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Identification and Prioritization of Risk Factors in Healthcare Supply Chain Using an Integrated Fuzzy-Delphi and Fuzzy-TOPSIS Method

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Abstract

The healthcare supply chain has many challenges that prevent access to critical medical supplies, particularly in a crisis and global uncertainty. The most significant risks must be identified and prioritized to cope with the healthcare supply chain management. This study applies integrated multi-criteria decision making (MCDM) method to identify and prioritize critical risks in healthcare supply chain management based on literature review and the healthcare specialists' feedback and advice. Among multiple risk factors, ten major risk factors were identified using a Fuzzy-Delphi method. Subsequently, a Fuzzy-TOPSIS approach was used to prioritize these risks, providing a structured and robust decision-making process. The results indicate that Supply Chain Disruptions, demand uncertainty, Pandemic Crisis are the most important risks. The paper focuses on identifying and prioritizing key risks but does not extend to specific mitigation measures. Analyzing the most sensitive risk factors, this study helps to strengthen the risk management techniques, hence leading to enhanced resilience of healthcare delivery systems. The results offer practical implications for healthcare organizations to avoid and mitigate various risks that affect the sustainable and resilient supply chain. These findings can help policymakers and healthcare leaders deepen their understanding of risk environments to improve risk management and supply chain efficiencies, and ultimately ensure better patient care outcomes for the region, as well as globally.

Keywords
Healthcare Supply Chain, Risk Factors, Fuzzy Delphi, Fuzzy TOPSIS, Healthcare sector

1. Introduction
Healthcare Supply Chain Management (HSCM) is crucial for ensuring the smooth and efficient delivery of medical supplies, equipment, and services essential for patient care. Effective HSCM plays a vital role in improving the quality of healthcare, reducing operational costs, and ensuring timely access to necessary resources. However, the healthcare supply chain is susceptible to a wide range of risks. These risks have become even more evident in the wake of global crises such as the COVID-19 pandemic, which exposed significant vulnerabilities in healthcare supply chains worldwide. This research focuses on identifying and prioritizing the key risk factors in HSCM. There are still significant research gaps, particularly in the context of developing countries like Bangladesh, where the healthcare supply chain faces unique challenges such as resource limitations, regulatory issues, and supply chain disruptions (Kavaler & Spiegel 2003). This study aims to address these gaps by identifying and prioritizing the critical risk factors in HSCM, using an integrated Fuzzy-Delphi and Fuzzy-TOPSIS methodology. The findings are expected to contribute to the development of strategies for mitigating risks and improving supply chain resilience, thus supporting the overall sustainability and efficiency of healthcare services in Bangladesh.

Numerous studies have contributed to identifying the risk factors that influence Healthcare Supply Chain Management (HSCM). As critical indicators of HSCM risks, factors such as supply chain disruptions , regulatory challenges (Bria et al., 2012). These factors hinder the healthcare supply chain's ability to maintain continuity, reduce lead times, and ensure the timely availability of medical supplies. Supply chain disruptions, including natural disasters, pandemics, and transportation breakdowns, are consistently identified as major risks to healthcare operations (Bria et al. 2012). Effective risk mitigation strategies must be implemented to ensure the resilience of the supply chain. Regulatory challenges, such as stringent compliance requirements and constantly changing healthcare policies, also create complexities that can delay critical supply chain processes (Bria et al. 2012). Another significant risk in HSCM is the lack of technological infrastructure, which hinders real-time information sharing, visibility, and decision-making capabilities (Kavaler & Spiegel 2003). Inadequate technological systems can lead to inefficiencies in procurement, tracking, and distribution, making it difficult to respond to emergencies. Human resource constraints, including shortages of skilled personnel and inadequate training, further exacerbate these challenges. Well-trained and empowered healthcare professionals are essential for ensuring supply chain efficiency and reducing risks in critical areas such as procurement and logistics.

Supplier reliability is another crucial factor, as delays or inconsistencies in the delivery of essential supplies can lead to significant disruptions in healthcare services (Rodriguez-Acelas et al. 2017). Similarly, demand uncertainty, driven by fluctuating patient needs and unpredictable healthcare crises, complicates inventory management. Proper inventory management, including the ability to maintain optimal stock levels and reduce waste, is essential for managing risk [10]. Finally, logistical challenges, including transportation inefficiencies and geopolitical risks, must be addressed to ensure the smooth flow of medical supplies across the supply chain (Rodriguez-Acelas et al. 2017). Among the many MCDM techniques available, the integrated Fuzzy-Delphi and Fuzzy-TOPSIS methods have gained prominence for their ability to handle uncertainty and incorporate expert opinions. The Fuzzy-Delphi method is used to systematically gather and refine expert opinions on the most critical risk factors through multiple rounds of feedback. This iterative process ensures that expert judgments are refined over time, leading to a consensus on the most significant risks. This combination of methods is widely accepted for its ability to prioritize risk factors in complex, multi-criteria problems while incorporating both qualitative and quantitative aspects.

In healthcare supply chain management (HSCM), these techniques are instrumental in identifying and ranking risk factors such as supply chain disruptions, regulatory challenges, and human resource shortages. The specific objectives are as follows: (i) To identify the major risk factors affecting healthcare supply chains. (ii) To prioritize and rank the identified risks using the Fuzzy-Delphi and Fuzzy-TOPSIS methods. For addressing these questions, the research employed a structured and integrated approach combining the Fuzzy-Delphi and Fuzzy-TOPSIS methodologies. The Fuzzy-Delphi method was selected for its ability to refine expert opinions through an iterative process, ensuring that the key risk factors are identified with a high degree of consensus among stakeholders. The involvement of healthcare professionals, supply chain managers, and experts in the field allowed for a comprehensive assessment of potential risks. This method enabled the collection and validation of subjective judgments in a systematic manner, reducing the ambiguity and bias often associated with expert input.

1.1 Objectives

The specific objectives of this research are:

To identify the major risk factors affecting healthcare supply chains

To prioritize and rank the identified risks using the integrated Fuzzy-Delphi and Fuzzy-TOPSIS methods

2. Method

The research framework includes two different methods designed to evaluate the supply chain risks in Bangladesh's healthcare sector. First, key challenges were identified through a careful process that involved input from four industry experts. Next, these identified factors were ranked based on their importance, creating a clear order of priority.

2. 1 Data Collection and Validity

Data for this study was collected from 4 experts in the healthcare supply chain, including professionals from various sectors. The questionnaire consisted of 10 questions, four of which focused on the respondents' professions and experience. To ensure the reliability of the questionnaire, the Cronbach α measure was employed, resulting in a value of 0.778, which indicates that the data collected is suitable for further analysis. In addition, feedback was obtained from experts specifically for assessing the interrelationships among key challenges in risk management.

2.2 Fuzzy Delphi Method

The Fuzzy Delphi Method (FDM) improves on the standard Delphi approach by using fuzzy theory for accounting for decision-makers' language preferences. This method has been widely employed in a variety of domains, including management, engineering, and physical sciences, mostly for screening expert opinions represented as fuzzy sets.

2.2.1 Establishing the linguistic variables' triangular fuzzy number A fuzzy set with a triangle membership function is called a triangular fuzzy set. The following is the equation for a triangular fuzzy set

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{q-w_1}{w_2-w1} & , q_1 \leq w \leq q_2 \\ \frac{w_3-w}{w_3-w_2} & , q_2 \leq w \leq q_3 \\ 0 & , Otherwise \end{cases}$$

A triangular fuzzy number a_{ij} is defined as w_{ij} = (w_{ij}, b_{ij}, c_{ij}), in which i ∈ {1,2,..,n} denotes the experts and j ∈ {1,2,..,m} denotes the barriers, Where n and m are the numbers of experts and barriers, respectively. The fuzzy number set for the linguistic variables are collected from a research framework shown in Table 3. (Sun 2010) (1)

2.2.2 Collecting experts' opinions concerning the relevance of the challenges

Following the identification of the hurdles, a questionnaire based on the linguistic criteria described in the preceding table is distributed to four experts (decision makers) from academia and industry to assess their significance. This study uses fuzzy triangular numbers to analyze risk factors. The method uses a geometric mean methodology to determine the group decision made by the experts. (Ma et al. 2011).

2.2.2 Defuzzification

Defuzzification, which is commonly used when working with fuzzy logic controllers, is the process of transforming a fuzzy set into an appropriate crisp set. It requires selecting a defuzzification strategy based on the system of the problem, such as mean-max, centroid, max-membership, or weighted-average. This approach is important for converting fuzzy control commands into precise values (Ibrahim 2016).

$w_{-j} = (w_j, e_j, r_j)$,

Where $wj = min\{wij\}$,

$ej = \sqrt[n]{\prod_{i=1}^{n} e_{ij}}$ (2)

and, $rj = max\{rij\}$.

This study uses a geometric mean model to determine the group decision of the experts .The simple center of gravity method is used to defuzzyfy the fuzzy weights to get a crisp value (tj), which is given by the following formula:

$$tj = \frac{a_j+b_j+c_j}{3} \quad (3)$$

y ∈ {1,2,..,m}

2.2.3. Determination of significant challenges.

The final step in the fuzzy Delphi technique is to identify substantial hurdles by comparing each challenge's weight to the "S" criterion. The value of is determined by averaging the weights of each barrier. The screening principle is as follows:

$$t = \frac{\Sigma t_i}{n} \quad (4)$$

A risk factor is chosen if $t_i \geq S$

Risk factor is rejected if $t_i < S$.

To compare the values, they must first be translated into crisp values. Figure 1 depicts the Fuzzy Delphi Methodology used to gain consensus on supply chain risk management concerns.

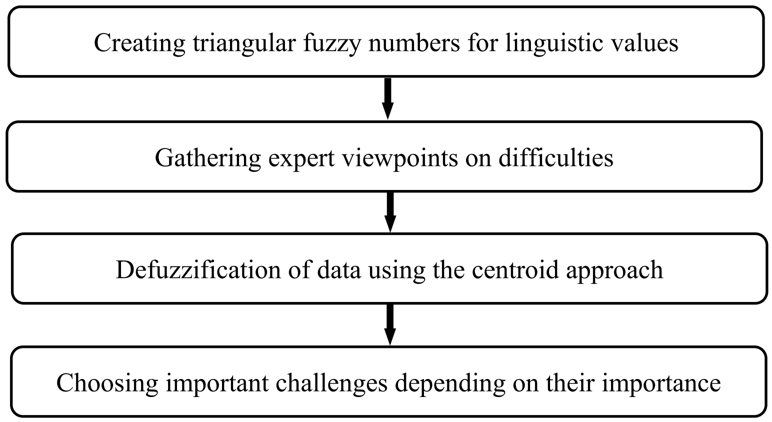

Figure 1. Methodology of Fuzzy Delphi Method

Fuzzy TOPSIS Method

Fuzzy TOPSIS is a decision-making approach that addresses imperfect information and uncertainties by combining the Order of Priority by Comparison to Ideal Solution (TOPSIS) methodology and fuzzy set theory. Type-2 fuzzy sets, triangular membership functions, and fearful fuzzy linguistic word sets are used to increase membership accuracy by conveying uncertainty. Applications for fuzzy TOPSIS include e-sourcing, mobile device selection, project risk assessment, and car efficiency assessment (Salih et al., 2019).The fuzzy TOPSIS method, a modification on the standard TOPSIS approach, was developed to handle uncertainty in multi-criteria decision-making (MCDM) procedures. To address the inadequacies of the sharp TOPSIS method, it includes fuzzy logic and new mathematical notions, providing an improved methodology for prioritizing possibilities in complex decision-making (Çelikbilek & Tüysüz, 2020).

2.2.1 Setting up the triangular fuzzy number for both the challenges & the risk criteria

The linguistic variables & the triangular fuzzy number are listed.

2.2.2 Collecting expert's opinion based on risk criteria

To evaluate and rank the discovered risk factors, 15 expert opinions are gathered based on six risk criteria. The risk criteria are presented in table 1 below:

Table 1. Risk Criteria & their description

Risk criteria	Risk Criteria Description
Cost	Cost refers to the financial consequences and variations associated with procurement, production, and distribution operations. It has the ability to increase costs, create a resource shortage, and cause market instabilities, all of which pose a significant risk to healthcare supply chain resilience.
Safety	One of the most critical risk criteria in the supply chain is safety, which includes measures to ensure employee health and safety, regulatory compliance, and the prevention of incidents or interruptions. Finally, safety ensures the healthcare supply chain's overall integrity and dependability.
Environment	Sustainable practices are necessary to reduce long-term environmental damage and ensure compliance throughout the healthcare supply chain, as environmental impacts carry the danger of both ecological harm and regulatory implications.

2.1.3 Developing a fuzzy TOPSIS technique for ranking

The fuzzy TOPSIS approach is comprised of multiple phases. This section provides a quick description of the steps.

Step - 1: Creating fuzzy decision matrix.

Following the finalization of the primary risk factors and the collecting of expert opinions, linguistic variables are converted into fuzzy integers. The fuzzy numbers associated with each criterion are then aggregated. The formula for this technique is as follows:

If the fuzzy ratings of all decision makers are described as a triangular fuzzy number ($z_k = q_k, w_k, e_k$), a = 1,2,3,……….,a, then the aggregated fuzzy ratings is given by

$$q = \min \{q_k\} \quad (5)$$

$$w = \frac{\sum_{k=1}^{k} w_k}{k} \quad (6)$$

$$e = \max\{e_k\} \quad (7)$$

Similarly aggregated fuzzy weights are calculated for three criteria's based on the four expert's opinion shown in table 2.

Table 2. Fuzzy weights for six risk criteria

Risk Criteria	Aggregated Fuzzy Weight
Cost	(0.22,0.22,0.22)
Safety	(0.22,0.22,0.22)
Environment	(0.22,0.22,0.22)

Step – 2: Normalization of the fuzzy decision matrix

The choice matrix is normalized by dividing each element by its column sum. The normalized fuzzy decision matrix z is calculated as follows:

$$z = [q_{ij}]_{mxn} \text{ where } i = 1,2,3,\ldots..,n. \quad (8)$$

$$q_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \quad (9)$$

Step – 3: Computing the weighted normalized matrix

The weighted normalized matrix for six risk criteria is computed by multiplying the weights of evaluation criteria with the normalized fuzzy decision matrix $z_{ij.}$

Step – 4: Computing the Fuzzy Positive Ideal Solution (FPIS) & the Fuzzy Negative Ideal Solution (FNIS) and the distance of each risk factor from them

The distance (e_i^+, e_i^-) of each weighted risk factor where I – 1, 2, 3,……, m from the FPIS & the FNIS (12) is shown below :

Step 5: Compute the closeness coefficient (CC_i) of each risk factor

The formula to calculate the closeness co-efficient is given below:

$$CC_i = \frac{e_i^-}{e_i^+ + e_i^-} \quad (13)$$

Step – 06: Ranking of the risk factors

The proximity co-efficient value represents the perimeter of the risk factor ranking. The highest value of the proximity coefficient reflects the most critical risk variables.

Figure 2 depicts the flow diagram for the Fuzzy TOPSIS Method, which takes observers through the sequential phases needed in making decisions about how to prioritize the primary difficulties.

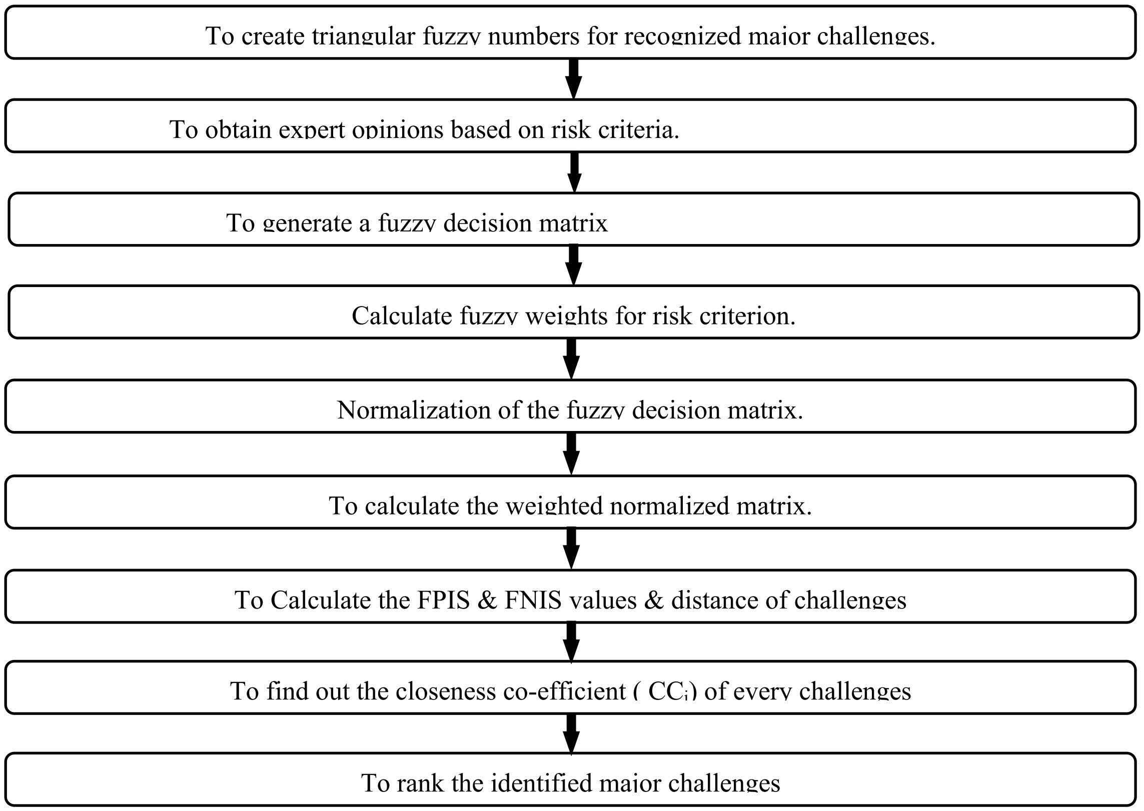

Figure 2.Flow diagram of Fuzzy TOPSIS Method

3. Results and Discussion

This section presents the identification, prioritization, and analysis of supply chain challenges in healthcare, using the Fuzzy Delphi and Fuzzy TOPSIS methods.

4.1 Identification of Major risk factors Using the Fuzzy Delphi Approach

To identify the key risks in healthcare supply chains, we reviewed existing literature and gathered expert opinions. From this process, we identified 14 common risks. The data collected from experts, Table 3: Collected Data from the experts on identifying major risks. After applying the Fuzzy Delphi Approach, we calculated the defuzzified

Table 3. Collected Data from the experts on identifying major Factor

Risk Factors	Expert Opinion 1	Expert Opinion 2	Expert Opinion 3
R1	(5,6,7)	(5,6,7)	(5,6,7)
R2	(5,6,7)	(4,5,6)	(4,5,6)
R3	(2,3,4)	(2,3,4)	(2,3,4)
R4	(6,7,8)	(7,8,9)	(6,7,8)
R5	(6,7,8)	(7,8,9)	(6,7,8)

R6	(2,3,4)	(2,3,4)	(4,5,6)
R7	(7,8,9)	(6,7,8)	(6,7,8)
R8	(7,8,9)	(6,7,8)	(7,8,9)
R9	(1,2,3)	(2,3,4)	(2,3,4)
R10	(8,9,10)	(6,7,8)	(8,9,10)
R11	(6,7,8)	(10,10,10)	(7,8,9)
R12	(10,10,10)	(6,7,8)	8,9,10
R13	(2,3,4)	(1,2,3)	(1,2,3)
R14	(6,7,8)	(6,7,8)	(4,5,6)

Defuzzification of the expert's opinion
A total of 3 expert's opinions are taken which are defuzzyfied to find crisp values that are below & above the threshold value.

Table 4. Defuzzification of the expert's opinion

Challenges	Minimum	Geometric mean	Maximum	Defuzzification weighted value
R1	5	6.41	7	6.61
R2	5	6.22	7	6.32
R3	2	2.84	4	3.14
R4	6	7.71	9	7.90
R5	7	8.62	9	8.66
R6	2	4.41	6	4.56
R7	7	7.48	9	7.49
R8	7	8.10	9	7.97
R9	1	2.23	4	2.41
R10	8	8.45	10	8.15
R11	6	8.65	10	8.22
R12	7	9.21	10	8.74
R13	1	2.30	4	2.433
R14	4	5.96	8	5.99

3.1.1 Selection of Major Challenges
After defuzzification, we calculated the mean weighted values for each factor. The selected and rejected challenges are listed below:

A total of 10 risk challenge's weighted values are above the threshold value. The selected & rejected risk factors are identified in the following table.

Table 5. Selected & Rejected Challenges

Selected Challenges	Rejected Challenges
R1-Supply Chain Disruptions	R3- Regulatory Challenges
R2- Lack of Technological Infrastructure	R6- Supplier Reliability Issues
R3- Regulatory Challenges	R9- Political Instability
R4- Human Resource Shortages	R13- Economic Downturns
R5- Demand Uncertainty	
R6- Supplier Reliability Issues	
R7- Inventory Management Inefficiencies	
R8- Logistical Challenges	
R9- Political Instability	
R10- Transportation Failures	
R11- Natural Disasters	
R12- Counterfeit Products	
R14- Cybersecurity Risks	

3.2 Ranking Major Challenges Using the Fuzzy TOPSIS Approach

The Fuzzy TOPSIS method was employed to rank the identified challenges based on three risk criteria. These criteria are outlined in Table 4. We collected opinions from experts to evaluate and prioritize these challenges, with results shown in Table 11. We created an integrated decision matrix based on the experts' insights, incorporating fuzzy weights for each risk criterion. The first step in the Fuzzy TOPSIS methodology involved generating a fuzzy decision matrix using specific equations, with results presented in Table 11. Additional details, including the normalized matrix, weighted normalized matrix, and distance calculations, are provided in Tables 6 to 10 for 3 risk factors.

Table 6. Integrated Matrix based on the expert's opinions

	FW1	**FW2**	**FW3**
Risks	(0.22,0.22,0.22)	(0.22,0.22,0.22)	(0.22,0.22,0.22)
	Criteria -1	**Criteria -2**	**Criteria -3**
R1	(3.200,4.280,5.480)	(3.000,4.640,6.360)	(3.240,4.760,6.400)
R2	(6.440,7.800,8.640)	(3.080,4.880,6.520)	(3.680,5.240,6.640)
R3	(2.840,4.400,6.200)	(5.720,7.480,8.760)	(4.240,5.800,7.240)

Creating Normalized matrix

A normalized matrix is created in the second step using equation (8) and (9).

Table 7. Normalized Matrix

	FW1	**FW2**	**FW3**
Risks	(0.22,0.22,0.22)	(0.22,0.22,0.22)	(0.22,0.22,0.22)
	Criteria -1	**Criteria -2**	**Criteria -3**
R1	(0.518,0.664,0.888)	(1.107,0.716,0.522)	(0.405,0.595,0.800)
R2	(0.329,0.364,0.441)	(1.078,0.680,0.509)	(0.460,0.655,0.830)
R3	(0.458,0.645,1.000)	(0.580,0.444,0.379)	(0.530,0.725,0.905)

Table 8. Weighted Normalized Matrix

Risks	**Criteria - 1**	**Criteria - 2**	**Criteria - 3**
R1	(0.114,0.146,0.195)	(0.243,0.157,0.115)	(0.089,0.131,0.176)
R2	(0.072,0.080,0.097)	(0.237,0.150,0.112)	(0.101,0.144,0.183)
R3	(0.101,0.142,0.220)	(0.128,0.098,0.083)	(0.117,0.160,0.199)

Compute the FPIS and FNIS and the distance of each risk factors from them
The FPIS and the FNIS value is found in fourth step using equation (10), (11) and (12).

Table 9. Distance between FPIS and weighted Risks

Risks	RC-1	RC-2	RC-3	Sum
R1	0.849	0.830	0.869	**2.548**
R2	0.917	0.835	0.858	**2.61**
R3	0.847	0.897	0.842	**2.586**

Table 10. Distance between FNIS and weighted Risks

Risks	RC-1	RC-2	RC-3	Sum
R1	0.155	0.180	0.137	**0.472**
R2	0.084	0.174	0.146	**0.404**
R3	0.162	0.105	0.162	**0.429**

3.2.1 Computing Closeness Coefficient (CCi) Values & Ranking Risks

The final step of the Fuzzy TOPSIS method involved calculating the closeness coefficient (CCi) for each Risk using Equation (13). The final rankings are summarized in Table 11 below:

Table 11. Final ranking of the biggest Risks based on CCi values

Risks	CC_i	Rank
Supply Chain Disruptions	0.195	**1**
Lack of Technological Infrastructure	0.161	**4**
Human Resource Shortages	0.137	**9**
Demand Uncertainty	0.168	**2**
Inventory Management Inefficiencies	0.141	**8**
Logistical Challenges	0.150	**6**
Transportation Failures	0.130	**10**
Natural Disasters (e.g., earthquakes, floods)	0.1516	**5**
Pandemics Crises	0.159	**5**
Counterfeit Products	0.145	**7**
Cybersecurity Risks	0.166	**3**

4. Discussion

The healthcare supply chain encounters various Risks that critically influence its effectiveness, resilience, and sustainability. Supply Chain Disruptions (CCi = 0.195) emerge as the most significant issue, driven by factors such as natural disasters, geopolitical instability, and transportation breakdowns, which halt the movement of critical resources and delay essential deliveries. Effective risk management, such as alternative sourcing and contingency planning, is essential to mitigate these disruptions. Demand Uncertainty (CCi = 0.168) ranks second, reflecting the difficulty of accurately forecasting fluctuating patient needs, particularly during emergencies like pandemics. This often leads to overstocking or shortages, highlighting the importance of advanced demand forecasting systems and flexible inventory management. Cybersecurity Risks (CCi = 0.166) rank third, emphasizing the increasing threat of cyberattacks targeting healthcare infrastructure. These attacks compromise data integrity and disrupt operations, underscoring the need for robust IT security measures. Natural Disasters (CCi = 0.151) and Logistical Challenges (CCi = 0.150) rank fourth and fifth, respectively, as earthquakes, floods, and poor logistics planning can damage infrastructure, delay shipments, and reduce supply chain reliability. Other critical issues include Counterfeit Products (CCi = 0.145) and Human Resource Shortages (CCi = 0.145), where inadequate workforce training and the infiltration of fake medical supplies compromise patient safety and supply chain efficiency. Transportation Failures (CCi = 0.141) and Inventory Management Inefficiencies (CCi = 0.137) also contribute significantly, causing delays and stock mismanagement. Addressing these challenges requires comprehensive strategies, including investment in resilient infrastructure, enhanced workforce development, stringent quality controls, and adoption of advanced technologies like AI-driven logistics and blockchain for traceability. Tackling these issues holistically will ensure a more robust and sustainable healthcare supply chain capable of meeting future demands.

4.0 Conclusion

This ranking of healthcare supply chain challenges underscores the multifaceted nature of risks that affect supply chain performance. While some factors like demand uncertainty, pandemics, and cybersecurity risks top the list due to their potential for widespread disruption, others such as logistical inefficiencies, regulatory hurdles, and human resource shortages also play a significant role in undermining supply chain stability. To build resilient healthcare supply chains, it is crucial for stakeholders to prioritize risk mitigation strategies based on the severity and likelihood of these challenges, ensuring timely responses to emerging risks. Moreover, the research's focus on the healthcare supply chain may restrict the applicability of the findings to other sectors, potentially limiting their broader relevance. Additionally, the study's reliance on expert opinions may introduce biases based on the participants' backgrounds and perspectives. The analysis of challenges in healthcare supply chain management reveals significant complexities that organizations face in their pursuit of sustainability. Through a thorough process involving the Fuzzy Delphi technique for identifying key risk factors and the Fuzzy TOPSIS method for prioritization, **10 major risk factors** were pinpointed. Among these, "inaccurate forecasts" was identified as the most critical risk factor, highlighting the need for reliable prediction models to support effective inventory management and operational efficiency. Errors in forecasting can lead to stock shortages or overstock situations, affecting patient care and operational costs.On the other hand, "limited access to market information" was found to have the least impact, suggesting that healthcare organizations in Bangladesh generally have adequate access to market data. This insight indicates that efforts should be directed towards improving forecasting accuracy and addressing other significant risks.The Fuzzy TOPSIS approach provides a clear prioritization of these risks, guiding healthcare organizations in focusing their resources on mitigating the most pressing challenges. By concentrating on the most significant risks, organizations can enhance their resilience and sustainability in the healthcare supply chain.

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