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A Data-Driven Framework for Blood Supply Chain Network Design under Uncertainty Using Improved Clustering and Multi-Criteria Decision-Making

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Abstract

The blood supply chain is a critical component of healthcare systems, where inefficient planning may lead to severe shortages, wastage, and delayed response to emergency needs. The perishability of blood products, demand fluctuations, limited collection capacities, and geographical coverage requirements make the design of a reliable and responsive blood supply network a challenging decision-making problem under uncertainty. Therefore, developing an integrated framework that can improve resource allocation, facility location, and demand coverage is essential for enhancing the operational performance of such systems. To address this challenge, this study proposes a bi-level stochastic model for the optimal design of a blood supply chain under uncertainty. Within the proposed framework, an improved constrained clustering approach is employed to group demand points, and the locations of temporary blood collection facilities are determined using a combined MAUT–TOPSIS ranking method. The weights of the decision-making criteria are calculated using the entropy method. By considering multiple scenarios, capacity limitations, and geographical coverage constraints, the developed model optimally addresses the resource allocation problem in the blood supply network. The numerical results obtained from a real-world case study in Tehran show that the proposed clustering structure and combined ranking method significantly reduce unmet blood demand under the worst-case scenario compared with the conventional approach. Specifically, the total unmet blood demand across three time periods decreased from 17,592 units to 14,050 units, representing approximately a 20% improvement in system performance. Furthermore, the comparison of multi-criteria decision-making methods indicates that the combined MAUT–TOPSIS approach increases the total collected blood from 1,699 units under TOPSIS and 1,885 units under MAUT to 2,460 units. This finding corresponds to improvements of approximately 45% and 31%, respectively, in the blood collection system under the worst-case scenario.

Keywords: Blood supply chain, Bi-level stochastic programming, Improved clustering, Multi-criteria decision making, Uncertainty modeling, Combined MAUT-TOPSIS.

1 | Introduction

The blood supply chain is one of the most critical and sensitive supply chains in healthcare systems, playing a vital role in saving human lives. The perishable nature of blood, limited resources, fluctuations in demand,

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and emergency conditions such as natural disasters or public health crises make the efficient and flexible design of this supply chain highly important [1]. Any disruption or inefficiency in the collection, storage, and distribution processes may lead to irreversible human and economic consequences [2]. Traditionally, the design and management of blood supply chains have mainly relied on conventional models and classical decision-making approaches, which are often unable to adequately cope with the inherent uncertainties of such systems. Although the application of machine learning in this field has increased in recent years, its use has mostly been limited to specific tasks such as blood demand forecasting or patient classification. In particular, most previous studies have treated machine learning techniques merely as auxiliary tools for data analysis and have not directly integrated them into the structural modeling framework of the blood supply chain.

To address this gap, this study develops an integrated framework for blood supply chain network design under uncertainty by combining constrained clustering, multi-criteria decision-making, and mathematical programming. First, hospitals as demand points are grouped using a constrained K-means algorithm based on their geographical coordinates. The initial clusters are then improved through two refinement steps to obtain a more balanced, spatially coherent structure, which is used as an input to the optimization model. Second, temporary blood collection facility locations are evaluated through a combined TOPSIS–MAUT approach. Candidate locations are assessed according to multiple criteria, whose weights are determined using the entropy method. The resulting scores indicate the relative priority of each candidate location and are incorporated into the mathematical model.

Finally, a multi-period bi-level stochastic programming model is formulated to optimize facility location, donor allocation, and blood flow decisions across four levels of the network, including donors, blood collection centers, distribution centers, and hospitals. The proposed framework aims to improve resource allocation, geographical coverage, and system responsiveness under uncertain demand and capacity conditions.

2 | Literature Review

Recent studies on blood supply chain network design have addressed different aspects of uncertainty, resilience, and operational efficiency. A considerable body of research has focused on robust and stochastic optimization approaches to deal with uncertain supply and demand, facility disruptions, and crisis conditions. In this regard, green and robust blood supply chain models have been developed to simultaneously reduce operational costs, shortages, and environmental impacts [3], while two-stage robust stochastic frameworks have been proposed for disaster-prone settings, such as a possible earthquake in Tehran, by considering blood group substitution and blood components [4]. Other studies have extended location–allocation models to crisis environments by incorporating demand uncertainty, facility disruptions, network failures, and the perishability of blood products, with the aim of improving delivery time, cost efficiency, and service reliability [5], [6]. Fuzzy and mixed-integer programming models have also been applied to address uncertainty in facility location, capacity planning, and network configuration decisions, particularly under pandemic and emergency conditions [7], [8], and [9].

In parallel, data-driven and machine-learning-based approaches have recently received increasing attention in blood supply chain management. These studies have mainly employed machine learning and neural learning methods to predict operational decisions, estimate demand patterns, or approximate the solutions of large-scale optimization models, thereby reducing computational time and improving cost-related performance [10], [11], [12]. Although these contributions have significantly advanced the modeling and management of blood supply chains, most of them address only specific dimensions of the problem. Some focus primarily on robust or green network design, some use machine learning mainly as a predictive or auxiliary analytical tool, and others emphasize facility location or resource allocation under crisis conditions.

As blood supply chain models became more complex, recent studies have increasingly highlighted the need for data-driven, intelligent decision-making. In disaster-oriented settings, [11] integrated neural learning mechanisms into multi-level blood supply chain networks to leverage historical earthquake data to improve facility location, transportation, and emergency allocation decisions. These studies showed that intelligent selection of collection centers and optimal assignment of ambulances and helicopters can reduce transportation cost, response time, and unmet blood demand. Study [13] extended this data-driven direction by using deep learning and neural networks to forecast time-series demand for different blood products before embedding the predicted demand into a sustainable multi-objective network design model. In line with this trend, [14] examined the inefficiency of decentralized decisions between hospitals and blood centers and showed that coordinated structures can reduce over-ordering, overproduction, and waste. [15] combined XGBoost-based demand forecasting with MILP optimization to support tactical planning, achieving demand fulfillment with zero waste and lower costs. [16] further introduced Industry 5.0 concepts by integrating resilience, sustainability, agility, human-centricity, ARIMA forecasting, and IoT/AR technologies.

Based on the reviewed studies, several research gaps can still be identified in the blood supply chain literature. First, most existing models have not explicitly incorporated the geographical structure of demand points into the network design process through an improved clustering mechanism. Second, the selection of temporary blood collection facilities has rarely been addressed using an integrated multi-criteria decision-making approach that considers both the relative importance of criteria and the ranking of candidate locations. Third, limited attention has been given to the simultaneous integration of clustering outputs and facility ranking scores into a stochastic mathematical programming model under uncertainty. To address these gaps, the present study employs a constrained K-means algorithm to cluster hospitals based on their geographical locations and improves the initial clustering structure through refinement steps. In addition, a combined TOPSIS–MAUT approach, supported by entropy-based criterion weighting, is applied to rank candidate locations for temporary blood collection facilities. The outputs of these two stages are then incorporated into a multi-period bi-level stochastic programming model to design a realistic, flexible, and data-driven blood supply chain network under uncertainty.

3 | Problem Statement

This study aims to design an efficient blood supply chain under uncertainty using a three-stage approach. First, hospitals are clustered as demand centers through a constrained K-means algorithm, and the initial clusters are improved in two refinement stages to achieve balanced and geographically coherent groups. Second, temporary blood collection facilities are located using a combined TOPSIS–MAUT multi-criteria decision-making approach, with criterion weights determined by the entropy method. Finally, the outputs of these two stages are incorporated into a multi-period bi-level stochastic programming model to optimize location, allocation, and blood flow decisions across four main network levels, including donors, collection centers, distribution centers, and hospitals. The proposed framework is illustrated in Fig. 1.

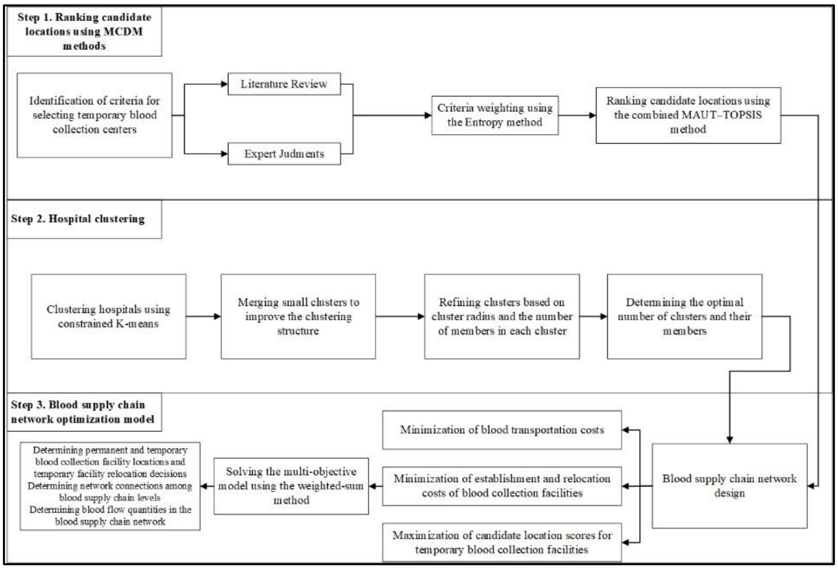

Fig. 1. Proposed framework for blood supply chain network design under uncertainty.

3.1 | Combined MAUT–TOPSIS Approach for Multi-Criteria Facility Location

The combined MAUT–TOPSIS approach is based on the integration of subjective and objective evaluations in multi-criteria decision-making. This integration allows both the decision-makers' preferences and the mathematical structure of comparison among alternatives to be considered simultaneously. In this framework, MAUT first transforms the raw criterion values into utility-based scores by applying appropriate utility functions. This transformation allows capturing nonlinear preferences, risk attitudes, and the relative importance of the criteria. However, MAUT alone does not explicitly evaluate the relative position of alternatives within the decision space. To overcome this limitation, TOPSIS is incorporated by introducing the concepts of the ideal and negative-ideal solutions. This integration enables the alternatives to be ranked according to their relative closeness to the optimal solution. Therefore, the combined approach takes advantage of the strengths of both methods while reducing their individual limitations, providing a precise, balanced, and flexible framework for analyzing complex decision-making problems.

It should be noted that this section only presents the steps of the proposed combined method. To avoid unnecessary expansion of the paper, the detailed steps of the entropy weighting method are not reported. The steps of the combined MAUT–TOPSIS method are presented as follows. Suppose that a decision matrix X consists of m alternatives and n criteria. Let i denote the $\mathrm{i-th}$ alternative and j denote the $\mathrm{j-th}$ criterion. The procedure of the algorithm is then described in the following steps.

Step 1 (Normalization of the decision matrix). The decision matrix is normalized to make the criteria comparable. For benefit and cost criteria, the normalized values can be calculated using Eq. (1), respectively:

$$\mathrm{x}^{\mathrm{B}}_{\{\mathrm{ij}\}} = \frac{\left(\mathrm{x}_{\{\mathrm{ij}\}} - \min\left(\mathrm{x_j}\right)\right)}{\left(\max\left(\mathrm{x_j}\right) - \min\left(\mathrm{x_j}\right)\right)}, \mathrm{x}^{\mathrm{C}}_{\{\mathrm{ij}\}} = \frac{\left(\min\left(\mathrm{x_j}\right) - \mathrm{x}_{\{\mathrm{ij}\}}\right)}{\left(\min\left(\mathrm{x_j}\right) - \max\left(\mathrm{x_j}\right)\right)}. \quad \textbf{(1)}$$

Step 2 (Application of the utility function). Each normalized value $x'_{\{ij\}}$ is transformed into a utility value $u_{\{ij\}}$ by applying an appropriate utility function according to the decision-maker's preferences.

Step 3 (Weighting the utility values). The utility values obtained in the previous step are multiplied by the corresponding criterion weights, as shown in *Eq. (2)*:

$$\mathrm{v}_{\{\mathrm{ij}\}} = \mathrm{w_j} * \mathrm{u}_{\{\mathrm{ij}\}}. \quad \textbf{(2)}$$

Step 4 (Determination of the ideal and negative-ideal solutions). The ideal and negative-ideal solutions are determined according to the type of each criterion. For benefit criteria, they are calculated using *Eq. (3)*:

$$A_j^+ = \max_i(v_{ij}), A_j^- = \min_i(v_{ij}). \quad (3)$$

For cost criteria, they are calculated using *Eq. (4)*:

$$A_j^+ = \min_i(v_{ij}), A_j^- = \max_i(v_{ij}). \quad (4)$$

Step 5 (Calculation of the distance from the ideal and negative-ideal solutions). The Euclidean distances of each alternative from the ideal and negative-ideal solutions are computed using Eq. (5):

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^+)^2}, D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^-)^2} \quad (5)$$

Step 6 (Ranking of alternatives). For each alternative, the relative closeness coefficient C_i is calculated using Eq. (6). A larger value of C_i indicates a more preferred alternative.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+}. \quad (6)$$

2-3.2 | Demand Point Clustering in the Blood Supply Chain Network

In supply chain network design, particularly in blood supply chain systems, clustering is an effective tool for improving distribution planning and resource allocation. In this context, clustering is used to group blood demand points, such as hospitals and healthcare centers, into geographically proximate and operationally meaningful groups. This structure enables a more efficient allocation of resources and contributes to improving the overall performance of the network.

In this study, the initial clustering is performed using a constrained K-means algorithm. This method allows clusters to form while satisfying predefined limits on the number of members per cluster. The initial clustering structure is then refined in subsequent stages to obtain a more balanced and optimized configuration. During this process, clusters that require adjustment are reviewed and modified to improve spatial coherence and support a more balanced allocation of resources.

Another important advantage of clustering is its ability to reduce the complexity of decision-making models. Instead of considering each hospital or healthcare center individually, clustered demand points are treated as the main units of analysis in the optimization model. This approach reduces the number of decision elements, simplifies the model structure, decreases computational time, and lowers the required computational resources. Therefore, clustering not only improves resource allocation but also enhances the computational efficiency of the proposed framework. Due to space limitations and the detailed nature of the clustering procedure, the complete algorithmic steps are not presented in this paper; further details can be found in [17].

3.3 | Blood Supply Chain Network Design

The proposed model is a multi-objective mixed-integer programming model developed to design and optimize the blood supply chain under uncertainty. It includes decisions related to facility location, allocation, and blood flow across different levels of the network over multiple time periods and under various scenarios. The sets, parameters, and decision variables used in the model are presented in *Table 1*.

Table 1. Mathematical model notation.

Indices	Definition
Sets	
$i = 1,2,\dots,I$	Set of blood donors.
$j = 1,2,\dots,J$	Set of candidate locations for establishing blood collection centers.
$k = 1,2,\dots,K$	Set of blood distribution centers.
$h = 1,2,\dots,H$	Set of clusters.
$t = 1,2,\dots,T$	Set of time periods.
$s = 1,2,\dots,S$	Set of scenarios.
Parameters	
f_j	Permanent facility establishment cost at location j.
v_{jlt}	Temporary facility relocation cost from location j to location l in period t.
o^s_{ijt}	Blood collection operating cost for donor i at location j in period t under scenario s.
a^s_{jk}	Blood transportation cost from collection center j to distribution center k under scenario s.
$á^s_{kh}$	Blood transportation cost from distribution center k to cluster h under scenario s.
h_k	Blood holding cost at the distribution center k.
d^s_{kt}	Required blood quantity at center k in period t under scenario s.
$d́^s_{ht}$	Blood demand at cluster h in period t under scenario s.
$Dist_{kh}$	Distance from distribution center k to cluster h.
p_s	Scenario occurrence probability.
r_{ij}	Distance from donor i to location j.
r	Maximum allowable donor–collection center distance.
N_t	The maximum number of blood collection facilities in period t.
n_{kt}	Number of clusters covered by distribution center k in period t.
$CapP^s_{jt}$	Permanent blood collection center capacity at location j in period t under scenario s.
$CapT^s_{jt}$	Temporary blood collection center capacity at location j in period t under scenario s.
$CapH^s_{ht}$	Cluster capacity at cluster h in period t under scenario s.
PUH^s_{ht}	Blood surplus penalty cost at cluster h in period t under scenario s.
PUS^s_{ht}	Blood shortage penalty cost at cluster h in period t under scenario s.
G_{jt}	Combined TOPSIS–MAUT score for temporary facility j in period t.
u_k	Maximum blood inventory at center k.
M	A sufficiently large positive number.
Decision Variables	
x_j	If a permanent blood collection facility is located at site j, equals 1; o.w, 0.
y^s_{ijt}	If donor i is assigned to collection center j in period t under scenario s, equals 1; o.w., 0.
z_{ljt}	If a temporary blood collection facility is relocated from site l in period $t-1$ to site j in period t, equals 1; o.w., 0.
β^s_{kht}	If distribution center k is assigned to cluster h in period t under scenario s, equals 1; o.w., 0.
Q^s_{ijkt}	Blood quantity collected from donor i at collection center j and transported to distribution center k in period t under scenario s.
t^s_{kht}	Blood quantity transported from distribution center k to cluster h in period t under scenario s.
inv^s_{kt}	Blood inventory at distribution center k in period t under scenario s.
sur^s_{ht}	Surplus blood quantity at cluster h in period t under scenario s.
sho^s_{ht}	Blood shortage quantity at cluster h in period t under scenario s.

$$\begin{aligned}\min Z_1 = &\sum_{j\epsilon J} f_j x_j \\ &+ \sum_{j\epsilon J}\sum_{l\epsilon J}\sum_{t\in T} v_{jlt}\, z_{ljt} \\ &+ \sum_{i\epsilon I}\sum_{j\epsilon J}\sum_{t\in T}\sum_{s\in S} p_s o_{ijt}^s Q_{ijkt}^s \\ &+ \sum_{i\epsilon I}\sum_{j\epsilon J}\sum_{t\in T}\sum_{s\in S} p_s a_{jk}^s Q_{ijkt}^s + \sum_{k\in K}\sum_{t\in T}\sum_{s\in S} p_s h_k\, inv_{kt}^s \\ &+ \sum_{k\in K}\sum_{h\in H}\sum_{t\in T}\sum_{s\in T} p_s' a_{kh}^s t_{kht}^s + \sum_{h\in H}\sum_{t\in T}\sum_{s\in T} p_s PUH_{ht}^s sur_{ht}^s \\ &+ \sum_{h\in H}\sum_{t\in T}\sum_{s\in T} p_s PUS_{ht}^s sho_{ht}^s ,\end{aligned} \quad (7)$$

$$\min Z_2 = \sum_{k\in K}\sum_{h\in H}\sum_{t\in T}\sum_{s\in S} p_s Dist_{kh} \beta_{kht}^s, \quad (8)$$

$$\max Z_3 = \sum_{j\epsilon J}\sum_{l\epsilon J}\sum_{t\in T} G_{jt}\, z_{ljt}, \quad (9)$$

s.t.

$$inv_{kt}^s + \sum_{i\in I}\sum_{j\in J} Q_{ijkt}^s - inv_{kt-1}^s = d_{kt}^s, \quad \forall k \in K, \forall t \in T, \forall s \in S, \quad (10)$$

$$X_j + \sum_{l\in J} Z_{jlt} \le 1, \quad \forall j \in J, \forall t \in T, \quad (11)$$

$$\sum_{l\in J} Z_{ljt} \le \sum_{l\in J} Z_{jlt-1}, \quad \forall j \in J, \forall t \in T, \quad (12)$$

$$Z_{ljt} + Z_{jlt} \le 1, \quad \forall j, l \in J, \forall t \in T, \quad (13)$$

$$\sum_{j\in J} X_j + \sum_{j\in J}\sum_{l\in L} z_{ljt} = N_t, \quad (14)$$

$$y_{ijt}^s \le x_j + \sum_{l\in J} z_{ljt}, \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S, \quad (15)$$

$$r_{ij} Y_{ijt}^s \le r, \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S, \quad (16)$$

$$Q_{ijkt}^s \le M Y_{ijt}^s, \quad \forall i \in I, \forall l \in J, \forall k \in K, \forall t \in T, \forall s \in s, \quad (17)$$

$$\sum_{i\in I}\sum_{k\in K} Q_{ijkt}^s \le c_{jt}^s X_j + b_{jt}^s \sum_{l\in J} Z_{jlt}^s, \quad \forall j \in J, \forall t \in T, \forall s \in S \quad (18)$$

$$I_{kt}^s \le u_k \quad \forall k \in K, \forall t \in T, \forall s \in S, \quad (19)$$

$$\sum_{k\in K} \beta_{kht}^s = 1, \quad \forall h \in H, \forall t \in T, \forall s \in S, \quad (20)$$

$$\sum_{k\in K} \beta_{kht}^s \le n_{kt}, \quad \forall k \in K, \forall t \in T, \forall s \in S, \quad (21)$$

$$t_{kht}^s \le M \beta_{kht}^s, \quad \forall k \in K, \forall h \in H, \forall t \in T, \forall s \in S, \quad (22)$$

$$sur_{ht-1}^s + \sum_{k\in K} t_{kht}^s - sur_{ht}^s + sho_{ht}^s = \acute{d}_{ht}^s, \quad \forall h \in H, \forall t \in T, \forall s \in S, \quad (23)$$

$$t_{kht}^s \le M \beta_{kht}^s, \quad \forall h \in H, \forall k \in K, \forall t \in T, \forall s \in s, \quad (24)$$

$$\sum_{h\in H} t_{kht}^s \le CapH_{ht}^s, \quad \forall h \in H, \forall k \in K, \forall t \in T, \forall s \in s, \quad (25)$$

$$x_j, y_{ijt}^s, z_{ljt}, \beta_{kht}^s \in \{0,1\}, \quad \forall i \in I, \ \forall l \in J, \forall j \in J, \forall k \in K, \forall h \in H, \forall t \in T, \forall s \in s, \quad (26)$$

$$Q^{s}_{ijkt}, t^{s}_{kht}, inv^{s}_{kt}, sur^{s}_{ht}, sho^{s}_{ht} \geq 0, \ \forall i \in I, \forall l \in J, \forall k \in K, \forall h \in H, \forall t \in T, \forall s \in s. \quad (27)$$

The proposed model is designed to optimize the blood supply network by considering cost, distance, and facility-location priorities. Objective *Function (7)* minimizes the total operational cost, including facility establishment, relocation, and maintenance costs, as well as blood storage and transportation costs across distribution centers and demand clusters. Objective *Function (8)* minimizes the geographical distance between distribution centers and clusters, to improve routing efficiency and reduce transportation time and cost. Objective *Function (9)* maximizes the location score for temporary blood collection facilities, computed using the combined TOPSIS–MAUT method. The constraints define the operational and logical requirements of the network. *Constraint (10)* ensures a balance in blood inventory at distribution centers. *Constraint (11)* guarantees that only one type of blood collection facility, either temporary or permanent, can be active at each location in each period. *Constraint (12)* maintains the continuity of temporary facility relocation, while *Constraint (13)* prevents a temporary facility from immediately returning from location l to location j in the same period after being relocated from j to l. *Constraint (14)* ensures that the total number of active facilities in each period equals the predefined value. *Constraint (15)* guarantees the proper assignment of donors to blood collection centers. *Constraint (16)* restricts the geographical distance between donors and collection centers, and *Constraint (17)* imposes an upper bound on the amount of blood supplied by donors.

Constraints (18) and *(19)* control the capacity of blood collection centers and the maximum inventory level. *Constraints (20)* and *(21)* determine the assignment of clusters to distribution centers. *Constraints (22)* and *(23)* regulate the amount of blood delivered to clusters and ensure inventory balance at the cluster level. *Constraints (24)* and *(25)* ensure that blood shipments are consistent with the corresponding capacity limitations. Finally, *Constraints (26)* and *(27)* define the domains of the decision variables. To obtain a compromise solution among the multiple objectives, this study applies a weighting method. The objective weights are determined based on the opinions of experts in the relevant field so that the relative importance of each objective is properly reflected in the decision-making process. Assuming that the model includes (m) constraints and (n) objective functions, the weighted formulation is expressed in *Eq. (28)*.

$$\begin{aligned} &\min/\max F(x) = w_1 f_1(x) + w_2 f_2(x) + \cdots + w_n f_n(x), \\ &\sum_{i=1}^{n} w_i = 1, w_i \geq 0, \\ &g_j(x) \leq 0, j = 1,2,\dots,m, \\ &x \geq 0. \end{aligned} \quad (28)$$

4 | Numerical Results

In the first step, data related to the evaluation of candidate locations for establishing blood collection centers were collected and assessed based on several criteria. Emergency accessibility (C1) and structural resistance (C2) were considered benefit criteria, meaning that locations with faster accessibility and higher structural reliability received higher scores. Distance from flood-prone or high-risk areas (C3) was treated as a cost criterion, where riskier locations received lower scores .In addition, proximity to key healthcare centers (C4), physical capacity (C5), availability of supporting infrastructure such as electricity and water (C6), and social and environmental security (C7) were considered benefit criteria. Locations with stronger performance in these aspects were assigned higher scores. Finally, the operational costs of establishing and operating C8 were considered a cost criterion. Since the model is solved over five time periods, the initial decision matrix is not reported to avoid increasing the length of the paper; instead, the score of each location in each period is presented in *Table 2*.

Table 2. Scores obtained by the Combined MAUT_TOPSIS.

Period /Candidate locations	T=1	T=2	T=3	T=4	T=5
J=1	0.8497	0.6284	0.4144	0.6297	0.1944
J=2	0.3934	0.4943	0.2439	0.6560	0.5567
J=3	0.7509	0.770	0.4564	0.6903	0.6320
J=4	0.9579	0.5179	0.502	0.2491	0.8483
J=5	0.4564	0.8014	0.6675	0.987	0.5954

In the second part of the case study, 122 hospitals in Tehran were clustered using their geographical coordinates, resulting in 15 independent clusters. The clustering process was performed under membership-size constraints, with a minimum of 3 and a maximum of 15 members per cluster, to maintain operational workload balance. The initial clustering results are presented in *Fig. 2*. In the first refinement step, small, scattered clusters were merged with neighboring clusters to improve the coherence and stability of the overall structure. For example, clusters 1 and 8 were combined into A1, while clusters 2 and 9 were merged into A2. In the second refinement step, clusters with a large coverage radius but a small number of members were integrated into denser clusters. Accordingly, clusters 12 and 4 were merged into cluster 12-4, and clusters 5 and 6 were combined into cluster 5-6. The results of these refinements are illustrated in *Fig. 3*.

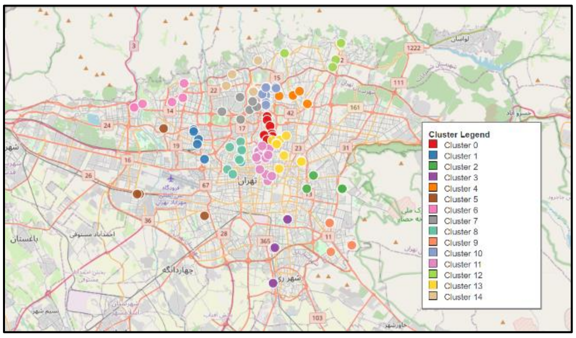

Fig. 2. Initial clustering using the constrained K-means method.

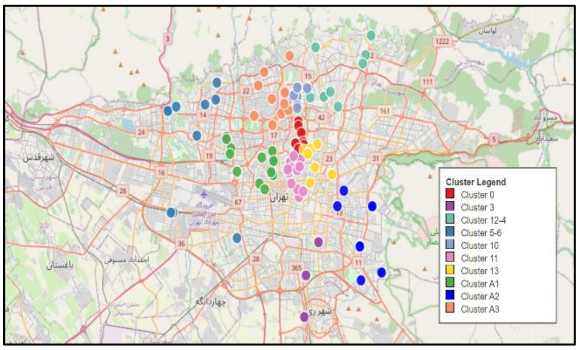

Fig. 3. Final refined clustering structure after improvement steps.

The mathematical model is solved considering 15 donors, 5 candidate locations for blood collection centers, 5 distribution centers, 10 customer clusters, 3 time periods, and 3 uncertainty scenarios. The computational results reported in Table 3 indicate that establishing two permanent blood collection centers at locations 1 and 4 is the most cost-effective decision. In addition, locations 3 and 4 are selected as temporary facilities, and no relocation occurs between them at any time.

The selection of these locations is consistent with their high, stable scores obtained from the TOPSIS–MAUT evaluation, as reported in *Table 2*. In particular, location 5 achieves the highest score of 0.987 at t=4, indicating strong operational potential in that period. Moreover, the continued selection of location 3 across different periods confirms the logic and consistency of the proposed model in identifying suitable temporary facility locations. These results demonstrate the model's effectiveness in selecting appropriate sites for temporary blood collection facilities. Furthermore, *Fig. 4* presents the allocation results of blood distribution centers under the worst-case scenario s=3 in the third period.

Table 3. Results for establishing permanent and temporary facilities.

Permanent Blood Collection Facilities	Temporary Blood Collection Facilities (T=1)	Temporary Blood Collection Facilities (T=2)	Temporary Blood Collection Facilities (T=3)
$x_1 = 1$	$z_{331} = 1$	$z_{332} = 1$	$z_{333} = 1$
$x_4 = 1$	$z_{551} = 1$	$z_{552} = 1$	$z_{553} = 1$

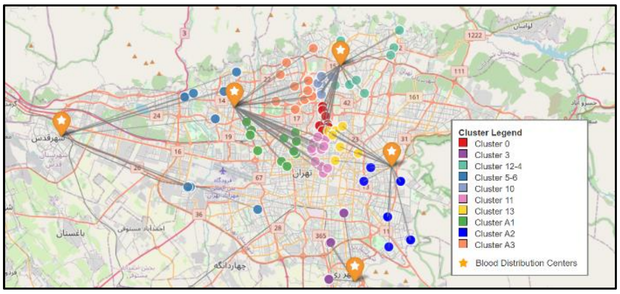

Fig. 4. Allocation of blood distribution centers to clusters under the worst-case scenario in the third period.

Fig. 5 compares two blood resource allocation settings, namely the proposed clustering approach and the conventional 15-cluster structure. The results indicate that the proposed clustering approach consistently reduces unmet blood demand across all time periods. In the first period, unmet demand decreases from 6,649 units in the conventional clustering structure to 4,512 units in the proposed approach. A similar pattern is observed in the second and third periods, where unmet demand is reduced from 5,522 and 5,421 units to 4,579 and 4,960 units, respectively. These reductions demonstrate the positive impact of the proposed clustering strategy on improving the spatial structure of the network and enhancing the efficiency of blood distribution. Since the analysis is conducted under the worst-case scenario, the results also confirm the ability of the proposed model to maintain stable, effective operational performance under adverse and critical conditions.

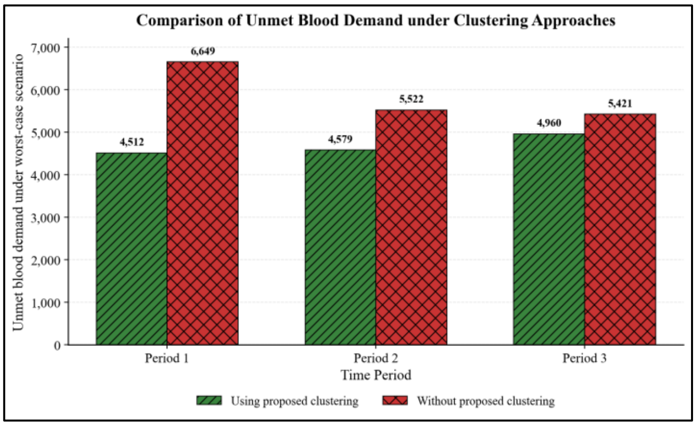

Fig. 5. Comparison of blood shortage levels under the conventional and proposed clustering approaches in the worst-case scenario.

As shown in Fig. 6, the combined MAUT–TOPSIS approach outperforms the individual MAUT and TOPSIS methods in blood supply performance across all periods under the worst-case scenario. This superiority can be attributed to the complementary nature of the two methods. MAUT effectively captures decision-makers' preferences and risk attitudes through utility-based evaluation, whereas TOPSIS improves ranking by considering the relative position of each alternative with respect to the ideal and negative-ideal solutions. The integration of these two perspectives provides a more balanced and flexible decision-making framework, enabling the model to collect the highest amount of blood in each period even under pessimistic conditions. These results highlight the effectiveness and reliability of the combined approach in dealing with uncertainty and decision-making complexity in the blood supply chain.

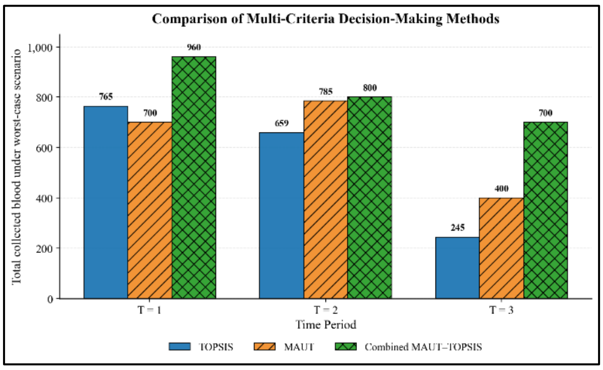

Fig. 6. Comparison of the combined MAUT–TOPSIS approach with the individual TOPSIS and MAUT methods.

5 | Conclusion

The results of this study demonstrate that integrating improved clustering, multi-criteria decision-making, and bi-level mathematical modeling can significantly enhance the performance of the blood supply chain. The comparison between the proposed model and conventional approaches shows that optimized clustering of demand centers and intelligent ranking of temporary blood collection locations play a key role in reducing unmet blood demand, improving geographical coverage, and enhancing resource utilization.

The findings also indicate that the proposed approach provides a more balanced allocation of resources and a more stable network response, particularly under critical scenarios. Overall, the developed model can be considered a flexible, data-driven, and practical decision-support tool for planning critical supply chains such as blood supply networks. Moreover, the proposed framework has the potential to be extended to other healthcare and logistics applications.

For future research, advanced methods such as deep learning algorithms can be employed to improve demand forecasting and resource allocation decisions. In addition, blockchain technology may be incorporated to enhance transparency, traceability, and data security in blood supply chain processes.

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