spatial factors such as various emergency categories, social classes, age, race, etc. • Developing competitive location models to represent situations where private long-term nursing care centers compete for clients. • Incorporating logistics considerations into locating long-term nursing care centers.
Off-site public access devices	• Extending models to determine locations for placing OPADs by considering more realistic factors, such as uncertainty in demands; the weight of each building (e.g., based on its population); traffic patterns; and building accessibility influenced by locked doors, multiple floors, hours of operation, etc. • Developing location models for OPADs, especially for interactive and web-based ones, which can be covered by other related HCFs, such as emergency centers and trauma centers if required. • Proposing integrated models for locating/relocating OPADs and other related HCFs.

Table 19 (*continued*)

The types of HCFs	The future research directions in terms of the HCF type
Trauma centers	• Extending the existing models to capture more realistic assumptions, such as uncertainty of demand, multi-type demand and multiple server setting. • Developing location models for trauma centers in multi-period settings. • Presenting hierarchical facility location models for trauma centers. • Combining ambulance stations, helicopter depots, and trauma centers with hybrid transportation modes. • Developing integrated models for simultaneously locating/relocating trauma centers and other related permanent and temporary emergency HCFs, such as emergency departments, OPADs, temporary medical centers, etc. • Incorporating scenarios that may occur in disasters into the location of trauma centers.
Ambulance stations	• Considering more realistic assumptions in locating ambulances and their stations, such as ambulance capacity, interruptions, dynamic setting, real-time setting, and general travel and service probability distributions. • Extending the hierarchical location models for ambulance stations and other related HCFs, such as trauma centers, OPADs, emergency centers, etc. • Integrating ambulance station and deployment decisions with other EMS strategic and tactical decisions, such as fleet size, staff number, crew planning, standby sites, etc. • Extending location models for ambulance stations with considering their role in disasters. • Integrating ambulance station decisions with most related operational decisions, i.e., relocation and dispatching decisions. • Incorporating real-time (online) deployment or dispatching strategies into locating ambulance stations. • Developing multi-stage stochastic programming to more accurately determine ambulance station locations under a set of stochastic scenarios. • Proposing exact or bounded-error algorithms for solving existing ambulance location models.
Temporary medical centers	• Incorporating uncertainty of demand and service capacities into existing TMC location models. • Developing multi-stage stochastic programming models to adequately model disaster operations management under different scenarios. • Presenting models for simultaneously locating different types of TMCs, such as field hospitals and CCPs simultaneously. • Integrating the location of helipads with TMCs. • Adapting existing location models with disruptions to locate TMCs whose service capacities fluctuate in disasters. • Considering concerns of disaster management and humanitarian logistics in the location of non-emergency HCFs which can play a temporary role in large-scale emergencies. • Developing location models for TMCs with disruptions impacting both TMCs and links, under different disaster scenarios.
Points of dispensing	• Integrating related humanitarian logistics decisions with POD location decisions. • Applying the MCDM approach to locate PODs. • Developing accurate methods for solving the resulting POD location models. • Studying POD location when different disasters (e.g., bioterrorist attacks during an earthquake) can happen simultaneously.
Other types: medical Laboratories, mobile healthcare units, home healthcare centers, rehabilitation centers, doctors' offices, drugstores, emergency centers, and other facilities given in Fig. 2, which are not healthcare providers	• Using the basic location models to solve location problems of these facilities, given that little study has been done on locating these facilities. • Investigating real-world case studies on location problems of these facilities. • Developing specialized location models for these facilities. • Studying the location of these facilities in competitive environments. • Incorporating the location of these facilities into the existing location models developed for other HCFs.

settings.

- Considering medical waste in proper location of HCFs.
- Studying network design problems involving healthcare providers in medical supply chains, which include the various players in health systems (see Fig. 1).
- Incorporating disaster management (humanitarian logistics) considerations into determination of non-emergency and permanent emergency HCF locations, which can provide special services in disaster-level events.
- Integrating location of permanent and temporary emergency facilities with other facilities in the disaster management and humanitarian logistic networks.
- Considering reliability and resilience considerations in HCF location models under possibility of interruptions and disruptions, and other uncertainties.
- Studying the HFC facility location problems in competitive environments using cooperative and non-cooperative game-theoretic models (see, e.g., [89]).
- Applying integrated HCF location models, such as location-routing, location-inventory, and location-pricing to HCF location.
- Using continuous location models in HCF applications.
- Applying the existing location models with disruption risk to address HCF location problems with unreliable HCFs or to incorporate disaster management considerations.
- Incorporating engineering economic models into the design phase of multi-period models, which leads to more realistic estimation of costs and revenues (see, e.g., [144]).
- Studying HCF location problems with multiple servers at various levels.
- Extending hierarchical HCF location models to consider given priorities in health treatment procedures.
- Introducing environmental and sustainability concerns into the HCF location models.

- Studying HCFs for animal visitation, animal-assisted activities, animal-therapy, and any health-related programs for animals considering infection prevention and control concerns [220].
- Considering the concept of medical tourism and globalization issues in location management of HCFs.
- Developing a holistic model to optimally design (redesign) a health system's physical network for a new (existing) city or district.
- Studying location of IT-based and web-based (online) HCFs, e.g., interactive OPADs, mobile HCFs, or temporary ambulance stations, possibly by using radio-frequency identification (RFID), internet of things (IoT), and Big Data.

8. Conclusions

In this paper, we have reviewed almost the entire emergency and non-emergency healthcare literature on facility location analysis over the last decade (2004-2016). By analyzing the existing surveys, we show that the lack of a comprehensive review of HCF location is a significant shortcoming in the healthcare literature. Therefore, we introduced a comprehensive framework to classify HCFs in terms of location management. The optimization models in each classification of HCFs are analyzed in a detailed table with ten descriptive dimensions (consideration of uncertainty, multi-period setting, particular input/setting, objective function, decision variable, constraint, basic discrete location problem, mathematical modeling approach, solution method, and case study inclusion) so as to identify gaps in research and provide essential future research directions.

Throughout this literature review, we identify and highlight several research gaps in every section. Beyond the future research possibilities identified in each section, we summarize overall potential research directions in terms of (i) a computational perspective (modeling and solution methodology) and (ii) different types of location problems in health systems.

In conclusion, this review indicates that there is still a lot of room for the study of more realistic HCF location problems, and the development of both new optimization models and solution methods in HCF location planning. Moreover, the existing HCF location problems can be adapted for other service industries or may be extended to new general problems in location theory. We hope that the challenges presented in this article arouse interest in readers and encourage them to conduct research in healthcare location modeling, an area that is indispensable from both industry and societal perspectives.

Acknowledgments

The authors sincerely acknowledge the oversight and assistance provided during the review process by the three anonymous referees as well as Editor-in-Chief Prof. Stefan Nickel. Their guidance has helped us to significantly improve this survey paper. They would also like to thank those who made comments on an earlier version of this paper that was presented at 2015 MSOM annual conference.

Appendix A. (Supplementary details on HCF types)

A.1. Non-emergency facilities

The class of non-emergency facilities contains a large number of HCFs which are divided into 10 subclasses as indicated in Fig. 3. Clients for this group of facilities are not under emergency circumstances. Moreover, except for clients for home healthcare facilities, clients in this group refer to physicians, surgeons or paramedics for prevention, examination, diagnosis, treatment (both surgical and non-surgical), or checkup either on an in-patient or on an out-patient basis.

A.1.1. Primary care facilities (hospitals, clinics, off-site public access devices, etc.)

This class of HCFs provides the most basic and the broadest scope of healthcare services for clients of all ages across all social, economic, and geographic categories. Primary care facilities (PCFs) comprise a wide range of primary care providers, such as public and specialized hospitals and clinics, polyclinics, ambulatory healthcare centers, and off-site public access devices. Due to the essential services that these facilities provide, ease of access for clients is crucial. In keeping with the need for proximity, primary care clients usually refer to the nearest PCF.

It should be noted that ambulatory care centers are PCFs that provide diagnosis, observation, consultation, treatment, and intervention services directly to out-patients who do not require in-patient services. These PCFs offer a mix of telemedicine, imaging, short-term observation care, and surgery. Technology used in these centers allows patients to avoid being kept overnight for monitoring. Many routine checks can be done through remote digital technologies [221].

In many countries, there can be found PCFs that are operated as an independent, non-profit entity, governed by a volunteer board of directors. These PCFs provide accessible, affordable, quality primary medical, dental, and mental healthcare services to everyone, regardless of ability to pay.

A.1.2. Blood banks

Blood banks are centers or caches that collect, process, store, and distribute blood and blood products. Blood banks include several types of centers, such as blood transfusion providers, blood centers, blood stations, and mobile units.

A.1.3. Specialized services facilities

Specialized services units provide exceptional services, such as radiography, CT scan, MRI, radiation therapy, electro-encephalogram (EEG), electro-cardiogram (ECG), etc., which are located either as independent units, or within hospitals or other health centers. For a more detailed review, we divided this class of HCFs into three subsections: organ transplant centers, detection and prevention centers, and other specialized services units.

A.1.3.1. Organ transplant centers. Organ transplant centers are hospitals or other HCFs that have an established transplant program including transplants for end-stage organ disease, such as marrow or cord blood transplants. These facilities, in cooperation with blood centers, test patients, examine the possibility of transplantation, and perform organ transplantation procedures.

A.1.3.2. Detection and prevention centers. Detection and prevention centers are established to save lives and improve the quality of life by early diagnosis of serious medical conditions and prevention of disease. They implement public vaccination programs or perform tests to detect potential cancerous cells. These facilities often contain units for radiology, radiography, CT scan, MRI, etc.

A.1.3.3. Other specialized services facilities. Other specialized services facilities are not in either of the above two classes of HCFs. These facilities provide some services, such as exercise stress test, radiation therapy, EEG, ECG, etc.

A.1.4. Medical laboratories

Medical laboratories are units where various tests are done on clinical specimens in order to get information about the state of clients' health for the diagnosis, treatment, and prevention of disease. These are classified into two main types: hospital-based or stand-alone private (or public) laboratories. They can be clinical pathology, clinical microbiology, or clinical biochemistry laboratories.

A.1.5. Mobile healthcare units

Mobile healthcare units are often clinics on wheels that provide medical, dental, and behavioral healthcare to patients who have difficulty reaching the other HCFs. Since developing countries frequently face the dilemma of very restrictive budget limitations for healthcare expenditures and a growing population [116], mobile healthcare units are potentially very cost-effective vehicles for delivery of primary care and some other health services. Mobile units cannot provide all of the services available in a hospital, and they should be seen as supplemental in nature, providing services, such as outpatient surgeries, dental services, and urgent primary care.

A.1.6. Home healthcare centers

Home healthcare centers are facilities and institutions that dispatch nurses and paramedical technicians to provide home healthcare services. According to the international classification for health accounts (ICHA) 2000, home healthcare comprises medical and paramedical services that are delivered to patients at home. Included in this category are obstetric services, home dialysis, home visit by a general practitioner, telematics services, etc.

A.1.7. Rehabilitation centers

Rehabilitation centers are outpatient or residential HCFs providing rehabilitative care. According to ICHA 2000, rehabilitative care comprises medical and paramedical services delivered to patients during rehabilitation. Rehabilitative care includes services where the emphasis lies on improving the functional levels of patients where the functional limitations are either due to a recent illness or injury, or of a recurrent nature (regression or progression). It requires frequent (daily to weekly) patient assessment, and review of the clinical course and treatment plan for a limited time period (several days to several months) until the condition is stabilized or a pre-determined treatment course is completed. Rehabilitation centers including centers for optometry, audiometry, physiotherapy, occupational therapy, speech therapy, etc.

A.1.8. Doctors' offices

Doctors' offices including specialists' and general practitioners' offices, dental and psychology offices, etc., are solely private. Hence, services that doctors offer in their offices are often primary care described in Section 3.1. However, for greater generality, doctors' offices have been categorized into a separate section. In both urban and rural areas of developed countries as well as urban areas of developing countries, the distance between patients and HCFs is a factor influencing a patient's decision regarding where to get medical services (e.g., a doctor's office or a clinic). In contrast, in rural areas of developing countries, due to lack of efficient transportation infrastructure, low incomes, or high travel costs, distance is the decisive factor in deciding whether or not to use medical services [116].

A.1.9. Drugstores

Drugstores are sometimes considered as a variety of HCFs that, after obtaining accreditation, provide medicines, dietary supplements, cosmetics products, and medical devices for clients.

A.1.10. Long-term nursing care centers

This class of HFCs contains facilities, such as nursing homes, long-term rehabilitation centers, hospices, etc. According to ICHA 2000, long-term healthcare comprises ongoing health and nursing care given to in-patients who need assistance because of chronic impairments, and a reduced degree of independence and activities of daily living. Long-term care is typically a mix of medical care (including nursing care) and social services. Long-term care in institutions is of three types: inpatient long-term nursing care, day cases of long-term nursing care, and long-term home care.

A.2. Emergency facilities

A.2.1. Permanent emergency facilities

Occasionally, due to illness, injury, or urgent medical conditions, patients require immediate treatment. Such patients should be immediately transmitted to one of the emergency facilities by ambulance (air or land). Indeed, emergency facilities location directly affects mortality and injury rates of an area's inhabitants. Hence, determining the best location of emergency facilities is crucial. We divided these facilities into four subcategories: emergency off-site public access devices, emergency centers, trauma centers, and ambulance stations.

A.2.1.1. Emergency off-site public access devices. Off-site public access devices (OPADs) are non-interactive or interactive medical devices designed to provide healthcare services in out-of-HCF environments. OPADs are able to receive individuals' health status information by connecting the sensors to the body and/or asking some queries, and provide appropriate diagnosis and prescription. Furthermore, these facilities can be equipped with signature capture devices in order to present documentation to the individual, collect their signature, and empower them to check-in for their scheduled appointments. In cases where individuals must make co-payments, OPADs can also collect payment. In the provision of healthcare, OPAD placement programs could facilitate maximization of coverage, improvement of services quality, and reduction in response times and costs.

A known subclass of non-interactive emergency OPADs are automated external defibrillators (AEDs), which are portable devices to check the heart rhythm and send electric shocks to the heart in order to try to restore a normal rhythm. AEDs are used to treat sudden cardiac arrest ([222]).

OPADs could be of either non-emergency or emergency type. However, due to the co-characteristics of these two types, greater importance of emergency devices in determining optimal locations, and that OPADs generally need to have the ability to provide emergency services (e.g., to give medical guidelines, to contact with ambulances, or emergency centers, etc.), the emergency type of these HCFs could be more important in terms of location management.

A.2.1.2. Emergency centers. Generally, emergency centers are independent centers, or embedded in hospitals or other healthcare centers, but in a separate section from other units, which are also known as emergency departments, casualty rooms, or emergency rooms. These facilities provide medical care to unscheduled patients requiring immediate and urgent medical attention, who show up or are brought by an ambulance. Due to the uncertain nature of patients' arrivals, these centers have to provide a wide range of initial treatment to their clients. Emergency centers are open 24 hours a day and their staffing levels vary depending on patient volume.

A.2.1.3. Trauma centers. Trauma centers are hospitals equipped and staffed to provide comprehensive specialized medical and nursing services to patients suffering from traumatic injuries.

Trauma centers typically have helicopter platforms to transfer patients, and require specialized and experienced multi-disciplinary treatment and specialized resources. When the number of trauma centers is limited, helicopters play an important role in effective treatment of injuries.

A.2.1.4. Ambulance stations. Ambulance stations are structures for storage of ambulance vehicles and other medical supplies, and they are responsible for ambulance dispatch (air or land). Ambulances are equipped with highly trained medical personnel and equipment to revive patients which can take either of two forms: (i) providing care to patients outside of HCFs or (ii) transferring sick or injured patients to or between HCFs. Since the response time is a critical factor in the reduction of mortality and morbidity rates, determining optimal ambulance station locations, as well as the optimal deployment (location or relocation) of ambulances in the stations, is pivotal.

A.2.2. Temporary emergency facilities

Temporary emergencies (natural disasters, military attacks, infectious disease disasters, etc.) that rarely occur, lead to a big surge in the demand for medical supplies. In such situations, location of HCFs directly affects mortality and injury rates, and thus the optimal locations of these HCFs play a vital role in risk mitigation, coverage maximization, rapid distribution of resources, waste avoidance, and reduction in response time. These facilities are divided into two subcategories: temporary medical centers and points of dispensing.

A.2.2.1. Temporary medical centers. This class of HFCs contains facilities, such as hospitals, clinics, field hospitals, Red Crescent and/or Red Cross tents, etc. as providers of healthcare services to people affected by disasters, which could be of a catastrophic nature. Determining the best locations of these HCFs plays a pivotal role in mitigating the number of serious injuries and mortalities.

Casualty collection points (CCPs) are temporary centers, which are used for provision of first aid to accommodate a large number of people coming to them on foot, who are subsequently transferred to hospitals or shelters, if required. In pre-disaster planning phase, CCPs are initially established in public or private facilities, such as colleges, schools, and public parks which are open, large enough, and relatively free from falling debris. Then, in catastrophic disaster situations, they may be operationalized when existing centers are destroyed or cannot satisfy the demand ([169]).

A.2.2.2. Points of dispensing. A point of dispensing (POD) is a mass medication dispensing site for provision of medicine and medical supplies (i.e., vaccines, drugs, and therapeutics) to protect the general population from infectious disease disasters, which are events in which a biological agent/disease involves a large portion of people, such as bioterrorist attacks, pandemics, or an outbreak of an emerging infectious disease (further study of infectious disease disasters can be found in [216]).

References

[1] Weber A. Theory of the location of industries [translated by CJ Friedrich from Weber's 1909 book]. Chicago: The University of Chicago Press; 1929.
[2] Gould PR, Leinbach TR. Approach to the geographic assignment of hospital services. Tijdschr voor Econ En Soc Geogr 1966;57(5):203–6.
[3] Rahman S-u, Smith DK. Use of location-allocation models in health service development planning in developing nations. Eur J Oper Res 2000;123(3):437–52.
[4] Brotcorne L, Laporte G, Semet F. Ambulance location and relocation models. Eur J Oper Res 2003;147(3):451–63.
[5] Daskin MS, Dean LK. Location of health care facilities. In: Brandeau ML, Sainfort F, Pierskalla WP, editors. Operations Research and Health Care. New York: Springer; 2004. p. 43–76.
[6] Li X, Zhao Z, Zhu X, Wyatt T. Covering models and optimization techniques for emergency response facility location and planning: a review. Math Methods Oper Res 2011;74(3):281–310.
[7] Rais A, Viana A. Operations research in healthcare: a survey. Int Trans Oper Res 2011;18(1):1–31.
[8] Wang F. Measurement, optimization, and impact of health care accessibility: a methodological review. Ann Assoc Am Geogr 2012;102(5):1104–12.
[9] Gutiérrez EV, Vidal CJ. Home health care logistics management problems: a critical review of models and methods. Rev Fac Ing 2013;68:160–75.
[10] Ingolfsson A. EMS planning and management. In: Zaric GS, editor. Operations Research and Health Care Policy. New York: Springer; 2013. p. 105–28.
[11] Güneş ED, Nickel S. Location problems in healthcare. In: Laporte G, Nickel S, Saldanha da Gama F, editors. Location science. Cham: Springer; 2015. p. 555–79.
[12] Berman O, Krass D. Stochastic location models with congestion. In: Laporte G, Nickel S, Saldanha da Gama F, editors. Location science. Cham: Springer; 2015. p. 443–86.
[13] Hulshof PJ, Kortbeek N, Boucherie RJ, Hans EW, Bakker PJ. Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. Health Syst 2012;1(2):129–75.
[14] Langabeer II JR, Helton J. Health care operations management: a systems perspective. 2nd ed. Burlington: Jones & Bartlett Publishers; 2015.
[15] de Vries J, Huijsman R, de Vries J, Huijsman R. Supply chain management in health services: an overview. Supply Chain Manag: Int J 2011;16(3):159–65.
[16] Dobrzykowski D, Deilami VS, Hong P, Kim S-C. A structured analysis of operations and supply chain management research in healthcare (1982–2011). Int J Prod Econ 2014;147(2):514–30.
[17] Wang Y, Wallace SW, Shen B, Choi T-M. Service supply chain management: a review of operational models. Eur J Oper Res 2015;247(3):685–98.
[18] Lemmens S, Decouttere C, Vandaele N, Bernuzzi M. A review of integrated supply chain network design models: key issues for vaccine supply chains. Chem Eng Res Des 2016;109:366–84.
[19] Narayana SA, Pati RK, Vrat P. Research on management issues in the pharmaceutical industry: a literature review. Int J Pharm Healthc Mark 2012;6(4):351–75.
[20] Shah N. Pharmaceutical supply chains: key issues and strategies for optimisation. Comput Chem Eng 2004;28(6):929–41.
[21] Thakur V, Ramesh A. Healthcare waste management research: a structured analysis and review (2005–2014). Waste Manag Res 2015;33(10):855–70.
[22] Altay N, Green III WG. OR/MS research in disaster operations management. Eur J Oper Res 2006;175(1):475–93.
[23] Galindo G, Batta R. Review of recent developments in OR/MS research in disaster operations management. Eur J Oper Res 2013;230(2):201–11.
[24] Hoyos MC, Morales RS, Akhavan-Tabatabaei R. OR models with stochastic components in disaster operations management: a literature survey. Comput Ind Eng 2015;82:183–97.
[25] Caunhye AM, Nie X, Pokharel S. Optimization models in emergency logistics: a literature review. Socio-Econ Plan Sci 2012;46(1):4–13.
[26] Anaya-Arenas AM, Renaud J, Ruiz A. Relief distribution networks: a systematic review. Ann Oper Res 2014;223(1):53–79.
[27] Çelik M, Ergun Ö, Johnson B, Keskinocak P, Lorca Á, Pekgün P, Swann JL. Humanitarian logistics. In: Mirchandani P, editor. New directions in informatics, optimization, logistics, and production. Maryland: INFORMS Tutorials in Operations Research; 2012. p. 18–49.
[28] Gutjahr WJ, Nolz PC. Multicriteria optimization in humanitarian aid. Eur J Oper Res 2016;252(2):351–66.
[29] Özdamar L, Ertem MA. Models, solutions and enabling technologies in humanitarian logistics. Eur J Oper Res 2015;244(1):55–65.
[30] McLay LA. Discrete optimization models for homeland security and disaster management. In: Aleman D, Thiele A, editors. The operations research revolution. Maryland: INFORMS Tutorials in Operations Research; 2015. p. 111–32.
[31] Wright PD, Liberatore MJ, Nydick RL. A survey of operations research models and applications in homeland security. Interfaces 2006;36(6):514–29.
[32] Larson RC. Decision models for emergency response planning. In: Kamien D, editor. The McGraw-Hill handbook of homeland security. Columbus: Ohio: McGraw-Hill; 2005. p. 911–27.
[33] Simpson N, Hancock P. Fifty years of operational research and emergency response. J Oper Res Soc 2009;60(1):S126–39.
[34] Başar A, Çatay B, Ünlüyurt T. A taxonomy for emergency service station location problem. Optim Lett 2012;6(6):1147–60.
[35] Goldberg JB. Operations research models for the deployment of emergency services vehicles. EMS Manag J 2004;1(1):20–39.
[36] Snyder LV, Atan Z, Peng P, Rong Y, Schmitt AJ, Sinsoysal B. OR/MS models for supply chain disruptions: a review. IIE Trans 2016;48(2):89–109.
[37] Drezner Z, Hamacher HW, editors. Facility location: applications and theory. Berlin: Springer; 2002.
[38] Eiselt HA, Marianov V, editors. Foundations of location analysis. New York: Springer; 2011.
[39] Daskin MS. Network and discrete location: models, algorithms, and applications. 2nd ed. New York: John Wiley & Sons; 2013.
[40] Revelle CS, Eiselt HA, Daskin MS. A bibliography for some fundamental problem categories in discrete location science. Eur J Oper Res 2008;184(3):817–48.

[41] Laporte G, Nickel S, Saldanha da Gama F, editors. Location science Cham, Springer; 2015.
[42] Daskin MS, Coullard CR, Shen Z-JM. An inventory-location model: formulation, solution algorithm and computational results. Ann Oper Res 2002;110 (1-4):83–106.
[43] Farahani RZ, Rashidi Bajgan H, Fahimnia B, Kaviani M. Location-inventory problem in supply chains: a modelling review. Int J Prod Res 2015;53 (12):3769–88.
[44] Prodhon C, Prins C. A survey of recent research on location-routing problems. Eur J Oper Res 2014;238(1):1–17.
[45] Ahmadi-Javid A, Seddighi AH. A location-routing problem with disruption risk. Transp Res Part E: Logist Transp Rev 2013;53:63–82.
[46] Ahmadi Javid A, Azad N. Incorporating location, routing and inventory decisions in supply chain network design. Transp Res Part E: Logist Transp Rev 2010;46(5):582–97.
[47] Ahmadi-Javid A, Seddighi AH. A location-routing-inventory model for designing multisource distribution networks. Eng Optim 2012;44(6):637–56.
[48] Ahmadi-Javid A, Ghandali R. An efficient optimization procedure for designing a capacitated distribution network with price-sensitive demand. Optim Eng 2014;15(3):801–17.
[49] Fattahi M, Mahootchi M, Govindan K, Husseini SMM. Dynamic supply chain network design with capacity planning and multi-period pricing. Transp Res Part E: Logist Transp Rev 2015;81:169–202.
[50] Plastria F, Vanhaverbeke L. Maximal covering location problem with price decision for revenue maximization in a competitive environment. OR Spectr 2009;31(3):555–71.
[51] Ahmadi-Javid A, Hoseinpour P. A location-inventory-pricing model in a supply chain distribution network with price-sensitive demands and inventory-capacity constraints. Transp Res Part E: Logist Transp Rev 2015;82:238–55.
[52] Ahmadi-Javid A, Hoseinpour P. Incorporating location, inventory and price decisions into a supply chain distribution network design problem. Comput Oper Res 2015;56:110–9.
[53] Daskin MS. What you should know about location modeling. Nav Res Logist 2008;55(4):283–94.
[54] Kariv O, Hakimi SL. An algorithmic approach to network location problems. II: the p-medians. SIAM J Appl Math 1979;37(3):539–60.
[55] Megiddo N, Supowit KJ. On the complexity of some common geometric location problems. SIAM J Comput 1984;13(1):182–96.
[56] Kuby MJ. Programming models for facility dispersion: the p-dispersion and maxisum dispersion problems. Geogr Anal 1987;19(4):315–29.
[57] Huang R, Kim S, Menezes MB. Facility location for large-scale emergencies. Ann Oper Res 2010;181(1):271–86.
[58] Mete HO, Zabinsky ZB. Stochastic optimization of medical supply location and distribution in disaster management. Int J Prod Econ 2010;126(1):76–84.
[59] Paul JA, Hariharan G. Location-allocation planning of stockpiles for effective disaster mitigation. Ann Oper Res 2012;196(1):469–90.
[60] Daskin MS, Snyder LV, Berger RT. Facility location in supply chain design. In: Langevin A, Riopel D, editors. Logistics systems: design and optimization. New York: Springer; 2005. p. 39–65.
[61] Melo MT, Nickel S, Saldanha-da-Gama F. Facility location and supply chain management–a review. Eur J Oper Res 2009;196(2):401–12.
[62] Rubenfire A. Growing hospital systems stretch supply chains. Mod Healthc 2016;46(5):20–2.
[63] Chartier Y, Emmanuel J, Pieper U, Prüss A, Rushbrook P, Stringer R, Townend W, Wilburn S, Zghondi R, editors. Safe management of wastes from health-care activities. 2nd ed. Geneva: World Health Organization; 2014.
[64] Ghiani G, Laganà D, Manni E, Musmanno R, Vigo D. Operations research in solid waste management: a survey of strategic and tactical issues. Comput Oper Res 2014;44:22–32.
[65] Burkey ML, Bhadury J, Eiselt HA. A location-based comparison of health care services in four US states with efficiency and equity. Socio-Econ Plan Sci 2012;46(2):157–63.
[66] Fo A, Mota I. Optimization models in the location of healthcare facilities: a real case in Brazil. J Appl Oper Res 2012;4(1):37–50.
[67] Chu SC, Chu L. A modeling framework for hospital location and service allocation. Int Trans Oper Res 2000;7(6):539–68.
[68] Galvao RD, Acosta Espejo LG, Boffey B. A hierarchical model for the location of perinatal facilities in the municipality of Rio de Janeiro. Eur J Oper Res 2002;138(3):495–517.
[69] Mitropoulos P, Mitropoulos I, Giannikos I, Sissouras A. A biobjective model for the locational planning of hospitals and health centers. Health Care Manag Sci 2006;9(2):171–9.
[70] Oliveira MD, Bevan G. Modelling the redistribution of hospital supply to achieve equity taking account of patient's behaviour. Health Care Manag Sci 2006;9(1):19–30.
[71] Ndiaye M, Alfares H. Modeling health care facility location for moving population groups. Comput Oper Res 2008;35(7):2154–61.
[72] Griffin PM, Scherrer CR, Swann JL. Optimization of community health center locations and service offerings with statistical need estimation. IIE Trans 2008;40(9):880–92.
[73] Ratick SJ, Osleeb JP, Hozumi D. Application and extension of the Moore and ReVelle hierarchical maximal covering model. Socio-Econ Plan Sci 2009;43 (2):92–101.
[74] Smith HK, Harper PR, Potts CN, Thyle A. Planning sustainable community health schemes in rural areas of developing countries. Eur J Oper Res 2009;193(3):768–77.
[75] Mestre AM, Oliveira MD, Barbosa-Póvoa A. Organizing hospitals into networks: a hierarchical and multiservice model to define location, supply and referrals in planned hospital systems. OR Spectr 2012;34(2):319–48.
[76] Shariff S, Moin NH, Omar M. Location allocation modeling for healthcare facility planning in Malaysia. Comput Ind Eng 2012;62(4):1000–10.
[77] Güneş E, Yaman H, Çekyay B, Verter V. Matching patient and physician preferences in designing a primary care facility network. J Oper Res Soc 2012;65(4):483–96.
[78] Cocking C, Flessa S, Reinelt G. Improving access to health facilities in Nouna district, Burkina Faso. Socio-Econ Plan Sci 2012;46(2):164–72.
[79] Mitropoulos P, Mitropoulos I, Giannikos I. Combining DEA with location analysis for the effective consolidation of services in the health sector. Comput Oper Res 2013;40(9):2241–50.
[80] Kim D-G, Kim Y-D. A Lagrangian heuristic algorithm for a public healthcare facility location problem. Ann Oper Res 2013;206(1):221–40.
[81] Ghaderi A, Jabalameli MS. Modeling the budget-constrained dynamic uncapacitated facility location–network design problem and solving it via two efficient heuristics: a case study of health care. Math Comput Model 2013;57 (3):382–400.
[82] Beheshtifar S, Alimoahmmadi A. A multiobjective optimization approach for location-allocation of clinics. Int Trans Oper Res 2015;22(2):313–28.
[83] Rahmaniani R, Rahmaniani G, Jabbarzadeh A. Variable neighborhood search based evolutionary algorithm and several approximations for balanced location–allocation design problem. Int J Adv Manuf Technol 2014;72(1-4):145–59.
[84] Mestre AM, Oliveira MD, Barbosa-Póvoa AP. Location–allocation approaches for hospital network planning under uncertainty. Eur J Oper Res 2015;240 (3):791–806.
[85] Stummer C, Doerner K, Focke A, Heidenberger K. Determining location and size of medical departments in a hospital network: a multiobjective decision support approach. Health Care Manag Sci 2004;7(1):63–71.
[86] Smith HK, Harper PR, Potts CN. Bicriteria efficiency/equity hierarchical location models for public service application. J Oper Res Soc 2012;64(4):500–12.
[87] Graber-Naidich A, Carter MW, Verter V. Primary care network development: the regulator's perspective. J Oper Res Soc 2015;66(9):1519–32.
[88] Shishebori D, Babadi AY. Robust and reliable medical services network design under uncertain environment and system disruptions. Transp Res Part E: Logist Transp Rev 2015;77:268–88.
[89] Marianov V, Ríos M, Taborga P. Finding locations for public service centres that compete with private centres: effects of congestion. Pap Reg Sci 2004;83 (4):631–48.
[90] Marianov V, Taborga P. Optimal location of public health centres which provide free and paid services. J Oper Res Soc 2001;52(4):391–400.
[91] Ares JN, De Vries H, Huisman D. A column generation approach for locating roadside clinics in Africa based on effectiveness and equity. Eur J Oper Res 2016;254(3):1002–16.
[92] Şahin G, Süral H, Meral S. Locational analysis for regionalization of Turkish Red Crescent blood services. Comput Oper Res 2007;34(3):692–704.
[93] Cetin E, Sarul LS. A blood bank location model: a multiobjective approach. Eur J Pure Appl Math 2009;2(1):112–24.
[94] Elalouf A, Hovav S, Tsadikovich D, Yedidsion L. Minimizing operational costs by restructuring the blood sample collection chain. Oper Res Health Care 2015;7:81–93.
[95] Zahiri B, Torabi S, Mousazadeh M, Mansouri S. Blood collection management: methodology and application. Appl Math Model 2015;39(23-24):7680–96.
[96] Fahimnia B, Jabbarzadeh A, Ghavamifar A, Bell M. Supply chain design for efficient and effective blood supply in disasters. Int J Prod Econ 2015.
[97] Jabbarzadeh A, Fahimnia B, Seuring S. Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application. Transp Res Part E: Logist Transp Rev 2014;70(1):225–44.
[98] Bruni ME, Conforti D, Sicilia N, Trotta S. A new organ transplantation location–allocation policy: a case study of Italy. Health Care Manag Sci 2006;9 (2):125–42.
[99] Beliën J, De Boeck L, Colpaert J, Devesse S, Van den Bossche F. Optimizing the facility location design of organ transplant centers. Decis Support Syst 2013;54(4):1568–79.
[100] Zahiri B, Tavakkoli-Moghaddam R, Pishvaee MS. A robust possibilistic programming approach to multi-period location-allocation of organ transplant centers under uncertainty. Comput Ind Eng 2014;74(1):139–48.
[101] Zahiri B, Tavakkoli-Moghaddam R, Mohammadi M, Jula P. Multi-objective design of an organ transplant network under uncertainty. Transp Res Part E: Logist Transp Rev 2014;72:101–24.
[102] Verter V, Lapierre SD. Location of preventive health care facilities. Ann Oper Res 2002;110(1-4):123–32.
[103] Zhang Y, Berman O, Verter V. Incorporating congestion in preventive healthcare facility network design. Eur J Oper Res 2009;198(3):922–35.
[104] Zhang Y, Berman O, Marcotte P, Verter V. A bilevel model for preventive healthcare facility network design with congestion. IIE Trans 2010;42 (12):865–80.
[105] Gu W, Wang X, McGregor SE. Optimization of preventive health care facility locations. Int J Health Geogr 2010;9(1):9–17.
[106] Vidyarthi N, Kuzgunkaya O. The impact of directed choice on the design of preventive healthcare facility network under congestion. Health Care Manag Sci 2015;18(4):459–74.

[107] Davari S, Kilic K, Ertek G. Fuzzy bi-objective preventive health care network design. Health Care Manag Sci 2015;18(3):303–17.
[108] Aboolian R, Berman O, Verter V. Maximal accessibility network design in the public sector. Transp Sci 2015;50(1):336–47.
[109] Aboolian R, Berman O, Krass D. Profit maximizing distributed service system design with congestion and elastic demand. Transp Sci 2012;46(2):247–61.
[110] Zhang Y, Berman O, Verter V. The impact of client choice on preventive healthcare facility network design. OR Spectr 2012;34(2):349–70.
[111] Mahar S, Bretthauer KM, Salzarulo PA. Locating specialized service capacity in a multi-hospital network. Eur J Oper Res 2011;212(3):596–605.
[112] Benneyan JC, Musdal H, Ceyhan ME, Shiner B, Watts BV. Specialty care single and multi-period location–allocation models within the Veterans Health Administration. Socio-Econ Plan Sci 2012;46(2):136–48.
[113] Syam SS, Côté MJ. A comprehensive location-allocation method for specialized healthcare services. Oper Res Health Care 2012;1(4):73–83.
[114] Guo M, Li B, Zhang Z, Wu S, Song J. Efficiency evaluation for allocating community-based health services. Comput Ind Eng 2013;65(3):395–401.
[115] Saveh-Shemshaki F, Shechter S, Tang P, Isaac-Renton J. Optimizing locations and capacities of new tuberculosis testing laboratories. IIE Trans Healthc Syst Eng 2012;2(4):248–58.
[116] Doerner K, Focke A, Gutjahr WJ. Multicriteria tour planning for mobile healthcare facilities in a developing country. Eur J Oper Res 2007;179(3):1078–96.
[117] Kim D-G, Kim Y-D. A branch and bound algorithm for determining locations of long-term care facilities. Eur J Oper Res 2010;206(1):168–77.
[118] Cardoso T, Oliveira MD, Barbosa-Póvoa A, Nickel S. An integrated approach for planning a long-term care network with uncertainty, strategic policy and equity considerations. Eur J Oper Res 2015;247(1):321–34.
[119] Bonnet B, Dessavre DG, Kraus K, Ramirez-Marquez JE. Optimal placement of public-access AEDs in urban environments. Comput Ind Eng 2015;90:269–80.
[120] Chan TC, Demirta D, Kwon R. Optimizing the deployment of public access defibrillators. Manag Sci 2016. http://dx.doi.org/10.1287/mnsc.2015.2312.
[121] Chan TC, Li H, Lebovic G, Tang SK, Chan JY, Cheng HC, Morrison LJ, Brooks SC. Identifying locations for public access defibrillators using mathematical optimization. Circulation. 2013;127(17):1801–9.
[122] Myers D, Mohite M. Locating automated external defibrillators in a university community. J Oper Res Soc 2009;60(6):869–72.
[123] Siddiq AA, Brooks SC, Chan TC. Modeling the impact of public access defibrillator range on public location cardiac arrest coverage. Resuscitation. 2013;84(7):904–9.
[124] Sun CL, Demirta D, Brooks SC, Morrison LJ, Chan TC. Overcoming spatial and temporal barriers to public access defibrillators via optimization. J Am Coll Cardiol 2016;68(8):836–45.
[125] Silva F, Serra D. Locating emergency services with different priorities: the priority queuing covering location problem. J Oper Res Soc 2008;59(9):1229–38.
[126] Branas CC, MacKenzie EJ, ReVelle CS. A trauma resource allocation model for ambulances and hospitals. Health Serv Res 2000;35(2):489.
[127] Branas CC, Revelle CS. An iterative switching heuristic to locate hospitals and helicopters. Socio-Econ Plan Sci 2001;35(1):11–30.
[128] Côté MJ, Syam SS, Vogel WB, Cowper DC. A mixed integer programming model to locate traumatic brain injury treatment units in the Department of Veterans Affairs: a case study. Health Care Manag Sci 2007;10(3):253–67.
[129] Syam SS, Côté MJ. A location–allocation model for service providers with application to not-for-profit health care organizations. Omega 2010;38(3):157–66.
[130] Erdemir ET, Batta R, Rogerson PA, Blatt A, Flanigan M. Joint ground and air emergency medical services coverage models: a greedy heuristic solution approach. Eur J Oper Res 2010;207(2):736–49.
[131] Cho S-H, Jang H, Lee T, Turner J. Simultaneous location of trauma centers and helicopters for emergency medical service planning. Oper Res 2013;62(4):751–71.
[132] Gendreau M, Laporte G, Semet F. A dynamic model and parallel tabu search heuristic for real-time ambulance relocation. Parallel Comput 2001;27(12):1641–53.
[133] Harewood S. Emergency ambulance deployment in Barbados: a multi-objective approach. J Oper Res Soc 2002;53(2):185–92.
[134] Beraldi P, Bruni ME, Conforti D. Designing robust emergency medical service via stochastic programming. Eur J Oper Res 2004;158(1):183–93.
[135] Tavakoli A, Lightner C. Implementing a mathematical model for locating EMS vehicles in Fayetteville, NC. Comput Oper Res 2004;31(9):1549–63.
[136] Doerner KF, Gutjahr WJ, Hartl RF, Karall M, Reimann M. Heuristic solution of an extended double-coverage ambulance location problem for Austria. Cent Eur J Oper Res 2005;13(4):325–40.
[137] Alsalloum OI, Rand GK. Extensions to emergency vehicle location models. Comput Oper Res 2006;33(9):2725–43.
[138] Andersson T, Värbrand P. Decision support tools for ambulance dispatch and relocation. J Oper Res Soc 2007;58(2):195–201.
[139] Ingolfsson A, Budge S, Erkut E. Optimal ambulance location with random delays and travel times. Health Care Manag Sci 2008;11(3):262–74.
[140] Rajagopalan HK, Saydam C, Xiao J. A multiperiod set covering location model for dynamic redeployment of ambulances. Comput Oper Res 2008;35(3):814–26.
[141] Beraldi P, Bruni ME. A probabilistic model applied to emergency service vehicle location. Eur J Oper Res 2009;196(1):323–31.
[142] McLay LA. A maximum expected covering location model with two types of servers. IIE Trans 2009;41(8):730–41.
[143] Rajagopalan HK, Saydam C. A minimum expected response model: formulation, heuristic solution, and application. Socio-Econ Plan Sci 2009;43(4):253–62.
[144] Coskun N, Erol R. An optimization model for locating and sizing emergency medical service stations. J Med Syst 2010;34(1):43–9.
[145] Sorensen P, Church R. Integrating expected coverage and local reliability for emergency medical services location problems. Socio-Econ Plan Sci 2010;44(1):8–18.
[146] Schmid V, Doerner KF. Ambulance location and relocation problems with time-dependent travel times. Eur J Oper Res 2010;207(3):1293–303.
[147] Noyan N. Alternate risk measures for emergency medical service system design. Ann Oper Res 2010;181(1):559–89.
[148] Lim CS, Mamat R, Braunl T. Impact of ambulance dispatch policies on performance of emergency medical services. IEEE Trans Intell Transp Syst 2011;12(2):624–32.
[149] Chanta S, Mayorga ME, McLay LA. Improving emergency service in rural areas: a bi-objective covering location model for EMS systems. Ann Oper Res 2011;221(1):133–59.
[150] Schmid V. Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. Eur J Oper Res 2012;219(3):611–21.
[151] Shariat-Mohaymany A, Babaei M, Moadi S, Amiripour SM. Linear upper-bound unavailability set covering models for locating ambulances: application to Tehran rural roads. Eur J Oper Res 2012;221(1):263–72.
[152] Saydam C, Rajagopalan HK, Sharer E, Lawrimore-Belanger K. The dynamic redeployment coverage location model. Health Syst 2013;2(2):103–19.
[153] Toro-Díaz H, Mayorga ME, Chanta S, McLay LA. Joint location and dispatching decisions for Emergency Medical Services. Comput Ind Eng 2013;64(4):917–28.
[154] Zhang Z-H, Jiang H. A robust counterpart approach to the bi-objective emergency medical service design problem. Appl Math Model 2014;38(3):1033–40.
[155] Erkut E, Ingolfsson A, Sim T, Erdoğan G. Computational comparison of five maximal covering models for locating ambulances. Geogr Anal 2009;41(1):43–65.
[156] Iannoni AP, Morabito R, Saydam C. An optimization approach for ambulance location and the districting of the response segments on highways. Eur J Oper Res 2009;195(2):528–42.
[157] Erkut E, Ingolfsson A, Erdoğan G. Ambulance location for maximum survival. Nav Res Logist 2008;55(1):42–58.
[158] van den Berg PL, Aardal K. Time-dependent MEXCLP with start-up and relocation cost. Eur J Oper Res 2015;242(2):383–9.
[159] Rajagopalan HK, Saydam C, Setzler H, Sharer E. Ambulance deployment and shift scheduling: an integrated approach. J Serv Sci Manag 2011;4(1):66–78.
[160] Aringhieri R, Carello G, Morale D. Supporting decision making to improve the performance of an Italian emergency medical service. Ann Oper Res 2016;236(1):131–48.
[161] Iannoni AP, Morabito R, Saydam C. Optimizing large-scale emergency medical system operations on highways using the hypercube queuing model. Socio-Econ Plan Sci 2011;45(3):105–17.
[162] Gendreau M, Laporte G, Semet F. The maximal expected coverage relocation problem for emergency vehicles. J Oper Res Soc 2006;57(1):22–8.
[163] Naoum-Sawaya J, Elhedhli S. A stochastic optimization model for real-time ambulance redeployment. Comput Oper Res 2013;40(8):1972–8.
[164] Zhang Z-H, Li K. A novel probabilistic formulation for locating and sizing emergency medical service stations. Ann Oper Res 2015;229(1):813–35.
[165] Zhi J, Keskin BB, Melouk SH. A multi-period dynamic location planning model for emergency response. IIE Trans Healthc Syst Eng 2015;5(4):211–24.
[166] Jia H, Ordóñez F, Dessouky M. A modeling framework for facility location of medical services for large-scale emergencies. IIE Trans 2007;39(1):41–55.
[167] Paul JA, Batta R. Models for hospital location and capacity allocation for an area prone to natural disasters. Int J Oper Res 2008;3(5):473–96.
[168] Apte A, Heidtke C, Salmerón J. Casualty collection points optimization: a study for the District of Columbia. Interfaces 2014;45(2):149–65.
[169] Drezner T. Location of casualty collection points. Environ Plan C: Gov Policy 2004;22(6):899–912.
[170] Drezner T, Drezner Z, Salhi S. A multi-objective heuristic approach for the casualty collection points location problem. J Oper Res Soc 2006;57(6):727–34.
[171] Lee EK, Chen C-H, Pietz F, Benecke B. Modeling and optimizing the public-health infrastructure for emergency response. Interfaces 2009;39(5):476–90.
[172] Murali P, Ordóñez F, Dessouky MM. Facility location under demand uncertainty: response to a large-scale bio-terror attack. Socio-Econ Plann Sci 2012;46(1):78–87.
[173] Lee EK, Pietz F, Benecke B, Mason J, Burel G. Advancing public health and medical preparedness with operations research. Interfaces 2013;43(1):79–98.
[174] Ramirez-Nafarrate A, Lyon JD, Fowler JW, Araz OM. Point-of-dispensing location and capacity optimization via a decision support system. Prod Oper Manag 2015;24(8):1311–28.
[175] Baray J, Cliquet G. Optimizing locations through a maximum covering/p-median hierarchical model: Maternity hospitals in France. J Bus Res 2013;66(1):127–32.
[176] Galvão RD, Acosta Espejo LG, Boffey B, Yates D. Load balancing and capacity constraints in a hierarchical location model. Eur J Oper Res 2006;172(2):631–46.

[177] Kim D-G, Kim Y-D, Lee T. Heuristics for locating two types of public health-care facilities. Ind Eng Manag Syst 2012;11(2):202–14.
[178] Cromley EK, McLafferty SL. GIS and public health. 2nd ed. New York: Guilford Press; 2012.
[179] Aboueljinane L, Sahin E, Jemai Z. A review on simulation models applied to emergency medical service operations. Comput Ind Eng 2013;66(4):734–50.
[180] Harper PR, Shahani A, Gallagher J, Bowie C. Planning health services with explicit geographical considerations: a stochastic location–allocation approach. Omega 2005;33(2):141–52.
[181] Menditto A, Patriarca M, Magnusson B. Understanding the meaning of accuracy, trueness and precision. Accrédit Qual Assur 2007;12(1):45–7.
[182] Starfield B. Primary care: balancing health needs, services, and technology. New York: Oxford University Press; 1998.
[183] Walters DJ, Toombs M, Rabuka LA. Strengthening the foundation: the role of the physician in primary health care in Canada. Canadian Medical Association Journal 1994;150(6):839–47.
[184] Society, the Individual, and Medicine (SIM). Primary care: definitions and historical developments. Ottawa: University of Ottawa Medical School, Retrieved form 〈http://wwwmeduottawaca/sim/data/Primary_Carehtm〉 2016, June.
[185] World Health Organization (WHO). Declaration of Alma-Ata. International Conference on Primary Health Care, Alma-Ata, September, 1978. Retrieved form 〈http://www.euro.who.int/en/publications/policy-documents/declaration-of-alma-ata,-1978〉 2016, June.
[186] Şahin G, Süral H. A review of hierarchical facility location models. Comput Oper Res 2007;34(8):2310–31.
[187] Hodgson M. An hierarchical location-allocation model for primary health care delivery in a developing area. Soc. Sci Med 1988;26(1):153–61.
[188] Prastacos GP. Blood inventory management: an overview of theory and practice. Manag Sci 1984;30(7):777–800.
[189] Beliën J, Forcé H. Supply chain management of blood products: a literature review. Eur J Oper Res 2012;217(1):1–16.
[190] Kim WR, Biggins SW, Kremers WK, Wiesner RH, Kamath PS, Benson JT, Edwards E, Therneau TM. Hyponatremia and mortality among patients on the liver-transplant waiting list. N. Engl J Med 2008;359(10):1018–26.
[191] Zenios SA, Chertow GM, Wein LM. Dynamic allocation of kidneys to candidates on the transplant waiting list. Oper Res 2000;48(4):549–69.
[192] Alagoz O, Maillart LM, Schaefer AJ, Roberts MS. Determining the acceptance of cadaveric livers using an implicit model of the waiting list. Oper Res 2007;55(1):24–36.
[193] Lucey MR, Brown KA, Everson GT, Fung JJ, Gish R, Keeffe EB, Kneteman NM, Lake JR, Martin P, McDiarmid SV. Minimal criteria for placement of adults on the liver transplant waiting list: a report of a national conference organized by the American Society of transplant physicians and the american association for the study of liver diseases. Liver Transplant Surg 1997;3(6):628–37.
[194] Cohon JL. Multiobjective programming and planning. New York: Dover Publications; 2004.
[195] Caffrey SL, Willoughby PJ, Pepe PE, Becker LB. Public use of automated external defibrillators. New Engl J Med 2002;347(16):1242–7.
[196] Dao THD, Zhou Y, Thill J-C, Delmelle E. Spatio-temporal location modeling in a 3D indoor environment: the case of AEDs as emergency medical devices. Int J Geogr Inf Sci 2012;26(3):469–94.
[197] Folke F, Gislason GH, Lippert FK, Nielsen SL, Weeke P, Hansen ML, Fosbøl EL, Andersen SS, Rasmussen S, Schramm TK. Differences between out-of-hospital cardiac arrest in residential and public locations and implications for public-access defibrillation. Circulation 2010;122(6):623–30.
[198] Folke F, Lippert FK, Nielsen SL, Gislason GH, Hansen ML, Schramm TK, Sørensen R, Fosbøl EL, Andersen SS, Rasmussen S. Location of cardiac arrest in a city center strategic placement of automated external defibrillators in public locations. Circulation 2009;120(6):510–7.
[199] Lerner EB, Fairbanks RJ, Shah MN. Identification of out-of-hospital cardiac arrest clusters using a geographic information system. Acad Emerg Med 2005;12(1):81–4.
[200] Warden CR, Daya M, LeGrady LA. Using geographic information systems to evaluate cardiac arrest survival. Prehosp Emerg Care 2007;11(1):19–24.
[201] Brooks SC, Hsu JH, Tang SK, Jeyakumar R, Chan TC. Determining risk for out-of-hospital cardiac arrest by location type in a Canadian urban setting to guide future public access defibrillator placement. Ann Emerg Med 2013;61 (5) 530-8. e2.
[202] Hogan K, Revelle C. Concepts and applications of backup coverage. Manag Sci 1986;32(11):1434–44.
[203] Chaiken JM. Transfer of emergency service deployment models to operating agencies. Manag Sci 1978;24(7):719–31.
[204] Chiyoshi F, Iannoni AP, Morabito R. A tutorial on hypercube queueing models and some practical applications in emergency service systems. Pesqui Oper 2011;31(2):271–99.
[205] Larson RC. Decision models for emergency response planning. In: Herrmann J, editor. The McGraw-Hill handbook of homeland security. Columbus: McGraw-Hill; 2005. p. 911–27.
[206] Daskin MS. A maximum expected covering location model: formulation, properties and heuristic solution. Transp Sci 1983;17(1):48–70.
[207] Batta R, Dolan JM, Krishnamurthy NN. The maximal expected covering location problem: revisited. Transp Sci 1989;23(4):277–87.
[208] Galvao RD, Morabito R. Emergency service systems: the use of the hypercube queueing model in the solution of probabilistic location problems. Int Trans Oper Res 2008;15(5):525–49.
[209] Larson RC. Approximating the performance of urban emergency service systems. Oper Res 1975;23(5):845–68.
[210] Larson RC. Hypercube queueing model. In: Gass S,I, Fu M,C, editors. Encyclopedia of operations research and management science. New York: Springer; 2013.
[211] Bélanger V, Kergosien Y, Ruiz A, Soriano P. An empirical comparison of relocation strategies in real-time ambulance fleet management. Comput Ind Eng 2016;94(1):216–29.
[212] Alanis R, Ingolfsson A, Kolfal B. A Markov chain model for an EMS system with repositioning. Prod Oper Manag 2013;22(1):216–31.
[213] Budge S, Ingolfsson A, Zerom D. Empirical analysis of ambulance travel times: the case of Calgary emergency medical services. Manag Sci 2010;56(4):716–23.
[214] Haghani A, Yang S. Real-time emergency response fleet deployment: Concepts, systems, simulation & case studies. In: Zeimpekis V, Tarantilis CD, Giaglis GM, Minis I, editors. Dynamic fleet management. New York: Springer; 2007. p. 133–62.
[215] Oran A, Tan KC, Ooi BH, Sim M, Jaillet P. Location and routing models for emergency response plans with priorities. In: Aschenbruck N, Martini P, Meier M, Tölle J, editors. Future security. Berlin: Springer; 2012. p. 129–40.
[216] Rebmann T. Infectious disease disasters: bioterrorism, emerging infections, and pandemics. In: Grota P, editor. APIC text of infection control and epidemiology. 4th ed. Arlington: The Association for Professionals in Infection Control and Epidemiology (APIC); 2014 p. 120-1-22.
[217] Lee EK, Maheshwary S, Mason J, Glisson W. Decision support system for mass dispensing of medications for infectious disease outbreaks and bioterrorist attacks. Ann Oper Res 2006;148(1):25–53.
[218] Herrmann JW. Disseminating emergency preparedness planning models as automatically generated custom spreadsheets. Interfaces 2008;38(4):263–70.
[219] Richter A, Khan S. Pilot model: judging alternate modes of dispensing prophylaxis in Los Angeles county. Interfaces 2009;39(3):228–40.
[220] Darling KT. Animals visiting healthcare facilities. In: Grota P, editor. APIC text of infection control and epidemiology. 4th ed. Arlington: The Association for Professionals in Infection Control and Epidemiology (APIC); 2014 p. 122-1-8.
[221] Royse D. Who needs beds? New ambulatory centers offer everything except inpatient care. Mod Healthc 2015;45(37):20–2.
[222] National Heart, Lung, and Blood Institute (NHLBI). What is an automated external defibrillator? Maryland: National Institutes of Health; 2011. Retrieved from 〈https://www.nhlbi.nih.gov/health/health-topics/topics/aed〉 2016, June.