Design of Preventive Healthcare Services: A Brief Review

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Abstract

The main purpose of preventive healthcare services is to minimize the risk of serious health conditions and increase the probability of early detection and diagnosis of serious illness. Therefore, the effectiveness and efficiency of a preventive healthcare service design play a crucial role in increasing the level of participation in such services. Additionally, the recent Covid-19 outbreak once again showed that implementing an effective preventive healthcare service design can make substantial savings on healthcare expenditures while promoting the welfare of society. Preventive healthcare-related location studies are relatively young compared to other studies considering other healthcare facility location studies. Although academic research on determining preventive healthcare facilities dates back to the early 2000s, there exists a body of literature that can be a review study topic. Hence, in this study, we present a brief review of the literature that considers location and design problems related to preventive healthcare facilities. We also discuss the basic features of the preventive healthcare service design problem and solution approaches proposed.

Keywords
Facility location, preventive healthcare, discrete location problems, and public health.

1. Introduction
Solving and recovering from health-related problems is much easier if an illness is diagnosed at an early stage. This also reduces the costs of diagnosing and treating the illness. Preventive services and programs are proven to be contributing to better life quality of patients by reducing the likelihood of receiving radical treatments such as surgery or chemotherapy, as well as saving their lives (Zhang et al. 2020). Previous studies showed that even a small amount of improvement in the participation of these services can save massive amounts of money for healthcare organizations and governments (Davari et al. 2016). Preventive healthcare is considered the most effective and efficient way of preventing disease and increasing public health in both developed and developing countries. These services aim to minimize the risk of getting caught to a serious illness and increase the probability of early diagnosis. Cancer screening programs, mammograms, anti-smoking advice, flu shots, and blood tests are among the most well-known services.

Within the past three decades, preventive services have been an integral part of several healthcare reform programs worldwide, and there has been an increased emphasis on the quality and performance of these services (Verter and Lapierre 2002). People receiving preventive healthcare services have the option and flexibility of choosing when and where to receive service. Thus, the accessibility and attractiveness of facilities in preventive healthcare services play a crucial role in increasing the participation of the population in these programs.

The problem of designing preventive healthcare facilities is closely related to the field of location science as well as service operations. Facility location problems consider optimally locating, relocating, or expanding facilities, e.g. police stations, hospitals, retail branches, warehouses, schools, fire stations, bank branches, post stations, and military installations, concerning one or multiple objectives (Karatas et al. 2019). The problem of locating preventive healthcare is a relatively new field of study in location science literature. Although the literature on designing preventive healthcare services is sparse, the increasing demand for these services coupled with the lessons learned from the Covid-19 pandemic led to the need for designing more efficient and effective networks. The pandemic once again showed that success in fighting diseases is strongly related to the preparedness level of healthcare facilities and the effective use of resources (Wu et al. 2020, Eriskin et al. 2022). Therefore, the topic of preventive healthcare design and location optimization has attracted considerable attention from the operations research community over nearly two decades.

In this study, our main ambition is to provide a brief review of studies that consider the problem of designing preventive healthcare services. In particular, we discuss and give a framework of the most common location and allocation modeling perspectives concerning the objectives sought as well as solution approaches implemented. The rest of the paper is organized as follows: In Section 2 we describe the problem features of the preventive healthcare network design problem. In Section 3 we review the prominent studies in the domain and give a synthesis of these studies with respect to different features. We finally conclude with a few remarks in Section 4.

2. Problem Features

In this section, we discuss the basic features of the preventive healthcare facility location and service design problem. We first give a classic formulation for the problem of interest. Next, we give a classification of the prevention and screening types since they play an important role in the design phase of the service facilities. Next, we give an overview of factors used to model the accessibility of facilities and their attractiveness. Finally, we present the widely used patient choice models that are used to mimic the behavior of clients in receiving preventive healthcare services.

2.1 Problem structure

Preventive healthcare facility location problems generally have the following characteristics:
• Each facility should ensure a minimum amount of demand (client) for accreditation purposes.
• Clients have the option and flexibility to receive preventive healthcare services.
• Accessibility and attractiveness of the facilities play a crucial role in patient choices.

Thus, the location problem requires a different modeling approach to account for these characteristics. In this regard, by using the model proposed in Verter and Lapierre (2002) and Ahmadi et al. (2017), a preventive healthcare facility location problem can be formulated as follows:

Sets and Indices:

$i \in I$: set of demand nodes that represent patients
$j \in J$: set of nodes that represent candidate locations for facilities

Parameters:

d_{ij} : distance between node i and candidate location
w_i : the population at node i
σ_{ij} : expected number of patients from node i visiting facility located at j
$D_i^{\max}$: maximum acceptable travel distance for demand point i
$W^{\min}$: minimum required number of clients at an established facility
p : number of facilities to be established

Decision Variables:

$$x_j = \begin{cases} 1, & \text{if a facility is established at location } j \\ 0, & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1, & \text{if client } i \text{ is assigned to facility located at } j \\ 0, & \text{otherwise} \end{cases}$$

Mathematical Model:

$$\max \sum_{i \in I} \sum_{j \in J} \sigma_{ij} y_{ij} \tag{1}$$

subject to

$$\sum_{j \in J} x_j = p \tag{2}$$

$$\sum_{j \in J} y_{ij} \le 1, \qquad \forall i \in I \tag{3}$$

$$\sum_{i \in I} \sigma_{ij} y_{ij} \ge W^{\min} x_j, \qquad \forall j \in J \tag{4}$$

$$y_{ij} \le x_j, \ \forall i \in I, j \in J \tag{5}$$

$$x_j \in \{0,1\}, \qquad \forall j \in J \tag{6}$$

$$y_{ij} \in \{0,1\}, \qquad \forall i \in I, j \in J \tag{7}$$

In the above formulation, the objective function (1) maximizes the total expected number of patients who receive the service. Constraint (2) ensures that the number of facilities established equals p. Constraint set (3) guarantees that a patient can be served only by a single established facility. The minimum workload requirement is satisfied in constraint set (4). Constraint set (5) is a technical constraint which ensures that a patient can receive service only from open facilities. Constraint sets (6) and (7) declare variable domains.

2.2 Prevention and screening types

Healthcare prevention programs are classified into three groups with respect to the objective of the service provider as primary, secondary, and tertiary prevention (Zhang et al. 2020). The first group (primary) of programs aim at minimizing the incidence likelihood of disease without showing any symptoms, e.g., vaccinations, immunizations of healthy people, and regular exercise. The actions taken in this category target improving lifestyle quality by altering risky behavior such as smoking, alcohol consumption, and insufficient physical activity. The second type (secondary) of programs seeks to detect diseases before they progress. The actions taken in this group target treating healthy people who have a certain amount of risk or patients that are at the very early stage of a disease, e.g., screening for high blood pressure, use of pap smears to detect and identify cervical cancer, and self-examination of diseases. The third group (tertiary) of programs aims at treating symptomatic patients with the objective of alleviating the severity and decreasing the complications of a disease, e.g., sugar control in a diabetic to mitigate vision and nerve problems. In other words, actions taken in this category consider rehabilitating or reducing the established diseases. Figure 1 displays the levels and types of prevention strategies together with their target populations, objectives, and some possible actions that can be taken at each step.

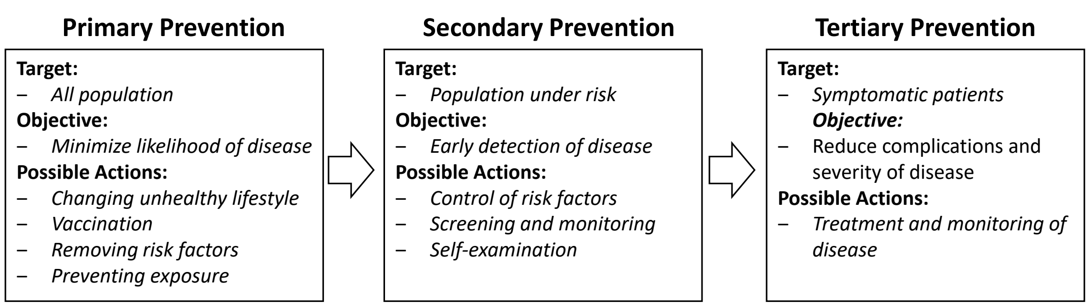

Figure 1. Prevention types and strategies

Factors affecting the utilization and impact of preventive healthcare services are different from those of regular healthcare facilities, such as hospitals, and emergency services. In other words, compared to the people who need immediate medical attention, those who should receive a preventive healthcare service may not feel the necessity of receiving that particular service due to several different reasons. Thus, recognizing the significance of accessibility and quality of service and their impact on the level of participation in a preventive program, most of the literature tackling the structural design of these services considers maximizing the participation and/or quality of services. Although prevention is always more effective than actual disease treatment both in terms of cost and life quality, their uptake is not satisfying in many countries (Lin et al. 2022). At this point, the prominent determinants of the system design and configuration are the number, size, and type of facilities to be established, the distance of a service provider to the population nodes, waiting and service times, etc.

Considering that cancer is one of the most important causes of morbidity and mortality worldwide, there exist several effective screening programs to reduce the incidence and mortality from the disease. At this point, the extent of the screening as well as the screening periods play an important role in the success of the programs (Adab et al. 2004). Screening operations can be classified into two groups as *organized* and *opportunistic* screening. For instance, mammography is an opportunistic screening service for women on their preference and initiative. Similarly, breast cancer screening is an organized service and it is generally a free service offered by the government in certain periods to asymptomatic women that are within a certain age range (Eichholzer 2016).

In organized screening programs, the invitations for the screening are coordinated and sent by centralized registers systematically. This brings additional responsibilities such as eligibility requirements, quality assurance, follow-up, and assessment. Opportunistic screening programs, on the other hand, do not operate via central registers, but in accordance with the individual's decision and willingness. In these operations, invitations to a particular screening depend on the individual's preference or encounter with healthcare providers (Miles et al. 2004). Additionally, in organized screening, the screening method for a particular type of cancer is determined by the government with fixed screening intervals whereas in opportunistic screening it is chosen by clients and/or individual healthcare providers with variable intervals (usually more frequent than in organized programs). In organized screening, all persons with specific conditions or age ranges are invited. Opportunistic screening programs, on the other hand, invite clients who are recommended by healthcare professionals, who work in particular jobs in which healthcare coverage may include reimbursement for screening. Since the public benefit provided by organized screening strongly depends on the success of the network and steps taken throughout the process, appropriately funded organized screening is expected to have greater capability to yield maximum benefit.

2.3 Accessibility of facilities

The concept of preventive healthcare is inherently different from other primary healthcare services required for urgent or acute issues. One of the most important differences is that, in preventive healthcare, the willingness of the patient is the main determinant to participate in a program. In other words, the patients have a choice in whether to receive the service offered in their region as well as selecting the facilities to patronize. Since the level of participation is crucial in these services, these programs are designed to be attractive and accessible to a patient with the objective of maximizing the total participation level.

Since a patient should volunteer to receive the service, it is up to him/her to participate in the program. Therefore, the performance and public benefit provided by these services are strongly related to the convenience of access to the service providers. There exist different metrics or planning factors that are regarded as the main determinants of accessibility and patient choice. The most common deterministic factors used in the literature include travel time and travel distance (proximity) to the facilities since these factors have a substantial impact on patient decisions (Vidyarthi and Kuzgunkaya 2015). However, several empirical studies showed that clients are also influenced by other factors that may or may not be controlled by planners and decision-makers. Some of these factors may include the reputation of the facility, quality of the treatment, availability of timely and reliable transportation, weather and road conditions, parking convenience, facility appearance, practitioner reputation, official ratings, waiting time, etc. can be used to assess the attractiveness of facilities (Krohn et al. 2021). All these factors alone or in combination play a role in the overall attractiveness of a facility and determine the demand.

Previous works showed that the accessibility of preventive healthcare facilities is a critical factor in improving participation levels to prostate cancer screening (Zimmerman, 1997). As empirical evidence, practical difficulties and negative attitudes toward the process are the main factors that led to mammography screening non-attendance (McNoe et al. 1996; Facione 1999). There also exist other studies such as Gerard (2003) which conclude that the amount of time waiting time (which is related to the congestion level of the network) has a significant impact on the client's choice of facility. For example, Müller (1998) showed that distance is an influencing factor in deciding what kind of medical services (e.g. a medical doctor or a hospital) to use for patients in urban areas, whereas it is a decisive factor in rural areas of developing countries. This argument is also supported by other research such as Haynes et al. (2003) and Varkevisser et al. (2008). Focusing on the design of public sector facility networks, Aboolian et al. (2015) argued that the expected total time including travel time from demand nodes to facilities, waiting time for the service as well as the actual service time at a facility constitutes an efficient proxy for accessibility.

2.4 Patient choice models

The behavior of clients in receiving preventive healthcare services is generally categorized into two models in the literature: the *optimal-choice* (also called "system optimal") model and the *probabilistic-choice* (also called "user-choice") model. The assumption of each patient choice model has an impact on the managerial decisions and the effectiveness of the network. In the former, it is assumed that a patient (or a client) always prefers the facility with the highest attractiveness, e.g., the closest open facility. In the latter, it is assumed that a patient may visit a facility with a specific probability which is expected to be proportional to the attractiveness of that particular facility. It should be noted that a large portion of facility location studies implements the optimal-choice models using distance or travel time as the major determinant of facility attractiveness. However, there are also many recent studies that incorporate probabilistic-choice models under various attractiveness assumptions.

Probabilistic-choice models can further be categorized into two types: *non-equilibrium allocations*, and *equilibrium allocations*. In the non-equilibrium allocations model, the competition among the users is not taken into consideration, whereas in the equilibrium allocations it is considered. In particular, non-equilibrium allocation can be implemented with three different approaches. The most common approach is the "all-or-nothing" allocation which is sometimes called the "binary" allocation or "winner-take-all" model. This approach is used in coverage problems frequently. In coverage problems, a person or demand that represents a population node is said to be covered if he/she is under a specified distance threshold to the nearest facility. Here, the term "coverage" represents the act of receiving a service that depends on the problem context. For instance, for an ambulance location problem, a patient is said to be covered if he/she can receive the health service within a prespecified emergency service time. Similarly, when locating sensors for providing a certain type of surveillance in a region of interest, a critical point is said to be covered if it is within the sensing range of a sensor. The all-or-nothing approach may not be realistic for situations where the coverage decreases with distance (Karatas and Eriskin 2021). Since covering models mostly consider the worst-case behavior of the network (Daskin, 2011), this approach may lead to unjustified solutions as well as potential errors if the coverage is inherently partial or decreases gradually within the distance (Karatas 2017).

The second approach is the Huff-type allocation model which covers a demand node partially by assigning a certain portion of it to a facility based on the facility's attractiveness level (Lin et al. 2022). In particular, the Huff-based model assumes that the probability of a client getting service from a facility is the inverse of the sum of the attractions of all service providers within the region. The more service providers that are installed within a predefined (or accessible) distance of a patient, the lower the probability that a particular service provider will be used by the patient. It should also be noted that the commonly used gravity model is a special case of the Huff-type allocation approach. For example, Gu et al. (2010) used a Huff-based competitive location model for preventive healthcare facilities in combination with the single distance measure.

The third approach is the multinomial logit (MNL) allocation approach. This approach uses a utility function that incorporates clients' characteristics as well as unobserved attributes and considers the clients who do not participate in the preventive programs. However, as an unrealistic side, the waiting time is not considered in the patient choice decision (Davari 2019, Ershadi and Shemirani 2021, Zhang et al. 2012).

To model the impact of congestion and waiting time, recent studies mostly implement equilibrium allocations to facility location models. The difficulty in incorporating the service time lies in the fact that it is an endogenous parameter that depends on the number of clients using a particular facility. For example, a shorter waiting time for a service attracts more clients, but this results in congestion as the clients start using that service. There are two basic equilibrium allocations: deterministic user equilibrium allocation, and stochastic user equilibrium allocation. In the former, the waiting time at a facility is included as an indispensable component of a deterministic utility, whereas in the latter a random component is further included to accommodate unobserved utilities. The facility with the highest (random) utility will be chosen to visit by users (Lin et al. 2022). Figure 2 displays the basic classification scheme for patient choice models.

Considering the impact of choosing a particular type of patient choice model, Zhang et al. (2012) investigated the effectiveness of the preventive healthcare network and developed a mixed integer program for each model to determine the number and locations of facilities as well as the required number of servers at each facility with the objective of maximizing total participation. They conclude that using a suitable client choice behavior model is crucial to the success of the network. The experiments show that different choice models yield significantly different facility location and capacity decisions. Hence, a thorough analysis and investigation of patient behavior is necessary (Figure 2).

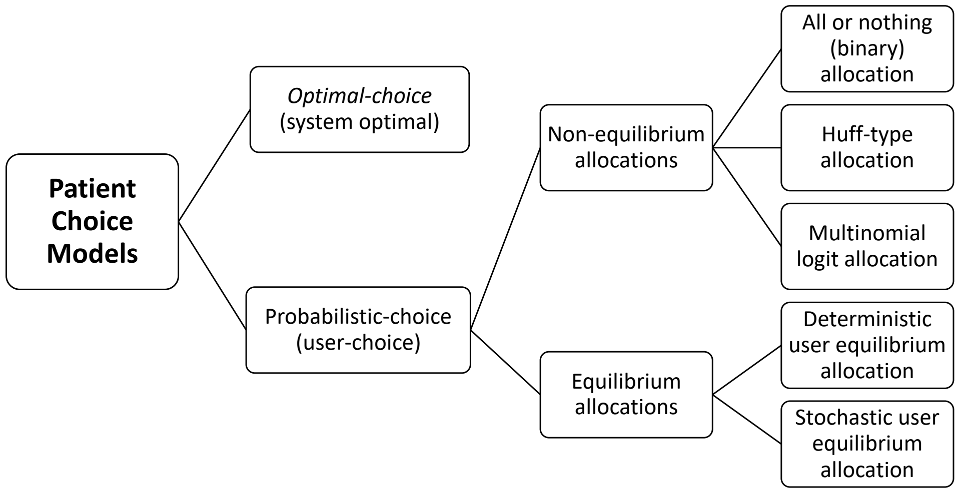

Figure 2. Patient choice model classification

In their study, Vidyarthi and Kuzgunkaya (2015) analyzed the impact of system optimal (i.e., directed) choice on the design of the preventive healthcare networks under congestion. They proposed a mixed integer nonlinear program (MINLP) which seeks to determine the location and size of facilities as well as the patient allocations to installed facilities to minimize the total travel, waiting, and service delay time. They also investigated the trade-off between waiting time and travel time in designing preventive healthcare networks. Similarly, Ershadi and Shemirani (2021) investigate the impact of probabilistic and optimal-choice behaviors for patients and consider the waiting time and workload limits of each facility in their model to ensure a certain level of service quality. Different from previous work, Lin et al. (2022), on the other hand, used the deterministic user equilibrium model to predict the demand at preventive healthcare facilities incorporating queuing theory.

3. Preventive Healthcare Facility Location Studies

The work of Verter and Lapierre (2002) is regarded as the first study which considers preventive healthcare facility location problems. In their study, the authors develop a mathematical model to determine the locations of preventive healthcare service facilities in order to maximize the level of participation in the program. Assuming that individuals seek services of the closest facility, they further adopted a linear decay function of distance for modeling participation level to a program. Their formulation accounts for the minimum workload requirement for each facility to ensure accreditation and sufficient quality of care. The authors adopted the travel time and distance factors as the main determinants of the facility attractiveness and did not incorporate service-related factors and congestion into their formulation.

There also exist studies that consider congestion and factors related to service quality. For instance, in their study, Zhang et al. (2009) adopted an M/M/1 queue methodology and proposed a nonlinear program that seeks to maximize the overall participation level. The expected total time included in the formulation is calculated as the sum of travel time, waiting time, and service time. Hence, with this formulation, the assumption that patients patronize the nearest facility is replaced with a minimum expected total time. In a follow-up study, Zhang et al. (2010) proposed a bi-level nonlinear optimization formulation for the problem and developed a model with two components. The lower level allocates patients to facilities whereas the upper level determines locations and capacities for facilities. As an alternative to deterministic choice models, Gu et al. (2010) developed a probabilistic choice model and presented a bi-objective formulation that seeks to maximize the overall level of participation. They adopted the Huff-based competitive model and proposed an interchange algorithm to solve the problem. The performance of the model and solution algorithm is demonstrated in a case study of breast cancer screening among Canadian women in Alberta, Canada.

Zhang et al. (2012) studied the impact of client choice behavior in the preventive healthcare sector. They formulated two preventive healthcare models, namely "optimal-choice" and "probabilistic-choice" models to model clients' choice behavior. In the probabilistic-choice model, clients may seek the service of each facility with a certain probability that changes with the attractiveness of the facilities. On the contrary, in the optimal-choice model, clients patronize only the most attractive facility. In their paper, the proximity to a preventive healthcare facility is assumed as the only measure of attractiveness. A genetic algorithm is provided to solve the preventive healthcare problem. The two preventive healthcare models are used for an illustrative case, the design of a network of breast cancer screening centers in Montreal, to analyze the impact of client choice behavior. Kim and Kim (2013) solved the network design problem under the assumption of two different patient types, i.e. low-income patients who can only use public facilities, and middle- and high-income patients who can use both public and private facilities. Aiming at maximizing the total number of patients served (both groups of patients), they developed an ILP formulation and solved it by using a Lagrangian heuristic algorithm.

In our review of the literature pertaining to the location of preventive healthcare facilities, we encountered studies that incorporate multiple objectives simultaneously. Among those, Davari et al. (2015) formulated two models, i.e., a fuzzy goal programming model, and a fuzzy chance-constrained model, for the preventive healthcare network design problems. The fuzzy goal programming model is a bi-objective model which seeks to maximize participation and equity under budget constraints. The next one is a modified version of this model by implementing fuzzy chance constraints which represent facility attractiveness by triangular fuzzy numbers and treats budget as a soft constraint. Both models are demonstrated in a case study for Istanbul, Turkey. Similarly, Roshan et al. (2017) proposed a bi-objective formulation for a preventive healthcare network where each facility is modeled as an M/M/1 queue system and the objective is to minimize travel and wait time as well as fixed installation and staffing costs. The authors developed an INLP formulation and solved it with three heuristics as multi-objective simulated annealing (MOSA), non-dominated sorting genetic algorithm (NSGA-II), and non-dominated ranking genetic algorithm (NRGA).

In another work, Davari et al. (2016) presented a mixed-integer programming model for designing preventive healthcare networks subject to budget constraints and equity considerations. They developed a skewed variable neighborhood search algorithm to solve their proposed model. Later, Davari (2019) extended the preventive healthcare service design problem by introducing the incremental and cooperative facility location scheme. In this extension, the model allowed adding facilities incrementally to the network one at a time and contributing to the service levels. Developing an INLP formulation, the author attempted to minimize the total cost of the network comprised of fixed installation costs and variable server costs. The model is solved via a variable neighborhood search. Javanmardi et al. (2017) proposed an INLP and its equivalent ILP formulation which aims to maximize participation by determining the optimal facility location and numbers as well as their capacities. They demonstrate the problem in a case study for Shiraz, Iran, and solve it to optimality with exact solvers.

Dogan et al. (2020), on the other hand, adopted a more holistic approach and proposed a multi-objective MILP formulation which ensures that the capacity of facilities for locating preventive healthcare facilities to ensure that maximum participation and timely service to potential clients while service capacities are not overly used. The model also allowed for modeling multi-purpose employment with the capability of meeting multiple types of screening programs with different target population groups. It also accounted for the potential population growth in the following 15 years as well as the accreditation of facilities and congestion. The model is demonstrated in a real-world case study for the Anatolian Side of Istanbul. In a more recent work, Krohn et al. (2021) adopted a random utility theory to analyze and predict client choice behavior based on utility maximization and use the multinomial logit model. They proposed an MINLP and an equivalent MILP formulation which determines facility locations and capacities while assuming that the deterministic utility is a linear function of travel time, quality of care, and waiting time. The authors also reported that there exists a nonlinear relationship between patient participation rates and the number of facilities. Similarly, Lin et al. (2022) adopted the deterministic user equilibrium model to predict the demand and proposed a bi-level modeling approach which determines the location and capacity of facilities at the upper level and the allocation of clients to facilities in the lower-level problem. The problem is formulated as an INLP model and solved via a genetic algorithm and method of successive averages technique.

Table 1 gives a synthesis of the basic characteristics of the aforementioned literature. The first column introduces the paper. The second and third columns state the objective of the mathematical model and decision variables, respectively. Column four states the basic model features and column five reports the attractiveness factor(s) used to model the patient choices. Columns six and seven reports the model type and the solution approach implemented, respectively. The final column displays whether a case study is performed or not.

Table 1. A synthesis of the preventive healthcare location and network design studies

Reference	**Objective**	**Decision(s)**	**Model features**	**Attractiveness**	**Model**	**Solution Method**	**Case study**
Verter and Lapierre (2002)	(max) participation	- Facility locations - Client allocations	- min workload requirement - no limit the number of facilities - closest facility assignment.	- travel distance / time	MILP	Branch-and-bound	Georgia, USA Montreal, Canada
Zhang et al. (2009)	(max) participation	- Facility locations - Client allocations	- incorporates congestion	- travel time - waiting time - service time	ILNP	Location–allocation heuristics	Montreal, Canada
Zhang et al. (2010)	(max) participation	- Facility locations -number of servers - Client allocations	- bi-level model - min workload requirement - incorporates congestion - limited number of servers	- travel time - waiting time - service time	MINLP	- Gradient projection method - Tabu search	Montreal, Canada
Gu et al. (2010)	(max) social welfare (max) coverage	- Facility locations -number of servers - Client allocations	- bi-objective model - limited number of facilities - min workload requirement	- travel distance - Huff-based competitive model.	ILP	Interchange algorithm	Alberta, Canada.
Zhang et al. (2012)	(max) participation	- Facility locations - Number of servers - Client allocations	- min workload requirement - limited number of servers - limited waiting time	- travel time - Multinomial logit model	MILP	Genetic algorithm	Montreal, Canada
Kim and Kim (2013)	(max) number of served patients	- Facility locations - Number of servers - Client allocations	- two patient types - public and private facilities - budget constraint	- travel distance	ILP	Lagrangian heuristic algorithm	Korea
Davari et al. (2015)	(max) participation (max) equity	-Facility locations -number of servers - Client allocations	- bi-objective model - budget constraint - fuzzy facility attractiveness	- travel distance / time	INLP	- Goal programming - Augmented ε-constraint method	Istanbul, Turkiye
Vidyarthi and Kuzgunkaya (2015)	(min) travel time, waiting time, service time	- Facility locations and capacities - Client allocations	- budget constraint - congestion included	- travel time - congestion - service delay	MILP	Cutting plane algorithm	Montreal, Canada
Davari et al. (2016)	(max) participation	- Facility locations - Number of servers - Client allocations	- budget constraint - congestion included	- travel distance / time	MILP	Variable neighborhood search	N/A

Reference	Objective	Decision(s)	Model features	Attractiveness	Model	Solution Method	Case study
Roshan et al. (2017)	(min) travel and wait time (min) installation and staffing costs	- Facility locations - Client allocations - Facility technology level	- bi-objective model - congestion included	- travel time	INLP	- MOSA - NSGA-II - NRGA	N/A
Javanmardi et al. (2017)	(max) participation	- Facility locations and capacities - Client allocations	- congestion included	- deterministic user equilibrium model	ILP	Exact solvers	Shiraz, Iran
Davari (2019)	(min) total cost of the network	- Facility locations	- incremental and cooperative facility location	- travel distance	INLP	Variable neighborhood search	N/A
Dogan et al. (2020)	(max) participation (min) unused service capacity (min) budget	- Facility locations - Client allocations	- multi-objective model - multiple target groups and screening programs - congestion included - min workload requirement - consider population growth in the future	- travel distance	MILP	Goal programming	Istanbul, Turkiye
Krohn et al. (2021)	(max) participation	-Facility locations and capacities - Client allocations	- congestion included - both travel time and waiting time considered	- user equilibrium model (travel time, quality of care, waiting time)	MILP	- Exact solvers - Benders decomposition	Sydney, Australia
Ershadi and Shemirani (2021)	(max) participation	-Facility locations and capacities - Client allocations	- compares probabilistic and optimal choices - min workload requirement - limited number of facilities	- travel time	MILP	Genetic algorithm	Isfahan, Iran
Lin et al. (2022)	(max) system total utility	-Facility locations -number of servers - Client allocations	- bi-level model - congestion included - both travel time and waiting time considered	- user equilibrium model	INLP	- Genetic algorithm - Method of successive averages	South Dakota, USA

5. Conclusion

The ultimate goal of this study is to introduce readers to the most prominent preventive healthcare service design and facility location problems. Although the literature on this topic is sparse, we encountered several studies published in the last two decades. Our review also revealed that although the problem investigated in this review is in the operations research arena for nearly two decades, it is gaining interest in the last 5 years. This is probably due to the social awareness on the benefit of using preventive and screening services as well as the lessons learned from the Covid-19 pandemic. The need for designing more efficient and effective healthcare systems and resource allocation plans led to an increased number of studies. We hope that this review can be a useful and inspirational source for further research on preventive healthcare facility location problems.

Our study reveals that one of the common features of these studies is that they are all discrete location models, i.e., facilities can be established only at candidate demand points (locations). Secondly, most studies only focus on the travel time and waiting time and their relationship in the mathematical formulations developed. One reason for that might be the simplicity of this assumption. However future studies could incorporate other factors such as service quality, service cost, parking time and availability, etc. Another future research direction can be the use of stochastic user equilibrium. Finally, the location and routing of mobile screening and preventive test centers could be a topic of research for future studies.

Disclaimer

Conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of any affiliated organization or government.

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