

Article

A Three-Echelon Healthcare Supply Chain Model for Blood Distribution During Crisis Times

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Abstract: We aim to implement a three-tiered healthcare supply chain model within the context of a portable blood hub during times of crisis to provide healthcare to the most vulnerable populations. Due to a lack of blood, the number of deaths related to this issue has significantly increased in recent years. A critical challenge for healthcare decision-makers is the efficient distribution of blood among different centers. This research proposes a new method to address this issue, simplifying future solutions to similar problems. As a result of our findings, we introduce a model that considers three tiers in healthcare blood supply: point one (blood collection centers), point two (blood hubs), and final destinations (hospitals and clinics) during disasters. For this study, we focused on six collection sites, five blood centers, and thirty-one medical facilities providing eight different blood types. Our model demonstrates that blood can be transported from collection sites to medical centers at a lower cost during crises. This approach requires considering the full three tiers of the healthcare supply chain rather than focusing solely on the supply chain level at blood hubs. Unlike previous studies, which focused only on individual levels of supply chain management, this study examined the entire value chain, from blood collection to delivery to the end recipient.

Keywords: three-echelon; healthcare; blood supply chain management; crisis time; mathematical modeling; Iran



Academic Editor: Wen-Chyuan Chiang

Received: 11 September 2024

Revised: 4 November 2024

Accepted: 5 November 2024

Published: 26 December 2024

Citation: Khiabani, A.; Rashidi Komijan, A.; Karbassi Yazdi, A.; Tan, Y.; Piñones, G.C.; Ishizaka, A. A Three-Echelon Healthcare Supply Chain Model for Blood Distribution During Crisis Times. *Systems* **2025**, *13*, 7. <https://doi.org/10.3390/systems13010007>

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1. Introduction

Due to constant changes in our world, making decisions can be extremely difficult. Additionally, many events occur without prior prediction, and making decisions about them is challenging. It is therefore necessary to provide decision-makers with a wide range of tools to make informed choices. A blood transfusion might be needed for several reasons including accidents [1]. Road accidents have caused many deaths in Iran, a country where traffic incidents have led to significant fatalities [2]. Traffic accidents result in approximately 1.35 million deaths worldwide annually, with almost 3700 people killed daily in car, bus, motorcycle, bicycle, truck, or pedestrian accidents. In these incidents, more than half

of the victims are pedestrians, motorcyclists, or cyclists. According to the latest WHO data published in 2020, road traffic accidents caused 17,803 deaths in Iran, accounting for 5.36% of the total deaths. Iran ranks 65th in terms of mortality rates, with 22.15 deaths per 100,000 population [3].

Many people have lost limbs or died as a result of these accidents. Healthcare systems are significantly impacted during crises, as sudden healthcare demands directly affect system functionality and drastically increase patient numbers. This study aimed to identify resilient health system “Gold units” in emergencies and demonstrate their capabilities. Third-party distribution networks, essential to the functioning of healthcare systems, are prone to failure. Traditionally, blood is distributed through cold chains and supply chains. A cold chain refers to preserving perishable products at specific temperatures. Table 1 shows the leading causes of injury-related deaths in Iran [4].

Table 1. Leading causes of injury death [4].

Rank	External Cause of Injury	Deaths
1	Road Injury	30,772
2	Self-inflicted	4245
3	Poisoning	2195
4	Fiers	2065
5	Falls	1912
6	Inter-Persona	1562
7	Drowning	1538
8	War	930
9	Burns (Excel Fire)	862
10	Asphyxiation (Excel Drown)	549

Nowadays, one of the most essential topics in blood supply chain management (SCM) is the type of blood, with type O being especially rare [5]. Additionally, blood demand can fluctuate due to seasonal factors [6]. Thanks to advanced technology, tools such as AI, IoT, and RFID contribute to the transparency and optimization of blood SCM [7]. Due to limited resources, many countries want to replace fixed blood hubs with portable ones, especially during crises. However, in some countries, deficient- and middle-income nations, institutions are designed to improve blood supply management and encourage donations [8].

Research has been conducted on blood hub supply chain management. Based on the experience of Canadian Blood Services, Blake and Hardy [9] proposed a generic model to evaluate network blood management policies. Fallahi et al. [10] designed a closed-loop blood supply chain network, considering quality and flow, and extended two new versions of differential evolution (DE) to address the design. Jabbarzadeh et al. [11] developed a dynamic supply chain network for blood supply in disaster situations, comparing the performance of robust optimization and expected value approaches. Meidute-Kavaliauskiene et al. [12] incorporated blockchain technology into the blood supply chain, prioritizing deployment barriers. This study extracted barriers from previous studies and expert interviews, with each case study’s barriers tailored using the Delphi method. Blood supply hubs were ranked based on these measurements using the MARCOS method. The best–worst method (BWM) was employed to determine the primary weights for this method. In a study by Valizadeh et al. [13], game theory was applied to model blood distribution networks. Various cooperative game theory (CGT) methods, such as the Shapley value,

f-value, core-center, and least-core, were investigated to minimize hospital construction and maintenance costs and maximize profit-sharing between hospitals.

DE approaches may encounter challenges when addressing the intricate dynamics of networks, especially during catastrophes. Unforeseen severe situations can test robust optimization methods, which prioritize stability over adaptability. Integrating blockchain technology in the supply chain presents challenges such as high implementation costs and a lack of technical expertise. Determining accurate main weights for the BWM can also be a complex task. Furthermore, comprehensive data are essential for precise profit-sharing calculations in game theory models, which can be computationally demanding [14].

While much research has been conducted on blood hubs worldwide, this study is unique as it considers a three-echelon healthcare supply chain model in a portable blood hub during crises. In this study, blood suppliers operate at the first level. A blood supplier is a facility responsible for collecting blood from donors, processing it, and preparing it for use. The second level includes portable blood hubs. The concept of the “Golden Hour” in blood supply refers to the crucial first 60 min after trauma, when immediate medical attention significantly increases the victim’s survival chances after accidents, falls, or injuries [15]. The primary goals of first-hour treatment are to stop bleeding, provide oxygen, call for assistance, and arrange transport to a hospital where the victim can receive professional medical care. Under extreme or less severe conditions, Golden Hour™ Medic, Golden Hour™ Mobile, and Golden Hour™ One containers can preserve one to four units of whole blood for up to 72 h [16]. This study examined blood producers based in Tehran and how blood is distributed to injured individuals. Some locations and surrounding areas experience frequent accidents, indicating the need for blood hubs in those regions. Additionally, if specific blood types are not used promptly, they may expire, resulting in both blood shortages where it is urgently needed and reduced storage capacity. To address the blood distribution problem in a three-tier healthcare supply chain during crises, we propose a mixed-integer linear programming (MILP) model to minimize transportation costs while meeting demand. This approach will be supported by demand forecasting and inventory management to prevent shortages.

1.1. Research Gap

Earlier studies have focused on single-tier or dual-tier supply chain models, typically examining the collection and distribution aspects as distinct entities. There is a need for models that effectively optimize the operations of emergency blood supply chains, considering factors such as abrupt increases in demand, transportation disruptions, and the imperative requirement for prompt delivery. Most research has not considered the complete value chain, which encompasses everything from blood collection to patient delivery, often focusing on a particular domain instead. There has been limited research on the scalability of blood supply chain models, particularly regarding different regions, crises, and blood types. In previous research considering fluctuating demand, different blood types have been studied to reduce costs and explore portable solutions [17]. Although many papers have been published on this topic, they have often focused on specific aspects of the model or particular solution techniques [18–20]. Some earlier studies concentrated on optimizing facility placements and transportation but did not consider the mobility of blood hubs, even during crises. According to some studies, these hubs are either fixed or semi-fixed and are not regarded as dynamic facilities. In other research, closed-loop supply chain management has been used; however, in the real world, it is sometimes necessary to consider using portable hubs. Furthermore, most prior research did not account for blood type. Table 2 provides a summarized review of previous research and presents detailed information on the studies discussed.

Table 2. Previous studies.

Authors	Number of Echelons	Regional Case Study	Decision Focus	Method/s	Situation
[21]	Collection, Distribution, Value Recovery Centers	Mexico	Minimizing costs, optimizing CO ₂ emissions, maximizing social factors.	Bi-objective sustainable supply chain design using stochastic programming and vehicle routing problem. Sensitivity analysis is also applied.	Blood decomposition in medical supply chains.
[22]	Collection, Inventory, Delivery	Yazd, Iran	Robust optimization, mobile blood facilities, minimizing spoiled blood.	Open vehicle routing problem (OVRP), Bertsimas and Sim's robust approach.	Geographically dispersed locations.
[23]	Collection, Processing, Delivery	Lisbon, Portugal	Strategic and tactical decisions for optimization.	Optimization models focusing on strategic and tactical planning levels.	Focuses on the complexities of blood supply chains, especially in ensuring demand fulfillment and compliance with safety regulations.
[24]	Donors, Collection, Distribution, Hospitals	Not specified (Iran implied)	Minimizing costs, maximizing environmental and social effects.	SA algorithm, harmony search (HS) algorithm.	Uncertain condition during a disaster and after it.
[25]	Collection, Storage, Delivery	Tehran, Iran	Facility location, allocation, and disaster response.	A dynamic robust location-allocation model combined with meta-heuristic algorithms.	Blood supply chain networks under disaster situations, addressing uncertainties and facility disruptions.
[11]	Donors, Facilities, Blood Centers	IBTO, Iran	Robust blood supply during disasters.	Differential evolution.	Supply of blood in disasters.
[13]	Collection, Storage, Hospital Service Centers	Tehran, Iran	Cost reduction, hospital collaboration, game theory.	Open vehicle routing problem (OVRP), Bertsimas and Sim's robust approach.	Geographically dispersed locations.
[26]	Four layers (donation areas, collection centers, blood centers, hospitals)	Istanbul (Asian side), Turkey	Minimizing total cost and blood shortages under uncertainty and disruption.	Fuzzy objective function.	Natural disasters.
[27]	Three echelons (supply facilities, distribution centers, hospitals)	Earthquake-prone regions in Iran	Location-allocation, inventory management, and disruption management.	A bi-objective, two-stage stochastic programming model.	Blood supply chains is difficult due to uncertainties.
[28]	Two echelons (local collection facilities, regional centers)	Mashhad, Iran	Location-allocation, inventory management, considering disruption risks and compatibility.	Bi-objective stochastic programming with robust optimization.	Blood supply chain management under uncertainties such as disruptions, perishability, and blood group compatibility.
[29]	Two echelons (collection points, central labs)	Tehran, Iran	Optimizing vehicle routing and logistics for blood sample collection.	Open vehicle routing problem (OVRP), Bertsimas and Sim's robust approach	Geographically dispersed locations.

1.2. Contribution

This research aimed to identify ways to reduce blood transportation costs during crises. This information can be distributed to the nearest hospitals and clinics, and the amount of blood allocated to each can be calculated. The findings of this research enhance the management of the blood supply system, particularly during emergencies. The study presents a comprehensive framework designed to improve blood distribution efficiency. This was achieved by developing a dynamic optimization model that reduces transportation costs and enhances decision-making accuracy. Integrating a portable blood hub and considering various blood types increases the model's applicability to real-world scenarios, optimizing resource allocation for life-saving purposes. The model finds that blood demand is erratic and variable in emergencies, essential for efficient crisis management. By defining hospital and clinic demands during crises, the model ensures the robust, cost-effective, and timely management of blood supplies. This model is an optimal guide for resource placement and allocation during emergencies.

The discoveries made in this study significantly contribute to improving blood supply chain management, especially in emergencies. This research introduces a comprehensive framework to increase blood distribution efficiency. This was achieved through a dynamic optimization model that reduces costs and enhances decision-making. The model's applicability to real-world situations is strengthened by integrating a portable blood hub and accounting for different blood types, all aimed at enhancing resource allocation for life-saving purposes. The model accounts for the unpredictable and fluctuating nature of blood demand during emergencies, which is crucial for effective crisis management. Integrating hospitals, blood facilities, and donors enhances the efficiency of the entire process from collection to patient delivery. The model ensures effective blood supply management over time by specifying hospital inventory levels at the end of each cycle. Decision-makers who use this model as a guide for resource allocation and placement can improve the overall effectiveness of the blood supply chain and its disaster response. It proposes a portable blood hub system for managing blood supply networks during various crises. Blood type distribution ensures the effective management and allocation of all blood types according to demand.

The contributions of this research are:

1. Lowered transportation costs and improved decision-making accuracy.
 2. Integrating a portable blood hub and accounting for various blood types.
 3. Developing an optimal model for effective and prompt management of blood supplies at low cost.
- The objective was to create a dynamic optimization model that reduces transportation costs and enhances crisis decision-making processes.
 - By incorporating a portable blood hub into its design, the model considers various blood types, increasing its relevance in real-life emergencies.
 - Our system ensures effective blood supply management, particularly during emergencies, by responding to unpredictable demand.
 - By providing a resource allocation and placement guide, we aim to enhance the efficiency of blood distribution to hospitals and clinics and ensure that this life-saving resource reaches those in need promptly.

Research Question 1: How can a dynamic optimization model be developed to effectively reduce blood transportation costs during crises while improving the accuracy of decision making for blood distribution?

Research Question 2: How does integrating a portable blood hub and accounting for various blood types enhance the model's applicability in real-life emergencies, ensuring efficient and timely resource allocation to hospitals and clinics?

1.3. Structure Organization

The paper is divided into six sections. After the introduction, the next section discusses the research contribution, aims, and research gap. This is followed by a literature review that evaluates previous studies to identify gaps between this research and prior work. The methodology section, presented in Section 3, includes a problem statement outlining the purpose and approach of the research, followed by a mathematical model that highlights the model's assumptions. The problem definition and mathematical model further detail the objective functions, constraints, variables, sets, and indices used in the models. Section 4 analyzes the data, demonstrating the results when applied to the collected data. Section 5 focuses on implementing managerial policies, and the insights from the analysis presented in Section 4. Finally, the paper concludes with a discussion that highlights the paper's contributions.

2. Literature Review

In healthcare research, blood hubs are a popular topic. Studies have focused on different aspects of blood supply chain management (SCM) that consider various scenarios and situations. Jabbar Zadeh et al. [11] designed a dynamic supply chain network for blood supply in disasters, creating a robust model with real-world applications. This study aimed to develop an optimization model that assists in locating and allocating blood facilities during multiple post-disaster periods to optimize patient care. The proposed model will be applied in a case study using real-world data to create a blood supply network for potential disaster scenarios. Razavi et al. [30] developed a mathematical model to effectively distribute blood types and address the issue of blood storage life, particularly for field hospitals in disaster areas. This model ensures optimal blood transfusion routing at the lowest cost by managing blood type availability and equitable allocation among hospitals. A multi-objective mathematical model is used to handle uncertain conditions in crisis response, applying a resilient optimization technique to address unpredictable data in such scenarios. A hybrid approach, genetic algorithm and multi-choice goal programming (GAMCGP), was employed for the proposed model and successfully applied to a real-world blood supply chain in Mazandaran, northern Iran, with sensitivity analyses conducted on the model parameters.

Valizadeh et al. [13] analyzed the blood supply chain using game theory as a robust mathematical model, presenting an optimization model for blood supply chains that focused on the location and management of various centers. The model aims to minimize total hospital costs including construction, patient allocation, patient service, time-out fines, non-absorbed blood fines, and outsourcing costs. Hosseini Motlagh et al. [28] addressed the complexities of managing blood supply chains, considering uncertainties like fluctuating blood demand, facility outages, and the perishable nature of blood products. They developed a bi-objective, two-stage stochastic programming model to optimize location allocation and inventory management, reducing the supply chain costs and enhancing transfusion safety.

Jami et al. [31] aimed to reduce the cost and time associated with blood delivery throughout the blood supply chain network (BSCN) during disasters. Using a bi-objective mathematical model to optimize response time, the study considered four facility categories—temporary blood collection centers, field hospitals, main blood processing centers, and medical centers. Moghimi Esfandabadi et al. [32] proposed a model to enhance blood center attractiveness

during COVID-19 by reducing costs and shortages, ultimately improving donation efficiency and overcoming barriers. This model employs a two-objective framework to minimize supply chain costs and maximize center attractiveness, using the ε -constraint method to generate Pareto solutions.

Blake and Hardy [9] introduced a simulation-based methodology to evaluate network inventory policies in regional blood distribution sites in Canada. Their approach uses a generic framework to represent ten regional networks, comparing different networks against model results to validate the framework. Another study focused on a closed-loop blood supply chain network that considered transportation flow and quality, ensuring smooth product movement through the supply chain. Mathematical formulations capture the flow and quality features within the network, with closed-loop design proving more efficient economically and environmentally. Eskandari-Khanghahi et al. [24] proposed a sustainable supply chain network design for a blood platelet bank, considering uncertain supply conditions and demand points such as donor groups, collection facilities, distribution centers, and hospitals. Their model aimed to minimize the total cost, reduce environmental impact, and maximize the social benefits.

Sadri et al. [33] demonstrated how blockchain traceability can improve transparency and security in the blood donation supply chain (BDSC). Leveraging blockchain's decentralization, immutability, and security, this study defined role-based access levels with smart contracts, enhancing traceability within the BDSC. Rostami et al. [29] proposed a robust open vehicle routing model to minimize logistics costs for blood sample collection from dispersed locations, emphasizing the perishable nature of blood samples, which requires timely collection within two hours. Abdolazimi et al. [22] developed a multi-level blood supply chain network for the COVID-19 pandemic, incorporating humanitarian considerations and selecting optimal locations to minimize spoiled blood. The model's solutions were evaluated using a modified weighted Chebyshev algorithm with the TOPSIS algorithm.

Kochakhashani et al. [34] established a mathematical framework for planning pharmaceutical supply chains during COVID-19, integrating cold and non-cold chains while considering factors like temperature, shelf life, and priority. This four-echelon supply chain design minimizes financial burdens while meeting service expectations. Recognizing uncertainty, the model employs a "wait-and-see" approach and a clustering technique for managing pharmaceutical factors. Khalilpourazari et al. [35] utilized neural learning and prior knowledge to minimize disaster impacts, aiming to reduce expenses, unmet demand, and transit time. Implemented during the 2017 Iran–Iraq earthquake, the model provides insights into creating cost-effective blood supply chains.

Seyfi et al. [26] proposed a model using trapezoidal fuzzy numbers and spherical fuzzy membership degrees to design a blood supply network for disaster scenarios in Istanbul, Turkey. This model minimized costs and blood shortages, employing fuzzy objective functions and variables. Haghjoo et al. [25] developed a comprehensive location-allocation model addressing facility interruptions and demand uncertainty in catastrophic situations. Using advanced optimization techniques, the model helps maintain continuous blood supply operations. Hosseini-Motlagh et al. [28] proposed a two-stage stochastic programming approach to handle the unpredictability of red blood cell supply chains, focusing on cost reduction and transfusion safety. Shokouhifar and Sabbaghi [36] suggested a lateral transshipment-based inventory management approach to reduce shortages and waste in blood supply chains.

Ghorashi et al. [37] used the multi-objective grey wolf optimizer to address emergency blood supply chain challenges including site allocation and routing, improving emergency blood transportation across facilities. Shokouhifar and Ranjbarimesan [38] employed LSTM and other machine learning methods to forecast blood demand during pandemics, strength-

ening blood supply networks. Mousavi et al. [21] developed a socially and environmentally sustainable blood supply chain network to reduce greenhouse gas emissions, focusing on environmental accountability and supply chain efficiency.

3. Methodology

3.1. Problem Statement

Iran's diverse landscapes including mountainous areas, isolated rural regions, and varied terrains pose challenges to establishing an efficient blood supply infrastructure that is capable of swift crisis response. The country is susceptible to natural disasters such as earthquakes and dust storms. Numerous hospitals and clinics in Iran have a high demand for blood due to the frequent occurrence of accidents. Maintaining a blood reserve is crucial for emergencies, given the frequent accidents and injuries. While a cohesive system might function effectively in stable conditions, meeting the increased demand and addressing logistical challenges in crisis situations require substantial time and effort.

A three-tiered system with mobile blood centers can ensure a reliable blood supply during crises or in remote locations. This model demonstrates how blood can be directed to areas with the greatest need, improving the efficiency of the supply chain. Mobile blood clinics increase blood accessibility in impoverished or remote regions, ensuring availability for patients most likely to benefit from treatment. In a disaster like an earthquake, an immediate blood supply is essential for treating injuries, performing surgeries, and providing other critical medical care. An efficient blood delivery infrastructure is crucial to meet Iran's rising demand for blood, driven by frequent natural disasters. A three-tiered supply system could save lives in remote or crisis-affected regions by maintaining blood reserves strategically and reducing response times. This approach ensures that hospitals consistently maintain an adequate blood supply to meet their daily needs, enabling the healthcare system to adapt to fluctuations in demand and enhancing the overall patient outcomes.

3.2. Mathematical Model

This paper examined a three-echelon network in the blood supply chain, comprising collection sites, blood centers, and clinical centers. The model consists of three levels:

Level I: Blood donation involves collecting blood from donors at ten fixed collection centers nationwide, which are easily accessible to the public. Once collected, the blood is refined and prepared for distribution. These collection centers operate continuously to meet the city's blood supply needs.

Level II: This level is an intermediary between collection sites (providers) and clinical centers (consumers). Although the blood centers are fixed locations, they can be added or removed depending on demand. Adjusting the number of blood centers based on healthcare system requirements helps optimize logistic costs related to blood transportation.

Level III: This distribution level encompasses the refined blood from Level I, which is transferred to the blood hub distribution sites in Level II. There are 60 hospitals at this level that regularly require different blood types including AB+, AB−, O−, O+, A−, A+, B−, and B+.

3.3. Setup Parameters and Data

The first step in preparing the data for this research was to define the echelon parameters. These parameters included the distribution of blood collection centers and the demand points, which consist of hospitals and clinics. Each echelon in our system is characterized by several factors including supply capacity, lead time, cost, storage capacity, transportation cost, demand rate, available blood types, and location.

3.4. Assumption

- The network includes donor centers, blood distribution centers, and customers (hospitals);
- The location of donor centers and customer sites are determined;
- Blood distribution centers may be established at certain potential nodes (cities);
- Blood distribution centers are removable, meaning a center can be established in one period and removed in subsequent periods;
- Inventory is only held at blood distribution centers;
- Donor centers and blood distribution centers use rental vehicles for transportation.

Before analysis, the locations of donor centers and hospitals were designated and organized to simplify the problem and eliminate uncertainties in critical supply chain nodes. Blood distribution centers can be located in multiple cities, acting as intermediary hubs that bridge the gap between suppliers and recipients. These facilities can be established or dismantled over time due to their flexibility, which is particularly beneficial in crisis management when demand and infrastructure availability may vary. Blood distribution centers primarily handle inventory management; donor centers and hospitals do not maintain stock. This approach emphasizes efficient inventory management, enhancing the operational efficiency of the supply chain. Additionally, donor and blood distribution facilities use leased vehicles for transportation, allowing the transportation capacity to be adjusted in response to fluctuations in demand and resource availability.

3.5. Problem Definition and Mathematical Model

The objective function of this model is to minimize the total cost of the supply chain including the transportation costs, holding costs, establishment and removal costs of blood centers, and the vehicle rental costs for transportation. Each collection site can produce various blood products and transport them to different blood centers through defined arcs. Only blood centers can hold inventory, while collection sites and clinical centers do not. Heterogeneous vehicles are rented to transport blood products, and due to their limited capacity, each vehicle can only visit one node per trip. This setup differs from the typical vehicle routing problem. For example, a car may be loaded at a collection site, travel to a blood center to unload, return to the collection site, and load again for the next trip. Figure 1 provides a schematic view of the network, illustrating three distinct stages: the production, storage, and distribution of blood products.

The primary blood supply originates from blood collection sites spread across various regions, forming part of the production stage. Blood centers, operating in the storage stage, are responsible for storing and distributing blood products. At the beginning of each period, potential locations for blood centers are identified, and decisions regarding their activation or deactivation are made to minimize the operating costs while meeting demand. Finally, medical centers serve as the end users during the distribution phase, setting the demand that blood centers must fulfill promptly and affordably.

The mathematical model's results determine whether a blood center should be opened, maintained, or removed. Additionally, it identifies the optimal number of blood products to transfer and the required number of vehicles in each period.

For this study, which involved a moderately sized network, exact methods like mixed-integer linear programming (MILP) can provide optimal solutions within a reasonable time. In some cases, heuristic or metaheuristic approaches (e.g., genetic algorithms, simulated annealing) may be practical alternatives, offering near-optimal solutions more quickly, though not exact. However, due to the size and structure of this case study, exact methods are preferable, and this model is designed to yield an exact solution, demonstrating its superiority. Figure 1 illustrates the flow between levels.

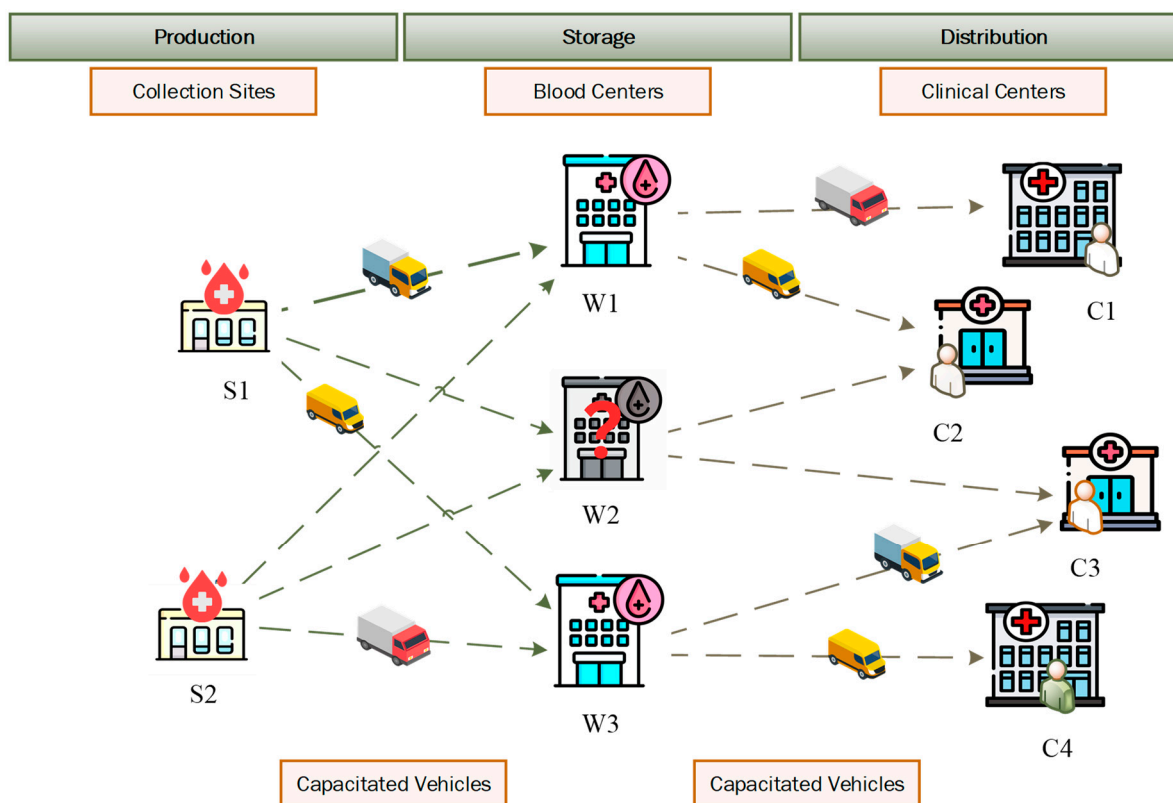


Figure 1. Schematic view of the proposed three-echelon blood supply chain network with multi-vehicle delivery.

Accordingly, the mathematical model is as follows:

Sets and indices:

S	Set of collection sites
W	Set of blood centers
C	Set of clinical centers
N	Set of all nodes of the network (indexed by i, j ; $N = S \cup W \cup C$)
V	Set of vehicle types (indexed by v)
P	Set of blood products (indexed by p)
T	Set of time periods (indexed by t)
A	Set of available arches

Parameters

TC_{ijvt}	Transportation cost for a vehicle v to cover arch $i - j$ in week t
HC_{pt}	Holding cost of blood product p in week t
$HirC_{vt}$	Hiring cost of vehicle type v in week t
EC_{it}	Establishment cost of blood center i in week t
RC_{it}	Removal cost of blood center i in week t
vol_p	Volume of blood product p
R_p	Required resource to produce one unit of blood product p
Cap_{it}	Capacity of collection center i in week t
Cap'_{iv}	Capacity of blood center i
Cap''_{iv}	Capacity of vehicle type v
Dem_{ipt}	Demand of clinical center i for blood product p in week t
$Time_{ijv}$	Travelling time for vehicle v to pass arch $i - j$
TT	Total available working time in a week
BM	A large number

Variables

X_{ijvt}	Number of times vehicle type v travels from node i to j in week t
Y_{it}	Binary variable equals one if blood center i is established in week t , 0 otherwise
Z_{ivt}	Required number of vehicle type v for node i in week t
Q_{ijpvt}	Number of blood product p transported from node i to j by vehicle v in week t
Inv_{pit}	Inventory of blood product p in blood center i at the end of week t

Table 3 points out the description and units of each variable and parameters of this research.

Table 3. Information of parameters and variables.

Variable/Parameter	Description	Units
TC_{ijvt}	Transportation cost for vehicle v covering arc i - j in week t	Currency (Rials) per vehicle per week
HC_{pt}	Holding cost of blood product p in week t	Currency per unit of blood product per week
$HirC_{vt}$	Hiring cost of vehicle type v in week t	Currency per vehicle per week
EC_{it}	Establishment cost of blood center i in week t	Currency per blood center per week
RC_{it}	Removal cost of blood center i in week t	Currency per blood center per week
vol_p	Volume of blood product p	Liters (L) per unit of blood product
R_p	Required resources to produce one unit of blood product p	Resources per unit of blood product
Cap_{it}	Capacity of collection center i in week t	Units of blood product per week
Cap'_v	Capacity of blood center i	Units of blood product per blood center
Cap''_v	Capacity of vehicle type v	Units of blood product per vehicle
Dem_{ipt}	Demand of clinical center i for blood product p in week t	Units of blood product per week
$Time_{ijv}$	Traveling time for vehicle v to pass arc i - j	minutes per trip
TT	Total available working time in a week	minutes per week
BM	A large number used in optimization constraints	Dimensionless
X_{ijvt}	Number of times vehicle type v travels from node i to j in week t	Number of trips per week
Y_{it}	Binary variable: 1 if blood center i is established in week t , 0 otherwise	Binary (0 or 1)
Z_{ivt}	Required number of vehicle type v for node i in week t	Number of vehicles
Q_{ijpvt}	Number of blood product p transported from node i to j by vehicle v in week t	Units of blood product per trip
Inv_{pit}	Inventory of blood product p in blood center i at the end of week t	Units of blood product

The three-echelon blood supply chain network is formulated as follows:

$$\text{Min} \sum_{i \in N} \sum_{j \in N: (i,j) \in A} \sum_{v \in V} \sum_{t \in T} TC_{ijvt} * X_{ijvt} + \sum_{p \in P} \sum_{i \in W} \sum_{t \in T} HC_{pt} * Inv_{pit} \quad (1)$$

$$+ \sum_{i \in W} \sum_{t \in T} EC_{it} * Y_{it} * (1 - Y_{i(t-1)}) + \sum_{i \in W} \sum_{t \in T} RC_{it} * (1 - Y_{it}) * Y_{i(t-1)} + \sum_{v \in V} \sum_{i \in SUW} \sum_{t \in T} HirC_{vt} * Z_{ivt}$$

$$\sum_{i \in S} \sum_{v \in V} Q_{ijpvt} + Inv_{pj(t-1)} = \sum_{i \in C} \sum_{v \in V} Q_{jipvt} + Inv_{pj(t-1)} \quad \forall j \in W; p \in P; t \in T \quad (2)$$

$$\sum_{j \in W} \sum_{v \in V} \sum_{p \in P} R_p * Q_{ijpvt} \leq Cap_{it} \quad \forall i \in S; t \in T \quad (3)$$

$$\sum_{i \in S} \sum_{v \in V} \sum_{p \in P} vol_p * Q_{ijpvt} + \sum_{p \in P} vol_p * Inv_{pj(t-1)} \leq Cap'_v * Y_{jt} \quad \forall j \in W; t \in T \quad (4)$$

$$\sum_{p \in P} vol_p * Q_{ijpvt} \leq Cap''_v * X_{ijvt} \quad \forall (i, j) \in A; v \in V; t \in T \quad (5)$$

$$\sum_{\substack{j \in N: \\ (i,j) \in A}} Time_{ijv} * X_{ijvt} \leq TT * Z_{ivt} \quad \forall i \in S \cup W; v \in V; t \in T \quad (6)$$

$$\sum_{i \in W} \sum_{v \in V} Q_{ijpvt} \geq Dem_{pjt} \quad \forall j \in C; p \in P; t \in T \quad (7)$$

$$\sum_{p \in P} Inv_{pit} + \sum_{p \in P} Inv_{pi(t-1)} + \sum_{j \in S} \sum_{v \in V} X_{jivt} + \sum_{j \in C} \sum_{v \in V} X_{ijvt} + \sum_{j \in S} \sum_{p \in P} \sum_{v \in V} Q_{jipvt} + \sum_{j \in C} \sum_{p \in P} \sum_{v \in V} Q_{ijpvt} \leq BM * Y_{it} \quad \forall i \in W, t \in T \quad (8)$$

The objective function, formulated to minimize various costs, includes transportation costs, holding costs, the establishment and removal costs of blood centers, and vehicle rental costs. The objective function is applied when a vehicle v travels along a specific arc to transport cargo between the origin and destination nodes. The second component of the objective function accounts for the cost of holding each unit of blood product in a facility for the duration of each time period. During each operational week, the third and fourth components cover each blood center's deployment and removal costs. The final component calculates the weekly cost of deploying each vehicle for operation.

Relation (2) serves as a transshipment constraint, ensuring flow balance within blood centers. This constraint guarantees that the total quantity of blood products delivered or stocked at a facility by the end of the period aligns with the quantity received and carried over from the previous period. Given that each facility has limited storage capacity for blood products, constraints (3) and (4) ensure that excessive deliveries do not exceed the capacities of collection sites and blood centers. Similarly, constraint (5) prevents vehicle capacity violations. Constraint (6) ensures that the total travel time of a vehicle does not exceed its available working time. Relation (7) is the demand constraint, which ensures that the quantity of blood products delivered to the destination from various sources is sufficient to meet the total demand for that specific product. Accepting additional products at the destination is also permitted. Constraint (8) ensures that if inventory is held or blood products are transferred to or from a blood center during a time period, the center must be open during that period.

According to Khiabani et al. [39], nonlinearity is inevitable in certain mathematical models for complex problems. However, nonlinearity significantly increases the CPU time, critical in supply chain models where the solution time must be minimized. Additionally, nonlinear models may result in local optima rather than global ones. Although the objective function in this model is nonlinear, it can be transformed into a linear form by substituting $Y_{it} * Y_{i(t-1)}$ with a new binary variable (i.e., α_{it}). In this case, constraints (9) and (10) are added to the model.

$$2\alpha_{it} \leq Y_{it} + Y_{i(t-1)} \quad \forall i \in W, t \in T \quad (9)$$

$$Y_{it} + Y_{i(t-1)} \leq \alpha_{it} + 1 \quad \forall i \in W, t \in T \quad (10)$$

Therefore, objective (1) is changed to the linear form (11):

$$\begin{aligned} & Min \sum_{i \in N} \sum_{\substack{j \in N: \\ (i,j) \in A}} \sum_{v \in V} \sum_{t \in T} TC_{ijvt} * X_{ijvt} + \sum_{p \in P} \sum_{i \in W} \sum_{t \in T} HC_{pt} * Inv_{pit} \\ & + \sum_{i \in W} \sum_{t \in T} EC_{it} * Y_{it} - \sum_{i \in W} \sum_{t \in T} EC_{it} * \alpha_{it} + \sum_{i \in W} \sum_{t \in T} RC_{it} * Y_{i(t-1)} \\ & - \sum_{i \in W} \sum_{t \in T} RC_{it} * \alpha_{it} + \sum_{v \in V} \sum_{i \in SUW} \sum_{t \in T} HirC_{vt} * Z_{ivt} \end{aligned} \quad (11)$$

Nonlinearity in optimization models increases the computational complexity and solution time, often resulting in local rather than global optima. Transforming the model into a linear function simplifies calculations, enables faster processing, and ensures the global optimality of solutions. This transformation improves efficiency, particularly for large-scale, time-sensitive applications like supply chains.

4. Case Study

The proposed model's performance was evaluated by analyzing a real-world case study. This case study used real-world data from a healthcare system in a western province of Iran; however, confidentiality requirements prevent the authors from disclosing the name of the healthcare system. In this case, six collection sites, five potential blood centers, and thirty-one medical centers serves as consumers. Demand for eight types of blood products was projected for the next eight weeks. We also considered two types of vehicles for transporting products between the collection sites and blood centers and the capacities of each collection site and blood center. Product demand, vehicle rental costs, the costs associated with establishing and removing blood centers, and storage costs were all based on real-world data. To solve the model, the CPLEX solver in GAMS was run on a Core i7 8th Gen system with 16 GB of RAM. Table 4 presents a summary of the results. The second column shows the total transportation costs across the network, while the third column provides the inventory costs. At the end of each week, all products were delivered to the consumer nodes, resulting in a zero inventory value for this scenario. Columns 4 through 6 display the costs associated with establishing and removing blood centers and hiring vehicles, which are the optimal values for the model. Finally, the final column shows the optimum solution achieved within 65 min of CPU time. The study's findings indicate that only four out of the five designated blood centers were utilized, with blood center 5 remaining inactive throughout the eight weeks. Additionally, blood center 2 was only activated at the beginning of the second week, following the opening of blood center 1. Table 4 summarizes these results, and Figure 2 illustrates the weekly availability of the blood centers.

Table 4. Brief summary of the results.

Cost	Transport	Inventory	Establish	Removal	Hiring	Z_{obj}
Value	12,253	0	3465	0	33,948	46,412

	T1	T2	T3	T4	T5	T6	T7	T8
W1								
W2								
W3								
W4								
W5								

- Active Blood Center
- Removed Blood Center
- Deactivated Blood Center

Figure 2. Availability of blood centers per week, during the eight weeks of operation (None of the blood centers established in the mentioned period were removed).

Transportation costs depend on the type of vehicle, v , used for journeys between nodes i and j each week, t . This factor is crucial for supply chain models, particularly in emergencies when rapid adaptation is essential. Optimized routes and efficient vehicle usage help the supply chain manage transportation within budget constraints. Weekly

blood product storage costs, known as inventory holding costs, are also accounted for. The findings indicate that inventory costs are low, suggesting that stock levels of blood products are carefully controlled, either through accurate forecasting to minimize excess or by employing just-in-time inventory practices. This balance ensures that the supply meets the demand without incurring high storage costs.

Establishing and decommissioning blood facilities within a given week incurs costs. The lack of initial setup expenses suggests that the existing blood center network was sufficient, with no need to open additional centers. However, high relocation or closure costs highlight the system's flexibility in responding to emergencies by reconfiguring resources. Vehicle leasing costs per week for each type of vehicle, v , constitute a significant expense. This cost underscores the importance of maintaining a reliable fleet for timely blood supply delivery. The model determines the number of vehicles required based on the demand and capacity constraints, which is critical for sustaining service levels throughout the crisis.

The results also illustrate the volume of blood products, p , transported by vehicle v from node i to node j each week, t . The model ensures that blood product delivery aligns with the healthcare facility demand, considering vehicle capacity and facility capabilities. Constraints in the model regulate the capacity of blood centers, vehicle limits, and healthcare facility demand, effectively managing the inventory and transportation expenses. This suggests that the model skillfully balances supply and demand.

Low transportation costs indicate successful route optimization and efficient vehicle allocation. The model records suggest that trips and routes were adjusted to save costs while meeting the delivery needs. Maintaining this supply–demand balance minimizes inventory costs, preventing surplus goods from being held unnecessarily and reducing the carrying costs. This points to the effective management of the blood facility inventory levels, aligning closely with the demand.

Without requiring new infrastructure, the model's adaptability may explain why additional blood facilities were unnecessary during the study period. High decommissioning costs reflect the strategic relocation or closure of centers—a critical feature in crisis management when resources must be quickly redeployed. This adaptability is essential for reducing costs and enhancing operational efficiency. Finally, vehicle fleet operation costs are the largest expense. The model calculates the necessary fleet size within the time and capacity constraints to meet the demand, highlighting that although vehicle leasing is costly, it is crucial to ensure continuity during crises.

Table 5 shows the number of vehicles required for each location and week based on the optimal allocation of vehicles. Throughout the week, the total number of vehicles needed varied between 32 and 40. Figures 3 and 4 illustrate the usage frequency of vehicle types V1 and V2, respectively. It was observed that, historically, type V2 vehicles are preferred over type V1 due to their greater capacity, cost-effectiveness, and suitability for specific cargo volumes. In weeks 5 and 6, the maximum number of vehicle types available for specific locations was reached, with a peak of nine type V2 vehicles in use during week 1.

As shown in Figures 4 and 5, the collection sites predominantly used vehicle type V2 for transporting blood products in 91.6% of operations due to its suitable capacity and cost efficiency. Among the collection sites, S1 had the highest number of transfers with vehicle type V1, accounting for 19.6% of the total, while sites S3 and S4 did not use this vehicle type at all. For blood centers, however, the choice of vehicle was more balanced. Vehicle type V1 was used for approximately 24.2% of transfers from blood centers to medical centers, with center W3 having the highest usage of V1 vehicles (29%) and center W4 the lowest (19.6%).

The quantity of blood products transported from each collection site to each blood center can be tracked once they have been collected. For example, at collection site S1, seven

out of the eight possible types of blood products were transferred to the four active blood centers over the 8-week operation period. Table 6 shows the total amount of each product type prepared at collection site S1, with products P1 and P6 comprising a significant 49% of the site's output. In contrast, P3 represents just 5% of the total production. Blood centers W3 and W4 received 74% of all products shipped from site S1, making them the primary recipients of this site's output, as shown in Table 7. Blood center W2, in comparison, received only 11% of shipments, which was significantly lower than the others.

Table 5. Required optimum number of vehicle types, v , for specific node and week.

	t1	t2	t3	t4	t5	t6	t7	t8
s1.v1			1		4			
s1.v2	2	1	4	2	1	4	5	2
s2.v1					1			
s2.v2	4	4	2	5	1	5	5	4
s3.v2	5	3	1	2	1			1
s4.v2	4	3	2	3	4	4	2	4
s5.v1						4		1
s5.v2	3	4	4	5	2	4	4	4
w1.v1		1	2	1	2	1	1	1
w1.v2	9	2	2	3	3	3	2	2
w2.v1		1	1	1	3		2	1
w2.v2		4	3	5	3	6	3	4
w3.v1		1	1	2	2	1	1	1
w3.v2		4	2	4	3	2	4	3
w4.v1		1	1	1	2	1	2	1
w4.v2	9	4	6	2	3	5	4	4
Total	36	33	32	36	35	40	35	33

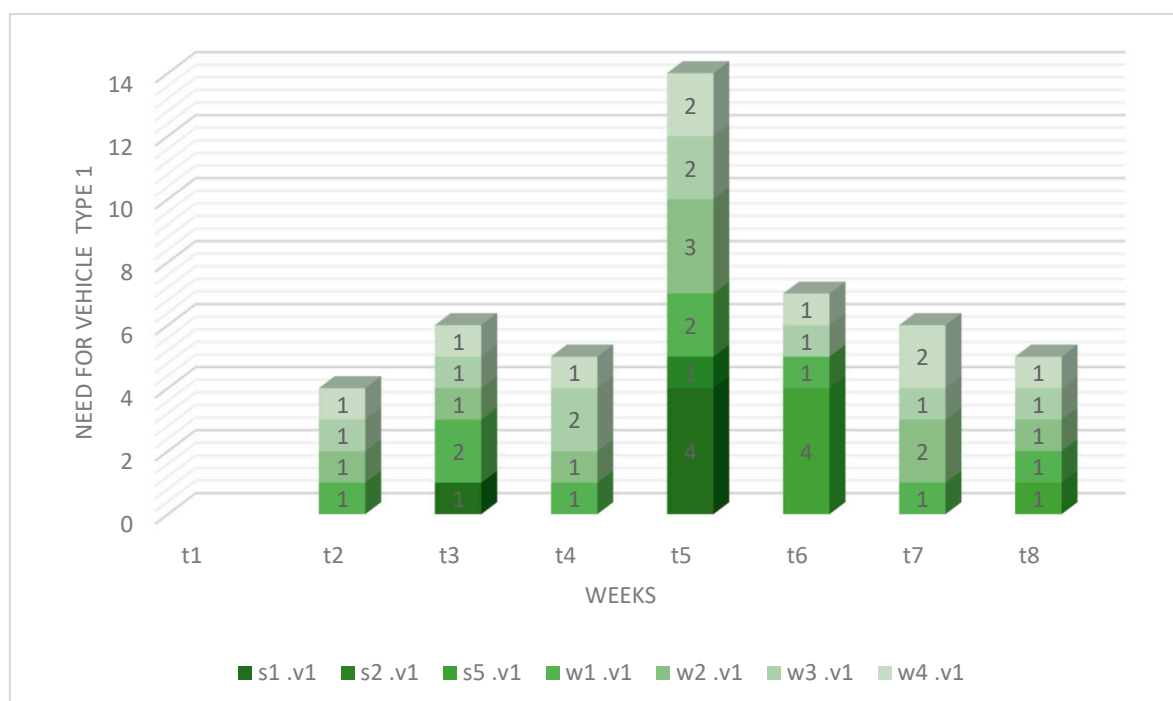


Figure 3. Number of vehicle type 1 usage during the 8 weeks.

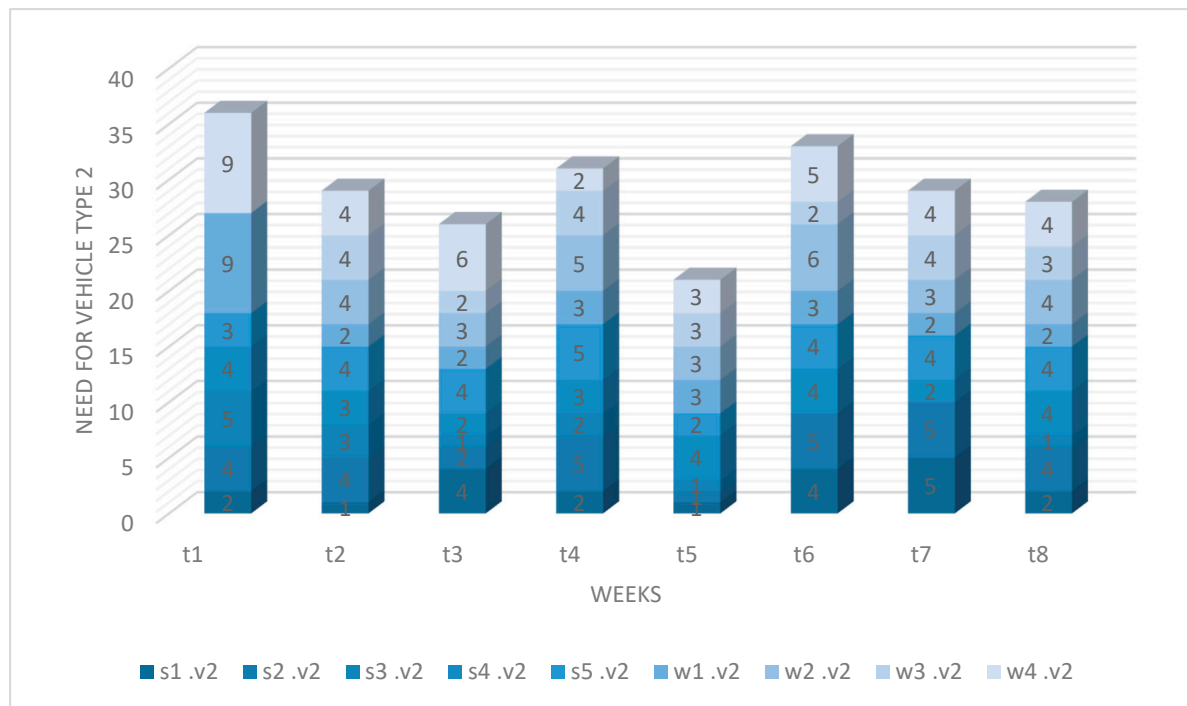


Figure 4. Number of vehicle type 4 usage during the 8 weeks.

Further details on the product volume transportation between site S1 and all available blood centers are presented in Table 8 and Figure 5. During weeks 2 and 3, the maximum volume of product P4 was transferred to blood center W1. Product P1 was the most frequently delivered to blood center W2 during weeks 3, 6, and 8, and its delivery to blood center W3 peaked during weeks 3, 4, 5, and 8. Finally, product P6 was the most frequently delivered to blood center W4 during weeks 6 and 7.

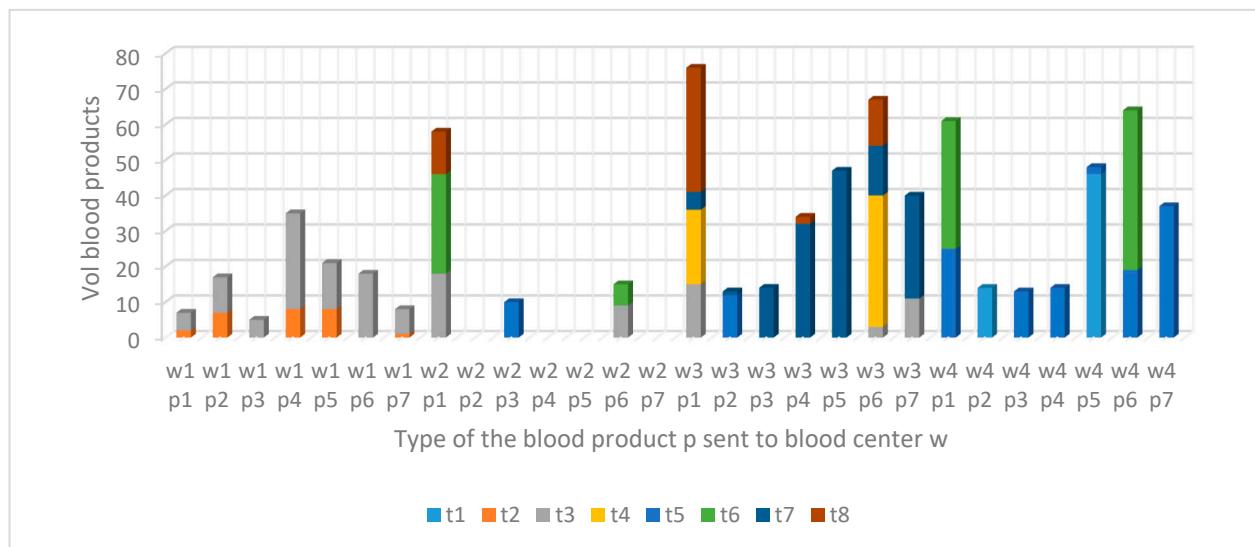


Figure 5. Transportation of products between site S1 and available blood centers per week in detail.

Table 6. Total blood products prepared at collection site S1 in 8 weeks.

S1	p1	p2	p3	p4	p5	p6	p7
Total	61	14	13	14	48	64	37

Table 7. Distribution of products from collection site S1 across blood centers in total.

S1	W1	W2	W3	W4
Total	111	83	291	251

Table 8. Transportation of products between site S1 and available blood centers per week in detail.

S1	t1	t2	t3	t4	t5	t6	t7	t8	Total
w1 p1		2	5						7
w1 p2		7	10						17
w1 p3			5						5
w1 p4		8	27						35
w1 p5		8	13						21
w1 p6			18						18
w1 p7		1	7						8
w2 p1			18			28		12	58
w2 p2									0
w2 p3					10				10
w2 p4									0
w2 p5									0
w2 p6			9			6			15
w2 p7									0
w3 p1			15	21			5	35	76
w3 p2					12		1		13
w3 p3							14		14
w3 p4							32	2	34
w3 p5							47		47
w3 p6			3	37			14	13	67
w3 p7			11				29		40
w4 p1					25	36			61
w4 p2	14								14
w4 p3					13				13
w4 p4					14				14
w4 p5	46				2				48
w4 p6					19	45			64
w4 p7					37				37

Due to the high demand from clinics within the range of centers W3 and W4, collection site S1 sent the majority of its shipments to W3 (39% of the total) in weeks 7 and 8, and to W4 (34% of the total) in weeks 5 and 6, as shown in Figure 5. This indicates that the model could efficiently manage supply and demand, directing resources to high-demand areas as needed without overextending the supply chain.

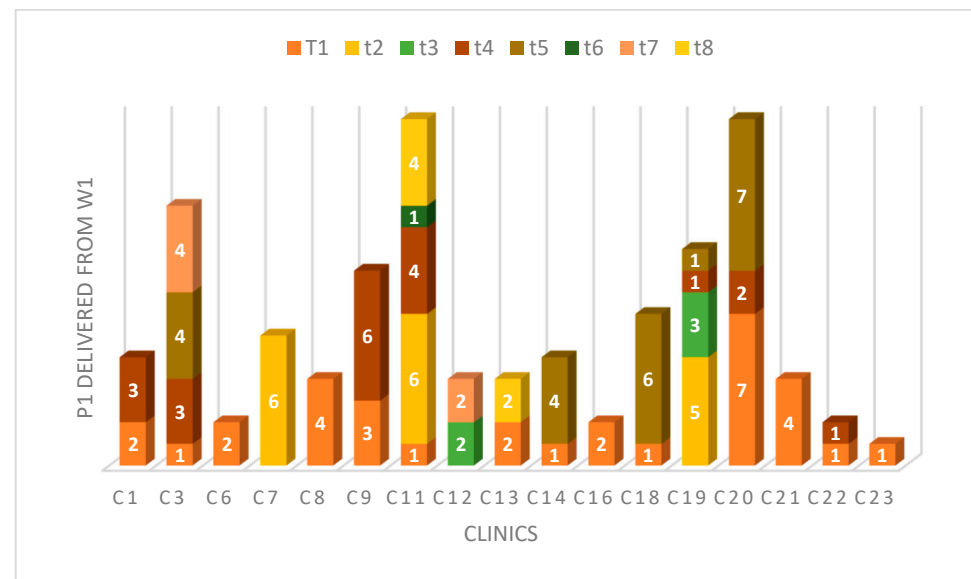
The model also enabled detailed tracking of the blood products delivered from each blood center to each clinical center. For instance, depending on the optimal solution, blood center W1 could fully or partially meet the requirements of 31 clinical centers. Table 9 shows the quantity of blood products delivered to all clinics requesting specific product types. Over the past eight weeks, product P2 was the most frequently delivered, reaching 19 clinical centers from blood center W1, while product P8 had the fewest deliveries.

Table 9. Summary of the total blood products delivered to clinic centers.

W1	p1	p2	p3	p4	p5	p6	p7	p8
Clinics	17	19	15	19	12	16	21	7
Delivered	109	200	122	162	111	157	147	73

This information helps illustrate the distribution of each product type to specific clinics. For example, Figure 6 and Table 10 display the distribution of product P1 to 17 clinics over the 8 weeks. During week 1, 33 packs of P1 were delivered to 14 and 17 clinics as demand for this product peaked. In contrast, week 6 was the least active period for P1 deliveries from blood center W1. Clinics C11 and C20 had the highest demand for product P1, while clinic C23 had the lowest, as shown in Figure 6.

Researchers can also analyze other blood products and centers similarly. The model also allows for the number of times each vehicle travels between nodes to be tracked, whether weekly or monthly. For simplicity, Table 11 presents the total number of trips made by each vehicle between blood center W1 and all of the associated collection sites and clinics.

**Figure 6.** Product P1 delivery from blood center W1 to all clinics in demand.**Table 10.** Amount of blood product 1 delivered from blood center 1 to each clinic weekly.

P1 from W1	t1	t2	t3	t4	t5	t6	t7	t8
c1	2			3				
c3	1			3	4		4	
c6	2							
c7		6						
c8	4							
c9	3			6				
c11	1	6		4		1		4
c12			2				2	
c13	2							2
c14	1				4			

Table 10. *Cont.*

P1 from W1	t1	t2	t3	t4	t5	t6	t7	t8
c16	2							
c18	1				6			
c19		5	3	1	1			
c20	7			2	7			
c21	4							
c22	1			1				
c23	1							
Total	33	17	5	20	22	1	6	6

Table 11. The number of times that each vehicle travels between two nodes in total weeks.

Arc	Vehicle	Total	Arc	Vehicle	Total
S1-W1	v2	24	W1-C11	v2	14
S2-W1	v2	40	W1-C12	v1	7
S3-W1	v2	46	W1-C12	v2	7
S5-W1	v1	38	W1-C13	v1	1
S5-W1	v2	61	W1-C13	v2	6
W1-C1	v2	3	W1-C14	v1	2
W1-C2	v1	10	W1-C14	v2	9
W1-C3	v1	1	W1-C15	v2	2
W1-C3	v2	14	W1-C16	v1	1
W1-C4	v1	2	W1-C16	v2	5
W1-C4	v2	3	W1-C17	v2	6
W1-C5	v2	1	W1-C18	v1	3
W1-C6	v1	1	W1-C18	v2	11
W1-C6	v2	2	W1-C19	v1	2
W1-C7	v1	1	W1-C19	v2	30
W1-C7	v2	15	W1-C20	v2	25
W1-C8	v1	1	W1-C21	v1	1
W1-C8	v2	1	W1-C21	v2	4
W1-C9	v1	4	W1-C22	v1	3
W1-C9	v2	4	W1-C22	v2	10
W1-C10	v1	1	W1-C23	v1	2
W1-C10	v2	5	W1-C23	v2	6
W1-C11	v1	2			

4.1. Managerial Implementation

Using the proposed model, decision makers can gain a comprehensive understanding of the current state of the blood supply chain. For example, blood center W1 required 444 trips over 8 weeks to transport products from 4 collection sites to the blood center and 23 clinics via 46 arcs. Table 8 and Figure 7 summarize these transportation details, showing the product origins, destinations, vehicle types, and the total number of deliveries per arc over the scheduled time period. The highest traffic between blood center W1 and the collection sites was observed at the fifth collection site, which delivered 99 loads using two

vehicle types. In contrast, only 24 deliveries occurred between W1 and site 1. Clinics C19 and C1 were identified as the recipients of the highest and lowest number of deliveries from blood center W1, respectively. Figure 7 visually represents these interactions, with orange arcs showing the inputs to blood center W1 and green arcs showing the outputs to the clinics. The journey count to and from each node is marked on each arc, distinguished by vehicle type.

The insights derived from this analysis apply to other model outcomes, covering all collection sites, blood centers, clinics, and weeks with high accuracy.

The model is flexible enough to consider a variety of vehicle types in terms of vehicle selection. This flexibility enables decision-makers to recommend vehicles with specific capacities, operational durations, and usage costs based on planning needs. The model selects the most cost-effective vehicle that meets each node's weekly demand for various blood products. Although this case study only included two vehicle types, the model can be adapted to incorporate additional types. In this instance, type 2 vehicles were generally preferred over type 1.

One of the model's key features regarding blood center activation is optimizing the number of blood centers to minimize the operating costs while maximizing the demand coverage. The model selected four out of five potential blood centers in the case study, achieving maximum demand coverage at minimal cost for the entire supply chain. Eliminating the fifth center not only maintained supply chain stability, but improved efficiency.

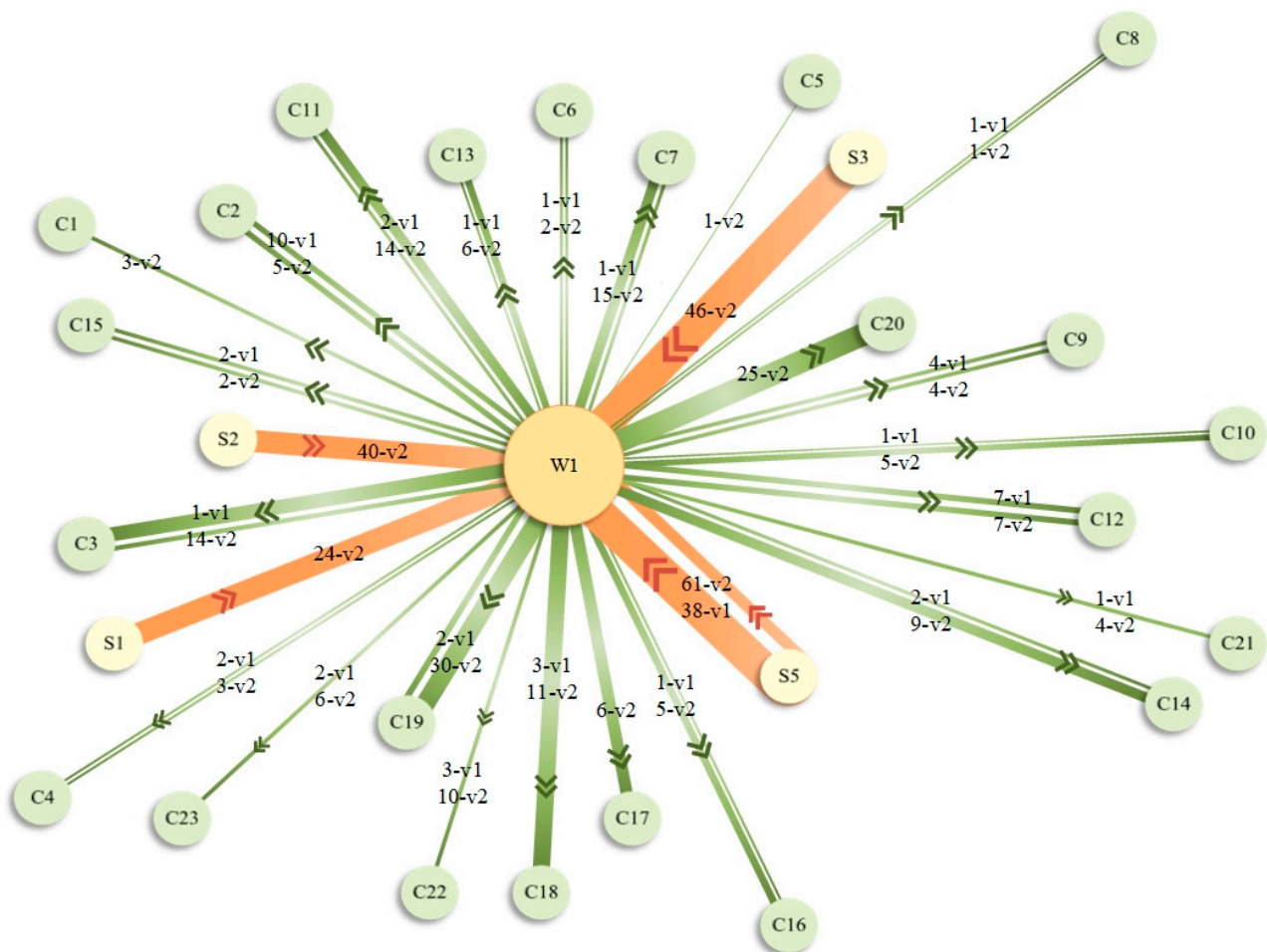


Figure 7. Systematic review of the inputs and outputs of blood center W1.

It should be noted that the authors did not address the allocation or selection of optimal locations for blood centers in this study. Instead, blood centers were activated or

deactivated in predetermined areas to maximize demand coverage within the minimal time and cost. This flexibility marks a novel aspect of this research. While this model may not enable healthcare managers to deploy mobile hubs in high-accident areas to reduce response times directly, decision-makers can achieve substantial efficiency gains. By understanding the fleet composition and identifying high-traffic routes, healthcare managers can collaborate with urban planners to enhance transportation safety along critical paths, potentially reducing the risk of accidents. Future research could explore additional factors such as disaster likelihood, the severity of supply chain impacts, and their influence on hub locations.

4.2. Sensitive Analysis

Figure 8 presents the sensitivity graph for the three-echelon blood supply chain network, based on a real-world case study. According to this graph, the clinical center demand, vehicle transportation cost, vehicle travel time, and vehicle hiring costs are the most sensitive parameters within a fluctuation range of -30% to $+30\%$. The percentage change in the objective function (total cost) is also reported.

An examination of the graph reveals that the blue line, representing vehicle transportation cost, had the steepest slope, indicating a strong, direct relationship with total cost. This factor showed the highest sensitivity, with total costs rising proportionally by -18% to $+26.14\%$ as the transportation costs increased. Controlling the transportation costs is therefore crucial for managing the overall operational expenses.

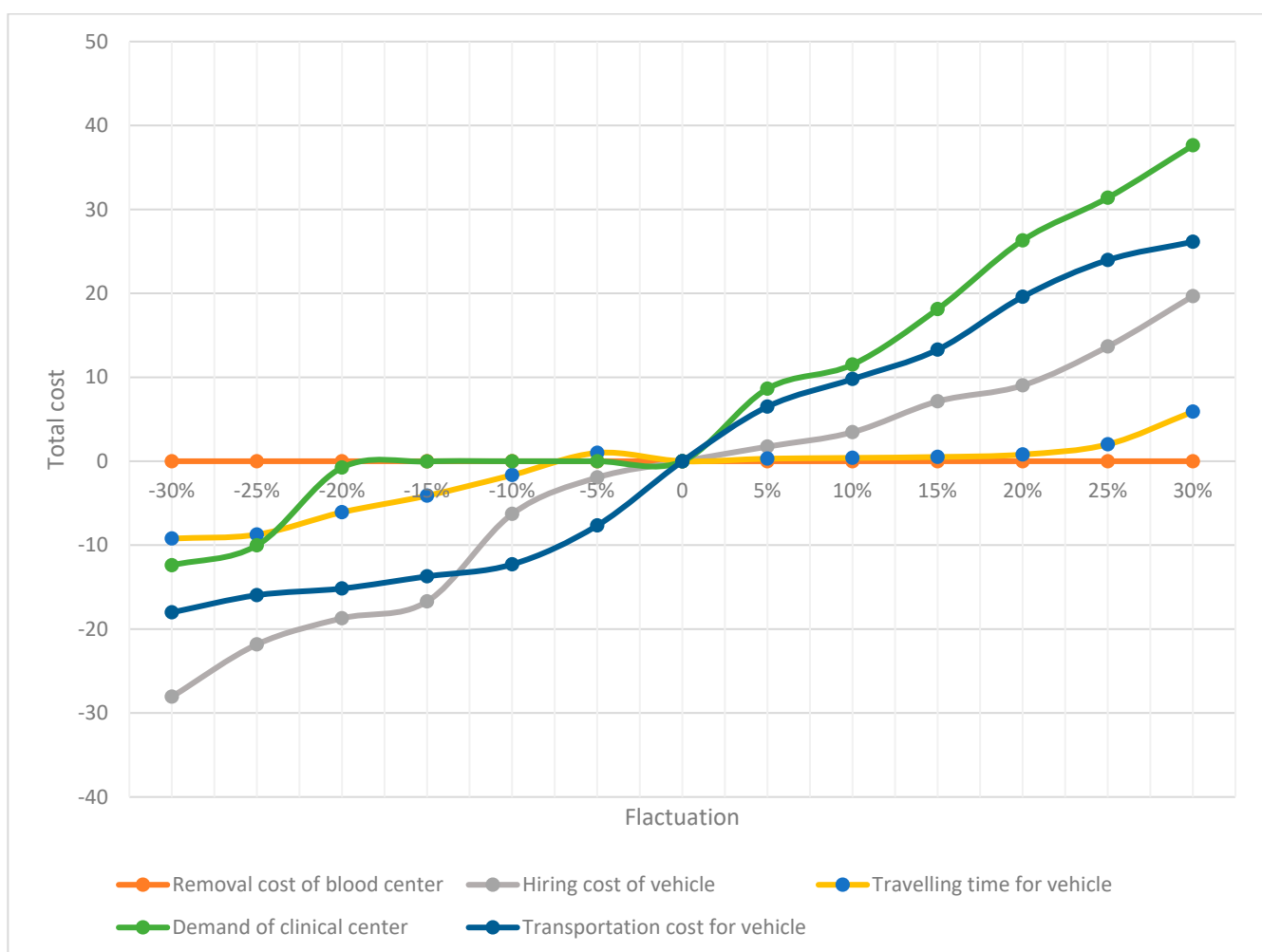


Figure 8. Sensitivity analysis chart for total cost.

The green line, which represents clinical center demand, also sloped upward but with a less pronounced gradient. The objective function showed resistance to decreases in demand up to -20% ; however, as the demand increased, the total cost rose at a similar rate. Thus, changes in demand can lead to moderate adjustments in total cost.

The yellow line, representing vehicle travel time, initially sloped upward but then flattened, indicating a curvilinear relationship with total cost. At lower travel times, the impact on total cost was substantial, ranging from -9.3% to $+0.3\%$. However, as the travel time increased, its influence diminished, suggesting that policies focused on travel time may have a limited effect.

The gray line, representing vehicle hiring costs, shows that reducing the hiring costs significantly impacted the total costs, with fluctuations ranging from -30% to -5% . In contrast, as the hiring costs increased, the slope was gentler, and the rate of change slower, showing that lowering the hiring costs can significantly reduce the total costs, while the increases have a limited impact.

The orange line for the removal costs was relatively flat, implying a minimal impact on total costs. This insensitivity suggests that removal costs are not significant drivers of the overall expenses, which was expected given the limited frequency of blood center closures in this case study. This result can also be generalized to establishment and holding costs.

The study's experimental findings highlight several key outcomes related to the proposed supply chain model's effectiveness, cost-effectiveness, and efficiency. By optimizing the supply chain at three distinct levels, collection, processing, and distributional, a reduction in total costs was achieved compared to conventional methods. The new model had improved hospital blood accessibility, ensuring that the required blood types were available at the right time and place, supported by strategically positioned portable blood hubs and efficient routing across the three tiers.

The model significantly reduced the response times for emergency blood needs through faster mobilization and the distribution of blood resources. Its adaptability allows it to respond effectively to crises, local emergencies, or larger regional disasters. The model also demonstrated flexibility by handling eight different blood types and accommodating specific demographic needs, ensuring timely satisfaction of requirements.

Unlike previous studies, which focused only on specific supply chain levels, this study took a holistic approach by considering the entire value chain. This comprehensive perspective is essential for addressing the complexities of blood circulation during emergencies. Integrating advanced optimization techniques allowed for informed decision making on scheduling, routing, and resource allocation, leading to notable improvements in outcomes.

The findings suggest that healthcare decision-makers should adopt multi-tiered supply chain models to enhance crisis response capabilities. Policies should encourage developing and adopting such models to ensure improved preparedness and resilience.

5. Conclusions

This paper presented a novel blood supply chain management model for crises structured across three levels and is one of the few recent studies in this field to address the entire supply chain, from blood collection to final delivery to hospitals and clinics. Based on a review of the existing literature, this study fills a gap by addressing the production level of blood hubs. The model considers all aspects of blood supply chain management, and unlike meta-heuristic models that provide approximate solutions, this study employed robust optimization, delivering exact solutions.

To clarify the contribution of this paper to the literature, the following questions were addressed: (1) How can this model inform decision-makers in crises, such as car accidents, to not only meet the needs of hospitals and clinics, but also assist distribution centers

with an efficient system that minimizes blood waste? (2) How can portable blood hubs be optimally designed for crisis management? Specifically, how can temporary blood distribution centers be organized based on donor numbers, clinic and hospital needs, and proximity while considering the time and cost of blood delivery?

One strength of this paper is its use of robust optimization to find exact solutions. While many studies have solved similar issues using meta-heuristic methods, these only sometimes yield exact results. This paper demonstrates that exact solutions can be achieved by employing a mathematical model.

This study also considered the distribution of blood types in the supply chain. Blood type requirements were considered to identify the optimal portable blood hub. While previous studies have examined blood type needs at hospitals and clinics, few have addressed how much and when each type is necessary for distribution among healthcare facilities.

The model efficiently met the blood supply demands while reducing the transportation costs, ensuring that hospitals and clinics receive timely blood supplies during emergencies. The effective management of blood supplies including inventory holding costs led to lower expenses and mitigated the risk of loss. Real-time modifications in inventory management allowed the system to adjust to varying demands, while relocation costs were adjusted to meet the evolving needs of blood centers. This adaptability is crucial during emergencies, where blood demand fluctuates quickly across regions. The model also enhances truck utilization, ensuring the timely and efficient transport of blood, which is essential for saving lives during crises.

A limitation of this research is that if the demand, number of vehicles, or number of centers exceeds specific levels, the model's effectiveness may be constrained. In such cases, exact methods may not be feasible, and meta-heuristics, which offer approximate solutions, may be necessary. Choosing an approximate solution, however, could have critical implications, as it may impact decision making in ways that affect lives.

For future research, several avenues can be explored: (1) utilizing artificial intelligence to develop predictive models that improve blood supply responsiveness during crises; (2) investigating energy-efficient, portable devices for blood collection and delivery in remote areas; (3) examining how blockchain could enhance traceability, security, and data integrity in portable blood hub operations during emergencies; and (4) modeling and analyzing delivery routes in healthcare cold chain networks using the minimax vehicle routing problem with time windows (VRPTW).

Author Contributions: Resources, methodology, writing—original draft preparation: A.K.; Supervision, project administration; A.R.K.; Data curation, validation, formal, writing—review and editing: A.K.Y.; Conceptualization, software, investigation: Y.T.; Visualization, funding acquisition: G.C.P.; Writing—review and editing, supervision, project administration: A.I. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Dataset available on request from the authors.

Conflicts of Interest: The authors have no relevant financial or non-financial interests to disclose.

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