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RESEARCH PAPER

Healthcare Resource and Staffing Optimization Model for Pandemic Response

Shaghayegh Heyhat[1], Donya Rahmani[2*]

[1]*Ph.D. Candidate, Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran.*
[2]*Associate Professor, Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran.*

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Abstract

This study presents a mathematical optimization model for resource allocation and staff management during a pandemic, focusing on balancing patient demand, facility capacity, and resource utilization. The model aims to minimize total costs, including staffing, resource procurement, and penalties for unmet demand, while ensuring efficient patient assignment and facility operation. A key feature of the model is the integration of cross-training strategy to enhance workforce flexibility, enabling staff to perform multiple roles and helping address staffing shortages during peak demand periods. The model accounts for multiple patient types, each with distinct resource requirements, and healthcare facilities with varying capacities for beds, ventilators, and staff. The results demonstrate that the model successfully optimizes resource allocation, achieving a 14.98% improvement in resource usage efficiency and a facility utilization rate of 69.19%. Through strategic implementation of staff transfers and cross-training policies, the model maintained high operational efficiency while improving facility utilization by 0.18%. These findings highlight the significance of a flexible workforce and strategic resource management in improving healthcare resilience and responsiveness during a pandemic.

Keywords:
Cross-Training,
Healthcare Optimization,
Pandemic Response,
Resource Allocation,
Staff Management.

Introduction

Infectious diseases have persistently posed significant challenges to global health, with outbreaks often leading to widespread societal disruptions. A notable contemporary example is the COVID-19 pandemic, which has highlighted the complexities and demands placed on healthcare systems worldwide (Haren & Simchi-Levi, 2020; Ivanov, 2021; Ivanov & Dolgui, 2020; Spieske et al., 2022). Caused by the SARS-CoV-2 virus, COVID-19 emerged in late 2019 and has since infected millions, resulting in substantial mortality and overwhelming healthcare infrastructures (Johns Hopkins Coronavirus Resource Center, 2020).

The challenges presented by pandemics extend beyond the immediate health risks of infectious diseases; they also place immense strain on healthcare resources and staffing. One of the primary issues is the sudden and overwhelming surge in demand for medical supplies and personnel (Barrett et al., 2020; Li et al., 2020; Paul & Chowdhury, 2021; Remko, 2020), which can quickly outstrip existing capacities. For instance, during the COVID-19 pandemic,

[*] Corresponding author: (Donya Rahmani)
Email: drahmani@kntu.ac.ir

healthcare systems faced critical shortages of essential resources, such as personal protective equipment (PPE), ventilators, and hospital beds, complicating the delivery of care (Chamola et al., 2020; Grimm, 2021; Litton et al., 2021; Sen-Crowe et al., 2021; Winkelmann et al., 2022). This overwhelming demand not only tested the limits of health systems but also highlighted the need for better preparedness and supply chain management in the face of such crises.

Compounding these resource challenges were staffing shortages, as illness and quarantine measures further reduced the available workforce (ASPR TRACIE, 2023). Remaining healthcare personnel were often required to take on additional responsibilities, leading to a cycle of increased workload and stress. In response to these challenges, many healthcare systems implemented cross-training strategies, enabling staff to perform multiple roles across different departments (ASPR TRACIE, 2024). This approach not only optimized the use of available personnel but also enhanced the flexibility of healthcare systems to adapt to the evolving needs of patients. Addressing these multifaceted challenges requires immediate interventions to support healthcare workers and long-term strategies aimed at enhancing resilience and preparedness for future pandemics. By prioritizing workforce support and resource optimization, health systems can better withstand the pressures of future outbreaks and ensure the effective delivery of care to those in need.

To address these challenges, we propose a comprehensive mixed-integer programming model that integrates three critical dimensions of pandemic healthcare management: patient severity stratification, resource allocation, and workforce flexibility. The proposed model makes the following considerations. First, our model innovatively incorporates a staff cross-training framework, recognizing that healthcare workforce adaptability is crucial during crisis periods. The framework considers four essential categories of healthcare professionals - general nurses, respiratory therapists, specialized nurses, and intensivists - and maps their potential for cross-specialty training based on skill compatibility. Second, our model incorporates dynamic patient flow management with length-of-stay considerations, allowing healthcare systems to better predict and manage resource needs over time. The model emphasizes patient severity classification, ensuring that patients are categorized based on their clinical needs, allowing for prioritized resource allocation. By incorporating travel time constraints and facility capacity limitations, our framework provides realistic solutions that consider both geographic access to care and system capacity constraints. Third, the model includes considerations for staff transfers between facilities and the gradual development of cross-training capabilities, providing healthcare administrators with practical tools for workforce development and deployment during crisis periods. Finally, our model addresses the critical need for flexibility in pandemic response by incorporating dynamic resource allocation capabilities. This allows healthcare systems to adapt to changing conditions while maintaining essential services across all facilities.

The remainder of this paper is structured as follows. A review of related literature on healthcare supply chain network design in the pandemic context is provided in Section 2. In Section 3, the problem statement is presented, and the model formulation is described. Numerical experiments are conducted in Section 4. The paper is concluded in Section 5.

Literature Review

The efficient allocation of limited resources has emerged as a critical challenge across various domains, particularly in healthcare crisis management and emergency response (Cao & Huang, 2012; Gupta et al., 2016). This became especially evident during the COVID-19 pandemic, which highlighted the crucial need for strategic distribution of healthcare resources including PPE, diagnostic equipment, medical facilities, and vaccines (Emanuel et al., 2020).

The challenges posed by pandemics, such as COVID-19, have led to a surge in research focused on optimizing healthcare resource management and planning. Bertsimas et al. (2021)

proposed a deterministic optimization model that facilitates the sharing of ventilators across hospitals in different states in the U.S. This approach aims to ensure that ventilators are allocated efficiently, optimizing their use during surges in demand. Lampariello and Sagratella (2021) contributed to the literature by addressing a single-period allocation problem concerning COVID-19 test kits. Their model focuses on optimizing utility functions that enhance disease detection capabilities across various geographical areas, thereby improving testing accessibility and effectiveness. Further exploring resource distribution, Santini (2021) tackled the challenge of effectively distributing swabs and reagents to laboratories. By developing a deterministic integer programming model, he aimed to maximize the volume of COVID-19 tests performed, thereby addressing critical needs in testing capacity during the pandemic. The focus on personal protective equipment (PPE) is also vital, particularly regarding the distribution of surgical and respiratory masks. Dönmez et al. (2022) developed a multi-period, multi-objective, non-linear resource allocation model aimed at health centers facing acute shortages of PPE. Their model seeks to reduce deprivation costs associated with shortages while minimizing infection risks for both patients and healthcare workers, illustrating the complexity and importance of resource allocation decisions in pandemic scenarios.

To address the inherent uncertainty in healthcare demand, Mehrotra et al. (2020) introduced stochastic programming techniques to simulate unpredictable patient demand resulting from the rapid spread of infectious diseases, aiming to enhance the redistribution of medical resources across hospitals. Building on this, Yin et al. (2023) developed a multi-stage stochastic programming model that accounts for dynamic transmission patterns and incorporates risk-averse considerations, emphasizing the importance of adaptable resource management strategies in healthcare settings. While previous studies have primarily focused on resource allocation among existing healthcare facilities, Liu et al. (2023) shifted the focus to the strategic placement of testing centers to meet the changing demand for test kits during pandemics. Their two-phase optimization framework involves pre-positioning strategies to achieve specific fill rates, followed by dynamic capacity adjustments in response to real-time demand fluctuations. This proactive approach highlights the need for flexibility in healthcare facility planning during crises. Li et al. (2023) examined production planning for masks amidst uncertain demand, employing a two-stage stochastic model that addresses assembly line balancing and capacitive lot sizing from a risk-averse perspective. This research underscores the interconnectedness of supply chain management and healthcare resource availability in pandemic situations. Fattahi et al. (2023) contributed to the discourse on resource planning by proposing strategies to optimize healthcare system responses during epidemics. Their study utilized a multi-stage stochastic program and agent-based modeling to simulate various uncertainties, providing a framework for real-time decision-making to ensure efficient access to patient care without extensive capacity expansion. Addressing production and inventory challenges, Vahdani et al. (2023) developed a model focused on the multi-period production of consumable and reusable medical products. Their work introduced a customized epidemiological model that incorporates behavioral responses to health awareness, thus enhancing the relevance of their findings to real-world scenarios. Post-pandemic, Alizadeh et al. (2024) explored the design of a green closed-loop supply chain through a scenario-based two-stage stochastic programming model that considers uncertainties in greenhouse gas emissions. Their research offers insights into sustainable supply chain practices in healthcare contexts, advocating for robust modeling techniques to manage environmental impacts effectively. Kiss and Elhedhli (2024) addressed the issue of resource pooling to increase healthcare capacity. They proposed a model for capacity procurement and PPE distribution, incorporating private sector partnerships to enhance logistics and resource availability. Their approach illustrates the potential for innovative strategies in managing healthcare resources under supply constraints while prioritizing demand-driven solutions.

In the realm of healthcare logistics during the COVID-19 pandemic, several studies have utilized robust optimization approaches to enhance resource distribution and management. Manupati et al. (2021) concentrated on the establishment of convalescent plasma bank facilities, aiming to determine optimal locations for plasma collection and streamline plasma flow. They developed a robust mixed-integer linear programming (MILP) model that accounted for supply chain costs, transportation time, and storage expenses, thus minimizing plasma waste due to perishability. Building on the theme of resource optimization, Baloch et al. (2022) focused on improving underutilized distribution networks to enhance government delivery systems for critical healthcare supplies. Their research tackled dynamic distribution planning, including the repurposing of storage facilities and the timely delivery of personal protective equipment (PPE) across various jurisdictions. By employing a robust framework that provided a mixed-integer programming formulation, they aimed to maximize demand fulfillment while addressing uncertainties in supply. Shang et al. (2022) examined the configuration of supply networks within the healthcare sector, emphasizing the optimization of warehouse locations, inventory management, and delivery routing. Their study highlighted the importance of vendor-managed inventory systems in responding to the complex logistics challenges posed by the pandemic. Ardakani et al. (2023) introduced a robust location-allocation model to enhance healthcare system resilience by incorporating alternative resources like backup and field hospitals, along with student nurses. A multi-objective optimization model minimized costs and maximized satisfaction for patients and medical staff, while addressing demand uncertainty. Furthermore, Basciftci et al. (2023) introduced a moment-based distributionally robust optimization approach to tackle uncertainties in disease transmission. Their work focused on identifying optimal locations for distribution centers, along with determining appropriate capacities, shipping volumes, and inventory levels. Through numerical experiments, they evaluated the distribution strategies for COVID-19 vaccines in the United States and testing kits in Michigan, providing valuable insights into effective resource management under varying scenarios.

A systematic review of the literature, as summarized in Table 1, reveals several critical gaps in healthcare resource management during crises. While recent studies have made significant advances in certain aspects of crisis management, substantial limitations remain unaddressed. First, although multi-time period planning has been widely adopted (e.g., Alizadeh et al. (2024); Bertsimas et al. (2021); Mehrotra et al. (2020)), these models typically focus on single-resource allocation, overlooking the complex interdependencies between different types of resources. Second, studies that do consider multiple resource types (Ardakani et al., 2023; Shang et al., 2022) tend to treat these resources as static entities, failing to capture the dynamic nature of healthcare operations. Third, while some recent works like Ardakani et al. (2023) and Fattahi et al. (2023) have begun to differentiate between patient types, they do not fully integrate this consideration with comprehensive resource allocation strategies. Most notably, the critical aspect of workforce flexibility through staff cross-training and transfer mechanisms remains entirely unaddressed in the existing literature.

Current models also demonstrate limitations in their scope and integration capabilities. For instance, while Vahdani et al. (2023) incorporated bed differentiation and multiple resource types in their compartmental model, they did not address the dynamic nature of staff deployment. Similarly, although Ardakani et al. (2023) considered multiple patient types and resource categories, their model lacks the flexibility needed for real-time staff allocation adjustments. The absence of integrated approaches that simultaneously consider facility capacity, dynamic resource distribution, and adaptable staff utilization represents a significant gap in the literature.

This study addresses these limitations through a comprehensive mixed-integer programming model that uniquely integrates staff cross-training capabilities with dynamic resource allocation during healthcare crises. Our approach provides a multi-dimensional solution through several innovative features: (1) an integrated staff transfer system that balances workload across facilities while maintaining minimum staffing levels, (2) a comprehensive patient flow management system that considers varying levels of care requirements (mild, moderate, and severe cases), (3) a multi-period planning horizon that accounts for both immediate resource needs and longer-term capacity adjustments, and (4) a dynamic workforce flexibility mechanism that enables healthcare workers to support multiple roles based on their capabilities and facility needs. This holistic approach provides a more flexible and adaptable framework for managing healthcare resources during crises, addressing the identified gaps in current research. As demonstrated in Table 1, our model uniquely combines multiple features that have previously only been addressed in isolation, representing a significant advancement in healthcare crisis management modeling.

Table 1. Summary of modeling methods and key features in healthcare supply chain network design during pandemics.

References	Modeling Method	Multi-Time Period	Demand Differentiation	Different Patient Types	Multiple Resource Types	Bed Differentiation	Medical Staff	Staff Cross-Training	Staff Allocation/Transfer
Mehrotra et al. (2020)	SP	✓	-	-	-	-	-	-	-
Bertsimas et al. (2021)	Deterministic	✓	-	-	-	-	-	-	-
Lampariello and Sagratella (2021)	Deterministic	-	-	-	-	-	-	-	-
Manupati et al. (2021)	RO	✓	-	-	-	-	-	-	-
Santini (2021)	Deterministic	✓	-	-	-	-	-	-	-
Baloch et al. (2022)	RO	✓	-	-	-	-	-	-	-
Dönmez et al. (2022)	Deterministic	✓	-	-	-	-	-	-	-
Shang et al. (2022)	RO	✓	-	-	✓	-	-	-	-
Ardakani et al. (2023)	RO	✓	✓	✓	✓	✓	✓	-	-
Basciftci et al. (2023)	RO	✓	-	-	-	-	-	-	-
Fattahi et al. (2023)	SP	✓	✓	✓	✓	-	-	-	-
Li et al. (2023)	SP	✓	-	-	✓	-	-	-	-
Liu et al. (2023)	SP	✓	-	-	-	-	-	-	-
Vahdani et al. (2023)	Compartmental model	✓	-	-	✓	✓	-	-	-
Yin et al. (2023)	SP	✓	-	-	-	-	-	-	-
Alizadeh et al. (2024)	SP	✓	-	-	✓	-	-	-	-
Kiss and Elhedhli (2024)	SP	✓	-	-	-	-	-	-	-
This paper	***Deterministic***	✓	✓	✓	✓	✓	✓	✓	✓

Problem Statement and Model Formulation

Problem Description

The COVID-19 pandemic has strained healthcare systems, creating an urgent need for optimized resource allocation to meet patient demand effectively. This model is designed to allocate healthcare resources across multiple facilities, focusing on critical resources such as general beds, ICU beds, ventilators, and trained healthcare personnel. Specifically, the model addresses patient assignment to facilities based on demand, facility capacity, and resource availability, accounting for variations in patient severity (mild, moderate, severe) and geographic origin.

Given the dynamic nature of patient inflow and facility constraints, the model also considers staff availability and cross-training strategies to enhance workforce flexibility. The model maintains consistent maximum patient-to-staff ratios based on established healthcare regulations, such as California's mandated nurse-to-patient ratios law (AB 394), which sets specific staffing requirements across different units (e.g., ICU, medical-surgical units) to ensure patient safety (California State Legislature, 1999; National Nurses United, 2024). By incorporating cross-training options for healthcare staff, the model enables certain roles (e.g., general nurses, respiratory therapists) to be adapted as needed to support critical areas during peak demand. Additionally, facility-based resource expansion decisions are incorporated, including adding new beds and ventilators, and hiring staff as needed to meet changing patient demands.

The objective of this resource allocation model is to minimize total costs, which include operational costs (facility opening, resource expansion, staffing adjustments) and penalties related to unmet patient demand. Constraints ensure that patient demands are met within facility capacity, resources are deployed efficiently, travel times are minimized, and staffing requirements are optimized. The model also factors in budget constraints to limit additional resource costs and penalizes patient shortages, supporting a balanced and cost-effective allocation of healthcare resources in response to surges in pandemic cases. Figure 1 provides an illustrative example of the problem, depicting a network with five demand points and three healthcare facilities. It highlights the connections between demand zones, healthcare facilities, and the allocation of critical resources and staff within the model.

Problem Assumption and Notation

- Resource expansion is assumed to be feasible, with the ability to scale up medical facilities, beds, and equipment as needed to meet demand surges.
- Cross-training is allowed by the model, which assumes that sufficient training can be provided to staff to meet demand across roles.
- A consistent maximum patient-to-staff ratio is assumed by the model.
- Patient assignment to facilities is limited by the maximum allowable travel times.
- Transfers can be made between facilities to address staff shortages.

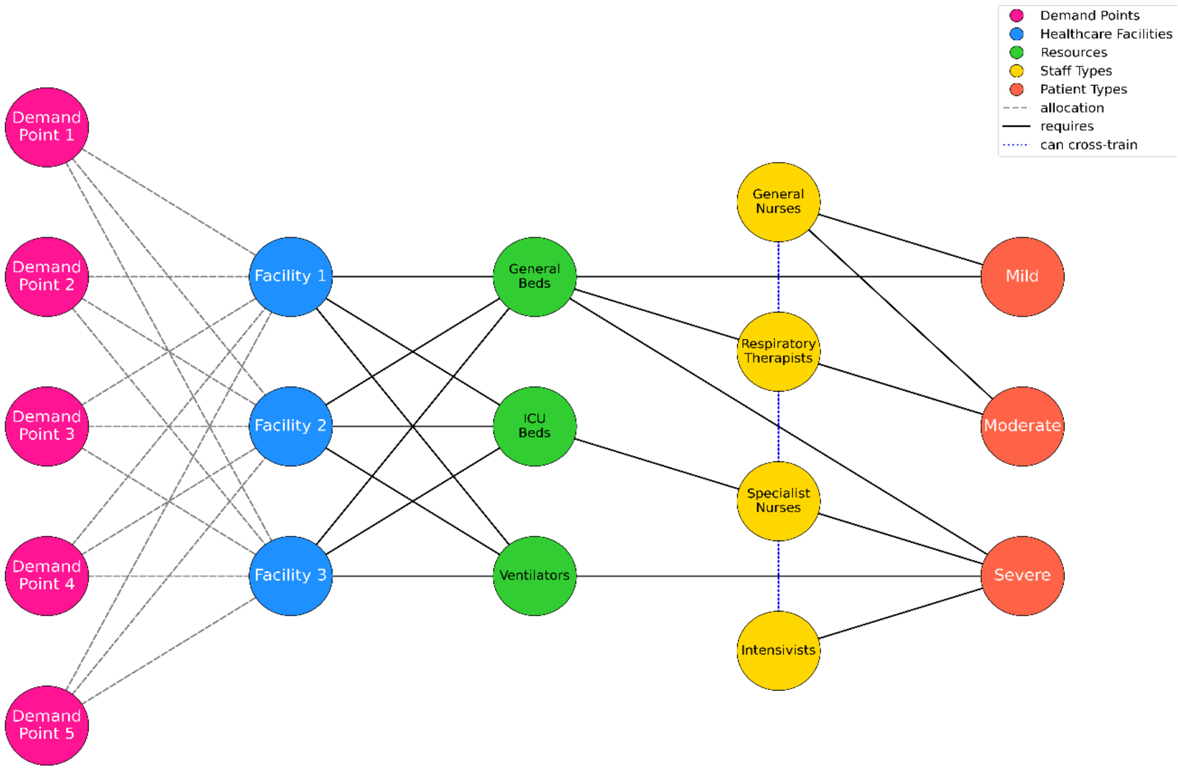

Figure 1. A network diagram illustrating the interconnections between demand points, healthcare facilities, resources, staff types, and patient categories in a healthcare system. Colored nodes represent different components, with lines indicating relationships.

The sets, the parameters, and the decision variables used in the model are given below.

Table 2. Sets and indices used in the healthcare model.

Notation	Definition
I	Set of patient types, indexed by $i \in I := \{1,2,\ldots,I\}$.
J	Set of healthcare facilities, indexed by $j \in J := \{1,2,\ldots,J\}$.
K	Set of origin points (e.g., patient origins or locations), indexed by $k \in K := \{1,2,\ldots,K\}$.
R	Set of resources, indexed by $r \in R := \{1,2,\ldots,R\}$.
S	Set of staff types, indexed by $s \in S := \{1,2,\ldots,S\}$.
T	Set of time periods, indexed by $t \in T := \{1,2,\ldots,T\}$.

Table 3. Input parameters used in the healthcare model.

Notation	Definition
d_{ikt}	Demand for patient type i from origin k in period t.
c_j	Capacity of facility j.
a_{jrt}	Initial availability of resource r at facility j in period t.
u_{ir}	Resource usage rate for patient type i for resource r.
p_r	Cost of adding one unit of resource r.
f_j	Fixed cost of opening facility j.
τ_{kj}	Travel time from origin k to facility j.
π_i	Penalty cost of refusing patient type i.
L_i	Average length of stay for patient type i.
α	Maximum allowed travel time for patients.
κ	Unit transportation cost per hour of travel time between two regions
B	Total budget for adding resources.
SR_{is}	Staff requirement per patient of type i for staff type s.
InS_{jst}	Initial availability of staff type s at facility j in period t.
θ_s	Maximum number of patients that staff type s can care for per day.
φ_s	Minimum required number of staff type s per day.
$SCap_{ss'}$	Cross-training capability between staff types s and s'.
$CostH_s$	Cost of hiring new staff of type s.

Table 4. Notation and definitions of decision variables used in the healthcare model.

Notation	Definition
$y_j \in \{0,1\}$	Binary variable indicating whether facility j is open.
x_{ijkt}	Number of patients of type i assigned from origin k to facility j in period t.
z_{jrt}	Number of additional resources r added at facility j in period t.
w_{ikt}	Number of patients of type i from origin k not admitted in period t.
h_{ijkt}	Number of patients of type i from origin k currently hospitalized in facility j in period t.
q_{ijkt}	Number of patients of type i discharged from facility j in period t.
A^s_{jst}	Number of staff type s assigned to facility j in period t.
Hr^s_{js}	Number of new staff type s hired at facility j.
$Tr^s_{jj'st}$	Number of staff type s transferred from facility j to j' in period t.
$Cr^s_{jss't} \in \{0,1\}$	Binary variable indicating if staff type s is cross-trained to type s' at facility j in period t.

Mathematical Model

Using the notations, we formulate the following mixed-integer linear programming model:

$$\min \sum_{j\in J} f_j\, y_j + \sum_{j\in J}\sum_{r\in R}\sum_{t\in T} P_r\, z_{jrt} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} \kappa\, \tau_{kj}\, x_{ijkt} + \sum_{i\in I}\sum_{k\in K}\sum_{t\in T} \pi_i\, w_{ikt} + \sum_{j\in J}\sum_{s\in S} \mathrm{CostH_s Hr^s_{js}} \tag{1}$$

S.t:

$$\sum_{j\in J:\tau_{kj}\le\alpha} x_{ijkt} + w_{ikt} = d_{ikt} \quad \forall i \in I, k \in K, t \in T \tag{2}$$

$$\sum_{i\in I}\sum_{k\in K} h_{ijkt} \le c_j y_j \quad \forall j \in J, t \in T \tag{3}$$

$$\sum_{i\in I}\sum_{k\in K} u_{ir} h_{ijkt} \le a_{jrt} + z_{jrt} \quad \forall j \in J, r \in R, t \in T \tag{4}$$

$$\sum_{j\in J}\sum_{r\in R}\sum_{t\in T} p_r z_{jrt} \le B \tag{5}$$

$$x_{ijkt} \le M y_j \quad \forall i \in I, j \in J, k \in K, t \in T \tag{6}$$

$$h_{ijkt} = h_{ijkt-1} + x_{ijkt} - q_{ijkt} \quad \forall i \in I, j \in J, k \in K, t \in T \setminus \{1\} \tag{7}$$

$$q_{ijkt} = \frac{1}{L_i} \sum_{t'=\max(1,t-L_i+1)}^{t} x_{ijkt'} \quad \forall i \in I, j \in J, k \in K, t \in T \tag{8}$$

$$\sum_{i\in I}\sum_{k\in K} SR_{is} h_{ijkt} \le \theta_s A^s_{jst} + \sum_{s'\in S} SCap_{ss'} Cr^s_{js'st}\, \theta_{s'} \quad \forall j \in J, s \in S, t \in T \tag{9}$$

$$A^s_{jst} \ge \varphi_s y_j \quad \forall j \in J, s \in S, t \in T \tag{10}$$

$$A^s_{jst} = A^s_{jst-1} + Hr^s_{js} + \sum_{j'\in J, j'\neq j} \left(Tr^s_{j'jst} - Tr^s_{jj'st}\right) \quad \forall j \in J, s \in S, t \in T \setminus \{1\} \tag{11}$$

$$Cr^s_{jss't} \le Scap_{ss'}, \quad \forall j \in J, s, s' \in S, t \in T \tag{12}$$

$$\sum_{j'\in J, j'\neq j} Tr^s_{jj'st} \le 0.2 A^s_{jst} \quad \forall j \in J, s \in S, t \in T \tag{13}$$

$$x_{ijkt}, z_{jrt}, w_{ikt}, h_{ijkt}, q_{ijkt}, A^s_{jst}, Hr^s_{js}, Tr^s_{jj'st} \in Z_0^+ \quad \forall i \in I, j \in J, k \in K, r \in R, s \in S, t \in T \tag{14}$$

$$y_j, Cr^s_{jss't} \in \{0,1\} \tag{15}$$

The mathematical model presented designed to optimize the allocation of healthcare resources, patient assignments, and staffing across multiple healthcare facilities and time periods, while minimizing the associated costs. The objective function (1) aims to minimize several cost components, including facility opening costs, resource expansion costs, transportation costs, penalty costs for refused patients, and staff hiring costs. Constraints (2) ensure demand satisfaction. Constraints (3) guarantee that the total number of patients assigned to facility j during period t does not exceed its capacity. Constraints (4) ensure that the resources required at each facility to accommodate patients are less than or equal to the available resources plus any added resources. This ensures that the facility has sufficient resources (e.g., beds, ventilators) to meet patient demands. Constraints (5) ensure that the total cost of adding resources across all facilities and resource types does not exceed a predefined budget B. Constraints (6) enforce that patients can only be assigned to open facilities. Constraints (7) model the dynamics of patient hospitalization, ensuring that the number of patients at a facility in a given period is the sum of those admitted and those hospitalized from the previous period, minus those discharged. Constraints (8) ensure that patients stay for a defined period (L_i) before being discharged, modeling the length of stay for each patient at each facility. Constraints (9) ensure that there is sufficient staffing at each facility to meet patient care demands. These staffing levels can also be adjusted by transferring staff between facilities. Constraints (10) guarantee that a minimum number of staff of each type is assigned to open facilities. Constraints (11) model the staffing dynamics over time, accounting for staff hiring, and transfers between facilities. Constraints (12) ensure that cross-training between staff roles follows the predefined cross-training capability matrix. Constraints (13) limit the number of staff transfers between facilities to ensure that transfers do not exceed a certain proportion of the staff at a facility. Finally, constraints (14) and (15) determine the types of decision variables.

Numerical Experiments

To evaluate the performance of the proposed model, we perform numerical experiments with a small-scale example. The experiments are conducted using GAMS 24.1.2 software on a personal computer (Lenovo, equipped with an Intel(R) Core (TM) i5-9300H 2.40 GHz CPU and 16.0 GB RAM) running the Microsoft Windows 10 operating system.

Data

To address resource allocation and patient demand management within healthcare facilities, parameters and assumptions are generated to capture a range of conditions for patient demand, resource availability, and logistical constraints. These data settings, provided in Table 5, are designed to serve as a framework for simulating the allocation of healthcare resources under diverse scenarios. Key parameters include patient demand and type-specific requirements, such as average length of stay and necessary resources (e.g., beds, ventilators, and specialized staff). Additional parameters account for facility capacity, operating costs, and budget limits for expansion, ensuring that both strategic and operational aspects are comprehensively represented. Staffing requirements and constraints, such as cross-training and daily workload capacity, are included to highlight the importance of personnel availability and flexibility in resource management.

Table 5. Data settings for the healthcare resource allocation model.

Parameter	Value/Range	Units
d_{ikt}	1 - 100	Patients
c_j	100 - 200	Patients
a_{jrt}	50 - 100	Units
u_{ir}	Mild: General Beds, Moderate: General Beds, Severe: General Beds, ICU Beds, Ventilator	Resource types per patient
p_r	General Beds: 25-50, ICU Beds: 100, Ventilators: 500-1000	
f_j	10,000 - 20,000	
τ_{kj}	10 - 50	Minutes
π_i	Mild: 1000, Moderate: 1500, Severe: 2000	
L_i	Mild: 3-5 days, Moderate: 5-7 days, Severe: 7-10 days	Days
α	30	Minutes
B	1,000,000	
SR_{is}	Mild: General Nurse, Moderate: Respiratory Therapist, General Nurse, Severe: Specialist Nurse, Intensivist	Staff per patient
InS_{jst}	10 - 20	Staff members
$SCap_{ss'}$	General Nurse → Respiratory Therapist, Respiratory Therapist → Specialist Nurse, Specialist Nurse → Respiratory Therapist, Intensivists → Specialist Nurse	Binary
$CostH_s$	5,000 - 10,000	

Computational Results

Healthcare Facility Utilization Analysis

The analysis of healthcare facility utilization in this model reveals critical insights into system dynamics and resource allocation strategies during periods of high patient demand. The patterns observed underscore the challenges of balancing patient distribution, managing resource shortages, and maintaining operational capacity across multiple facilities to serve a wide range of patient needs.

A key observation, as shown in Table 6, is the need for strategic distribution of patient loads across facilities to prevent overburdening any single location. For example, facilities like Fac1 and Fac7 have consistently high utilization rates, reaching 100% capacity in multiple periods. This balanced approach aligns with best practices in healthcare resource management, where dispersing patient care reduces strain on individual facilities and lowers the risk of resource depletion. However, despite these efforts, some facilities still face higher capacity pressures than others. Fac1, for instance, experienced a decrease in moderate cases from 39 to 24 patients over time, while maintaining consistently high overall utilization, likely due to its proximity to high-demand regions or its operational efficiency. This pattern suggests a patient allocation strategy that considers both proximity and facility capability. Utilization rates, as reflected in Table 7, also vary significantly across the network, with facilities like Fac10 and Fac7 operating consistently above 98% capacity, indicating their critical role in managing patient volumes, while others maintain lower utilization—potentially reflecting their distance from high-demand areas or their larger resource capacity.

The continuous operation of all facilities throughout the observed periods reflects an anticipated need for maximized healthcare capacity. Rather than consolidating resources in fewer centers, the system opts for a comprehensive mobilization, which enhances its flexibility to handle demand fluctuations. This choice of system-wide activation is likely driven by the expectation of sustained patient inflow across patient severity levels and regional demands, reinforcing the necessity of each facility in meeting community needs.

Table 6. Operational analysis of healthcare facilities showing service area coverage and patient assignment patterns across severity levels and time periods, demonstrating resource utilization and capacity allocation.

Facility	Operational Status	Coverage Zones	Aggregate Patient Assignments Across Demand Points											
			Mild				Moderate				Severe			
			Time Periods											
			t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
Fac1	1	{3, 5, 15}	7	50			39	39	45	54	79	45		
Fac2	1	{1, 6, 13, 14}	36	85			21	18	30	87	99	20		
Fac3	1	{5, 12}		40				12	21	75		70		
Fac4	1	{10, 14, 15}	188	25			70	117	39	57	173			
Fac5	1	{2, 7, 15}	30	115			18	21	90	93	12	75		
Fac6	1	{9, 10, 13}		130					27	147				
Fac7	1	{4, 5, 14}	16	75			31	39	45	54	16	20		
Fac8	1	{1, 12, 15}	34	100			63	54	60	60	19			
Fac9	1	{1, 4, 8}	196	30			55	150	150	36	73	35		
Fac10	1	{7, 9, 11, 13}	195	35			76	150	87	57	269	5		

Table 7. Healthcare facility utilization patterns and severity-based patient distribution across ten medical centers, revealing operational capacity management.

Facility	Utilization Rate (%)			Total Severity-Based Inpatient Distribution											
				Mild				Moderate				Severe			
	Time Periods			Time Periods											
	t_2	t_3	t_4	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
Fac1	100	98.04	100	0	40	30	20	0	26	43	64	0	36	27	18
Fac2	82.05	76.07	99.15	0	68	51	34	0	12	26	74	0	16	12	8
Fac3	90.57	79.25	99.06	0	32	24	16	0	8	18	61	0	56	42	28
Fac4	97.03	79.21	99.01	0	20	15	10	0	78	65	90	0			
Fac5	90.22	98.37	98.37	0	92	69	46	0	14	67	105	0	60	45	30
Fac6	65.00	60.00	99.38	0	104	78	52	0		18	107	0			
Fac7	100	98.04	100	0	60	45	30	0	23	43	64	0	16	12	8
Fac8	97.48	99.16	99.16	0	80	60	40	0	36	58	78	0			
Fac9	77.55	96.43	76.53	0	24	18	12	0	100	150	124	0	28	21	14
Fac10	99.25	99.25	100	0	28	21	14	0	100	108	117	0	4	3	2

Resource expansion within this setup indicates a proactive approach to dynamically adjust capacity according to evolving demand patterns. For example, general beds were added progressively across the facilities, with Fac5 showing the most substantial increments (81, 91, and 100 beds in periods t2, t3, and t4 respectively) and Fac9 also demonstrating significant expansion (64, 99, and 99 beds). Facilities exhibiting consistently high resource additions, such as Fac6 (18, 46, and 96 beds) and Fac8 (34, 51, and 63 beds), may be those encountering sustained patient loads, requiring extra capacity to handle increased demand effectively. This adaptive response helps mitigate potential bottlenecks and underscores the importance of flexibility within healthcare resource allocation, particularly in high-demand periods.

However, despite these efforts to add resources, the model output, as shown in Table 8, reveals varying patterns of unmet demand across different acuity levels. The most significant shortages appear in severe cases, with several zones showing high unmet demand, such as Origin 3 (50, 60, and 61 patients in periods t2-t4), Origin 6 (3, 68, and 78 patients), and Origin 11 (62, 98, and 3 patients). For moderate cases, the unmet demands are generally lower but persistent, typically ranging from 1-4 patients across most origins. Mild cases show increasing shortages over time, with some origins experiencing significant gaps, such as Origin 3 (1, 100, and 58 patients across periods t2-t4).

Moreover, the model output highlights the importance of discharge and transfer policies in managing patient flow. The discharge rates show distinct patterns across severity levels. For mild cases, facilities maintain consistent discharge rates across periods (for example, Fac1 with 10 patients per period, Fac5 with 23 patients per period). Moderate cases show more variable discharge patterns, with facilities like Fac9 showing significant fluctuations (50, 100, and 62 discharges across periods) and Fac5 showing an increasing trend (7, 37, and 64 discharges). Severe cases generally maintain stable but lower discharge rates, such as Fac1 (9 patients per period) and Fac3 (14 patients per period), reflecting the longer care requirements for higher acuity patients (see Table 9).

Staff Allocation and Utilization Trends

The analysis of staff allocation across different facilities and time periods reveals critical insights into workforce management in a healthcare setting. The data, as detailed in Table 10, indicates the number of various staff categories—such as general nurses, respiratory therapists, specialized nurses, and intensivists—assigned to each facility (Fac1 through Fac10) across four time periods (t1 to t4). Initially, all facilities maintain optimal staffing levels of 100% during the first two time periods (t1 and t2). However, as time progresses to t3 and t4, we observe significant fluctuations in staff allocation. For instance, facilities like Fac3 and Fac4 experience notable decreases in general nurse staffing, with Fac3 dropping to just 6 and Fac4 to 7 in t3. This reduction could be indicative of declining patient needs or an operational shift, possibly influenced by changes in patient inflow, staff availability, or other logistical considerations.

Table 8. Regional distribution of patient refusals across fifteen demand points, categorized by case severity and tracked over multiple time periods.

Demand Point	**Unmet Patient Demand**											
	Mild				**Moderate**				**Severe**			
	Time Periods											
	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
1		5	56	31			2	1		4	33	20
2		3	35	86		1	2				52	5
3		1	100	58			1	1		50	60	61
4		2	14	64		4	2	1		40	68	51
5		1	67	44		1	3	1		1	53	13
6		1	14	16		1		2		3	68	78
7		4	24	67			1	2		1	30	20
8		1	12	51		1	1	1		65	74	9
9		3	27	29			1	2		44	19	70
10		3	63	47		2		1		16	39	70
11		2	32	5		1	2	1		62	98	3
12		4	65	57		2	1	1		4	55	13
13			67	76		4	4	2		12	49	80
14		4	9	11		2		2		54	2	55
15			4	80			2	2		98	19	17

Table 9. Resource allocation and patient flow metrics across ten facilities, tracking bed additions and severity-stratified discharge rates over multiple periods.

Facility	Resource Additions (General Beds)				Patient Discharge Volume by Care Level											
					Mild				Moderate				Severe			
	Time Periods				Time Periods											
	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4	t_1	t_2	t_3	t_4
Fac1		39	18	45		10	10	10		12	20	16		9	9	9
Fac2			10	49		17	17	17		6	16	39		4	4	4
Fac3		1	34	37		8	8	8		4	18	32		14	14	14
Fac4		9	3	12		5	5	5		39	52	32				
Fac5		81	91	100		23	23	23		7	37	64		15	15	15
Fac6		18	46	96		26	26	26			9	58				
Fac7		46	9	31		15	15	15		13	28	33		4	4	4
Fac8		34	51	63		20	20	20		18	38	40				
Fac9		64	99	99		6	6	6		50	100	62		7	7	7
Fac10		63	57	41		7	7	7		50	79	48		1	1	1

The analysis highlights staff transfers among facilities, particularly for specialized nurses, which occurred mainly in t3 and t4. For example, Fac2 sends 13 specialized nurses to Fac6 in t4, while Fac8 sends 16 specialized nurses to Fac2 in t3 and 14 specialized nurses to Fac9 in t4. Additionally, there are transfers of other staff types, with Fac3 sending 16 intensivists to Fac5 in t4, and Fac4 sending both respiratory therapists (t3) and specialized nurses (t4) to Fac3, 16 staff each. This mobility is essential for maintaining optimal staffing ratios, especially during fluctuating periods of patient admissions or discharges (see Table 11)

Additionally, cross-training demonstrates significant operational and patient outcome benefits across the healthcare network. The implementation of cross-training between respiratory therapists and specialist nurses across all ten facilities during periods t1-t4 yields three significant operational benefits. First, the cross-training initiative facilitates exceptional operational flexibility, enabling facilities to sustain peak utilization rates while maintaining care delivery standards. Statistical analysis reveals that facilities experiencing highest demand pressures, specifically Fac3 and Fac10, achieve respiratory therapist utilization rates of 108.9% and 104.5% respectively in t4, while maintaining consistent patient discharge patterns through 80 strategic cross-training implementations. Second, the impact on patient outcomes is particularly evident in the management of moderate-severity cases, where cross-trained personnel contribute to maintaining minimal patient shortages (mean range: 1-4 patients per origin point in t3-t4) despite high facility utilization rates (mean: 68.84% across facilities). Third, this enhanced staffing flexibility is achieved with a total operational cost of 3,677,990.853 units, requiring only 107 inter-facility staff transfers rather than additional workforce acquisition. The cross-training strategy proves particularly effective in facilities experiencing maximum capacity utilization, such as Fac7 (100% utilization in t4), where cross-trained personnel facilitate the maintenance of care standards while optimizing resource allocation efficiency.

These findings suggest that the strategic implementation of cross-training initiatives significantly enhances both operational capabilities and patient care metrics while maintaining cost-effective resource utilization across the healthcare network.

Staff utilization rates present a concerning picture, with several instances of critical overutilization observed. For example, Fac3's general nurse utilization reaches 96.9% in t4, while Fac10's respiratory therapists hit 104.5% in t4, and Fac5's specialized nurses peak at 112.5% in t3. This trend of increasing utilization rates from t2 to t4 indicates that many facilities are relying heavily on their existing staff without bringing in new. The overutilization—exceeding 100% in some roles—points to potential staffing stress, which could lead to burnout and impact the quality of patient care. Conversely, some roles maintain very low utilization levels, such as Fac10's intensivists with rates of 0.3% in t3 and t4, and Fac10's specialized nurses at 0.3-0.5% throughout the periods, suggesting inefficiencies or misalignment in staffing.

Table 10. Healthcare workforce distribution and utilization patterns across ten facilities, measuring staff assignments, new hires, and operational efficiency for four medical specialties.

Facility	Clinical Role	Cross-Trained For	Staff Assigned				New Staff Hired	Utilization Rate		
			Time Periods					Time Periods		
			t_1	t_2	t_3	t_4		t_2	t_3	t_4
Fac1	General Nurse		100	100	80	60	0	6.6%	8.0%	10.8%
	Respiratory Therapists	Specialist Nurse	100	100	80	60	0	3.3%	6.7%	13.3%
	Specialist Nurse	Respiratory Therapist	100	100	100	4	0	4.5%	4.2%	56.2%
	Intensivist		100	100	100	60	0	3.0%	2.2%	2.5%
Fac2	General Nurse		100	100	80	60	0	9.2%	10.0%	14.8%
	Respiratory Therapists	Specialist Nurse	100	100	80	60	0	1.5%	4.1%	15.4%
	Specialist Nurse	Respiratory Therapist	100	100	80	67	0	2.0%	1.9%	1.5%
	Intensivist		100	100	80	80	0	1.3%	1.3%	0.8%
Fac3	General Nurse		100	100	6	6	0	4.5%	68.7%	96.9%
	Respiratory Therapists	Specialist Nurse	100	100	7	7	0	1.0%	32.1%	108.9 %
	Specialist Nurse	Respiratory Therapist	100	100	100	96	0	7.0%	5.3%	3.6%
	Intensivist		100	100	100	84	0	4.7%	3.5%	2.8%
Fac4	General Nurse		100	100	7	7	0	7.4%	84.8%	98.2%
	Respiratory Therapists	Specialist Nurse	100	100	84	64	0	9.8%	9.7%	17.6%
	Specialist Nurse	Respiratory Therapist	100	100	100	84	0			
	Intensivist		100	100	100	60	0			
Fac5	General Nurse		100	100	80	60	0	12.4%	16.0%	20.5%
	Respiratory Therapists	Specialist Nurse	100	100	100	24	0	1.8%	8.4%	54.7%
	Specialist Nurse	Respiratory Therapist	100	100	5	5	0	7.5%	112.5%	75.0%
	Intensivist		100	100	100	100	0	5.0%	3.7%	2.5%
Fac6	General Nurse		100	100	80	60	0	13.0%	13.6%	22.0%
	Respiratory Therapists	Specialist Nurse	100	100	100	80	0		2.2%	16.7%
	Specialist Nurse	Respiratory Therapist	100	100	80	60	0			
	Intensivist		100	100	80	2	0			
Fac7	General Nurse		100	100	9	9	0	9.1%	92.4%	86.1%
	Respiratory Therapists	Specialist Nurse	100	100	7	7	0	3.3%	76.8%	114.3 %
	Specialist Nurse	Respiratory Therapist	100	100	4	4	0	2.0%	37.5%	25.0%
	Intensivist		100	100	100	100	0	1.3%	1.0%	0.7%

Fac8	General Nurse		100	100	80	60	0	12.2%	13.9%	16.5%
	Respiratory Therapists	Specialist Nurse	100	100	80	60	0	4.5%	9.1%	16.3%
	Specialist Nurse	Respiratory Therapist	100	100	84	70	0			
	Intensivist		100	100	100	60	0			
Fac9	General Nurse		100	100	100	64	0	9.2%	11.6%	14.5%
	Respiratory Therapists	Specialist Nurse	100	100	80	60	0	12.5%	23.4%	25.8%
	Specialist Nurse	Respiratory Therapist	100	100	80	60	0	3.5%	3.3%	2.9%
	Intensivist		100	100	80	80	0	2.3%	2.2%	1.5%
Fac10	General Nurse		100	100	60	40	0	9.8%	15.6%	22.7%
	Respiratory Therapists	Specialist Nurse	100	100	14	14	0	12.5%	96.4%	104.5 %
	Specialist Nurse	Respiratory Therapist	100	100	100	80	0	0.5%	0.4%	0.3%
	Intensivist		100	100	100	60	0	0.3%	0.2%	0.3%

Table 11. Strategic personnel redistribution patterns across the healthcare network, depicting inter-facility staff movements by specialty and timing.

Source Facility	Destination Facility	Clinical Role	Workforce Redistribution Volume		
			Time Periods		
			t_2	t_3	t_4
Fac2	Fac6	Specialist Nurse			13
Fac3	Fac5	Intensivist			16
Fac4	Fac3	Respiratory Therapist		16	
	Fac3	Specialist Nurse			16
Fac8	Fac2	Specialist Nurse		16	
Fac8	Fac9	Specialist Nurse			14
Fac9	Fac2	Specialist Nurse		16	

Sensitivity Analysis

Facility Capacities and Distribution

The sensitivity analysis results provide valuable insights into how changes in the capacities of healthcare facilities impact various outcomes, such as total costs, shortages, staff utilization, and facility operations. Specifically, the analysis examines the effects of reducing the capacities of all healthcare facilities by fixed percentages—10%, 20%, and 30%—which are denoted in the analysis as three different scenarios. These reductions in capacity are intended to simulate varying levels of strain on the healthcare system, potentially due to factors like resource shortages, increased demand, or disruptions in supply chains. The detailed data can be found in Table 12.

The total cost is an important outcome in the analysis, which reflects the overall resource expenditure required to meet healthcare demands under different scenarios. In the baseline scenario, the total cost is calculated based on full facility capacities. As the capacities of the facilities are reduced by 10%, 20%, and 30%, the total cost increases in each successive scenario. Specifically, the total cost increases by 7.44% when the capacity is reduced by 10%, by 14.81% when reduced by 20%, and by 24.08% when reduced by 30%. These increases in cost suggest that as the capacity of the facilities decreases, more resources are required to compensate for the reduced operational efficiency, leading to higher overall expenditures.

In the baseline scenario, the shortage is at a certain level. As the facility capacities are reduced, the number of shortages increases. For example, when the capacity is reduced by 10%, the shortage rises by 9.07%, and the increase becomes more pronounced as the capacity reduction grows—by 14.38% when reduced by 20% and 22.62% when reduced by 30%. This trend indicates that as the available capacity decreases, the system struggles more to meet the healthcare demands, resulting in a greater number of shortages.

The number of facilities used in the model remains constant across all scenarios. Despite the reductions in capacity, the same number of facilities is utilized in all cases. This suggests that the model does not account for the expansion or reduction in the number of facilities based on capacity changes, focusing instead on how to allocate resources efficiently within the existing healthcare locations. As a result, while the capacities of individual facilities decrease, the number of facilities in use does not change.

Staff utilization is another critical outcome in the analysis, as it indicates how the demand for healthcare workers changes as the system's capacity is reduced. The utilization rates for various staff roles—such as general nurses, respiratory therapists, and intensivists—fluctuate across different facilities and time periods. In particular, the utilization of general nurses increases as the capacity reduction grows, with higher demand for nurses in the 20% and 30% capacity reduction scenarios compared to the baseline. This pattern reflects the increasing strain on the healthcare system, which leads to higher staff utilization as more workers are needed to handle the rising demand for care. Other staff roles, such as respiratory therapists and intensivists, also show varying utilization rates, often increasing in response to more challenging scenarios, though the rates may differ depending on the specific needs at each facility.

The number of staff transfers also changes in response to the capacity reductions. In the baseline scenario, there are a certain number of transfers, but as the capacities decrease, the number of transfers increases in the 10% reduction scenario. However, this number begins to decrease in the 20% and 30% reduction scenarios, suggesting that the system adapts by redistributing staff more effectively or utilizing cross-training programs. The cross-training count, which represents the instances of training staff to perform multiple roles, remains constant across all scenarios. This indicates that cross-training is a fixed strategy in the model, aimed at ensuring that staff are prepared to take on different roles without requiring additional changes in the system's parameters.

Table 12. Impact of capacity reductions on total cost, shortages, staff utilization, and operations across healthcare facilities.

Metric	**Baseline**	**10% Capacity Reduction**	**20% Capacity Reduction**	**30% Capacity Reduction**
Total Cost	3,658,137.34	3,930,274.28 (+7.44%)	4,199,934.59 (+14.81%)	4,538,824.18 (+24.08%)
Shortages	3,130	3,414 (+9.07%)	3,580 (+14.38%)	3,838 (+22.62%)
Number of Facilities Used	10	10	10	10
Staff Utilization				
General Nurse	0.125	0.157	0.210	0.169
Respiratory Therapist	0.153	0.061	0.114	0.161
Staff Transfers	185	288	232	202
Cross Training Instances	120	120	120	120

Costs and Shortages Under Penalty Scenarios

The sensitivity analysis of the resource allocation model reveals several significant insights about the relationship between shortage penalties and resource allocation decisions (see Figure 2). As the penalty multiplier increased from 1.0 to 3.0, the total cost rose from approximately 3.68 million to 10.53 million, representing an overall increase of 186.2%. This relationship was nearly linear, with each 0.5 increase in the penalty multiplier resulting in an approximately 46-47% increase in total costs. This linear relationship suggests that the system's cost structure is highly sensitive to shortage penalties, with a clear and predictable impact on overall expenses. However, the impact on shortages was less pronounced than might be expected. The total shortages decreased only modestly from 3,144 in the base case to 3,059 in the higher penalty scenarios, representing a maximum reduction of 2.7%. Notably, the majority of this improvement occurred between scenarios 1 and 2 (penalty multipliers 1.5 and 2.0), with no additional reduction in shortages observed beyond a penalty multiplier of 2.5. This suggests a diminishing returns effect in using financial penalties to reduce shortages.

Looking at the distribution of shortages across patient types, we observe a consistent pattern across all scenarios: approximately 1,340 mild cases, 151 moderate cases, and 1,568 severe cases remained unserved. The stability of these numbers across different penalty levels suggests that these shortages may be driven by structural constraints in the system (such as facility locations or staff availability) rather than cost considerations.

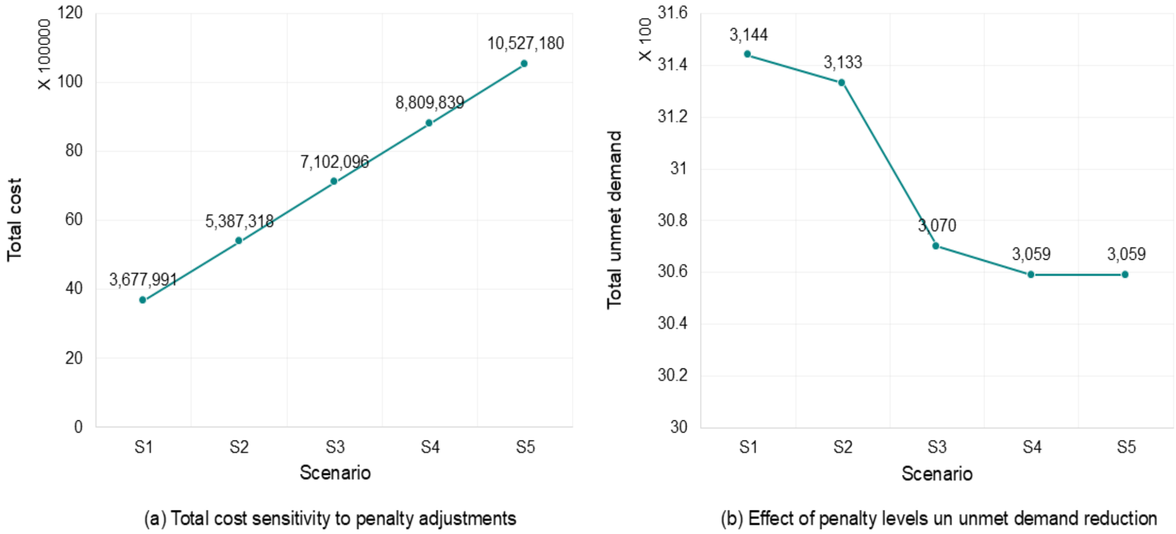

Figure 2. Impact of penalty levels on pandemic resource allocation.

These findings have important practical implications for healthcare policy makers and administrators. The analysis demonstrates that while financial penalties can drive increased resource allocation, they may not be the most efficient tool for improving healthcare system performance. The persistent high number of unserved severe cases (1,568) suggests a critical need to prioritize capacity expansion for higher acuity care, while the minimal impact on mild case shortages (steady at 1,340) indicates that alternative care delivery models or outpatient services might be needed for lower acuity patients. The results strongly suggest that policy makers should consider a more comprehensive approach that combines strategic facility planning, workforce development, and innovative care delivery models to address persistent shortages effectively. Simply increasing penalties or allocating more resources may not be cost-effective beyond certain thresholds; instead, structural reforms, such as facility redesign or staff redistribution, may be more effective in reducing shortages and improving overall system performance.

Resource Cost Variations on Allocation and Service Levels

The sensitivity analysis examining resource cost variations reveals nuanced relationships between cost structures, resource allocation decisions, and service delivery efficiency (see Figure 3). In the base scenario, the model allocated 1,346 resources at a total cost of approximately 3.68 million units. The system's response to cost variations demonstrated both expected patterns and surprising resilience, with important implications for healthcare resource planning.

The most significant finding emerged when resource costs were reduced by 50% (S1). Under these conditions, the model increased resource allocation substantially to 1,450 units, representing a 7.7% increase from the base case. This increased resource deployment translated into tangible improvements in service delivery: the number of patients served increased to 4,727 (from 4,693 in the base case), while unmet demand decreased to 3,110 (from 3,144). This asymmetric response suggests that the system has latent capacity for service improvement that becomes accessible when resource costs are sufficiently reduced.

However, the model exhibited remarkable stability when resource costs increased above the base level. As costs escalated up to double the base value (S5), resource allocation remained relatively steady, fluctuating only minimally between 1,361 and 1,367 units. This inelastic response to price increases indicates that the model prioritizes maintaining essential service levels even under cost pressures. The total system cost showed a surprisingly modest increase, rising only 0.87% to 3.71 million units in S5, despite the doubling of resource costs. This cost stability suggests effective optimization mechanisms within the model that help mitigate the impact of cost increases.

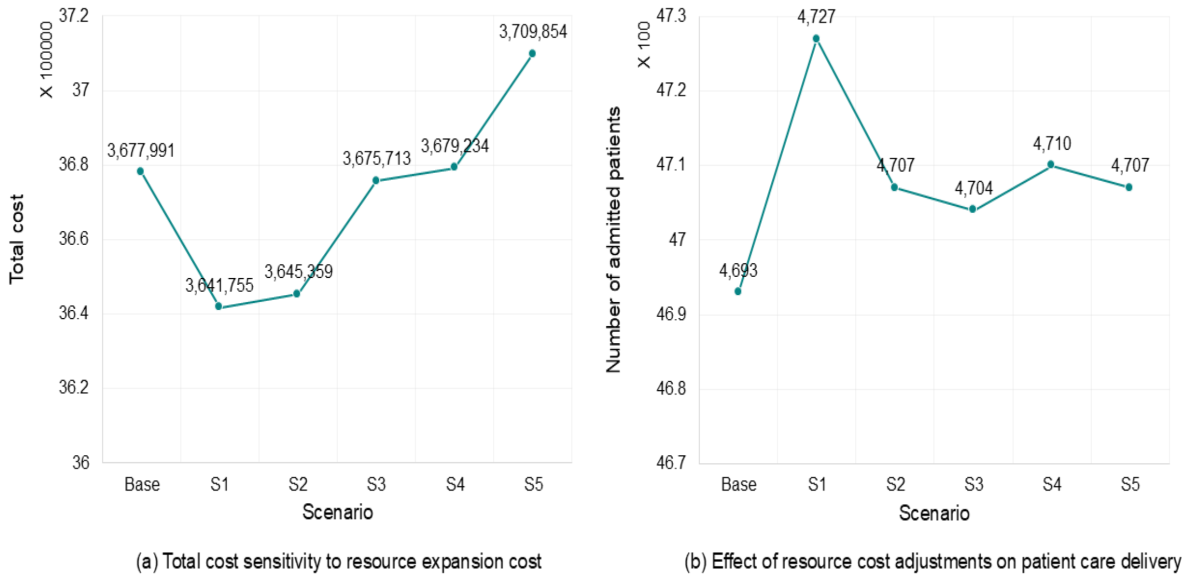

Figure 3. Impact of resource expansion costs on healthcare system performance.

A particularly striking finding is the consistent deployment of exactly 10 facilities across all scenarios. This invariance in facility numbers, combined with the relatively small variations in resource allocation patterns above base costs, demonstrates the model's structural stability. The results suggest that the underlying network configuration is robust and that the core resource allocation strategy can adapt to significant cost variations without requiring fundamental restructuring of the service delivery network.

These findings have profound implications for healthcare system design and management. The asymmetric response to cost reductions versus increases suggests that targeted subsidies or cost-reduction strategies might be more effective in improving system performance than dealing with cost increases. Furthermore, the system's resilience to cost increases, while maintaining relatively stable service levels, indicates that the model has successfully identified a core resource allocation strategy that balances efficiency with service reliability. This stability in facility operations and resource allocation patterns provides healthcare administrators with a degree of confidence in the robustness of their planning decisions, even in environments with volatile resource costs.

Staff Hiring Costs and Shortages in Healthcare Workforce Allocation

The sensitivity analysis of staff hiring costs reveals complex dynamics in healthcare workforce allocation, with several counterintuitive findings that merit careful examination (see Figure 4). The model demonstrated remarkable stability in its performance metrics across varying cost scenarios, suggesting robust optimization mechanisms in workforce deployment. The base scenario, with standard hiring costs, resulted in the highest total cost at 3.68 million units, while scenarios with both increased and decreased hiring costs achieved slightly lower total costs, ranging around 3.66 million units. This unexpected pattern indicates that the model successfully identified alternative optimal solutions that could adapt to different cost structures while maintaining or even improving system performance.

The relationship between hiring costs and service delivery efficiency revealed intriguing patterns. Most scenarios (S1-S3 and S5) maintained consistent service levels at 4,704 patients served with 3,133 unmet demands. However, scenario S4 emerged as particularly efficient, achieving the highest service level with 4,710 patients served and reducing unmet demand to 3,127 cases. This marginal but meaningful improvement suggests the existence of specific cost-structure conditions that enable more efficient resource allocation. The fact that this improved performance did not occur in a linear relationship with hiring costs (either increasing or decreasing) points to complex interactions between staffing costs and other system constraints.

The stability in service levels across scenarios, despite significant variations in hiring costs (ranging from 50% to 200% of base costs), reveals important insights about system constraints. This inelasticity to cost variations suggests that the primary limitations on service capacity lie not in staffing costs but in other structural constraints such as facility capacity, geographic distribution, or resource availability. The consistent performance across such wide cost variations indicates that the model has identified a fundamental staffing configuration that remains optimal or near-optimal regardless of cost fluctuations.

These findings have significant implications for healthcare workforce planning and policy making. First, the ability to maintain similar performance levels despite cost variations suggests that healthcare systems might have more flexibility in staff compensation strategies than previously thought, without necessarily compromising service quality. Second, the identification of specific scenarios (like S4) that achieve better performance indicates potential opportunities for optimizing cost structures to improve system efficiency. Third, the persistence of substantial unmet demand (around 3,130 patients) across all scenarios strongly suggests that addressing workforce challenges alone may be insufficient to significantly improve service capacity - a more comprehensive approach addressing multiple system constraints simultaneously may be required.

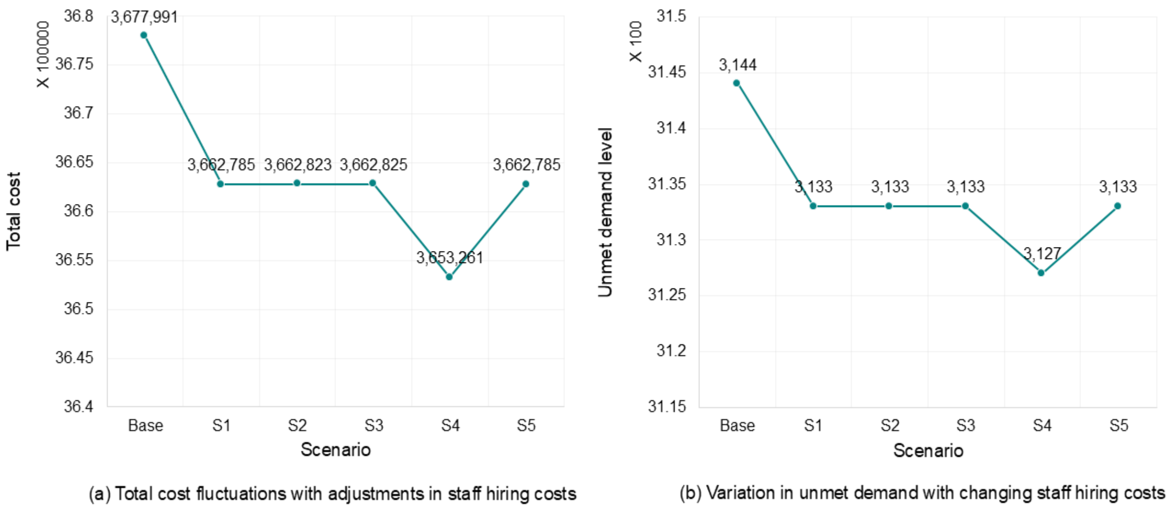

Figure 4. Effect of staff hiring cost adjustments on healthcare system efficiency.

The analysis also highlights the model's sophistication in finding alternative optimal solutions under different cost scenarios. The ability to maintain or even reduce total costs while preserving service levels demonstrates the existence of multiple viable staffing configurations, providing healthcare administrators with flexibility in workforce planning decisions. This resilience to cost variations could be particularly valuable in healthcare systems facing uncertain economic conditions or varying regional cost structures.

These insights suggest that healthcare administrators should focus not only on managing hiring costs but also on identifying and addressing the structural constraints that limit service capacity. The findings support a more nuanced approach to healthcare workforce planning, where staffing decisions are integrated with broader system optimization strategies rather than being treated as an isolated cost management challenge.

Conclusion

This study presented a resource allocation model during pandemics, considered various critical factors such as capacity, staffing, and resource availability. By employing a Mixed-Integer Programming model, the research optimized healthcare resource management while balancing patient demand, facility capacity, and staffing constraints across different time periods. The introduction of cross-training capabilities for staff roles, such as general nurses becoming respiratory therapists or specialized nurses, provided a dynamic solution to address fluctuating patient needs and staff shortages.

The results showed that the model efficiently managed the allocation of healthcare resources, minimizing the total costs associated with resource addition, travel, and staffing, while meeting patient demand. Staff utilization rates were closely monitored to ensure that staffing levels were sufficient to meet the demand for each patient type. The facility utilization rates, along with the cross-training count and staff transfer details, demonstrated how the system adapted to meet rising challenges such as increased patient volume or staff availability issues. In particular, the cross-training strategy helped mitigate potential staff shortages, and the ability to transfer staff between facilities ensured that no location was under-resourced, especially during peak demand periods.

Sensitivity analysis revealed that reducing healthcare facility capacities by 10%, 20%, and 30% increased the total cost and patient shortages significantly. This was primarily because the system compensated for reduced capacity by adding more resources and reallocating staff to other roles, thereby increasing overall staff utilization, particularly for general nurses. While the number of facilities used did not change, the model showed how resource allocation and staff management strategies could adapt to capacity constraints. These findings emphasized the critical role of strategic resource management and staff cross-training in mitigating the effects of capacity reductions on both operational performance and costs.

Several promising directions for future research emerge from this study. First, the integration of real-time data from public health surveillance systems, hospital admissions, and epidemiological tracking could enhance the model by allowing it to dynamically adjust resource allocation based on the pandemic's progression patterns and emerging hotspots. This could involve developing decision support systems that link epidemiological data with resource planning to better anticipate and respond to shifts in patient demand across different regions. Second, incorporating machine learning algorithms could improve the prediction of staff availability and patient surge patterns, enabling more proactive resource allocation decisions. Third, future research should address the ethical dimensions of resource allocation during healthcare crises, particularly examining how to balance cost optimization with equitable access to healthcare services across different socioeconomic groups and geographic regions. This could include developing multi-objective optimization models that explicitly consider fairness metrics and social vulnerability indices.

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