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A resilient, robust transformation of healthcare systems to cope with COVID-19 through alternative resources☆

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ABSTRACT

The COVID-19 pandemic - as a massive disruption - has significantly increased the need for medical services putting an unprecedented strain on health systems. This study presents a robust location-allocation model under uncertainty to increase the resiliency of health systems by applying alternative resources, such as backup and field hospitals and student nurses. A multi-objective optimization model is developed to minimize the system's costs and maximize the satisfaction rate among medical staff and COVID-19 patients. A robust approach is provided to face the data uncertainty, and a new mathematical model is extended to linearize a nonlinear constraint. The ICU beds, ward beds, ventilators, and nurses are considered the four main capacity limitations of hospitals for admitting different types of COVID-19 patients. The sensitivity analysis is performed on a real-world case study to investigate the applicability of the proposed model. The results demonstrate the contribution of student nurses and backup and field hospitals in treating COVID-19 patients and provide more flexible decisions with lower risks in the system by managing the fluctuations in both the number of patients and available nurses. The results showed that a reduction in the number of available nurses incurs higher costs for the system and lower satisfaction among patients and nurses. Moreover, the backup and field hospitals and the medical staff elevated the system's resiliency. By allocating backup hospitals to COVID-19 patients, only 37% of severe patients were lost, and this rate fell to less than 5% after establishing field hospitals. Moreover, medical students and field hospitals curbed the costs and increased the satisfaction rate of nurses by 75%. Finally, the system was protected from failure by increasing the conservatism level. With a 2% growth in the price of robustness, the system saved 13%.

1. Introduction

Infectious disease outbreak is a major global challenge leading to unpredictable disruptions in societies' economics, health, and wellbeing [1–3]. A vivid example of a disastrous disease outbreak is COVID-19 that as of August 2022 has incurred 6.4 million fatalities worldwide [4]. This infectious disease was reported for the first time in China (December 2019) and declared a global pandemic by World Health Organization (WHO) on March 11, 2020 [5]. COVID-19 has also led to other illnesses and fatalities due to postponed or canceled treatments for other diseases. In a German study, around a 20% reduction in hospital beds and operating room capacity was reported due to increased allocation of resources to COVID-19 patients [6]. The study also noted a significant drop in the number of elective surgical procedures in the emergency rooms as well as outpatient treatments in oncology clinics. Interrupted treatment delivery is expected to spawn treatment failure and elevated tumor relapse rates [7]. Due to high disease prevalence, the number of people needing hospital services has considerably overrun health service capacity, leading to collapses in both healthcare and economic systems in many nations such as India, Tunisia, and Brazil [8–10].

Healthcare systems are not fully prepared to cope with massive-scale disasters such as COVID-19 [11,12]. A primary reason is that their available resources are limited both in quantity and specialty to cope with the disease. Moreover, during the crisis, there is always a significant risk of decreased human resources

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(mainly nurses) caused by their infections, deaths, or even quitting their jobs due to the disease risk [13,14]. The WHO has warned that the severe global nursing shortage risks the lives of COVID-19 patients [15]. WHO has also warned of shortages in personal protective equipment (PPE) caused by rising demand, panic-buying, hoarding, and misuse [16]. Due to a significant mismatch between available resources and COVID-19 treatment under the infeasibility of expanding available capacity, healthcare systems have exploited “alternative” resources to augment their current capacities. Alternative hospitals, such as backup and field hospitals, have been enlisted to address the capacity challenge during the COVID-19 crisis in many countries. For example, during the first wave of the pandemic in Canada, the Jewish General Hospital in Montreal was assigned as a backup hospital, and the Windsor Regional Health Network opened a field hospital to treat COVID-19 patients [17]. In Denmark, medical students and retired doctors were summoned to help treat COVID-19 patients [18]. One strategy to offset the shortage of nurses is to increase their allocated patients, leading to their dissatisfaction and reduced quality of care provision [19]. There has also been a notable increase in demand for ventilators, especially for severe COVID-19 patients, and some countries, such as the United States, have reported shortages of ventilators for severe patients [20]. The mayor of New York and the Deputy Minister of Indonesia’s State-Owned Enterprises have asked the billionaire entrepreneur, Elon Musk, to use Tesla manufacturing facilities to produce ventilators for COVID-19 patients [21,22]. Finally, quality of care is of critical importance toward patient satisfaction and, thus, the effectiveness of patient outcomes [23], and there is a need for mechanisms to ensure that hospital services are readily accessible to COVID-19 patients [24].

Unfortunately, alternative resources offer a limited surge in capacity and incur tremendous costs to healthcare systems. Moreover, uncertainties associated with various aspects of the pandemic – especially its generated demand – make augmentation of alternative resources to the current system a nontrivial problem. These challenges require optimal allocation and utilization of merged resources that must perform in a resilient and robust fashion to tackle demand fluctuations. Healthcare systems aim to deploy these limited resources with minimal cost while meeting demand in the best possible ways. To fill this gap, this study proposes resilient, robust mixed-integer linear programming to optimize the usage of both available and alternative resources during COVID-19. In particular, our multi-objective model minimizes the cost of utilizing resources while maximizing satisfaction among nurses and patients.

Inspired by real practice, the proposed model makes the following considerations. First, to cope with the emergency situation caused by the pandemic, we designate three types of healthcare centers (HCs), namely, available, backup, and field hospitals, each with a certain level of resources (i.e., ward bed, Intensive care unit (ICU) bed, ventilator, and nurse), which are limited. Second, two types of nurses are considered based on skill level (i.e., expert and student), which can fluctuate (because they may become infected by COVID-19 or quit the job). Third, in our study, COVID-19 patients are divided into three groups based on the severity of their illness (i.e., severe, moderate, and outpatients). Patients in each group require certain resources for treatment. Forth, a coverage distance is also considered for allocating COVID-19 patients to medical centers based on patient type. Fifth, the role of uncertainty in the number of patients (demand) and its impact on the system is thoroughly analyzed. Furthermore, different types of PPE are considered in the model. Finally, the pandemic’s impact on both the price and number of ventilators that a hospital can purchase is addressed. This model enables us to investigate the tradeoff between system cost versus the satisfaction levels of nurses and COVID-19 patients. Resilience, robustness, and alternative resourcing all mitigate failure risk in a healthcare system. Therefore, we extensively analyze the resilience and robustness of optimal solutions, as well as their dependency on alternative resources.

We apply our proposed model to a case study in the city of Tehran, the capital of Iran – one of the world’s most afflicted cities with COVID-19 [25]. Here, both officials and hospitals had reported critical shortages of medical personnel, ward beds, and intensive care beds during the pandemic. The COVID-19 crisis led to reports indicating that nurses have been experiencing posttraumatic stress disorder due to extended overtime shifts and the constant threat of virus exposure [25,26]. Our proposed model is general enough to be applied to any geographical region across the globe. To this end, we focus on the general results that offer direct and actionable insights regarding the role of alternative care resources. To further improve the generalizability of the provided insights, we conducted an extensive sensitivity analysis regarding the key model parameters. The study makes the following four contributions. First, it proposes a general analytical framework that can be utilized by healthcare decision-makers (DMs) in any geographical region to jointly optimize the utilization of resources as well as the satisfaction levels of patients and nurses. Second, it investigates the effect of uncertainty regarding both the number of nurses and the number of patients in a healthcare system. This enables us to investigate the tradeoff between the cost of the system versus the satisfaction rates of nurses and COVID-19 patients. Third, it demonstrates the importance of alternative resources in a healthcare system during challenging periods in a pandemic, specifically scrutinizing the impact of ventilator supply restrictions on healthcare system performance. Fourth, it provides an extensive analysis of both the resilience and robustness of the optimal solutions and their dependency on alternative resources.

The paper is structured as follows. Section 2 provides a review of related literature. In Section 3, we describe the modeling approach and assumptions. Section 4 details the solution methodology. In Section 5, we apply the model to a real-life case study. Section 6 discusses managerial insights, and Section 7 concludes the paper and outlines future research.

2. Literature review

Epidemiological modeling, ICU capacity and ventilator inventory management, high-quality masking, the situation in global supply chains (SCs) during COVID-19, and plasma donations during the pandemic are all identified as different aspects of COVID-19 [26]. However, the rise in the number of COVID-19 patients, the surge in the percentage of patients with severe illness in hospitals, the shortage of nurses, and limited budgets are the main problems of COVID-19 that need to be managed precisely. For a better illustration of the current research gap and the importance of this study, the literature review is divided into the following subsections: Section 2.1 examines studies that have highlighted the resources required for treating COVID-19 patients, and Section 2.2 is dedicated to resilience in the healthcare system.

2.1. Resources required for treating COVID-19 patients

One of the most important strategies for dealing with pandemic outbreaks is to manage and control medical centers’ capacity under high demand fluctuations [27]. When demand (e.g., the need for care) exceeds supply (e.g., human resources, materials, equipment, etc.), hospital wait times often mount under a lack of planning, coordination, and communication in delivering care [28]. Govindan et al. [29] developed a practical decision-support system with demand management in the healthcare SC to segment the COVID-19 propagation chain, reduce stress in society, and mitigate healthcare SC disruptions. In [30], the satisfaction of all potential demand for each clinic during the pandemic was computed using an estimated population served by a particular clinic. Burdett et al. [31] considered mixed-integer linear programming by designating different patient types to analyze resource and hospital capacity needs for maximizing the number of cured patients. Burnweit and Stylianos [32] studied the need for establishing field hospitals, their capacities and access during the crisis for urgent patient treatment, as well as the dismantling or reuse of field hospitals post-crisis. In California, Caunhye and Nie [33] proposed a location-allocation model for medical centers to plan disaster responses based on a real case study. Liu et al. [34] presented a model for optimizing the location of medical centers and the allocation of medical services to reduce costs and maximize the number of patients rescued in emergencies. Results show that establishing temporary medical centers near crisis areas yields improvements in the productivity of medical services during the crisis. Acar and Kaya [35] studied a network design for location-relocation decisions of mobile hospitals using a two-stage random programming model under different scenarios. Oksuz and Satoglu [36] analyzed the location of existing hospitals versus the number and capacities of temporary medical centers during a crisis, computing the required number of temporary medical centers, their locations, and their added hospital capacities.

Direct contact among nurses and patients may result in high rates of infection among nurses, leading to reductions in the number of nurses treating COVID-19 patients. Abas et al. [37] applied a dynamic system simulation to predict the number of required nurses and medical staff. He et al. [38] developed an integrated nurse staffing-scheduling model under patient-demand uncertainty using two-stage stochastic programming that targets understaffing-risk control. In [39], the authors proposed a model that mixes linear optimization with simulation to estimate the number of required nurses, medical staff, and emergency beds. Naderi et al. [40] developed a model for the Toronto General Hospital (TGH) that captures the scheduling of all critical operating room resources and their dynamics. Their model helps the TGH managers to determine the right number and selection of resources on a daily basis, as well as the day's optimal overtime. Moosavi et al. [41] examined a staff scheduling problem for residential care during a pandemic, advising that residential care facilities raise staffing capacity for future pandemics.

About 15% of COVID-19 patients develop severe pneumonia, nearly 6% needing a ventilator [42]. Ventilator pricing has soared from $25,000 to $45,000 due to the significant increase in demand during the COVID-19 outbreak [43]. Most European health systems encountered ventilator shortages; e.g., Italy had access to less than 25% of the ventilators needed [44]. Wells et al. [45] projected the number of ventilators required in the USA at the COVID-19 peak. Iyengar et al. [46] explained the role of ventilators in treating COVID-19 patients, the main reasons for their shortage, and proposed several solutions such as enlisting 3D printers. In a study in Texas, USA, Huang et al. [47] proposed a method for optimizing stockpiles of mechanical ventilators vital for sustaining hospitalized influenza patients facing respiratory failure. The researchers considered mild, moderate, and severe patients in their case study. Mehrotra et al. [48] presented a model for allocation and possible reallocation of the available national ventilator stockpile with computational results estimating each state's shortfall of ventilators under various future demand scenarios.

2.2. Healthcare systems resilience

During COVID-19, many components of SCs became slow or even dysfunctional for uncertain durations. Therefore, various studies investigated SC challenges during COVID-19 under topics such as modeling viable SCs, ripple effects of SCs, and reconfigurable SCs [49]. Motivated by the COVID-19 outbreak, Ivanov [50] defined a viable SC as one that can maintain itself in a changing environment by redesigning its structures and replanning performance with long-term impacts. Studying the viability of SCs (especially multi-echelon SCs) is becoming an important topic, mainly because of their complicated structures, making them vulnerable to extraordinary disruptions at local nodes under ripple effects [51]. Rozhkov et al. [52] demonstrated the impact of the COVID-19 pandemic by studying adaptive operational decisions in different network design structures before and during the pandemic. They also investigated the role of preparedness and recovery decisions in SC operations. Sawik [53] proposed scenario-based stochastic models for optimizing SC operations under ripple effects that incur simultaneous disruptions in supply, demand, and logistics across the entire SC. He compared the resilient solutions for the resilient supply portfolios versus non-resilient solutions having no recovery resources available.

A mathematical model was developed to identify the interactive influence of SC disruptions and infectious disease dynamics via coupled production and disease networks [54]. Shang et al. [55] analyzed a supply network configuration problem and proposed a new robust model for coping with uncertain demand and delivery time. In [56], a novel perspective on SC resilience was introduced for considering resistance to extraordinary disruptions at the scale of viability. In this study, viability formation through dynamic game-theoretic modeling of a biological system was demonstrated that resembles an intertwined supply network.

The poor SC management during COVID-19 waves has resulted in a demand-supply mismatch. Specifically, an increase in the number of patients (i.e., demand) along with the reduction and shortage of active nurses can trigger massive disruptions in the healthcare systems. In this study, such disruptions include shortages of nurses, ward beds, ICU beds, ventilators, and qualified PPEs. We also define disruption as an increased ratio of patients per nurse and the rate of non-admitted COVID-19 patients.

To deal with sudden disruptions and lack of knowledge during a pandemic with disastrous scales such as COVID-19, we need a resilient healthcare system that can: (1) ensure a comprehensive response considering health, social, and economic considerations simultaneously, (2) adjust capacity to meet patient demands, (3) preserve functions and resources to maintain routine and acute care, and (4) curb vulnerability to catastrophic losses in a community's economy and wellbeing [57]. To this end, Hanefeld et al. [58] examined important aspects of health system resilience during the 2017 Ebola outbreak in Africa. They introduced health information systems, funding, and the health workforce as the three main resilience aspects of hospitals. Yu et al. [59] studied the factors impacting nurse resilience, indicating that nurse satisfaction correlates with resilience. This is because improving resilience among nurses would decrease their burnout and improve their function. Fallah-Aliabadi et al. [60] evaluated the indicators for determining the levels of hospital resilience. They identified a hospital's facility as constructive resilience, lifelines as infrastructure resilience, and services as administrative resilience, all playing a significant role in hospital performance during disasters. The impact of the COVID-19 pandemic on SC resilience was investigated in [61]. Results demonstrate agility, collaboration, digital preparedness, flexible redundancy, human resource management, contingency planning, and transparency as seven factors for building resilience in intertwined SCs during a pandemic outbreak.

Table 1 compares this research with the most relevant literature regarding location-allocation resilient healthcare network design for the COVID-19 pandemic. Poor management during a surge in the number of patients and a reduction in the number of active nurses can massively disrupt any healthcare system. We consider

Table 1
An overview of related studies.

Refs.	Problem type	Hierarchical level	Location	Planning horizon	Objective function	Time period	Solution approach	Real case	Uncertainty	Demand differentiation	Coverage distance	PPE	Disaster/ Disruption	Medical Staff	Field hospital	Bed differ-entiation	Resilience	Other feature
[40]	Operations research	Decomposition design	Yes	Operational	Min fixed and over time cost	Multi-period	Benders de-composition	Yes	Yes	Yes	No	No	No	No	No	Yes	No	Healthcare operations
[39]	Operations research	Integrated SC	Yes	Strategic	Min cost & Max the number of discharged patients	Multi-period	simulation	Yes	Demand	Yes	No	No	No	Yes	Yes	Yes	No	-
[36]	Operations research	Integrated SC	Yes	operational	Min cost	Multi-period	Stochastic	Yes	Supply	Yes	Yes	No	Yes	No	Yes	Yes	No	Mass casualty events
[60]	Public health	-	No	-	-	-	-	No	No	No	No	No	Yes	No	No	No	Yes	Structural and non-structural systems
[48]	Operations research	SC	Yes	operational	Min Cost	Multi-period	Stochastic	Yes	No	Yes	No	No	No	No	No	No	No	COVID-19-ventilator
[59]	Review methods	-	-	-	aims to identify personal and work-related factors of nurse resilience.	-	-	-	-	-	-	-	-	-	-	-	Yes	
[58]	Data collection	-	No	-	-	No	No	Yes	No	No	No	No	No	No	No	No	Yes	financial crisis
[37]	Health System	System dynamics approach	No	-	providing adequate nursing patient care	Multi-period	Statistical analysis	Yes	No	No	No	No	No	No	No	No	No	Nurse Workforce
[33]	Operations research	Integrated SC	Yes	operational	Min total weighted time to transport (1) casualties for treatment and (2) patients for treatment continuation.	Single	Stochastic	Yes	Demand	Yes	No	No	No	No	No	No	No	-
[31]	Operations research	Integrated SC	No	Operational	Max the patients treated	Multi-period	Data-collection	Yes	No	Yes	No	No	No	Yes	No	No	No	Book Keeping
[32]	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Not men-tioned	Data collection	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes		-
This research	Operations research	Network design	Yes	Tactical	Min cost, Max satisfaction of medical staff, and COVID-19 patients	Multi Period	Robust	Yes	Demand	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	For COVID-19

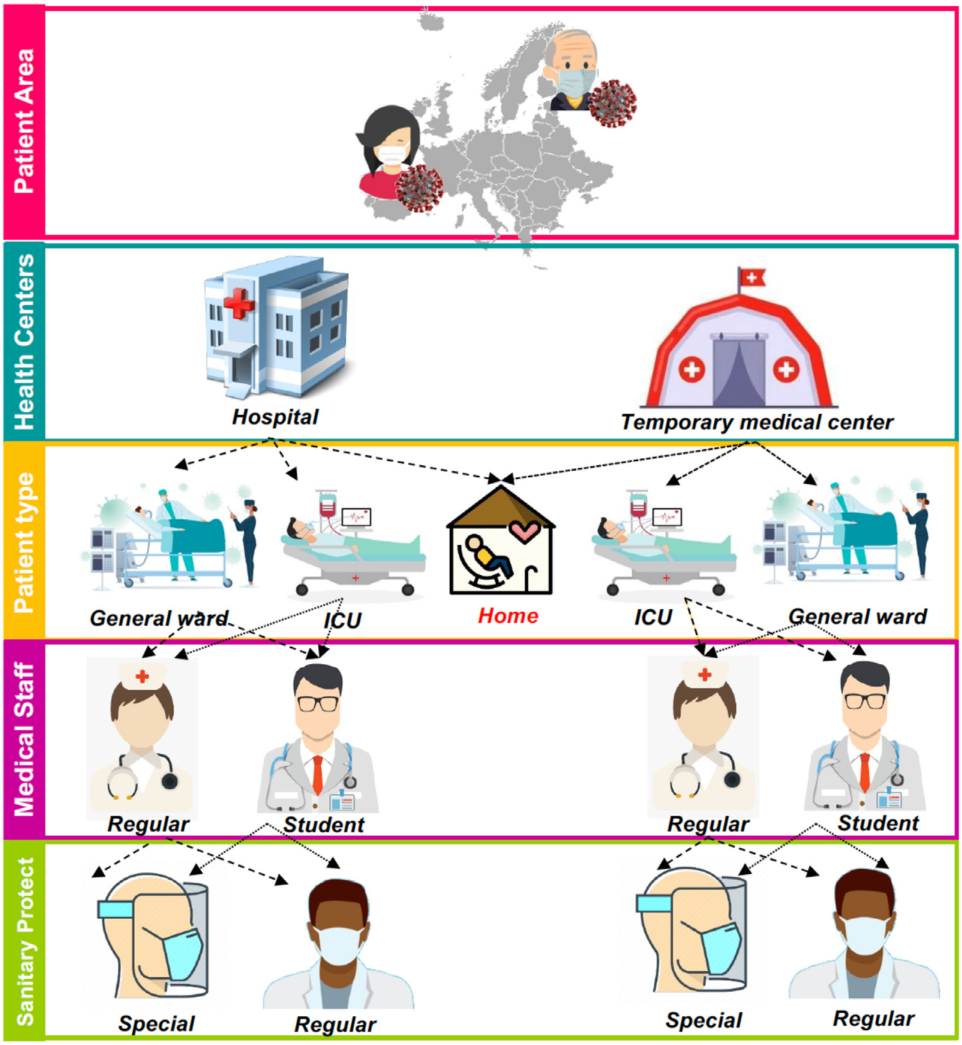

Fig. 1. The configuration of the proposed network.

disruption in terms of shortages of the key treatment resources such as ward beds, ICU beds, ventilators, and qualified PPEs, an increased ratio of patients per nurse, or the lost (i.e., non-admitted) COVID-19 patients. This study is the first to boost health system resilience and reliability by enlisting backup or field hospitals, student nurses, and new ventilators and assesses the system's robustness under demand fluctuations. Moreover, the impact of a reduced number of active nurses on the system cost and patient satisfaction is investigated. The influence of both field and backup hospitals, as well as the number of nurses on a health system cost, work overload, hospital occupancy, and satisfaction rates of COVID-19 patients and nurses, are thoroughly scrutinized here. Until now, the role of variation in PPEs, bed differentiation, distance limitation for COVID-19 patients, and some key aspects of a healthcare system, such as demand differentiation, disruption, and uncertainty, have eluded simultaneous treatment.

3. Problem description

Consider a network of HCs treating COVID-19 patients located in different geographical regions $i \in \{1, 2, \ldots, I\}$ in each period $t \in \{1, 2, \ldots, T\}$ during the pandemic. HCs are equipped with vital resources such as regular or special PPE, and regular or student nurses. Fig. 1 illustrates the proposed network.

Patient types: Inspired by [62] that has designated five different COVID-19 patient types (asymptomatic and mild patients were considered outpatients, patients requiring hospitalization and supplemental oxygen were considered moderate, and severe and critical patients required ICU beds), the patients in our study are categorized into three classes: *severe* (p_1), *moderate* (p_2), and *outpatients* (p_3). Since the disease among severe patients can be fatal, they require more advanced treatment, including ICU and ventilator support. Moderate patients may be treated in the general ward and may require supplemental oxygen. Finally, outpatients with mild clinical symptoms are examined, prescribed simple treatments, and sent back home. The patient type also involves a distance limit between the patient area and HCs. The idea is to prevent patient transfer to distant HCs. Therefore, patients with higher illness severity can be prioritized to access treatment through nearby HCs.

HC capacity types: To handle demand uncertainty, we consider three different HCs. The first type includes hospitals that only admit COVID-19 patients that we call *available hospitals*. The standard rate of hospital occupancy in available hospitals has been found to run at 85% [39]. Accordingly, we assume that a new HC should be considered for COVID-19 patients when at least 85% of beds, nurses, or ventilators in any available hospitals are occupied. The second type includes *backup hospitals*, which are clean hospitals, and are not allocated to COVID-19 at the onset of the planning

Table 2
List of notations and decision variables.

Sets	
i	Set of patient areas, $i = 1, 2, \ldots, I$
j	Set of HCs, $j = 1, 2, \ldots, J$
p	Type (severity) of patient; $p \in \{p_1, p_2, p_3\}$
n	Type of nurse; $n \in \{n_1, n_2\}$
u	Type of PPE; $u \in \{u_1, u_2\}$
t	Set of periods, $t = \{1, 2, \ldots, T\}$
Parameters	
B_j	Number of general ward beds in HC_j
$BICU_j$	Number of ICU beds in HC_j
V_j	Number of ventilators in HC_j
N_{jn}	Number of nurse type n in HC_j
$cost_j$	Set up cost for HC_j
H_{pnu}	Cost of admitting patient type p serviced by nurse type n using PPE type u
LC	Cost of refusing a patient
$SalA_{nu}$	Cost of overload working for nurse type n working with PPE type u
$CostV$	Cost of adding a new ventilator to an HC
d_{ij}	Distance from patient area i to HC_j
dp_i	Distance from patient area i to the closest HC
Dis_p	Distance limit for patient type p arrive at an HC
Dem_{ipt}	Number of newly infected patient type p in area i and in period t
Cap	Occupancy rate of an HC
θ	Maximum number of patients that each nurse can serve in a regular shift
ϑ	Maximum number of patients that each nurse can serve as overload
φ	A very large number
α_u	Functionality score of the u-type PPE
β_n	Satisfaction rate of patients serviced by nurse type n
σ_n	Dissatisfaction rate of nurse type n for overload working
ω_q	The weight of each objective function
q	The indicator of each objective function
Γ	Level of conservatism
Decision variables	
Q_{ijpnut}	Number of p-type patients from area i assigned to HC_j served by nurse type n with PPE type u in period t
Inv_{jpnt}	Number of p-type patients admitted to HC_j to be served by nurse type n in period t
Los_{pt}	Number of p-type patients who are not admitted by HC_j in period t
Re_{jpt}	Number of p-type patients discharged from HC_j in period t
NP_{jnut}	Number of patients that nurse n at HC_j should serve applying PPE u in period t
ANP_{jnut}	Number of extra patients that nurse n should serve in HC_j applying PPE u in period t
AV_j	Number of additional ventilators that can be added to HC_j
$y_j \in \{0, 1\}$	1, if HC_j is open, and 0, otherwise
$X_{ijpt} \in \{0, 1\}$	1, if p-type patient in area i is assigned to HC_j, in period t

horizon. Instead, they can be utilized for COVID-19 treatment only when there is a shortage of facilities in the available hospitals. Finally, the third type includes *field hospitals* not yet established but can be built for COVID-19 patients in case of capacity shortage in the other HC types.

Hospital beds, workforce, and PPE: All HCs are equipped with two types of beds. The first is available in the general ward, assignable to moderate patients, while the second is available in the ICU for severe patients. Moreover, our study assumes that when the number of severe patients exceeds that of available ventilators, a new ventilator can be added to the HC. However, the total number of ventilators cannot exceed that of ICU beds in the HC.

One of the challenges faced by HCs during the COVID-19 outbreak was maintaining a balance between the capacity of frontline health workers and demand. When the ratio of patients per nurse exceeds a standard ratio [39], nurses may suffer work overload. Moreover, a proportion of nurses may not be able to serve, either because of being infected through patient contact or because they decide to quit the job fearing threats in the COVID-19 work environment. To tackle the reduced number of active nurses [13,14,18], we consider the possibility of employing nursing students in our model. Finally, we assume that nurses can be equipped with two types of PPEs that differ mainly in protection rates and costs. Special PPE reduces the likelihood of infection; thus, nurse satisfaction rates would increase. An ideal scenario equips all nurses with the special PPE, yet this may not be feasible under high demand for PPE.

3.1. Decision variables and modeling assumptions

Table 2 summarizes the list of all notations and decision variables used in our model. We develop a multi-objective optimization model to jointly: (i) minimize the total cost of the healthcare network, (ii) maximize the satisfaction rate of patients, and (iii) maximize the satisfaction rate of nurses.

The following assumptions are considered in our model:

- A list of potential locations to establish a new HC is given.
- HCs are allowed to not admit a patient in case of a shortage of beds, ventilators, or nurses.
- Hospitalization duration depends on illness severity.
- For model tractability, seven discharge periods are considered as the planning horizon, each period marking four days.
- Based on expert opinion, severe and moderate patients must be hospitalized for three periods (i.e., 12 days) and two periods (i.e., 8 days), respectively.
- A distance limitation applies between a patient's area and HCs.

3.2. Model formulation

The first objective function, indicated by G_1, minimizes the total network cost. This objective function can be formulated as the following mixed-integer linear program:

$$\min G_1 = \underbrace{\sum_j cost_j y_j}_{\text{Fixed cost}} + \underbrace{\sum_j \sum_p \sum_n \sum_u \sum_t H_{pnu} Q_{ijpnut}}_{\text{Service cost for COVID-19 patients}} + \underbrace{\sum_p \sum_t LCLos_{pt}}_{\text{Cost of not admitting patients}} + \underbrace{\sum_j \sum_n \sum_u \sum_t SalA_{nu} ANP_{jnut}}_{\text{Cost of overload}} + \underbrace{\sum_j CostVAV_j}_{\text{Cost of adding new ventilator}} \tag{1}$$

Accordingly, the total cost of the network in Eq. (1) includes the fixed cost for establishing field hospitals, the cost of admitting and serving COVID-19 patients in the HCs, the cost of not admitting COVID-19 patients (shortage cost), the cost of patient overload on nurses, and the cost of adding new ventilators to an HC. The first cost term is zero for available and backup hospitals since they are already established and equipped at the beginning of the planning horizon.

The second objective function, denoted by G_2, maximizes the satisfaction rate among patients:

$$\max G_2 = \frac{1}{2}\left[\underbrace{\sum_i \sum_j \sum_p \sum_n \sum_u \sum_t \beta_n Q_{ijpnut}}_{\text{Satisfaction due to service}} + \underbrace{\sum_i \sum_j \sum_p \sum_n \sum_u \sum_t (dp_i/d_{ij}) Q_{ijpnut}}_{\text{Satisfaction due to distance}}\right] \tag{2}$$

Note that the first term in Eq. (2) reflects the satisfaction of patients serviced by different types of nurses, while the second term is the patient satisfaction in visiting a closer HC. We define $\frac{dp_i}{d_{ij}} \le 1$, where the numerator is the distance to the nearest HC, and the denominator is that to one having available capacity. Ideally, $d_{ij} = dp_i$, where the nearest HC has available capacity to admit the patient.

Finally, the third objective function maximizes the satisfaction of nurses indicated by G_3:

$$\max G_3 = \underbrace{\sum_j \sum_n \sum_u \sum_t N_{jn} NP_{jnut} \alpha_u}_{\text{Satisfaction due to PPE usage}} - \underbrace{\sum_j \sum_n \sum_u \sum_t N_{jn} ANP_{jnut} \sigma_n}_{\text{Dissatisfaction due to overload working}} \tag{3}$$

where the first term refers to the functionality score associated with using PPE during work, while the second term tracks the dissatisfaction rate of nurses because of work overload.

The number of severe patients admitted to an HC cannot exceed the total number of available ventilators:

$$\sum_i \sum_n \sum_u Q_{ij(p=1)nut} \le V_j + AV_j \quad \forall j,\ \ p=1,\ \ t \tag{4}$$

The total number of severe and moderate patients admitted to an HC cannot exceed that of available beds:

$$\sum_i \sum_{p \backslash p3} \sum_n \sum_u Q_{ijpnut} \le B_j \quad \forall j,\ \ t \tag{5}$$

(resp. ϑ):

$$NP_{jnut} \le \theta y_j \quad \forall j,\ \ n, u,\ \ t \tag{7}$$

$$ANP_{jnut} \le \vartheta y_j \quad \forall j,\ \ n, u,\ \ t \tag{8}$$

A p-type patient is never assigned to an HC farther away than the p-type patient distance limit Dis_p:

$$X_{ijpt} d_{ij} \le Dis_p \quad \forall i,\ \ j, p,\ \ t \tag{9}$$

The number of patients in each period equals that of remaining COVID-19 patients from the prior period, plus newly admitted patients minus those discharged:

$$\sum_n Inv_{jpnt} = \sum_n Inv_{jpn(t-1)} + \sum_i \sum_n \sum_u Q_{ijpnut} - Re_{jpt} \quad \forall j, p, t \tag{10}$$

As discussed previously, hospitalization duration depends on the illness severity. Treatment takes three periods for severe patients (p_1) and two periods for moderate patients (p_2). Outpatients (p_3) are never hospitalized:

$$Re_{jpt|p=1} = \sum_i \sum_n \sum_u Q_{ijpnu(t-3)|p=1} \quad \forall j, t \tag{11}$$

$$Re_{jpt|p=2} = \sum_i \sum_n \sum_u Q_{ijpnu(t-2)|p=2} \quad \forall j, t \tag{12}$$

$$Re_{jpt|p=3} = \sum_i \sum_n \sum_u Q_{ijpnut|p=3} \quad \forall j, t \tag{13}$$

The number of severe patients in an HC cannot exceed the total number of available ventilators in each period:

$$\sum_n Inv_{j(p=1)nt} \le V_j + AV_j \quad \forall j, (p=1), t \tag{14}$$

The total number of severe and moderate patients cannot exceed that of beds in an HC in any period t:

$$\sum_n Inv_{jp \backslash p3nt} \le B_j \quad \forall j,\ \ (p=1,2),\ \ t \tag{15}$$

The number of patients in a period cannot exceed that of patients served by available nurses in a period:

$$\sum_n Inv_{jpnt} \le \sum_n \sum_u N_{jn}(NP_{jnut} + ANP_{jnut}) \quad \forall j, p, t \tag{16}$$

The shortage equation calculates the number of patients who cannot be admitted to HCs in period t. This equals the total number of patients admitted to an HC subtracted from the total demand:

$$Los_{pt} = \sum_i Dem_{ipt} - \sum_i \sum_j \sum_n \sum_u Q_{ijpnut} \quad \forall\ p, t \tag{17}$$

A new HC can be allocated to newly infected patients when an existing HC is full. This occurs when an existing HC is occupied beyond its determined occupancy rate of beds (B_j), ventilators (V_j), or nurses ($N_{jn}\theta$):

$$y_j \le \left(Cap - \max\left\{\frac{\overline{\sum_j \sum_{p \backslash p3} \sum_n Inv_{jpnt}}}{\sum_j B_j}, \frac{\overline{\sum_j \sum_{p \backslash p3} \sum_n \sum_u Inv_{jpnt} + \sum_i \sum_j \sum_{p=3} \sum_n \sum_u Q_{ij(p=3)nut}}}{\sum_j \sum_n N_{jn}\theta}, \frac{\overline{\sum_j \sum_p \sum_n Inv_{j(p=1)nt}}}{\sum_j V_j}\right\}\right) \quad \forall\ (j>2) \tag{18}$$

Regardless of severity type, the total number of admitted patients in each period cannot exceed the maximum number of patients that a nurse can serve during a regular shift and overload:

$$\sum_i \sum_p Q_{ijpnut} \le N_{jn}\left(NP_{jnut} + ANP_{jnut}\right) \quad \forall j,\ \ n, u, t \tag{6}$$

Given an open HC_j, the maximum number of patients that each nurse can serve in a regular (resp. overload) shift is capped by θ

New COVID-19 patients can be allocated only to an open HC:

$$X_{ijpt} \le y_j, \quad \forall i,\ \ j, p,\ \ t \tag{19}$$

$$\sum_i \sum_n \sum_u Q_{ijpnut} \le \sum_i X_{ijpt}\varphi, \quad \forall\ j, p, t \tag{20}$$

$$\sum_i X_{ijpt} \le 1, \quad \forall\ j, p, t \tag{21}$$

The total number of ventilators per HC cannot exceed the number of ICU beds:

$$AV_j \le \left(BICU_j - V_j\right) y_j, \quad \forall\ j \tag{22}$$

Finally, the available hospitals (i.e., $HC_j\ : j = 1, 2$) are allocated to COVID-19 patients at the onset of the planning horizon. This requires the binding constraints $y_1 = y_2 = 1$. Moreover, to have feasible solutions, we define binary and integer variables in constraint (23) as follows:

$$y_j X_{ijpt} \in \{0, 1\} \textbf{and} \quad y_j = 1 \quad \forall (\ j = 1, 2) Q_{ijpnut}, Inv_{jpnt}, Los_{jpt}, Re_{jpt}, NP_{jnut}, ANP_{jnut} \ge 0 \quad \forall i, j, p, n, u, t \tag{23}$$

4. Solution methodology

This section discusses the methodology for solving the multi-objective optimization model described in Section 3.2. Note that constraint (18) is nonlinear; therefore, its transformation to a linear form will be discussed in Section 4.1. We then elaborate on converting the three-objective model into a single-objective optimization counterpart in Section 4.2. Finally, in Section 4.3, we develop a robust optimization approach to cope with the uncertainty in system parameters.

4.1. Linearization

To linearize constraint (18), we use an approach proposed by [63], with details in Appendix A. For the linearization, we define:

$$y_j \le 1 - (Cap - R_s) \tag{24}$$

where y_j is a binary variable giving permission to establish or assign a new hospital, R_s is a continuous variable, and Cap is the maximum occupation rate of hospitals in pre-emergency conditions.

Eqs. (25)–(27) reflect the average occupancy rates of available hospitals in terms of beds, nurses, and ventilators as follows:

$$R = \frac{\overline{\sum_j \sum_{p\backslash p3} \sum_n Inv_{jpnt}}}{\sum_j B_j} \tag{25}$$

$$R' = \frac{\overline{\sum_j \sum_{p\backslash p3} \sum_n \sum_u Inv_{jpnt} + \sum_i \sum_j \sum_{p=3} \sum_n \sum_u Q_{ij(p=3)nut}}}{\sum_j \sum_n N_{jn}\theta} \tag{26}$$

$$R'' = \frac{\overline{\sum_j \sum_p \sum_n Inv_{j(p=1)nt}}}{\sum_j V_j} \tag{27}$$

The linearization of Eq. (18) focuses on delaying establishment of a new hospital until the average occupancy rate of at least one resource reaches the determined Cap. Accordingly, if each of the Eqs. (25)–(27) equals or exceeds Cap, the model is allowed to allocate a new hospital to the COVID-19 patients. To do so, consider the following equations:

$$R_s = K + K' + K'' \tag{28}$$

$$K \le R \tag{29}$$

$$K \le \varphi L \tag{30}$$

$$K \ge R - \ \varphi(1 - L) \tag{31}$$

$$K' \le R' \tag{32}$$

$$K' \le \varphi L' \tag{33}$$

$$K' \ge R' - \ \varphi\left(1 - L'\right) \tag{34}$$

$$K'' \le R'' \tag{35}$$

$$K'' \le \varphi L'' \tag{36}$$

$$K'' \ge R'' - \ \varphi\left(1 - L''\right) \tag{37}$$

$$L + L' + L'' \le 1 \tag{38}$$

As the whole system tries to reduce the shortage, R_s mirrors the value of the resource having more capacity occupation, thus permitting the assignment or establishment of new hospitals. For instance, when the value $R_s = 0.9$, then $Cap - R_s < 0$, and $1 - (Cap - R_s) > 1$. Thanks to the linear version of constraint (18), the optimization problem becomes a mixed-integer linear program (MILP) solvable using CPLEX software.

4.2. Converting multi-objective to single-objective model

Many approaches, such as goal-programming, LP-metric, and ε-constraint methods, exist for converting a multi-objective model into a single-objective one [64–66]. All such methods are based on assigning a weight for the importance of each objective before running an optimization algorithm. The Weighted Sum Method is a classic scalarizing technique that converts multi-objective problems into scalar problems by summing all the objective weights. The simplicity of this approach has made it popular. However, one pitfall is its failure to find certain Pareto optimal solutions for a nonconvex objective space [67]. Using this approach, the optimum value of each objective function is evaluated separately as demonstrated by G_1^*, G_2^*, and G_3^*, respectively for the first, second, and third objective function. We next change the model structure to a normalized formulation. In doing so, since the first objective function is minimization while the second and third objective functions are maximization, the terms in the numerator of the second and third objective functions should be converged. The weight of each objective function is shown by $\omega_q (0 \le \omega_q \le 1)$ where q is the indicator of each objective function. At last, the single-objective model can be formulated as follows:

$$Min\ G_4 = \left[\omega_1 \frac{\left(G_1 - G_1^*\right)}{G_1^*} + \omega_2 \frac{\left(G_2^* - G_2\right)}{G_2^*} + \omega_3 \frac{\left(G_3^* - G_3\right)}{G_3^*}\right] \tag{39}$$

such that

$$\omega_1 + \omega_2 + \omega_3 = 1 \tag{40}$$

4.3. Robust optimal solutions

There are uncertainties as to COVID-19 data while predictions of total confirmed cases remain sensitive to underlying parameters. Among possible approaches (i.e., Fuzzy, stochastic, etc.), the robust optimization approach is enlisted since it can manage the uncertainty in our problem per the availability of historical data internal [68]. Moreover, when data are uncertain, robustness introduced by Bertsimas and Sim [69] may control the level of conservatism in finding optimal solutions. For more details, please refer to Appendix B.

In our model, we assume that the number of newly infected patients of each type per period, denoted by $\widetilde{Dem}_{ipt}$, is an uncertain parameter such that $\widetilde{Dem}_{ipt} = [\overline{Dem}_{ipt} - \widehat{Dem}_{ipt}, \ \overline{Dem}_{ipt} + \widehat{Dem}_{ipt}]$ where $\overline{Dem}_{ipt}$ and $\widehat{Dem}_{ipt}$ serve as the nominal value and maximum deviation, respectively. Thus, we can rewrite constraint (17) as follows:

$$Los_{pt} = \sum_i \left(\overline{Dem}_{ipt} + \Gamma'_1 \widehat{Dem}_{ipt}\right) - \sum_i \sum_j \sum_n \sum_u Q_{ijpnut} \quad \forall\ p, t \tag{41}$$

where $\Gamma'_1 \in [0, 1]$ is the uncertainty budget. Finally, we define index ρ, the perturbation level, to investigate the maximum deviation for each demand zone (i.e., $\widehat{Dem}_{ipt}$). Since $0 \le \rho \le 1$, $\widehat{Dem}_{ipt}$ can be calculated as $\rho \times \overline{Dem}_{ipt}$.

5. Illustration of results using a case study

In this study, we are mainly interested in general results, especially with critical insights into real practice. To this end, we applied our model to a case study in Tehran – Iran's capital city, which experienced one of the highest rates of COVID-19 cases and fatalities in the world – to demonstrate the practical application of our proposed model. The proven optimal solutions were found using GAMS 24.8.3 solver CPLEX on a Core i5 PC with 32 GB of RAM. Although the optimality gap of our results in this scale based on real data is zero, to solve large-scale problems with higher model complexity, other approaches such as heuristics and metaheuristics need to be considered.

5.1. A background about the case study

Tehran includes 22 urban areas, each one designated a patient area. During our study (June-August 2020), two hospitals were devoted to COVID-19 patients, while six clean hospitals were deemed backup hospitals. Moreover, 11 potential field hospitals were considered for allocation to COVID-19 patients in case of shortage in the two devoted HCs. Note that to deal with non-COVID cases, only a portion of clean hospitals can be considered as candidate backup hospitals. Fig. 2 shows a geographical view of patient areas 1–22, as well as available hospitals, backup hospitals, and potential locations for the field hospitals. As the COVID-19 pandemic boosted demand, nurse shortages escalated the potential ratio of patients per nurse to 12 [70].

The estimated costs over the treatment epoch for different types of COVID-19 patients as a function of the nurse type and the utilized PPE type are summarized in Table 3.

The number of ward and ICU beds, ventilators, and nurses in each HC and the set-up cost for establishing field hospitals are summarized in Table 4. Two of the HCs are the available hospitals, and six other HCs are backups that will be allocated to COVID-19 patients with no setup cost. Both the overload payments to the nurses and the distance limitations were obtained from Iran's Ministry of Health and Medical Education (MHME) and through consultations with experts. The distance limitations for severe and moderate patients are, respectively, 11,293 and 14,116 meters, with no limitation for outpatients.

Table 3
The cost of treating patients in HCs (IRR 10,000/ unit).

PPE type	Patient type	Nurse type	
		n_1	n_2
u_1	Severe	3800	4100
	Moderate	2000	2300
	Outpatient	500	800
u_2	Severe	4000	4300
	Moderate	2200	2500
	Outpatient	700	1000

To emphasize the critical importance of patient lives, the cost of non-admission (i.e., lost patient) is deemed significantly high. The costs of not admitting a patient and adding a new ventilator to an HC are 330,000 and 200,000 (IRR 10,000/unit), respectively. All distances in our case study were estimated from Google Map (summarized in Appendix C). The value of α_u (i.e., functionality score of the u-type PPE) was obtained from the US Environmental Protection Agency, and σ_n (overload-caused dissatisfaction rate for nurse type n) was obtained from [71]. The value of β_n (patient satisfaction rate served by nurse type n) was obtained from [72]. For a comprehensive analysis of the weight of the three objective values, we considered 16 different scenarios summarized in Appendix D. The standard ratio of patients per nurse during nurses' normal workload was considered equal to eight [39]. However, due to special conditions caused by the COVID-19 pandemic, we used the ratio of 12 during nurses' overload based on [70]. Finally, in this study, the number of newly infected patients at each period was deemed uncertain. Based on the data gathered from MHME, a uniform distribution was identified as the best fit for these data (see Appendix E). Next, we present the results of various analyses we conducted.

5.2. Impact of reduced number of active nurses on the objective functions

As discussed in Section 1, a proportion of nurses are unable to work during the pandemic. Therefore, to protect the system against disruption and to secure reliability, three different plans with 100, 80, and 60% ratios of nurse availability were considered.

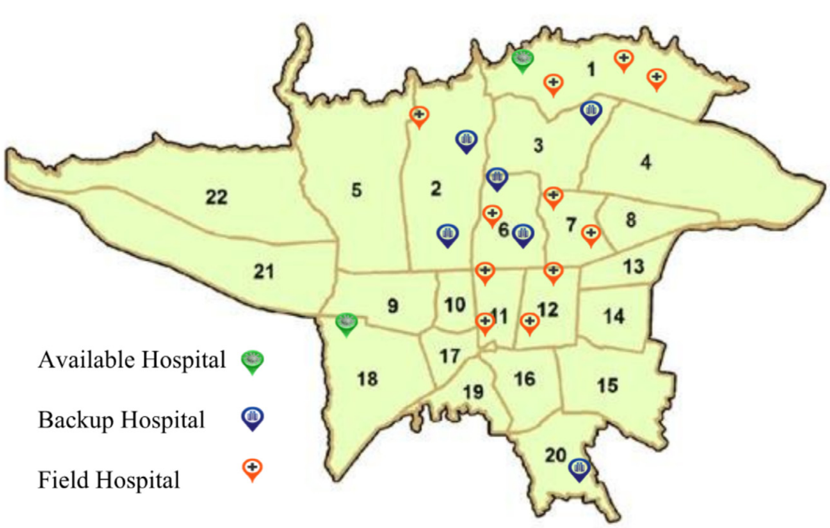

Fig. 2. A geographic view of patient areas, available hospitals, backup hospitals, and field hospitals.

Table 4
Number of B_j, $BICU_j$, V_j, N_{jn}, and set up cost for field hospitals in each HC.

HC type	HC	B_j	$BICU_j$	V_j	HC type	HC	Setup cost (IRR 10,000/ unit)	B_j	$BICU_j$	V_j
Available hospital	1	119	14	11	Field hospital	1	6,580,000	199	16	9
	2	446	30	20		2	7,000,000	190	22	12
						3	7,620,000	181	30	17
						4	6,980,000	169	26	15
Backup hospital	1	240	13	8		5	5,560,000	168	11	7
	2	266	12	7		6	5,300,000	165	10	6
	3	257	12	7		7	4,160,000	108	10	6
	4	240	11	7		8	4,120,000	106	9	6
	5	520	32	18		9	3,700,000	75	11	7
	6	400	14	8		10	2,980,000	59	8	5
						11	2,860,000	53	7	5

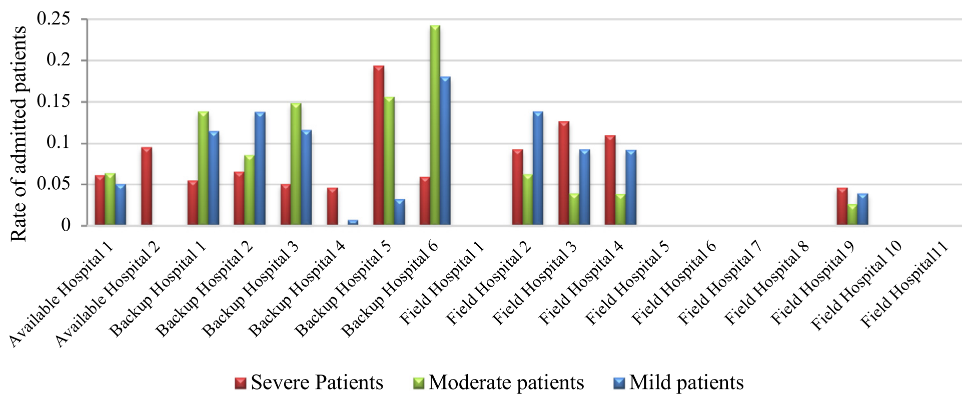

Fig. 3. Rate of admitted patients at each HC.

The obtained values for the first, second, and third objective functions shown by G_1, G_2, and G_3, for varying ω are demonstrated in Appendix D. The results suggest that, in general, a lower ratio of nurse availability worsens the optimal solutions, i.e., increasing healthcare cost and decreasing patient and nurse satisfaction.

5.3. Contribution of each HC

Fig. 3 illustrates the admission rate for all patient types by each HC. The optimal solutions suggest that all backup hospitals were selected, with four out of 11 potential field hospitals (field hospitals 2, 3, 4, and 9) opened for service. Backup hospitals 5 and 6 offered the highest contribution for treating COVID-19 patients, having the most required resources, i.e., nurses, ward beds, ICU beds, and ventilators. We also observe that due to the distance limitation, the moderate patients and outpatients are admitted to other HCs, although available hospital 2 is open at the beginning of the time horizon. Moreover, backup hospital 4 offered the lowest contribution, having fewer resources compared to other backups. For the same reason, field hospital 9 offered the lowest contribution among selected field hospitals. Therefore, under a budget cap or when allocating clean hospitals to treat COVID-19 patients, backup hospital 4 and field hospital 9 can be eliminated from the candidate HCs.

5.4. Contribution of backup and field hospitals to the number of lost patients

To highlight the importance of backup and field hospitals in our analysis, Table 5 illustrates the total number of lost patients (TNLP) under three scenarios: (A) only the available hospitals can admit COVID-19 patients, (B) both available and backup hospitals may admit COVID-19 patients, and (C) all HCs can admit COVID-19 patients. The results are presented as “average reduction” that indicates the proportional reduction in the number of lost patients relative to the worst-case scenario, i.e., scenario (A). Accordingly, under scenario B, although all moderate patients and outpatients are admitted, the admission rate for severe patients is 63%, meaning that a great proportion of severe patients remain unadmitted. Instead, under scenario C, at least 96% of severe patients can be

Table 5
The number of lost patients in scenarios A, B, and C.

Patient type	Scenario	Plan 1		Plan 2		Plan 3	
		TNLP	Average reduction	TNLP	Average reduction	TNLP	Average reduction
Severe	A	438		438		438	
	B	162	63%	162	63%	162	63%
	C	17	96%	17	96%	1	99.8%
Moderate	A	2162		2216		2312	
	B	0	100%	0	100%	0	100%
	C	0	100%	0	100%	0	100%
Outpatient	A	294		960		1584	
	B	0	100%	0	100%	0	100%
	C	0	100%	0	100%	0	100%

Table 6
Occupancy rates under optimal solution ($\omega_1 = 0.4, \omega_2 = 0.3,\ \omega_3 = 0.3$, and $\Gamma = 0$).

Type of HC	ROB	ROV	NAV	RPn_2	RNu_2
Available Hospital 1	92.4%	100%	3	47.5%	10.9%
Available Hospital 2	3.4%	50%	10	100.0%	0.0%
Backup hospital 1	35.4%	100%	5	48.7%	23.0%
Backup hospital 2	36.1%	100%	5	46.8%	12.0%
Backup hospital 3	42%	100%	5	42.0%	8.9%
Backup hospital 4	4.6%	100%	4	100.0%	0.0%
Backup hospital 5	19.2%	100%	14	100.0%	0.0%
Backup hospital 6	56.7%	100%	6	53.8%	22.3%
Field hospital 2	61.6%	100%	10	50.3%	22.9%
Field hospital 3	40.3%	100%	13	53.1%	13.5%
Field hospital 4	15.4%	100%	11	54.7%	14.4%
Field hospital 9	94.7%	100%	4	56.7%	27.8%

*ROB: Rate of occupied beds in the last period, *ROV: Rate of occupied ventilators in the last period, *NAV: Number of added ventilators, *RPn_2: Rate of patients served by nurse n_2, *RNu_2: Rate of nurses using PPE u_2

admitted, indicating a significant improvement in patient coverage. These results confirm that both backup and field hospitals greatly enhance patient coverage.

5.5. Occupation rate of facilities in HCs

Table 6 illustrates the allocated HCs, the rates of occupied beds and ventilators at the end of planning horizon, the total number of added ventilators, the rate of patients served by n_2, and the rate of nurses using u_2 in plan 2 where $\omega_1 = 0.4, \omega_2 = 0.3,\ \omega_3 = 0.3$, and $\Gamma = 0$. These results show the importance and contribution of each hospital in treating COVID-19 patients. Accordingly, by encountering a high number of patients, the rate of occupied ventilators in the final period is 100%, except for one hospital (i.e., available hospital 2). New ventilators should be added to all hospitals to secure the healthcare SC against shortage. Finally, available hospital 2 offers the lowest rate of occupied beds in the final period since it is located in a region far from the patient areas. Instead, field hospital 9, located in patient area 12, yields the highest rate compared to the opened field hospitals. Interestingly, the results also suggest relationships among the rate of occupied beds (in the last period), the rate of patients served by nurse type n_2, and the rate of nurses using PPE type u_2. Accordingly, when the rate of HC-occupied beds in the last period is lower, more regular nurses are allocated to COVID-19 patients and less special PPE is assigned to nurses.

5.6. Impacts of ventilator price and the maximum possible number of added ventilators

Ventilators are crucial for treating severe COVID-19 patients. During the pandemic, the need for this device noticeably increased, thus raising its price. Fig. 4 shows the impact of ventilator price on the total number of those added per HC. Intuitively, as ventilator price rises, the total number of added ventilators falls. For example, by increasing the price from 350,000 to 400,000, our model suggests buying significantly fewer ventilators, instead allocating more HCs to treat COVID-19 patients. Thus, adding new ventilators is not always helpful. DMs should consider the price of ventilators before admitting more severe patients to an HC.

The shortage of ventilators during COVID-19 mostly suffered from issues related to the global SC [46]. Therefore, in many countries, the vital decision about adding extra ventilators is mainly influenced by supply capacity rather than price. Fig. 5 shows the impact of the maximum number of ventilators added to a healthcare system on the rate of lost severe patients. The results demonstrate that increasing the total number of ventilators that can be added to the healthcare system reduces the rate of losing severe patients by more than 80%.

5.7. Increasing resilience through student nurses and field hospitals

Our analyses indicate that the failure to admit all COVID-19 patients is largely caused by capacity limitations regarding nurses. For further investigation, an extra nurse capacity of eight was considered to deliver services to more patients. Accordingly, a total of 16 patients can be allocated per nurse in case of HC nursing shortages. To implement this plan reasonably, a higher dissatisfaction rate and salaries are also considered for nurses working in this situation. Within this analysis, we also investigated the role of student nurses and field hospitals in the healthcare system. Table 7 illustrates the results under four different situations, all based on Plan 2 (i.e., ω_1=0.4, ω_2=0.3, and ω_3=0.3). Situation 1 represents the most resilient case, where both field hospitals and student nurses can be allocated to COVID-19 patients to boost the healthcare system's resilience. Situations 2 and 3 are partially resilient under which, respectively, student nurses and field hospitals are prohibited. Finally, situation 4 represents the least resilient situation, i.e., where no student nurses nor field hospitals can be utilized. These results suggest that by eliminating student nurses,

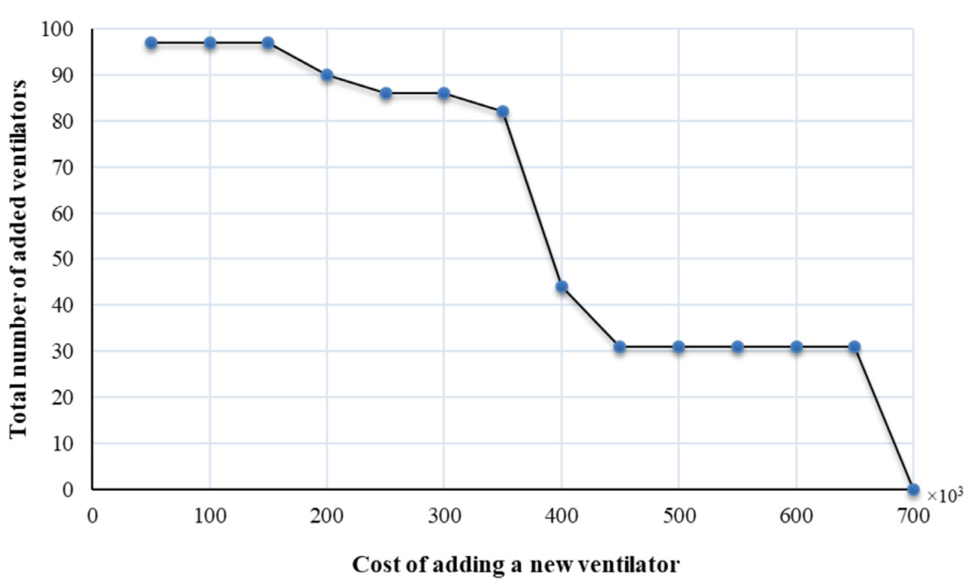

Fig. 4. The impact of the cost of adding a new ventilator and the total number of added ventilators in HCs.

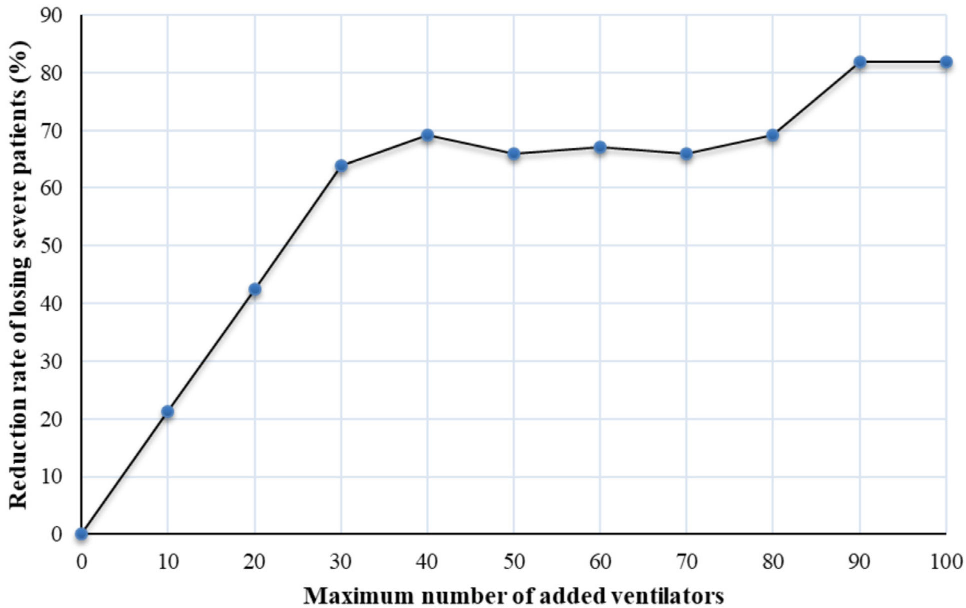

Fig. 5. The impact of the maximum possible number of added ventilators on the rate of lost severe patients.

Table 7
Situation of system with and without field hospitals and medical students.

Situation	Allocated hospitals	G_1	Change in G1 compared to Situation 1	G_2	Change in G2 compared to Situation 1	G_3	Change in G3 compared to Situation 1	NNAP	RUON	APOICU
1	available 1,2; back up 1-6; field hospital 2,3,4,9	71,405,620		7639.41		17,785.6		17 (severe)	2.3%	0.76
2	available 1,2; back up 1-6; field hospital 2to4, 7,8,10	78,777,880	10%	8224.1	7.7%	6,320.0	-64%	1 (severe)	29%	0.74
3	available 1,2; back up 1-6	92,684,940	30%	7675.9	0.5%	13,737.6	-23%	180 (severe)	10%	0.80
4	available 1,2; back up 1-6	94,828,620	33%	7891.17	3.3%	4,423.0	-75%	180 (severe)	55%	0.83

NNAP: Number of non-admitted patients, RUON: Rate of unexpected overload for nurses, APOICU: Average percentage of occupied ICU beds.

more HCs should be allocated. This increases the total healthcare cost while elevating patient satisfaction and decreasing nurse satisfaction. Boosting patient satisfaction occurs by utilizing more regular nurses and enabling access to a closer HC. Naturally, allocating more HCs increases the total number of ICU beds for admitting more severe patients, thus reducing the total number of lost COVID-19 patients. Moreover, through this situation, the satisfaction rate of nurses dramatically plummets due to the high pressure of nurse overload. Dismissing field hospitals for treating COVID-19 patients would also significantly increase the total cost of the healthcare system. In this situation, 80–100% of ICU beds are occupied on average in some periods, escalating fatalities among severe patients. The worst situation is when both student nurses and field hospitals are eliminated from the network (i.e., situation 4). In this situation, the total healthcare cost increases significantly while the satisfaction rate of nurses falls by 75%.

5.8. Impact of the robust optimization

To handle the uncertainty in the number of COVID-19 patients seeking treatment at each period, we applied a robust optimization approach proposed by Bertsimas and Sim [69]. To this end, we considered different values for the uncertainty budget, denoted by Γ, to assess their impacts on each objective function. Here, the extreme value $\Gamma = 0$ reflects a deterministic model, while $\Gamma = 1$ considers the maximum level of demand uncertainty. Fig 6a–c depict the impact of demand uncertainty on each objective value for the six different scenarios in Table 8.

Table 8
The value of ω in each scenario.

Scenario	ω_1	ω_2	ω_3
1	1	0	0
2	0.6	0.2	0.2
3	0.4	0.3	0.3
4	0	0.5	0.5
5	0.4	0.6	0
6	0.4	0	0.6

The results suggest that a higher uncertainty budget increases all three objective values with different rates. This trend is due to allocating more HCs to COVID-19 patients. By utilizing more HCs, patients enjoy access to closer HCs and receive more services from regular nurses, and nurses face fewer patient overloads. Consequently, the total system costs and the satisfaction rates of patients and nurses all rise.

Finally, to study the tradeoff between the level of conservatism and the cost of the robust solution, ten different realizations of the uncertain parameter were performed (refer to Appendix F for details). To characterize the value of the robust solution, we not only computed the total cost of the system (G_1) but also quantified the unexpected penalty value (UPV) for comparison, which captures the reduction in the number of lost patients under the robust solution. Specifically, a higher level of conservatism results in fewer lost patients under the robust solution. Fig. 7 portrays the effect of conservatism level (or uncertainty budget Γ) on total system cost (i.e., G_1) and UPV for deterministic and robust solutions.

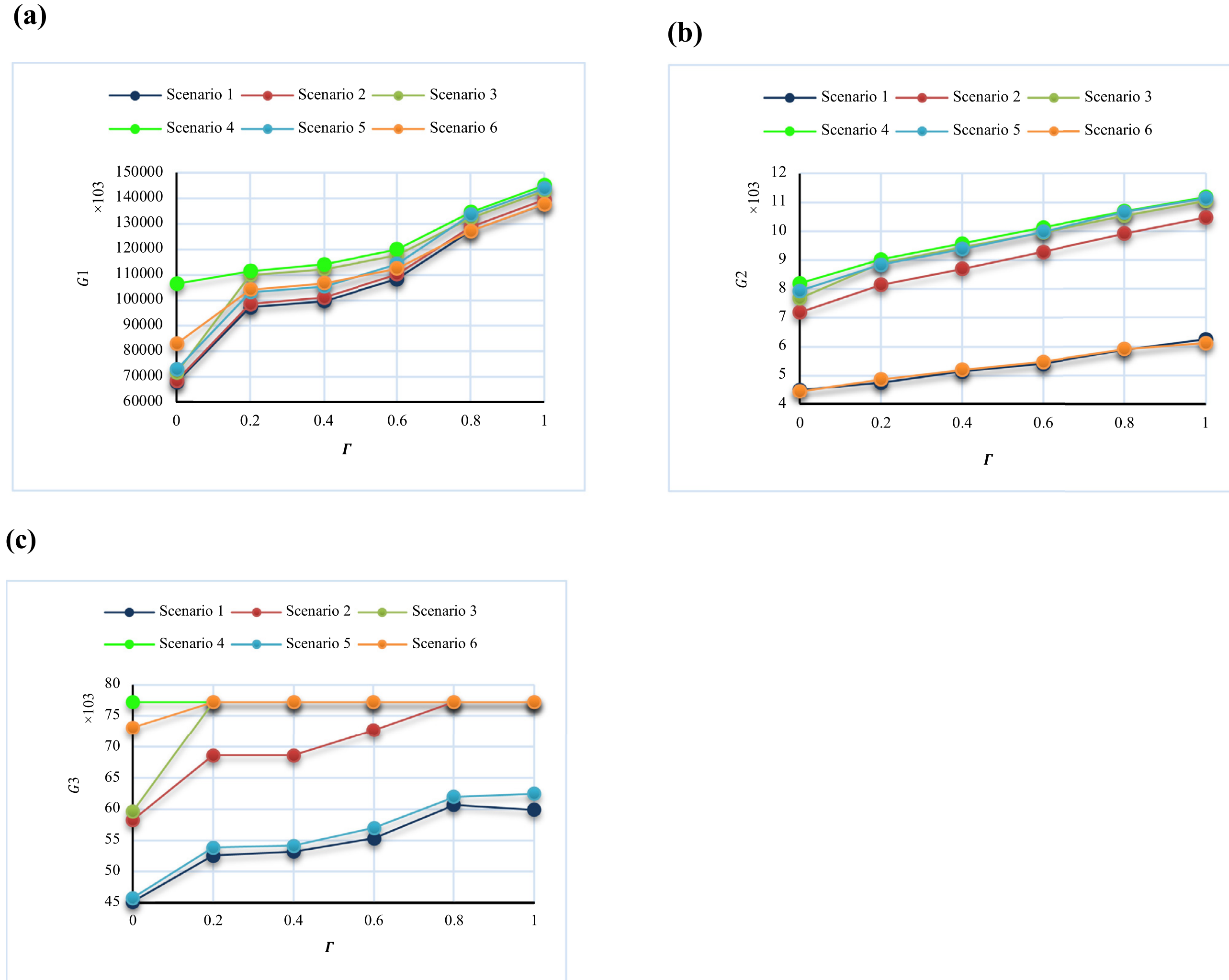

Fig. 6. The impact of the robust approach on different objective functions.

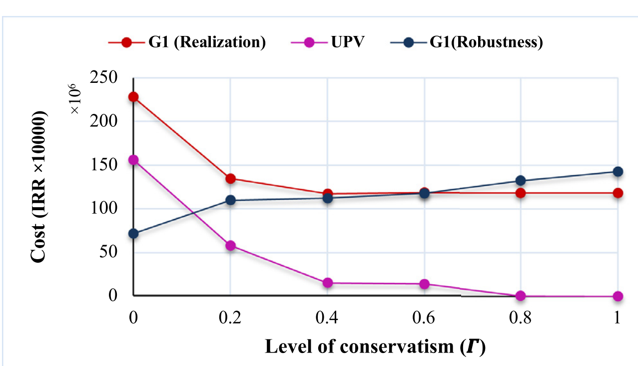

Fig. 7. The tradeoff between cost and budget of uncertainty.

The main takeaways from Fig. 7 are as follows. First, the robust and deterministic solutions are equal when Γ=0. Note that the actual cost under the robust solution is the total system cost plus the UPV. When Γ=0, the robust solution cannot reduce any unexpected lost patient compared to the deterministic solution. However, when the level of conservatism increases, the UPV decreases at the expense of a more robust solution (e.g., more field hospitals are established). More specifically, by increasing the level of conservatism from 0 to 0.2, the price of robustness equals 38,333,000 × 10^4 IRR. However, the system would save 93,310,200×10^4 IRR if there are new unexpected patients in the system. Also, by extending the level of conservatism from 0.2 to 0.4, the price of robustness increases only 2%, while the system cost reduces by 13% for new, unexpected patient admissions into the system.

6. Managerial insights

The COVID-19 pandemic has challenged the global health system, and strategic and tactical decisions should be made to overcome this crisis. The main purpose of the proposed approach for the healthcare network redesigning during the COVID-19 pandemic was to enable COVID-19 patients to access suitable treatment and alleviate pressure on the medical staff. Our main findings suggest some managerial insights for DMs to improve health systems coping with the pandemic.

First, under limited resources, some field hospitals offer minimal contributions; hence can be discarded under budget constraints. This point also applies to the backup hospitals that offer limited contributions. When planning, only HCs with the highest contributions should be selected. Second, as nurses are exposed to the risk of COVID-19, a portion of them may become dysfunctional. Therefore, by reducing the number of active nurses, the system cost increases, and the satisfaction rate of nurses declines. Third, by considering backup hospitals during COVID-19, all moderate and outpatients would have access to treatment facilities. However, establishing field hospitals becomes necessary to increase severe patient admission. Fourth, field hospitals and student nurses can significantly boost system resilience. Moreover, although nurse satisfaction would decline under patient overload, allowing nurses to provide service for more patients per shift would reduce the number of non-admitted patients and save more lives. By eliminating the role of field hospitals and student nurses from the network, the system would incur 33% more cost, and satisfaction for nurses would crumble by 75%. Fifth, the demand for ventilators logically escalates their price. Still, in cases of necessity and sufficient availability of ICU beds, it would be reasonable for DMs to add new ventilators to HCs even when their price skyrockets fourfold. Finally, by increasing the level of conservatism, the average and standard deviation of the first objective function, PV, and UPV decrease significantly. Moreover, protecting the health system from failure when facing an unexpected number of new patients is possible with a modest increase in the system's total cost. For example, by extending the level of conservatism from 0 to 0.2, the system saves 41% in costs. By increasing the level of conservatism from 0.2 to 0.4, the price of robustness grows by only 2%, while the system saves 13% when facing unexpected new patients into the system. Below a 0.4 level of conservatism, the value of UPV declines dramatically, and by obtaining the level of conservatism equal to 1, the value of UPV nearly zeroes out. These results can help DMs find a suitable level of conservatism for their systems.

7. Conclusion

According to the WHO, the COVID-19 outbreak has put public health in an emergency worldwide, and healthcare systems should be resilient enough to combat this epidemic successfully [73]. Aligned with this strategy, this study has proposed a new robust multi-objective, location-allocation healthcare network redesign modeling that minimizes the system's total cost while maximizing the satisfaction rate of COVID-19 patients and nurses. The proposed model considers different hospital types (available, backup, and field hospitals), regular and student nurses, different types of COVID-19 patients, different PPE, ICU and ward beds, ventilators, and coverage distance for each patient type – all applied to a real-life case study to investigate model applicability. Novelties in this study are as follows.

This study developed a location-allocation model for optimal resilient healthcare network design in the context of the COVID-19 pandemic aimed at boosting the resilience of the healthcare system by considering backup and field hospitals, student nurses, and new ventilators, as well as robustness by considering demand fluctuation in the model. As nurses play one of the most critical roles in combating COVID-19, with a proportion of them may be unable to work, the impact of their reduced active headcount on system cost and the satisfaction of patients has been demonstrated. Further, under limitations in budget or in allocating only clean hospitals to COVID-19 patients, this study has identified HCs offering the highest contribution, as well as the impact of eliminating each HC type from the healthcare system. Moreover, as the rising demand for ventilators affects the price, we illustrated the relationship between adding new ventilators to HCs and their price. Moreover, the impacts of field and backup hospitals plus student nurses as the three main pillars of resilience in health systems were thoroughly investigated. A conservative robustness approach was also applied to handle demand uncertainty, where ten different realizations were performed. This study also investigated the roles of PPE type, bed differentiation, and distance limitation for COVID-19 patients in the health system. Finally, a novel mathematical technique was developed to linearize a nonlinear constraint in the model.

Our findings have advised several courses of practical actions as follows. First, when backup hospitals become activated for COVID-19 patients, all moderate patients and outpatients are admitted to HCs while a proportion of severe patients remains non-admitted. However, when field hospitals become available, the number of non-admitted patients drops to 5%. Second, by enabling nurses to serve more patients per shift while eliminating student nurses from the health system, the total cost of the network and patient satisfaction rise from more allocated HCs, but this would incur a marked reduction in the satisfaction rate of regular nurses. Moreover, by eliminating field hospitals, 100% of ICU beds remain occupied in some periods, resulting in lost lives among severe patients. The worst situation occurs when student nurses and field hospitals are both eliminated from the network, resulting in 33% more total costs and a 75% reduction in the satisfaction rate of regular nurses, with an average of 83% occupancy for the ICU beds. Third, our analyses demonstrated that although conservatism increases the system's cost, it could also soften the expenses noticeably when facing a large number of unexpected new patients.

We acknowledge that our proposed framework comes with the following limitations. First, we assume that adding new ventilators is impossible unless there are enough ICU beds in the hospital. This is not always true in practice. A severe patient may be admitted (e.g., sitting up in chairs) even when no bed is available in the hospital. Under such conditions, assigning new ventilators to severe patients may be possible. Second, we assume that the number of allocated patients per nurse does not exceed a standard ratio. Again, this assumption may not apply during a pandemic. Finally, our proposed framework is limited in solving large-scale scenarios, where the running time required for obtaining optimal solutions increases dramatically. Therefore, other techniques such as heuristics and metaheuristic algorithms would be needed for large-scale problems to solve the optimization model.

The proposed approach for boosting healthcare system resilience to combat failure and shortage can also be applied to future pandemics. To do so, the mathematical modeling in this work can be calibrated for future pandemics, while sensitivity analysis would help DMs improve their health systems. To extend the current model, it is recommended to consider mobile hospitals for outpatients. Other approaches could utilize probability distributions to reflect treatment periods for COVID-19 patients. Another interesting model extension may include the notion of resource-sharing among all hospitals. Moreover, considering a lateral transfer of patients within hospitals merits further research efforts. For interested practitioners, considering the routing problem for severe patients is recommended.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

For linearizing constraint (18), consider the following model based on an approach applied by [63].

$$X = \min\{x_1,\ x_2\} \tag{A1}$$

where x_1 and x_2 are constants or decision variables. A set of constraints that enforce $X = \min\{x_1,\ x_2\}$ to be linear are required. Let Y be a binary decision variable, which would equal 1 if $x_1 < x_2$ and equal 0 if $x_1 > x_2$. Let M be a constant such that $x_1,\ x_2 \le M$ in any reasonable solution to the problem. The following constraint would enforce the definition of Y:

$$x_2 - x_1 \le MY \tag{A2}$$

$$x_1 - x_2 \le M(1 - Y) \tag{A3}$$

Then, the following constraints enforce$X = \min\{x_1,\ x_2\}$:

$$X \le x_1 \tag{A4}$$

$$X \le x_2 \tag{A5}$$

$$X \ge x_1 - M(1 - Y) \tag{A6}$$

$$X \ge x_2 - MY \tag{A7}$$

Constraints (A4) and (A5) result in $X \le \min\{x_1,\ x_2\}$, and combined with constraints (A6) and (A7) would become $X = x_1$ if $x_1 < x_2$ $(Y = 1)$, and $X = x_2$ if $x_2 < x_1$ $(Y = 0)$.

This approach can be modified for max function as follows:

$$X = \max\{x_1,\ x_2\} \tag{A8}$$

Let Y be a binary decision variable, which would equal 1 if $x_1 > x_2$ and equal 0 if $x_1 < x_2$.

$$x_1 - x_2 \le MY \tag{A9}$$

$$x_2 - x_1 \le M(1 - Y) \tag{A10}$$

Then, the following constraints enforce $X = \max\{x_1,\ x_2\}$:

$$X \ge x_1 \tag{A11}$$

$$X \ge x_2 \tag{A12}$$

$$X \le x_1 - M(1 - Y) \tag{A13}$$

$$X \le x_2 - MY \tag{A14}$$

Constraints (A11) and (A12) result in $X \ge \max\{x_1,\ x_2\}$, and combined with constraints (A13) and (A14) would become $X = x_1$ if $x_1 > x_2$ $(Y = 1)$, and $X = x_2$ if $x_2 > x_1$ $(Y = 0)$ Eqs. (A1)–(A14).

Appendix B

Using robust optimization approach, one can control the degree of conservatism when solving a problem with uncertain data. It results in an integer programming problem with polyhedral uncertainty called *budget of uncertainty* shown by Γ_i; a positive parameter to capture uncertainty in the ith constraint. Consider the following mixed-integer programming model:

$$\text{Min}\quad c'x \quad \text{s.t.} \quad Ax \le bx \in X \tag{B1}$$

where $A = (a_1,\ a_2, \ldots, a_i)$ is a $[m \times n]$ matrix, b is a vector, and X is a polyhedron. Consider b as an uncertain parameter in problem (B1) shown by $\tilde{b}_i$ that $\tilde{b}_i \in [b_i - \hat{b}_i, b_i + \hat{b}_i]$ where b_i, and $\hat{b}_i$ are the nominal value and maximum deviation, respectively. If the uncertainty influences the values of the right-hand side of constraints [74], then problem (B2) can be reformulated as follows:

$$Minc'x \text{ s.t. } Ax \le b_i - \Gamma'_i\hat{b}_i x \in X; \quad \forall i \tag{B2}$$

where $\Gamma_i^{'} \in [0, 1]$ is the uncertainty budget. Specifically, if $\Gamma_i^{'} = 0$, then ith constraint is uncontrollable against uncertainty, whereas it is absolutely protected against uncertainty if $\Gamma_i^{'} = 1$. In general, the higher the level of conservatism of the decision-maker is, the higher value of uncertainty budget is needed.

Appendix C

The distance between the HCs and the center of patient areas Tables C1 and C2.

Table C1
The distance between the available and backup hospitals and the center of patient area (Meter).

Patient area	Available hospital		Backup hospital					
	1	2	1	2	3	4	5	6
1	12841	25530	13958	17922	414	15518	18592	15155
2	9709	21522	8950	12935	4598	10515	13664	10159
3	3936	13945	8208	12321	8832	9252	13546	9781
4	15444	19943	12081	15125	6217	13657	15301	12702
5	2151	22817	7559	10896	13032	7878	12340	8993
6	8022	19510	5568	9678	8027	7098	10555	6891
7	4589	20622	4925	8696	11814	5587	10046	6453
8	15703	15750	9757	11931	9758	11164	11817	9912
9	5869	24764	3618	7364	12351	4255	8706	5126
10	7518	26382	11572	12952	19785	10900	14422	12419
11	10929	16310	4344	7522	10240	5888	7994	4945
12	17191	14422	10157	11538	11999	11370	11145	9959
13	6670	23203	3969	6465	14692	3637	7947	5024
14	11463	14332	2402	4433	13261	3439	4918	2087
15	19082	9792	10505	10257	15933	11228	9365	9692
16	15992	9999	6685	5684	16042	7024	4816	5525
17	19022	9146	10211	9651	16463	10823	8684	9290
18	23576	9412	15102	14531	18969	15776	13453	14242
19	13281	13460	5265	1542	18763	3851	2383	4048
20	13502	23114	12692	11659	24392	11304	12751	12684
21	15452	10355	6108	2852	18244	5541	1432	4538
22	21011	6241	11762	8045	23308	11065	6588	10189

Table C2
The distance between the field hospitals and the center of patient area (Meter).

Patient area	Potential Field hospital										
	1	2	3	4	5	6	7	8	9	10	11
1	23357	10851	12923	23896	10876	13399	22621	22862	9022	8738	13452
2	18508	5945	8732	19255	5884	8515	17645	18817	4807	3796	8842
3	18503	7567	11728	20041	5685	9494	16779	21072	8750	4462	10845
4	19455	8396	8249	19344	9760	10372	19473	17343	5415	8417	9536
5	16963	8844	12996	18984	6583	9786	14734	21047	11090	6782	11572
6	15505	3233	7143	16555	2449	5646	14394	16859	4122	405	6546
7	14886	6007	10135	16674	3750	6971	12957	18380	8416	4355	8723
8	15566	6357	4424	15236	8400	7468	15919	13123	3626	8013	6099
9	13558	5221	9176	15334	3076	5815	11680	17103	7918	4343	7641
10	17812	14289	17926	20417	12198	14220	14975	23833	17036	13112	16149
11	12705	783	3644	13391	3001	2791	12111	13324	2380	3670	3054
12	14340	7241	3929	13674	9464	7602	15074	11100	5141	9529	5862
13	12452	6846	10303	14551	5023	6602	10223	17006	9785	6624	8531
14	9750	2827	4076	10743	3874	360	9009	11592	5338	5731	2191
15	11302	8852	4611	10087	11046	7903	12692	6959	8036	11863	6004
16	7720	6515	3635	7539	8253	4487	8457	7152	7420	9770	3211
17	10440	8864	4681	9205	11000	7669	11894	6218	8351	11971	5828
18	14227	13320	9097	12252	15552	12504	16207	7515	12030	16175	10600
19	5859	8497	9202	8174	8401	6237	3734	11614	11224	10587	7375
20	14238	16276	18733	17088	14794	15068	11293	21551	19324	16486	16794
21	4702	7890	6775	5763	8799	5323	4782	8034	9873	10801	5402
22	2985	13261	10966	251	14409	10766	5903	5001	14706	16335	10274

Appendix D

Figs. D1, D2 and Table D1.

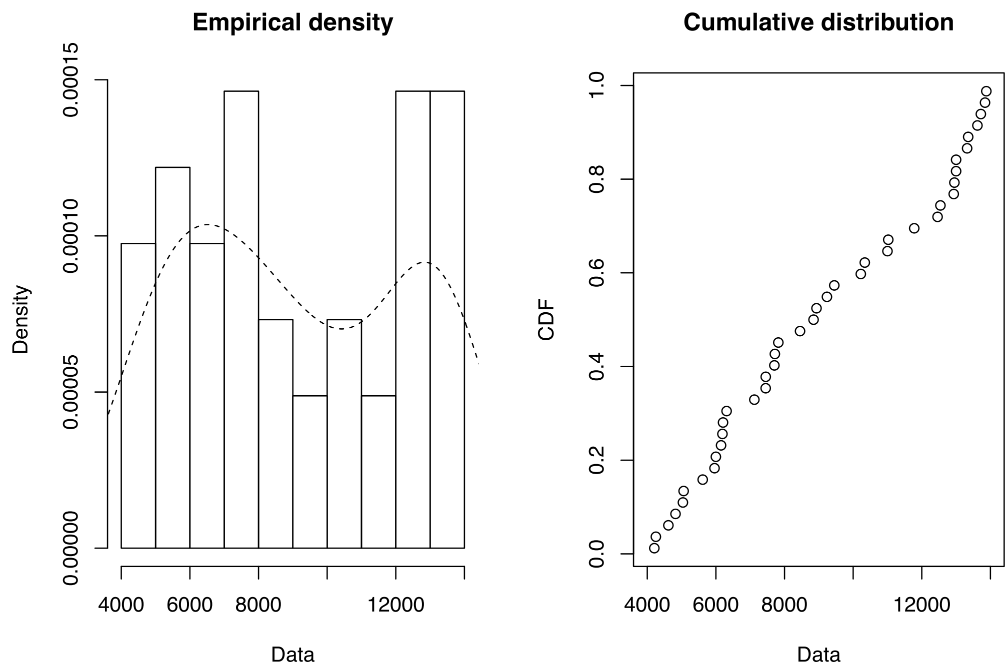

Fig. D1. Distribution of observations.

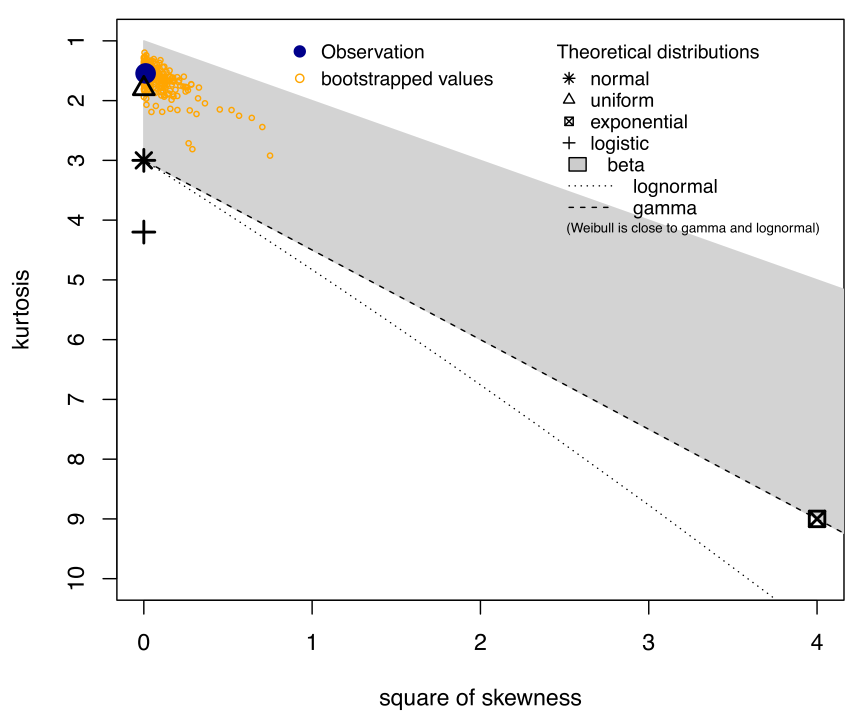

Fig. D2. Cullen and Frey graph.

Table D1
Characteristics of founded distributions for data.

Distribution	P-value	Best fit	AIC
Uniform	0.8639568	3552.551, 14672.132	756.5386
Weibull	0.3932373	shape: 3.188378, scale:10217.348659	780.5836
normal	0.3614575	Mean: 9112.341, Sd: 3209.947	782.4217
Poisson			47883.46
L-normal	0.4267309	Meanlog:9.0499036 Sdlog: 0.3760329	782.2426
n-binomial			781.2443

Appendix E

The optimum value for each objective function is gained without considering other objective functions. In other words, the optimum value for each objective function is obtained when ω for that objective function equals 1 and 0 for other objective functions. The optimum value for the first, second, and third objective function is shown by G_1^*, G_2^*, and G_3^*, respectively. For a better understanding of the impact of the availability of nurses and ω on the value of objective functions, a ratio of the optimum value and the value of each objective function is also provided Tables E1, E2 and E3.

Table E1
Value of objective functions with different ω in plan 1.

	ω_2	ω_3	Plan 1 (Personnel=100%), ($G_1^* = 67430000, G_2^* = 8235.52, G_3^* = 93065.60$)						
			G_1	G_1^*/G_1	G_2	G_2/G_2^*	G_3	G_3/G_3^*	G_4
1	0	0	67,430,000	1.00	4476.87	0.54	52941.90	0.569	0.00
0.8	0.2	0	67,458,000	1.00	6867.03	0.83	53425.35	0.574	0.03
0.6	0.4	0	69,331,000	0.97	7469.39	0.91	53224.70	0.572	0.05
0.4	0.6	0	73,274,000	0.92	8010.25	0.97	54371.85	0.584	0.05
0.2	0.8	0	73,828,000	0.91	8041.59	0.98	54783.90	0.589	0.04
0	1	0	106,500,000	0.63	8235.52	1.00	93065.60	1.000	0.00
0.8	0	0.2	67,477,000	1.00	4415.71	0.54	70027.20	0.752	0.05
0.6	0	0.4	67,477,000	1.00	4478.95	0.54	70027.20	0.752	0.10
0.4	0	0.6	79,977,000	0.84	4437.92	0.54	85833.60	0.922	0.12
0.2	0	0.8	89,096,000	0.76	4500.35	0.55	93065.60	1.000	0.06
0	0	1	2,617,300,000	0.03	336.85	0.04	93065.60	1.000	0.00
0.8	0.1	0.1	67,477,000	1.00	6847.53	0.83	70027.20	0.752	0.04
0.6	0.2	0.2	67,963,000	0.99	7055.25	0.86	70027.20	0.752	0.08
0.4	0.3	0.3	70,505,000	0.96	7517.01	0.91	71838.40	0.772	0.11
0.2	0.4	0.4	95,576,000	0.71	8231.76	1.00	93065.60	1.000	0.08
0	0.5	0.5	106,520,000	0.63	8235.52	1.00	93065.60	1.000	0.00

Table E2
Value of objective functions with different ω in plan 2.

	ω_2	ω_3	Plan 2 (Personnel=80%), ($G_1^* = 67897000, G_2^* = 8194.7, G_3^* = 77220.8$)						
			G_1	G_1^*/G_1	G_2	G_2/G_2^*	G_3	G_3/G_3^*	G_4
1	0	0	67,898,000	1.00	4501.18	0.55	45186.00	0.59	0.00
0.8	0.2	0	68,157,000	1.00	7043.84	0.86	44866.00	0.58	0.03
0.6	0.4	0	70,062,000	0.97	7572.89	0.92	45183.10	0.59	0.05
0.4	0.6	0	72,856,000	0.93	7937.53	0.97	45793.95	0.59	0.05
0.2	0.8	0	74,383,000	0.91	7993.23	0.98	46967.45	0.61	0.04
0	1	0	106,520,000	0.64	8194.66	1.00	77220.80	1.00	0.00
0.8	0	0.2	67,942,000	1.00	4402.13	0.54	58248.00	0.75	0.05
0.6	0	0.4	67,942,000	1.00	4401.29	0.54	58248.00	0.75	0.10
0.4	0	0.6	82,984,000	0.82	4448.89	0.54	73155.20	0.95	0.12
0.2	0	0.8	89,109,000	0.76	4466.14	0.55	77220.80	1.00	0.06
0	0	1	2,621,800,000	0.03	316.65	0.04	77220.80	1.00	0.00
0.8	0.1	0.1	67,943,000	1.00	6852.37	0.84	58248.00	0.75	0.04
0.6	0.2	0.2	68,544,000	0.99	7186.87	0.88	58248.00	0.75	0.08
0.4	0.3	0.3	71,617,000	0.95	7672.23	0.94	59603.20	0.77	0.11
0.2	0.4	0.4	95,588,000	0.71	8188.99	1.00	77220.80	1.00	0.08
0	0.5	0.5	106,520,000	0.64	8194.65	1.00	77220.80	1.00	0.00

Table E3
Value of objective functions with different ω in plan 3.

	ω_2	ω_3	Plan 3 (Personnel=60%), ($G_1^* = 68535000, G_2^* = 8011.847, G_3^* = 60502.4$)						
			G_1	G_1^*/G_1	G_2	G_2/G_2^*	G_3	G_3/G_3^*	G_4
1	0	0	68,535,000	1.00	4385.26	0.55	34919.40	0.58	0.00
0.8	0.2	0	68,953,000	0.99	7173.35	0.90	35791.40	0.59	0.03
0.6	0.4	0	70,614,000	0.97	7580.47	0.95	36103.05	0.60	0.04
0.4	0.6	0	71,775,000	0.95	7730.83	0.96	36499.60	0.60	0.04
0.2	0.8	0	73,206,000	0.94	7783.10	0.97	37410.75	0.62	0.04
0	1	0	106,190,000	0.65	8011.85	1.00	60502.40	1.00	0.00
0.8	0	0.2	68,578,000	1.00	4488.17	0.56	44696.00	0.74	0.05
0.6	0	0.4	70,416,000	0.97	4369.70	0.55	47406.40	0.78	0.10
0.4	0	0.6	87,701,000	0.78	4386.58	0.55	59603.20	0.99	0.12
0.2	0	0.8	89,537,000	0.77	4395.92	0.55	60502.40	1.00	0.06
0	0	1	2,716,500,000	0.03	176.81	0.02	60502.40	1.00	0.00
0.8	0.1	0.1	68,634,000	1.00	6919.44	0.86	44696.00	0.74	0.04
0.6	0.2	0.2	69,135,000	0.99	7233.75	0.90	44696.00	0.74	0.08
0.4	0.3	0.3	72,673,000	0.94	7640.64	0.95	47406.40	0.78	0.10
0.2	0.4	0.4	94,687,000	0.72	7985.05	1.00	60502.40	1.00	0.08
0	0.5	0.5	106,180,000	0.65	8011.85	1.00	60502.40	1.00	0.00

Appendix F

The tables show the impact of the five different budgets of uncertainty levels. Columns 2, 5, and 8 are PV, which is equal to the cost of losing the patients for the system. Columns 3, 6, and 9 represent UPV, which represents the cost of unexpected lost patients for the system. Columns 4, 7, and 10 are the value of the first objective function (G_1) in the deterministic and robust approaches. The last two rows of the tables, respectively, represent the average and the standard deviation of the penalty value, unexpected penalty value, and the first objective function Tables F1 and F2.

Table F1
Effectiveness of the model under realization (IRR$\times 10^4$).

	Deterministic			Robust (Γ =0.2)			Robust (Γ =0.4)		
Re No.	PV	UPV	G_1	PV	UPV	G_1	PV	UPV	G_1
1	183,480,000	177,870,000	249,486,800	48510000	47190000	123,770,600	13530000	13530000	115596200
2	214,830,000	209,220,000	280836800	72930000	71610000	148190600	19800000	19800000	121866200
3	134,310,000	128,700,000	200316800	59730000	58410000	134990600	19140000	19140000	121206200
4	201,960,000	196,350,000	267966800	66000000	64680000	141260600	13530000	13530000	115596200
5	114,510,000	108,900,000	180516800	49830000	48510000	125090600	14520000	14520000	116586200
6	165,330,000	159,720,000	231336800	54780000	53460000	130040600	11880000	11880000	113946200
7	126,390,000	120,780,000	192396800	59400000	58080000	134660600	13200000	13200000	115266200
8	137,940,000	132,330,000	203946800	67320000	66000000	142580600	15180000	15180000	117246200
9	166,980,000	161,370,000	232986800	53460000	52140000	128720600	11550000	11550000	113616200
10	172,920,000	167,310,000	238926800	61050000	59730000	136310600	20460000	20460000	122526200
Avr	161,865,000	156,255,000	227871800	59301000	57981000	134561600	15279000	15279000	117345200
S.D	31421563.1	31421563.1	31421563.1	7475865.8	7475865.8	7475865.8	3141246.4	3141246.4	3141246.4

*Re No.: Realization number *Avr: Average *S.D: Standard Deviation

Table F2
Effectiveness of the model under realization (IRR$\times 10^4$).

	Robust (Γ =0.6)			Robust (Γ =0.8)			Robust (Γ =1)		
Re No.	PV	UPV	G_1	PV	UPV	G_1	PV	UPV	G_1
1	13,530,000	12,540,000	117,240,200	4,620,000	0	116,451,800	2,970,000	0	116,272,200
2	19,800,000	18,810,000	123,510,200	6,930,000	0	118,761,800	6,270,000	0	119,572,200
3	19,140,000	18,150,000	122,850,200	8,250,000	330000	120,081,800	6,930,000	0	120,232,200
4	14,520,000	13,530,000	118,230,200	5,610,000	0	117,441,800	3,960,000	0	117,262,200
5	11,880,000	10,890,000	115,590,200	6,930,000	0	118,761,800	4,950,000	0	118,252,200
6	13,200,000	12,210,000	116,910,200	6,600,000	0	118,431,800	6,270,000	0	119,572,200
7	14,190,000	13,200,000	117,900,200	6,270,000	0	118,101,800	4,290,000	0	117,592,200
8	11,550,000	10,560,000	115,260,200	3,300,000	0	115,131,800	2,310,000	0	115,612,200
9	20,460,000	19,470,000	124,170,200	11,220,000	3300000	123,051,800	8,910,000	0	122,212,200
10	11,220,000	10,230,000	114,930,200	4,290,000	0	116,121,800	1,980,000	0	115,282,200
Avr	14,949,000	13,959,000	118,659,200	6,402,000	363000	118,233,800	4,884,000	0	118,186,200
S.D	3349296.8	3349296.8	3349296.8	2124339.0	983931.4	2124339.0	2101662.2	0.0	2101662.2

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