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Risk Factors Analysis in Blood Supply Chain: A Fuzzy Cognitive Mapping Approach

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Abstract

The blood supply chain (BSC) is a critical component of healthcare systems, where efficiency and reliability are paramount to ensuring timely and safe delivery of blood products to patients in need. Risk factors as the factors that directly affect the BSC could be considered permanently to ensure BSC's productivity. So, understanding and managing these risks is vital for ensuring a robust and resilient blood supply chain. This research employs the Fuzzy Cognitive Mapping (FCM) approach to identify key risk factors affecting the blood supply chain. The required data was gathered using pairwise comparison questionnaire from 10 experts of the regional office of the Blood Transfusion Organization in Tehran province and analysed using FCM Expert software. By mapping the complex interrelationships between various risks, the study reveals that "Delays in Allocation and Distribution," "Disruptions in Logistics Processes," and "Blood Shortages" are among the most influential factors, with significant implications for the overall performance of the supply chain. The analysis also highlights the importance of "Weak Collaboration" and "Insufficient Capacity," which exacerbate operational inefficiencies. The findings suggest that addressing these risks through enhanced collaboration, capacity building, and the integration of advanced technologies can substantially improve the resilience and effectiveness of blood supply chains. Furthermore, the study offers strategic recommendations and suggests avenues for future research.

Keywords:
Risk factor
Blood supply chain
FCM

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INTRODUCTION

The blood supply chain (BSC) plays a critical role in the healthcare system, ensuring that blood and blood products are available to meet the needs of patients across the country. However, the BSC faces several challenges that make its management particularly complex. These challenges include uncertain supply and demand, high service level requirements (Meneses et al., 2023). In addition to these challenges, the BSC must also address the perishability of blood products, which adds further complexity to supply chain management (Toude Bahambari and Soufi, 2021). Blood is a degradable product, and only a small fraction of donated blood is usable due to specific storage and processing requirements. For example, red blood cells have a shelf life of 35 to 42 days, platelets last only 5 to 7 days, and plasma can be stored for 1 to 3 years under specific conditions (Pirabán et al., 2019; Kazemi et al., 2024). This perishability necessitates precise planning and coordination across multiple facilities to avoid shortages, wastage, and to ensure that blood is available at the right time and place (Beliën & Forcé, 2012). Perishability of blood products enhances complexity to the supply chain (SC), making difficult the determination of optimal quantities of blood to be available for medical treatments (e.g., cancer, anemia), organ transplants, surgeries (e.g., open-heart surgery), or emergencies (Kazemi et al., 2024).

Given these complexities, efficient blood supply chain management is crucial. The BSC in Iran is a multi-facility and multi-product network that must comply with strict safety and public health directives. The blood supply chain is generally divided into 5 echelons: (1) blood collection, (2) blood testing, (2) blood processing, (4) blood storage, and (5) blood distribution. The process of receiving blood from donors is called blood collection. When blood is collected, should be tested to screen its viruses and diseases in terms of blood testing (. Next, in the processing phase, whole blood should be processed to separate its derivations such as red blood cells (RBC), plasma, and platelets. Once available for use, the blood derivations are allocated to inventories, typically at blood banks and hospitals, being ready to be distributed and used. The process of supplying the amount of blood required to satisfy the demand is examined during the distribution phase (Dillon et al., 2017; Pirabán et al., 2019).

Managing the BSC encompasses the major challenge of balancing storage and wastage of the blood units. Given the perishable nature of this product, storing an excessive number of blood units could result in the wastage of this limited resource. On the other hand, having shortages may result in tragic outcomes since lives can be lost if no stock is available when it is needed (Dillon et al., 2017). The BSC must be both efficient and sustainable in these six processes to guarantee the availability of blood for medical treatments, encompassing everything from blood collection from donors to transfusion to patients (Osorio et al., 2018).

The Iranian Blood Transfusion Organization (IBTO), established in 1974, has developed into a comprehensive system responsible for collecting, processing, and distributing blood and blood products nationwide. Iran's reliance on voluntary, non-remunerated blood donations is a key factor in ensuring the safety and reliability of its blood supply (WHO, 2017). However, the country faces significant challenges, including a high prevalence of traffic accidents, which placed Iran in the 7th rank among the ten most accident-prone countries between 1999 and 2018, leading to increased blood demand for trauma and surgeries (Kazemi et al., 2024). Despite this, only about 5% of the population donates blood, which has resulted in shortages that complicate the management of blood supply and increase the risk of higher fatality rates (Rajendran & Ravindran, 2019).

Besides the donations uncertainty, risks created from natural disasters, epidemic diseases such as COVID-19, increase this uncertainty. The majority of studies on BSC problems do not dedicate enough attention to these risks that disturb the decision-maker on the design, planning, and operations of a BSC (Samani & Hosseini-Motlagh, 2019). This paper addresses these gap in the literature by presenting fuzzy cognitive mapping (FCM) approach for analyzing the complex BSC systems with high interactions. Because of FCM's capabilities for analyzing feedback structures, dealing with qualitative variables, considering direct and indirect relationships between variables, modelling systems where explicit knowledge is limited but expert (implicit) knowledge is available, and its simplicity and accuracy in comparison to other methods, this paper applied FCM to analyze the main risks that affect the blood supply network in Iran.

The remainder of the paper is structured as follows: Section 2 reviews the recent literature on the blood supply chain, Section 3 outlines the research methodology and proposed framework, Section 4 presents the developed model and discusses its application in a real case study, and Section 5 concludes with recommendations for future research.

LITERATURE REVIEW

Blood supply chain studies began in the 1960s. Jacobs et al. (1996) presented a model in their research. In the field of location-allocation of facilities in the blood supply chain and relocation and network configuration and facilities (Beliën and Force, 2012). Wang and Ma (2015) proposed an approach based on the age of blood units in which they compared the two modes of age and the amount of inventory in the blood bank of hospitals, due to decreasing inventory or increasing the age of blood units exchanged between hospitals when there is a shortage. Habibi-Kouchaksaraei et al. (2018) proposed a robust optimization model for designing a bi-objective multi-period three echelons supply chain network of blood in a disaster. The proposed model determines the number and location of facilities and the best strategy to allocate them under three different scenarios, while the goals are to minimize costs and shortages of blood.

Dutta and Nagurney (2019) proposed a multitiered competitive supply chain network model for the blood banking industry, that captures the economic interactions among three blood service organizations, the hospitals or medical centers, and the player groups. They modeled the behavior of each category and used the theory of variational inequalities to derive the equilibrium conditions for the entire supply chain. Hosseini Motlagh et al. (2019) developed a bi-objective MLP model to design the collection, production, and distribution network of blood under uncertain conditions and through a multi-period planning horizon. In a research, Liu and Song (2019) proposed a discrete-time MILP model to cope with the underlying uncertainty through a rolling horizon approach in order to optimally manage the blood supply chain system in disaster relief. Their model also takes into account blood characteristics and blood emergency supply constraints.

Khalilpour Azari et al. (2020) developed an efficient model for a 6 echelon BSC which consists of donors, blood collection centers (permanent and temporary), regional blood centers, local blood centers, regional hospitals, and local hospitals. The solution aims to avoid the worst consequences of a disaster using a neural-learning process. Fallahi et al. (2021) formulated a closed-loop BSC that considers blood transportation equipment and the relevant quality features. Then, they used a differential evolution algorithm for solving the problem. Kenan and Diabat (2022) using two-stage stochastic programming formulated the BSC problem in disasters considering the uncertainty of both supply and demand. Solving the model with heuristic algorithms showed that bigger capacities of permanent collection facilities are favored over the mobility of temporary facilities. Suen et al. (2023) proposed a two-stage stochastic programming model to investigate the opportunity of incorporating frozen PLTs into the PLT supply chain. To investigate a more realistic situation when clear targets of blood shortage, wastage and substitution penalties are available, an extended goal programming model is built based on the proposed model. Aghsami et al. (2023) developed a mathematical model to minimize the total costs and maximize satisfaction of donors by waiting time reduction in a BSC system. They presented and solved a real-world case study using a new meta-heuristic algorithm to illustrate the model's applicability. Hosseini-Motlagh et al. (2024) investigated the challenge of adapting collection planning to dynamic fluctuations in potential blood donors' behavior by introducing an innovative updatable approach based on the rolling horizon planning approach. they present a robust optimization approach to mitigate uncertainty across various parameters such as donors' behavior, demand, transportation time, and operational cost. Given the impact of dynamic and diverse conditions. Ala et al. (2024) proposed a multi-objective BSC network design problem that aims to reduce the cost of establishing fixed and temporary facilities, transferring blood products, and the amount of shortage. They used a robust possibilistic MILP method in order to deal with distribution and locational decisions. Table 1 summarized some of the studies on BSC where conducted in the last 5 years.

Table 1: Recent studies on BSC

Reference	**Title**
Fanoodi et al. (2019)	Reducing demand uncertainty in the platelet supply chain through artificial neural networks and ARIMA models
Ghatreh Samani et al. (2019)	A multilateral perspective towards blood network design in an uncertain environment methodology and implementation
Gilani Larimi and Yaghoubi (2019)	A robust mathematical model for platelet supply chain considering social announcements and blood extraction technologies
Rajendran and Ravindran (2019)	Inventory management of platelets along blood supply chain to minimize wastage and shortage
Pritha and Nagurney (2019)	MultitieRB supply chain network competition: Linking blood service organizations, hospitals, and payers
Liu and Song (2019)	Emergency Operations Scheduling for a Blood Supply Network in Disaster Reliefs
Salehi et al. (2019)	Developing a robust stochastic model for designing a blood supply chain network in a crisis: a possible earthquake in Tehran
Hosseini-Motlagh et al. (2019)	Robust and stable flexible blood supply chain network design under motivational initiatives
Dehghani et al. (2019)	Proactive transshipment in the blood supply chain: A stochastic programming approach
Ezugwu et al. (2019)	Mathematical model formulation and hybrid metaheuristic optimization approach for near-optimal blood assignment in a blood bank system
Gilani Larimi et al. (2019)	Itemized platelet supply chain with lateral transshipment under uncertainty evaluating inappropriate output in laboratories
Samani (2019)	An enhanced procedure for managing blood supply chain under disruptions and uncertainties
Haghjoo et al. (2020)	Reliable blood supply chain network design with facility disruption: A real-world application
Wang and Chen (2020)	A distributionally robust optimization for blood supply network considering disasters
Ghorashi et al. (2020)	Modeling and optimization of a reliable blood supply chain network in crisis considering blood compatibility using MOGWO
Hamdan and Diabat (2020)	Robust design of blood supply chains under risk of disruptions using Lagrangian relaxation
Khalilpour Azari et al. (2020)	Designing an efcient blood supply chain network in crisis: neural learning, optimization and case study
Nezamoddini et al. (2020)	A risk-based optimization framework for integrated supply chains using genetic algorithm and artificial neural networks
Fallahi et al. (2021)	Designing a closed-loop blood supply chain network considering transportation flow and quality aspects
Kenan and Diabat (2022)	The supply chain of blood products in the wake of the COVID-19 pandemic: Appointment scheduling and other restrictions
Torrado and Barbosa-Póvoa (2022)	Towards an Optimized and Sustainable Blood Supply Chain Network under Uncertainty: A Literature Review
Asadpour et al. (2022)	An updated review on blood supply chain quantitative models: A disaster perspective
Mansur et al. (2023)	A mixed-integer linear programming model for sustainable blood supply chain problems with shelf-life time and multiple blood types

Reference	**Title**
Suen et al. (2023)	A two-stage stochastic model for a multi-objective blood platelet supply chain network design problem incorporating frozen platelets
Meneses et al. (2023)	Modelling the Blood Supply Chain
Aghsami et al. (2023)	A meta-heuristic optimization for a novel mathematical model for minimizing costs and maximizing donor satisfaction in blood supply chains with finite capacity queueing systems
Shih et al. (2023)	A multiple criteria decision-making model for minimizing platelet shortage and outdating in blood supply chains under demand uncertainty
Hosseini-Motlagh et al. (2024)	Dynamic optimization of blood collection strategies from different potential donors using rolling horizon planning approach under uncertainty
Entezari et al. (2024)	A Bi-objective stochastic blood type supply chain configuration and optimization considering time-dependent routing in post-disaster relief logistics
Ala et al. (2024)	Blood supply chain network design with lateral freight: A robust possibilistic optimization model
Kazemi et al. (2024)	Multi-objective Optimization of Blood Supply Network Using the Meta-Heuristic Algorithms

Reviewing the literature, it did not find any research which considers risk analysis in blood supply chain with an analytical fuzzy approach.

RESEARCH METHOD

This study applied a systematic approach namely fuzzy cognitive mapping for analyzing the risk factors of blood supply chain in Iran. The required data to implement the real world problem, attained from experts of regional office of the Blood Transfusion Organization in Tehran province.

FCM is chosen for its holistic way of analyzing the problem and the potential success factors affecting the system and developing improvement strategies. So, the initial step involves a thorough review of existing literature to identify key risk factors that impact the blood supply chain. This review focused on previous studies and reports, leading to the identification of 14 primary risk factors. The aggregated expert opinions were then used to construct an adjacency matrix, reflecting the relationships between BSC risk factors. Finally, the FCM technique was employed to model the interactions between risk factors within the blood supply chain. This involved analyzing the influence, sensitivity, and prioritization of each risk factor using static analysis outputs. The FCM was visually represented as a graphical model, highlighting the interrelationships between factors. Dynamic behavior analysis was then conducted using activation functions, which allowed for the examination of the system's response to various scenarios. This step also demonstrated the FCM's capability to simulate changes in risk factors and assess their overall impact on BSC. Fig. 1 illustrates the steps of risk factors' evaluation in BSC.

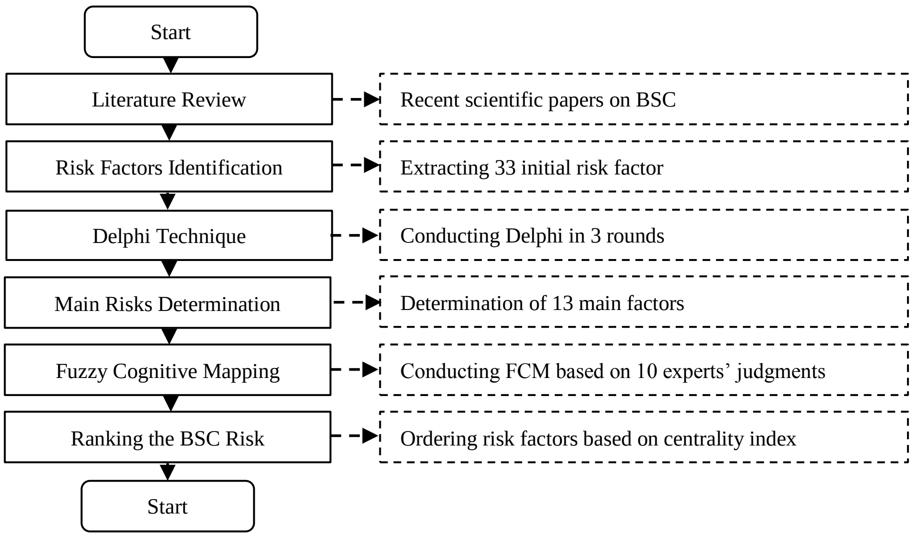

Fig 1. Research framework

FUZZY COGNITIVE MAP (FCM)

FCM first introduced by Kosco (1986), is a powerful method used to model and analyze complex systems with high levels of interaction between components. The reasoning process of fuzzy cognitive mapping is based on neuro-fuzzy system (Movahedi et al., 2022). Actually, FCM consists of a set of neural processing entities called concepts (neurons) and the causal relations among them. The activation value of such neurons regularly takes values in the [0, 1] interval, so the stronger the activation value of a neuron, the greater its impact on the network. Also, connected weights are relevant in this scheme. The strength of the causal relation between two neurons Ci and C_j is quantified by a numerical weight $w_{ij} \in [-1, 1]$.

There are three types of causal relationships between neural units in an FCM, being detailed as follows (Kharaghani et al. 2024; Tavakkol et al., 2023):

- wij > 0 indicate a positive causality,
- wij < 0 indicate a negative causality,
- wij = 0 indicate no causality.

Eq. 1 formalizes Kosko's activation rule, with A (0) as the initial value. A new activation vector is calculated at each step t and after a fixed number of iterations the FCM will be at one of the following states: (i) equilibrium point, (ii) limited cycle or (iii) chaotic behavior. The FCM is said to have converged if it reaches a fixed-point attractor, otherwise the updating process terminates after a maximum number of iterations T is reached.

$$A_i^{(t+1)} = f\left(\sum_{j=1, j\neq i}^{M} w_{ji} \times A_j^{(t)}\right) \qquad (1)$$

Subsequently, the values A_i^{t+1} and A_i^t, respectively, provide the value of the conceptual variable Ci at discrete times t+1 and t. In this case, A_j^t will be the value of the concept Cj in the t-th iteration of the simulation.

In the Eq. 1, f (0) denotes a monotonically non-decreasing function to clamp the activation value of each concept to the allowed intervals [0, 1] or [-1, 1]. The functions most extensively used based on literature are depicted as Bivalent, Trivalent, Saturation, Hyperbolic and Sigmoid function.

Stylios and Groumpos (2004) proposed a modified inference rule (Equation 2), where neurons also take into account its own past value. This rule is preferred when updating the activation value of independent neurons, i.e., neurons that are not influenced by any other neural processing entities.

$$A_i^{(t+1)} = f\left(\sum_{j=1, j\neq i}^{M} w_{ji} \times A_j^{(t)} + A_i^{(t)}\right) \qquad (2)$$

After analyzing the adjacency matrix, FCM is drawn. Subsequently, in the continuation of the modeling process, FCM implements the model and repeats the simulation based on the principles of the neural network method and using one of the common activation functions and continues the calculations until the system converges. As illustrated in equation 3, convergence occurs when the difference between the next two output values equals to or less than epsilon (ε=0.001).

$$\left|A_i^{(t+1)} - A_i^{(t)}\right| \leq \varepsilon \qquad (3)$$

The FCM network can be described using concepts such as input degree, output degree and centrality. The input degree (degree of influence) of the concept *i* is equal to the sum of the values of the column related to the variable *i* and the output degree (degree of to be influenced) is also equal to the sum of the values of the row related to variable *i* in the adjacency matrix. The centrality index is also obtained from the sum of the input and output degrees of that concept. Generally, using FCM, it is possible to evaluate the impact of concepts on each other, as well as the whole system. The steps of FCM modeling are as followings:

- *Step 1. Identification of the factors related to the problem*
- *Step 2. Evaluation of causal relationships among related factors by experts*
- *Step 3. Evaluation of the causal relationships' intensity among the factors (concepts).* In this step, the experts were asked to determine the causal

relationships' intensity using a linguistic scale. It should be noted that before determining the relevant intensities, a consensus on the direction (sign) of all system effects was reached by experts.

- *Step 4. Aggregation of the expert opinions.* After de-fuzzification of the individual fuzzy influence matrixes, the average of the experts' judgments, called "aggregated adjacency matrix" will be computed using equation (14)." The elements of the main diameter of matrix are considered equal to zero, which means that no measure leads to its formation.
- *Step 5. Developing the fuzzy cognitive map*. The analysis of the adjacency matrix from the fourth step, provides important information such as input degree, output degree, centrality index and density of fuzzy cognitive map to analyze the network structure.
- *Step 6. Implementation of the simulation process.* In order to check the dynamic state of the system and using relations (4) and (9), the values of the factors are calculated during the simulation and the new values will repeatedly replace the previous values.
- *Step 7. Checking the termination conditions.* After the system convergence, it will be possible to present the final values of the concepts.

RESULT AND DISSCUSION

To implement the proposed model in the real world, the experts of Iranian Blood Transfusion Organization (IBTO) were asked to judge about concepts causalities and the relationships strengths. Although determining the exact number of expert group members is challenging, it is recommended that the researcher be in contact with a small number of experts (for example, three to ten experienced individuals) (Ferreira et al., 2017). Therefore, in this phase of research, a group consisting of 10 experts at IBTO, were participated in this study. The criteria for selecting research experts were their theoretical expertise, practical experience, willingness, and ability to participate in the research. All discussions, inferences, and evaluations related to the identification and comparison of factors were determined under consideration of these experts.

Table 2: Main risk factors of the blood supply chain

Risk Factor	**Reference**
Blood Shortages	Pirabán et al., 2019; Khalili et al., 2020; Ghatreh Samani et al., 2018; Fahimnia et al., 2018; Nezamoddini et al., 2020; Nezamoddini et al., 2020
Blood Wastage	Ghatreh Samani et al., 2018; Fahimnia et al., 2018; Habibi-Kouchaksaraei et al., 2018; Khalili et al., 2020;
Blood Products Perishability	Kazemi et al., 2024; Sharifi et al., 2019; Hamdan & Diabat, 2020; Nezamoddini et al., 2020;
Demand and Supply Uncertainty	Meneses et al., 2023; Ghatreh Samani et al., 2018; Fahimnia et al., 2018; Khalili et al., 2020; Nezamoddini et al., 2020
Infrastructure and Technological Limitations	WHO, 2017; Khalili et al., 2020; Sharifi et al., 2019; Nezamoddini et al., 2020
Delays in Allocation and Distribution	Nezamoddini et al., 2020; Hamdan & Diabat, 2020; Eskandari-Khanghahi & Ghatreh Samani, 2018;
Disruptions in Logistics Processes	Hamdan & Diabat, 2020; Khalili et al., 2020; Sharifi et al., 2019; Ghatreh Samani et al., 2018; Fahimnia et al., 2018
Complexities in Inventory Processes	Sharifi & Ghaneipour, 2019; Nezamoddini et al., 2020; Khalili et al., 2020;
Exceeding Blood Requisition in Actual Usage	Habibi-Kouchaksaraei & Kazemi, 2020; Sharifi et al., 2019; Ghatreh Samani et al., 2018; Fahimnia et al., 2018; Nezamoddini et al., 2020
Weak Collaboration	Fahimnia et al., 2018; Khalili et al., 2020; Nezamoddini et al., 2020
Problems in Quality Control	Nezamoddini et al., 2020; Rajendran & Ravindran, 2019; Khalili et al., 2020; Hamdan & Diabat, 2020
Weak Screening	Hamdan & Diabat, 2020; Sharifi et al., 2019; Ghatreh Samani et al., 2018; Fahimnia et al., 2018; Nezamoddini et al., 2020

Risk Factor	**Reference**
Insufficient Capacity	Ghatreh Samani et al., 2018; Hamdan & Diabat, 2020; Fahimnia et al., 2018; Khalili et al., 2020; Sharifi et al., 2019; Nezamoddini et al., 2020
Problems in Safety Issue	Khalili et al., 2020; Sharifi et al., 2019; Ghatreh Samani et al., 2018; Fahimnia et al., 2018

After identifying the affecting factors on VC, they must be evaluated by the experts. For this purpose, a questionnaire was designed based on the factors in Table 3; then, the 20 selected indicators were mentioned in the first row and column of the questionnaire table, and the experts were asked to determine the intensity of causal relationships between the factors based on the linguistic variables mentioned in Table 2. Since the judgments of the experts were ambiguous and uncertain, the linguistic variables in this study were converted to triangular fuzzy numbers. Next, the fuzzified matrixes of the experts' judgments were obtained and their average is calculated in form of the "aggregated adjacency matrix". Table 2 demonstrates this matrix.

Table 2: Aggregated adjacency matrix for BSC risk factors

Factors		**F_1**	**F_2**	**F_3**	**F_4**	**F_5**	**F_6**	**F_7**	**F_8**	**F_9**	**F_{10}**	**F_{11}**	**F_{12}**	**F_{13}**	**F_{14}**
Blood Shortages	F_1	-	-0.12	0.00	0.00	0.00	0.67	0.16	0.00	0.00	0.19	0.00	0.00	-0.25	0.00
Blood Wastage	F_2	0.44	-	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.17	0.12
Blood Products Perishability	F_3	0.51	0.26	-	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00	0.00	-0.19	0.35
Demand and Supply Uncertainty	F_4	0.67	0.40	0.00	-	0.00	0.60	0.51	0.23	0.00	0.35	0.00	0.00	0.21	0.09
Infrastructure and Technological Limitations	F_5	0.20	0.28	0.16	0.00	-	0.35	0.68	0.00	0.00	0.36	0.27	0.20	0.62	0.37
Delays in Allocation and Distribution	F_6	0.39	0.24	0.45	0.21	0.00	-	0.43	0.00	0.19	0.34	0.00	0.00	0.00	0.00
Disruptions in Logistics Processes	F_7	0.53	0.36	0.22	0.00	0.00	0.79	-	0.00	0.00	0.30	0.00	0.00	0.00	0.35
Complexities in Inventory Processes	F_8	0.00	0.00	0.00	0.00	0.00	0.18	0.00	-	0.00	0.18	0.00	0.00	0.00	0.00
Exceeding Blood Requisition in Actual Usage	F_9	0.25	0.35	0.00	0.23	0.00	0.00	0.24	0.00	-	0.26	0.00	0.00	-0.18	0.25
Weak Collaboration	F_{10}	0.31	0.16	0.22	0.24	0.00	0.49	0.50	0.00	0.11	-	0.00	0.00	0.33	0.29
Problems in Quality Control	F_{11}	0.00	0.39	0.18	0.00	0.00	0.15	0.00	0.00	0.00	0.00	-	0.55	0.00	0.46
Weak Screening	F_{12}	0.00	0.34	0.23	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.27	-	0.00	0.55
Insufficient Capacity	F_{13}	0.47	0.69	0.00	0.39	0.00	0.15	0.35	0.00	0.00	0.38	0.00	0.00	-	0.29
Problems in Safety Issue	F_{14}	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.34	0.00	0.00	-

In the modeling process, the structure of fuzzy cognitive map was analyzed using the FCM Expert software. The output of FCM static analysis, which is based on the principles of graph theory, was analyzed and the results are presented as degree of input, degree of output and centrality index of the BSC risk factors. Risk factors are ranked in Table, 3 based on the descending order of the centrality index. It should be noted that the higher the centrality index score of a factor is, the more influence it has on the network and plays a more central role in the fuzzy cognitive map.

Table 3. Ranking the risk factors of BSC

Factors	Indicator	Input	Output	Centrality
Delays in Allocation and Distribution	F_6	3.59	2.25	5.84
Disruptions in Logistics Processes	F_7	2.98	2.55	5.53
Blood Shortages	F_1	3.77	1.39	5.16
Weak Collaboration	F_{10}	2.36	2.65	5.01
Insufficient Capacity	F_{13}	1.95	2.72	4.67
Blood Wastage	F_2	3.59	0.84	4.43
Demand and Supply Uncertainty	F_4	1.07	3.06	4.13
Problems in Safety Issue	F_{14}	3.12	1.01	4.13
Blood Products Perishability	F_3	1.86	1.93	3.79
Infrastructure and Technological Limitations	F_5	0	3.49	3.49
Problems in Quality Control	F_{11}	0.88	1.73	2.61
Weak Screening	F_{12}	0.75	1.6	2.35
Exceeding Blood Requisition in Actual Usage	F_9	0.3	1.76	2.06
Complexities in Inventory Processes	F_8	1.12	0.36	1.48

According to the results, "Delays in Allocation and Distribution" with the centrality score of 5.84 has the highest interaction with the BSC risk factors. Among the other risk factors, “Disruptions in Logistics Processes”, “Blood Shortages” and “Weak Collaboration” took the 2^{nd} to 4^{th} place, from the centrality point of view. The column related to the degree of output shows the total influence of each risk factor on other related risk factors; In this column, "Infrastructure and Technological Limitations", “Demand and Supply Uncertainty” and “Insufficient Capacity” with the output scores of 3.49, 3.06 and 2.72, respectively have the highest influences on the system’s risk factors. The input degree column also provides the total influence of the other risk factors on a given concept. Finally, "Blood Shortages", “Delays in Allocation and Distribution” and “Blood Wastage” with the input grade of 3.77, 3.59 and 3.59 has received the greatest influence from the system’s risk factors, respectively. Table 3 also provides other information of static analysis of fuzzy cognitive maps of the research.

Next, the FCM graphic structure of the BSC risk factors is presented in Fig. 2. In this fuzzy cognitive maps, the number of 14 risk factors are connected by 84 arcs that express the causal relationships between the related risk factors. The transfer function is considered “Sigmoid”, the activation rule is “Kosko’s activation rule with self-memory”, and the epsilon index (Convergence) is equal to 0.001.

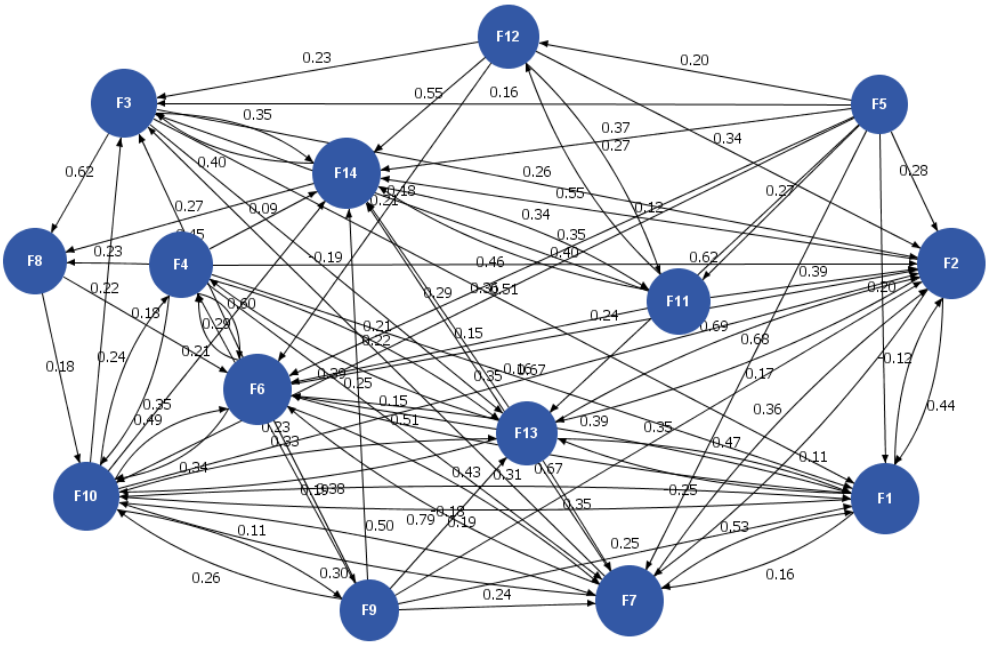

Fig. 2. Graphical structure of the value chain drivers in pharmaceutical industry

In order to visually understand the FCM in Fig. 2, after eliminating the causal relationships with weights less than |±0.4|, the corresponding FCM was again presented in Fig. 3; So, only the most important causal relationships are displayed and a more accurate understanding of FCM is obtained for the viewer.

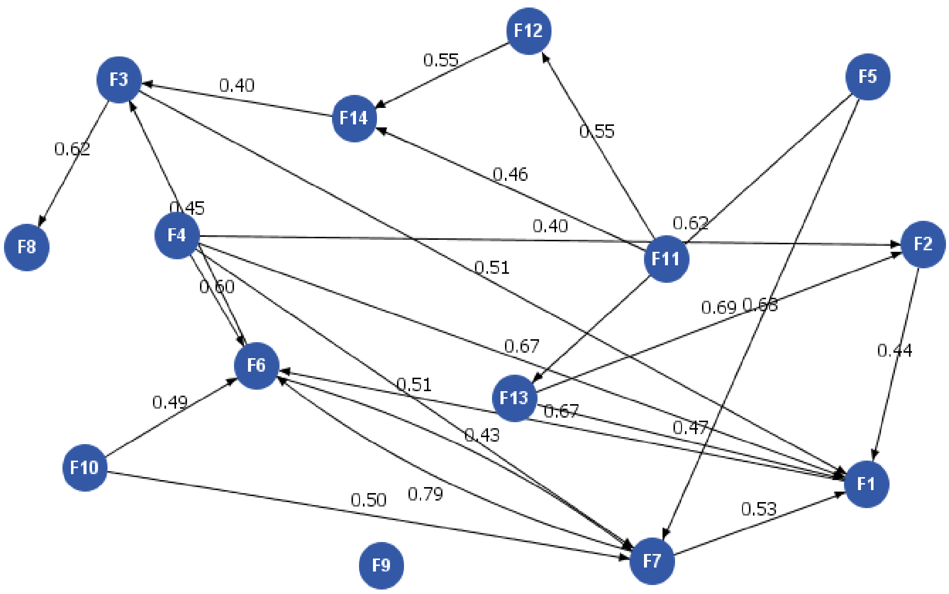

Fig. 3. Graphical structure with important causal relationships

Finally, model interface allows performing reasoning using the provided activation values. Before performing the inference process, the user must specify the activation values of input concepts used to activate the FCM-based system (see Editing concepts). This option will summarize the inference results through a chart and a table with the activation value of concepts at each iteration (see Fig. 4).

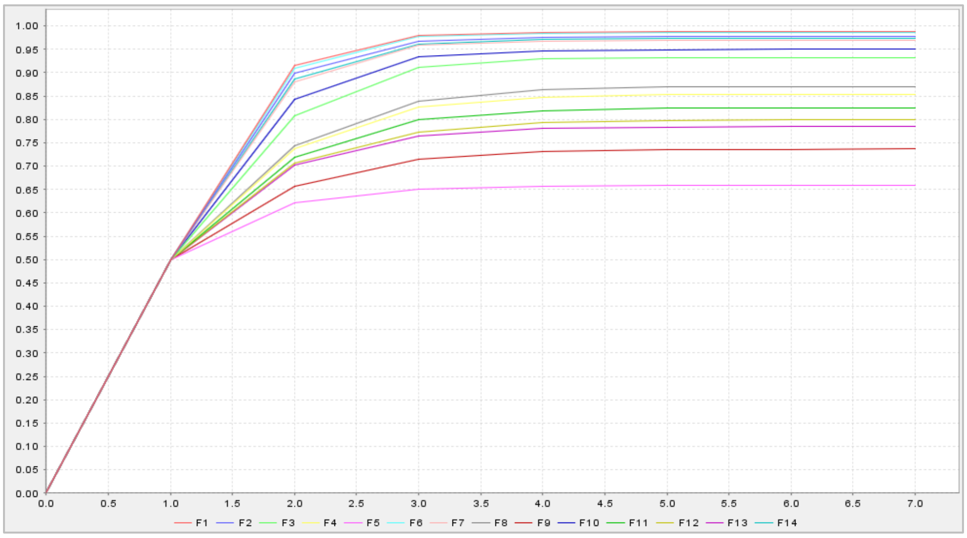

Fig. 4. The graphical interface results

The graphical interface visualizes the response vector obtained after adjusting the weights. It should be mentioned that the convergence index (ε) in this research considered 0.001.

CONCLUSIONS

This study has conducted an in-depth analysis of risk factors within the blood supply chain using Fuzzy Cognitive Mapping (FCM), providing crucial insights into the interconnected risks that can significantly impact the efficiency and reliability of blood supply operations. The centrality index derived from the FCM analysis has helped to identify and rank the most critical factors, highlighting key areas that demand immediate attention and strategic intervention. The findings revealed that "Delays in Allocation and Distribution" is the most central and influential risk factor in the blood supply chain, underscoring the critical need for optimizing distribution strategies and minimizing bottlenecks. Closely following this are "Disruptions in Logistics Processes" and "Blood Shortages," which further emphasize the necessity of a robust and agile logistics network that can adapt to varying demand levels and unforeseen disruptions. Other significant factors include "Weak Collaboration" and "Insufficient Capacity," both of which point to the need for stronger partnerships and improved resource management across the supply chain. "Blood Wastage" and "Demand and Supply Uncertainty" also emerged as critical risks, suggesting that better forecasting, inventory management, and technological integration could greatly reduce inefficiencies and wastage.

Given the identified risks, there is a clear need to develop more efficient and responsive allocation and distribution systems. This can be achieved through the adoption of advanced logistics technologies, such as real-time tracking systems and predictive analytics, to better manage distribution timelines and reduce the impact of potential disruptions. In addition, Improved collaboration among all stakeholders in the blood supply chain, including blood banks, hospitals, and transportation providers, is essential. Creating shared platforms for communication and data exchange can lead to more coordinated efforts and resource sharing, thereby enhancing overall capacity and responsiveness.

To tackle the issues of blood wastage and supply-demand imbalances, it is recommended to invest in more accurate demand forecasting tools and to optimize inventory management practices. This may include the implementation of machine learning algorithms for predictive modeling and the use of block chain technology for transparent tracking of blood products. Strengthening screening processes, adhering to stringent quality control standards, and adopting innovative preservation techniques for blood products can also help mitigate the risks associated with perishability and safety issues.

To further enhance the resilience and efficiency of blood supply chains, future studies could explore the integration of advanced machine learning models with FCM to develop more accurate predictive tools for managing demand fluctuations and optimizing inventory levels. Investigating the potential of block chain and the Internet of Things (IoT) for improving traceability, transparency, and real-time monitoring in the blood supply chain could provide new avenues for reducing risks and enhancing safety.

Research could also focus on developing comprehensive resilience models that consider the interdependencies between various risk factors, helping to create more robust blood supply chains that can withstand both internal and external shocks. Finally, future studies should examine the role of policy and regulatory frameworks in mitigating risks, particularly in areas such as collaboration, data sharing, and quality control, to ensure that best practices are consistently applied across all levels of the blood supply chain. By focusing on the suggested areas for future research, it is possible to develop more resilient, efficient, and safe blood supply chains that can better serve the needs of healthcare systems and improve patient outcomes globally.

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