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Hybrid Multi-Criteria Decision-Making Model for Optimal Selection of Cold Chain Logistics Service Providers

Mladen Krstić*, Snežana Tadić

Logistics Department, Faculty of Transport and Traffic Engineering, University of Belgrade, 11000 Belgrade, Serbia

* Correspondence: Mladen Krstić (m.krstic@sf.bg.ac.rs)

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Abstract: In the context of the global supply chain, the selection of Cold Chain Logistics Service Providers (CCLSPs) emerges as a paramount challenge, particularly for the transportation of temperature-sensitive goods. This study introduces a structured decision-making framework, addressing the need for efficient and reliable logistics services in this sector. Central to the framework is a hybrid Multi-Criteria Decision-Making (MCDM) model, which synergizes Fuzzy FActor RElationship (Fuzzy FARE) and Fuzzy Axial Distance based Aggregated Measurement (Fuzzy ADAM). This innovative approach is aimed at refining criteria weight determination and enhancing provider ranking accuracy. Special emphasis is placed on the integration of fuzzy logic to manage the inherent uncertainties present in subjective evaluations and decision data. The investigation underscores the criticality of factors such as stringent temperature control, robust infrastructure, and adherence to regulatory standards in the selection process. An application of this methodology is demonstrated through a case study involving the ranking of ten logistics providers in South-East Europe. The study's contributions are twofold: it advances the theoretical framework of supply chain management methodologies and offers a pragmatic tool for businesses operating within temperature-sensitive logistics networks. Prospective research directions include the adaptation of this framework to various regional contexts and the incorporation of emerging technologies, ensuring the framework's applicability and relevance in the dynamic domain of cold chain logistics.

Keywords: Cold chain; Logistics service provider; Multi-Criteria Decision-Making (MCDM); Fuzzy FActor RElationship (Fuzzy FARE); Fuzzy Axial Distance based Aggregated Measurement (Fuzzy ADAM)

1. Introduction

In contemporary global supply chains, the transportation of temperature-sensitive goods, often termed 'cold chain', emerges as a pivotal challenge, particularly in industries like pharmaceuticals, food, and biotechnology. Kumar et al. (2023) underscore that the success of these sectors is inextricably linked to the maintenance of product integrity within specific temperature parameters across the supply chain continuum. Rodrigue & Notteboom (2014) further highlight the critical nature of this aspect.

The process of selecting a CCLSP is characteristically complex, necessitating the evaluation of a multitude of factors such as transportation efficacy, storage facility adequacy, compliance with regulations, and overall dependability. As the demand for cold chain logistics services amplifies, the decision-making process grows in complexity, demanding an in-depth understanding of the distinct needs and challenges inherent in maintaining the cold chain.

Notwithstanding the recognized importance of CCLSP selection, a standardized framework or guideline for systematic assessment and comparison of potential providers remains conspicuously absent. This dearth of a methodological standard impedes organizations from making well-informed decisions, potentially resulting in cold chain disruptions, degradation of perishable goods' quality and safety, and unnecessary cost implications.

This research addresses the urgent requirement for a structured approach to CCLSP selection. By delineating key criteria and establishing a comprehensive evaluation framework, the study aspires to facilitate decision-makers in cold chain-reliant industries in making optimal choices that assure the integrity and reliability of their supply chains.

A sophisticated approach is adopted to augment the precision and robustness of the CCLSP selection process. The methodology integrates a hybrid Multi-Criteria Decision-Making model, amalgamating Fuzzy FARE for criteria weight determination and Fuzzy ADAM for provider ranking. Initially, Fuzzy FARE addresses the inherent uncertainties and imprecisions in subjective judgment related to criteria importance assignment. Utilizing fuzzy logic principles, this method enables decision-makers to articulate their preferences in a nuanced manner, reflecting the vagueness present in real-world decision scenarios. Subsequently, Fuzzy ADAM ranks Cold Chain Logistics Service Providers based on the weighted criteria, anticipating a more holistic and accurate assessment of potential CCLSPs, and fostering nuanced decision-making in the complex realm of cold chain logistics.

The paper proceeds as follows: The subsequent section delves into the study's background, supported by relevant literature. This is followed by a detailed exposition of the hybrid model application steps. The fourth section provides an in-depth analysis of the CCLSP problem, selection criteria, and discusses the model application, sensitivity analysis, and validation results. The penultimate and final sections offer a discussion of these results and concluding observations, respectively, along with directions for future research.

2. Background and Related Studies

Cold supply chains, integral for preserving the quality and safety of temperature-sensitive goods, are increasingly recognized as pivotal in logistics, influencing sectors such as pharmaceuticals, food, and biotechnology. Sharma et al. (2021) have emphasized the need for a nuanced understanding of the factors that impact the efficiency and reliability of these chains. While substantial research has been conducted into crucial aspects like temperature control, storage infrastructure, and regulatory compliance within cold supply chains (Chukwu & Adibe, 2021; Han et al., 2021; Kumar et al., 2022), a standard framework for the selection of CCLSPs remains notably absent.

Logistics service providers in cold chains play a critical role, significantly impacting the overall efficiency of the supply chain, as highlighted by Dai et al. (2020). These providers are responsible for maintaining prescribed temperature conditions during both transportation and storage. The literature, including Raut et al. (2019), acknowledges the importance of selecting the appropriate CCLSP, underlining the necessity of a systematic approach to ensure uninterrupted flow of temperature-sensitive goods. However, a comprehensive and standardized methodology for the evaluation and ranking of CCLSPs is not yet established in existing research, marking a significant gap.

The prevalent method for ranking and selecting logistics service providers is Multi-Criteria Decision-Making (MCDM), as evidenced in the works of Kaymaz & Çiçekli (2023), Nila & Roy (2023), and Sremac et al. (2018). MCDM techniques provide a systematic and all-encompassing means to evaluate and compare providers across multiple criteria. This study introduces a hybrid model, integrating Fuzzy FARE and Fuzzy ADAM, expanding on these techniques.

Ginevičius (2011) pioneered the FARE method for determining criteria weights in decision-making processes, a method which underscores the importance of inter-criteria relationships over subjective judgments. This method encompasses several key steps: defining the problem at hand, identifying relevant criteria and alternatives, and implementing a pair-wise comparison matrix to evaluate the interrelationships among criteria. Central to the FARE methodology is the computation of the geometric mean of matrix rows, resulting in a weight vector that accurately represents the significance of each criterion. FARE's systematic and efficient approach stands out when contrasted with other methods such as AHP and ANP. It minimizes the need for extensive expert evaluations while ensuring results that are both reliable and stable. The method's inherent transparency significantly mitigates bias, offering clarity on how the weights are influenced by the established relationships between criteria. However, FARE's reliance on linear relationships and potential requirement for substantial data are notable considerations. In response to these limitations, particularly the issue of subjectivity, Roy et al. (2020) adapted FARE for application in a fuzzy environment. This adaptation has expanded the method's utility, as evidenced by its extensive use in both its conventional and fuzzy forms. Recent applications in literature include prioritizing e-traceability drivers (Krstić et al., 2023b), selecting handling equipment (Krstić et al., 2023c), evaluating last mile solutions (Krstić et al., 2021), and assessing university competitiveness (Girdzijauskaitė et al., 2019), among others.

Krstić et al. (2023a) unveiled the ADAM method, establishing a new category within MCDM methodologies, termed as geometric methods. ADAM is distinctive in its approach to evaluating alternative rankings, which it accomplishes by measuring the aggregate dimensions of complex polyhedra. These polyhedra are defined by vertices, each representing criteria weights and alternative values. The method is particularly noted for its simplicity, ease of use, and intuitive graphical representation through the volumetric analysis of these polyhedra. A salient feature of ADAM is its ability to minimize the risk of rank reversal, thus enhancing the method's stability. It is noteworthy that variations in criteria weights exert only a minimal impact on the outcomes, thereby solidifying ADAM's status as a dependable decision-making tool, especially when numerous criteria are involved. The method's alignment with other MCDM methodologies is evidenced by its high average correlation indices, signifying a high degree of conformity. Further advancing this method, Krstić et al. (2023b) introduced a fuzzy extension of the ADAM method. This development broadened the method's applicability, allowing for more nuanced decision-making in scenarios characterized by uncertainty and imprecision. Despite being relatively new in the realm of MCDM methods, both the conventional and fuzzy versions of ADAM have already proven their applicability in a variety of contexts. These applications include the selection of city logistics concepts (Kovač et al., 2023), choosing distribution channels (Andrejić et al., 2023), and ranking strategies that enhance circularity (Agnusdei et al., 2023).

Despite these developments, the literature reveals a scarcity of studies integrating fuzzy logic-based MCDM models, particularly Fuzzy FARE and Fuzzy ADAM, for logistics service provider selection within cold supply chains. Therefore, this research aims to fill these gaps by establishing a robust framework for CCLSP evaluation, employing fuzzy logic-based MCDM models. This approach is intended to contribute both theoretically and practically to the domain of cold chain logistics.

3. Hybrid Fuzzy FARE-Fuzzy ADAM Model

This study introduces an innovative hybrid model within the domain of MCDM, integrating the fuzzy FARE and fuzzy ADAM methods into a cohesive framework. In this model, the fuzzy FARE method is utilized to determine and assign weights to various criteria. Subsequently, the fuzzy ADAM method is applied for the evaluation, ranking, and selection of the most suitable alternatives, based on these weighted criteria.

In the first step of the methodology, the problem's foundational structure is defined by identifying a set of alternatives and criteria, which are to be evaluated subsequently.

The second step introduces a fuzzy scale for the evaluation process. Here, Decision Makers (DMs) employ linguistic terms to assess the criteria and alternatives. These linguistic assessments are then transformed into Triangular Fuzzy Numbers (TFN), following the relations outlined in Table 1.

Table 1. Fuzzy scale for the evaluation

Linguistic Term	Abbreviation	Fuzzy Scale
“Extremely high”	“EH”	(8, 9, 10)
“Very high”	“VH”	(7, 8, 9)
“High”	“H”	(6, 7, 8)
“Fairly high”	“FH”	(5, 6, 7)
“Medium”	“M”	(4, 5, 6)
“Fairly low”	“FL”	(3, 4, 5)
“Low”	“L”	(2, 3, 4)
“Very low”	“VL”	(1, 2, 3)
“None”	“N”	(1, 1, 2)

Step 3 of the methodology aims at deriving criteria weights by employing the fuzzy FARE method. The process involves several detailed sub-steps:

Step 3.1: Formation of a Criteria Evaluation Matrix $\tilde{A}$: In this sub-step, a criteria evaluation matrix is constructed. The DMs provide linguistic evaluations, which are subsequently converted into TFN. Each TFN represents the perceived importance of one criterion in relation to another, denoted as $\tilde{a}_{ij} = (l, m, u)$, where *i* and *j* are the respective criteria being compared.

$$\tilde{A} = \left[\tilde{a}_{ij} \right]_{n \times n} \tag{1}$$

Step 3.2: Calculation of Potential Criteria Impact: In this step, the potential impact of each criterion, denoted as $\tilde{I}$, is determined. This is achieved by identifying the highest value ($\tilde{H}$) from the scale utilized in the evaluations.

$$\tilde{I} = \tilde{H}(n-1) \tag{2}$$

Step 3.3: Total Impact Determination: The total impact of each criterion, represented as $\tilde{I}_j$, is ascertained by summing the evaluations of all criteria in relation to criterion *j*.

$$\tilde{I}_j = \sum_{i=1}^{n} \tilde{a}_{ij}, \forall j = 1, \ldots, n, j \neq i \tag{3}$$

Step 3.4: Derivation of Fuzzy Criteria Weights: The final sub-step in Step 3 involves deriving the fuzzy criteria weights, $\tilde{w}_j$. This is executed by employing a formula that considers the real total impact of the criterion ($\tilde{I}_j^r$) in relation to the total potential impact ($\tilde{I}_H$).

$$\tilde{w}_j = \tilde{I}_j^r / \tilde{I}_H, \forall j = 1,\dots,n \tag{4}$$

$$\tilde{I}_H = \left(\min_j l^{\tilde{I}_j^r}, \text{mean}_j\, m^{\tilde{I}_j^r}, \max_j u^{\tilde{I}_j^r}\right) \tag{5}$$

$$\tilde{I}_j^r = \tilde{I}_j + \tilde{I}, \forall j = 1,\dots,n \tag{6}$$

Step 4: Application of the Fuzzy ADAM Method (Krstić et al., 2023b):

Step 4.1: Definition of Evaluation Matrix: A matrix $\tilde{E}$ is established to encapsulate the evaluations of alternatives in relation to criteria. Each element $\tilde{e}_{ij}$ in the matrix is characterized by fuzzy values (l^e, m^e, u^e).

Step 4.2: Sorting of Evaluations: A matrix $\tilde{S}$ is formed to store the sorted evaluations from matrix $\tilde{E}$ in a descending order.

Step 4.3: Determination of Fuzzy Coordinates: This step involves identifying the fuzzy coordinates for the fuzzy reference point ($\tilde{R}_{ij}$) and the fuzzy weighted reference point ($\tilde{P}_{ij}$). These coordinates are derived using trigonometric transformations, vital for the subsequent analysis.

$$\tilde{x}_{ij} = \left(l^{x_{ij}}, m^{x_{ij}}, u^{x_{ij}}\right) = \left(l^{s_{ij}} \times \sin\alpha_j, m^{s_{ij}} \times \sin\alpha_j, u^{s_{ij}} \times \sin\alpha_j\right), \forall j = 1,\dots,n; \forall i = 1,\dots,m \tag{7}$$

$$\tilde{y}_{ij} = \left(l^{y_{ij}}, m^{y_{ij}}, u^{y_{ij}}\right) = \left(l^{s_{ij}} \times \cos\alpha_j, m^{s_{ij}} \times \cos\alpha_j, u^{s_{ij}} \times \cos\alpha_j\right), \forall j = 1,\dots,n; \forall i = 1,\dots,m, \tag{8}$$

$$\tilde{z}_{ij} = \left(l^{z_{ij}}, m^{z_{ij}}, u^{z_{ij}}\right) = \begin{cases} (0,0,0), \text{ for } \tilde{R}_{ij} \\ \left(l^{w_j}, m^{w_j}, u^{w_j}\right), \text{ for } \tilde{P}_{ij} \end{cases}, \forall j = 1,\dots,n; \forall i = 1,\dots,m \tag{9}$$

$$\alpha_j = (j-1)\frac{90^\circ}{n-1}, \forall j = 1,\dots,n \tag{10}$$

Step 4.4: Obtaining Fuzzy Values: Here, $\tilde{V}_i^C$ represents the comprehensive fuzzy value for each alternative. The process requires intricate manipulation of fuzzy numbers and transformations to extract meaningful outcomes.

$$\tilde{V}_i^C = \bigoplus_{k=1}^{n-1} \tilde{V}_k, \forall i = 1,\dots,m \tag{11}$$

$$\tilde{V}_k = \frac{1}{3}\tilde{B}_k \otimes \tilde{h}_k, \forall k = 1,\dots,n-1 \tag{12}$$

$$\tilde{B}_k = \tilde{c}_k \otimes \tilde{a}_k \oplus \frac{\tilde{a}_k \otimes \left(\tilde{b}_k \ominus \tilde{c}_k\right)}{2} \tag{13}$$

$$\begin{aligned} l^{a_k} &= \min\left(\sqrt{\left(u^{x_{j+1}} - l^{x_j}\right)^2 + \left(u^{y_{j+1}} - l^{y_j}\right)^2}, \sqrt{\left(l^{x_{j+1}} - u^{x_j}\right)^2 + \left(l^{y_{j+1}} - u^{y_j}\right)^2}\right) \\ m^{a_k} &= \sqrt{\left(m^{x_{j+1}} - m^{x_j}\right)^2 + \left(m^{y_{j+1}} - m^{y_j}\right)^2} \\ u^{a_k} &= \max\left(\sqrt{\left(u^{x_{j+1}} - l^{x_j}\right)^2 + \left(u^{y_{j+1}} - l^{y_j}\right)^2}, \sqrt{\left(l^{x_{j+1}} - u^{x_j}\right)^2 + \left(l^{y_{j+1}} - u^{y_j}\right)^2}\right) \end{aligned} \tag{14}$$

$$\mathrm{b_k} = \tilde{z}_j \tag{15}$$

$$\tilde{\mathrm{c}}_{\mathrm{k}} = \tilde{\mathrm{z}}_{\mathrm{j+1}} \tag{16}$$

$$\begin{aligned} l^{B_k} &= l^{c_k} \times l^{a_k} + \frac{l^{a_k} \times \left(l^{b_k} - u^{c_k}\right)}{2} \\ m^{B_k} &= m^{c_k} \times m^{a_k} + \frac{m^{a_k} \times \left(m^{b_k} - m^{c_k}\right)}{2} \\ u^{B_k} &= u^{c_k} \times u^{a_k} + \frac{u^{a_k} \times \left(u^{b_k} - l^{c_k}\right)}{2} \end{aligned} \tag{17}$$

$$\tilde{h}_k = \frac{2\sqrt{\tilde{s}_k\left(\tilde{s}_k - \tilde{a}_k\right)\left(\tilde{s}_k - \tilde{d}_k\right)\left(\tilde{s}_k - \tilde{e}_k\right)}}{\tilde{a}_k} \tag{18}$$

$$\tilde{s}_k = \frac{\tilde{a}_k \oplus \tilde{d}_k \oplus \tilde{e}_k}{2} \tag{19}$$

$$l^{d_k} = \sqrt{\left(l^{x_j}\right)^2 + \left(l^{y_j}\right)^2}, m^{d_k} = \sqrt{\left(m^{x_j}\right)^2 + \left(m^{y_j}\right)^2}, u^{d_k} = \sqrt{\left(u^{x_j}\right)^2 + \left(u^{y_j}\right)^2} \tag{20}$$

and $\tilde{e}_k$ can be expressed as $\tilde{e}_k = (l^{e_k}, m^{e_k}, u^{e_k})$ in which

$$l^{e_k} = \sqrt{\left(l^{x_{j+1}}\right)^2 + \left(l^{y_{j+1}}\right)^2}, m^{e_k} = \sqrt{\left(m^{x_{j+1}}\right)^2 + \left(m^{y_{j+1}}\right)^2}, u^{e_k} = \sqrt{\left(u^{x_{j+1}}\right)^2 + \left(u^{y_{j+1}}\right)^2} \tag{21}$$

$$l^{s_k} = \frac{l^{a_k} + l^{d_k} + l^{e_k}}{2};\ m^{s_k} = \frac{m^{a_k} + m^{d_k} + m^{e_k}}{2};\ u^{s_k} = \frac{u^{a_{k+}} u^{d_{k+}} u^{e_k}}{2} \tag{22}$$

$$\begin{aligned} l^{h_k} &= \frac{2\sqrt{l^{s_k}\left|l^{s_k} - u^{a_k}\right|\left|l^{s_k} - u^{d_k}\right|\left|\ l^{s_k} - u^{e_k}\right|}}{u^{a_k}} \\ m^{h_k} &= \frac{2\sqrt{m^{s_k}\left|m^{s_k} - m^{a_k}\right|\left|m^{s_k} - m^{d_k}\right|\left|m^{s_k} - m^{e_k}\right|}}{m^{a_k}} \\ u^{h_k} &= \frac{2\sqrt{u^{s_k}\left|u^{s_k} - l^{a_k}\right|\left|u^{s_k} - l^{d_k}\right|\left|\ u^{s_k} - l^{e_k}\right|}}{l^{a_k}} \end{aligned} \tag{23}$$

$$l^{V_k} = \frac{l^B k \times l^{h_k}}{3}, m^{V_k} = \frac{m^B k \times ml^{h_k}}{3}, u^{V_k} = \frac{u^B k \times u^{h_k}}{3} \tag{24}$$

$$l^{V_i^C} = \sum_{k=1}^{n-1} l^{V_k}, m^{V_i^C} = \sum_{k=1}^{n-1} m^{V_k}, u^{V_i^C} = \sum_{k=1}^{n-1} u^{V_k} \tag{25}$$

Step 5: Ranking of Alternatives Using Crisp Values: The final step in the methodology is the ranking of alternatives based on crisp values. These values are derived from a formula that amalgamates the upper, middle, and lower values of the fuzzy numbers procured in the previous step, thus facilitating a conclusive ranking of the alternatives.

$$\mathrm{Crisp}\left(\tilde{V}_i^C\right)=\left(4\times m^{V_i^C}+u^{V_i^C}-2l^{V_i^C}\right)/3\left(u^{V_i^C}-2l^{V_i^C}\right) \tag{26}$$

4. Selection of CCLSPs

Section 4 delves into a comprehensive evaluation of the CCLSP selection process, employing a hybrid MCDM model. This section unveils the outcomes of the study, illuminating the complexities inherent in selecting among various providers within the realm of temperature-sensitive supply chains. A critical part of this section is the sensitivity analysis, aimed at examining the robustness of the study's findings. This analysis assesses how variations in the weights of different criteria influence the overall decision-making process. Such an evaluation is essential to understand the stability and adaptability of the model under different conditions. Additionally, a validation of the results is conducted to reinforce their reliability. This involves comparing the outcomes of the proposed model with those derived from other established MCDM methods. The validation process is crucial to ensure that the model not only aligns with the established methodologies but also effectively assists decision-makers in identifying the most suitable CCLSP.

4.1 Problem Statement

Section 4.1 of the paper delineates the intricate challenge of selecting CCLSPs within the context of South-East Europe's logistics sector. This study narrows its focus to a practical application, scrutinizing the selection process among ten prominent South-East Europe logistics service providers, denoted as $CCLSP_1$ to $CCLSP_{10}$. These entities have been selected due to their significant presence in the countries of South-East Europe.

The research delves into the specificities of this case study, aiming to uncover insights into the complexities of CCLSP selection in a regional setting. Key factors such as regulatory compliance, infrastructure capabilities, and regional particularities are considered. The primary objective is to develop a model that not only enhances the general understanding of challenges in CCLSP selection but also provides practical guidance for enterprises operating in the cold chain logistics domain of South-East Europe. The intent is to facilitate informed decision-making that is acutely attuned to the nuances of this specific regional market.

The selection of CCLSP involves evaluating various criteria to ensure the integrity and reliability of the supply chain. This study proposes nine critical criteria for CCLSP selection:

***Geographic Coverage* (*C₁*)**: This criterion assesses the provider's network and reach, ensuring effective coverage of essential distribution points. It focuses on minimizing transit times and optimizing the supply chain.

***Temperature Control Capabilities* (C_2)**: This criterion assesses the ability of the provider to consistently maintain and monitor precise temperature conditions during the transportation and storage of temperature-sensitive goods.

***Reliability and Track Record* (C_3)**: This criterion examines the provider's historical performance, specifically their reliability in delivering goods within the specified temperature ranges and their effectiveness in preventing disruptions while maintaining product integrity.

***Compliance with Regulations* (C_4)**: This criterion assesses provider's adherence to local and international regulations, such as Good Distribution Practice (GDP) or Hazard Analysis and Critical Control Points (HACCP) standards, is critically assessed.

***Technology and Monitoring Systems* (C_5)**: This criterion assesses the adoption and utilization of advanced technology, including real-time monitoring systems for tracking and managing shipment temperatures.

***Infrastructure and Facilities* (C_6)**: This criterion examines the quality and capacity of the provider's storage facilities, including refrigerated warehouses and transportation equipment, to meet the specific demands of cold chain logistics.

***Cost Efficiency* (C_7)**: This criterion assesses the overall cost structure, encompassing transportation fees, storage charges, and any additional costs, so as to ensure cost-effectiveness without compromising quality.

***Customs and Documentation Handling* (C_8)**: Ensuring the provider has efficient processes for handling customs procedures and necessary documentation, reducing the risk of delays and ensuring regulatory compliance. This criterion assesses the provider's efficiency in handling customs procedures and necessary documentation is evaluated to minimize the risk of delays and ensure regulatory compliance.

***Risk Management and Contingency Planning* (C_9)**: This criterion examines the provider's strategies for risk mitigation, including contingency plans for unforeseen events such as equipment failures or natural disasters.

***Environmental Sustainability* (C_{10})**: This criterion assesses the provider's commitment to environmental sustainability is assessed, including the use of eco-friendly technologies, energy-efficient transportation, and adherence to green logistics principles.

These criteria collectively contribute to a comprehensive evaluation framework for selecting a CCLSP that aligns with the specific requirements and priorities of businesses operating in temperature-sensitive supply chains.

4.2 Results

A panel of experts, specializing in the field of logistics, was convened to evaluate the criteria for selecting CCLSP. These experts employed linguistic evaluations, as outlined in Table 1, to assess the relative importance of each criterion. The pairwise linguistic evaluations, demonstrating the preferences among the criteria, are systematically presented in Table 2.

Table 2. Pair wise evaluation of criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
C_1	/	/	/	/	“VL”	/	/	/	/	“L”
C_2	“H”	/	“FH”	“L”	“VH”	“VL”	“FL”	“M”	“FL”	“EH”
C_3	“VL”	/	/	/	“L”	/	/	/	/	“FL”
C_4	“M”	/	“FL”	/	“FH”	/	“VL”	“L”	“VL”	“H”
C_5	/	/	/	/	/	/	/	/	/	“VL”
C_6	“FH”	/	“M”	“VL”	“H”	/	“L”	“FL”	“L”	“VH”
C_7	“FL”	/	“L”	/	“M”	/	/	“VL”	/	“FH”
C_8	“L”	/	“VL”	/	“FL”	/	/	/	/	“M”
C_9	“FL”	/	“L”	/	“M”	/	“N”	“VL”	/	“FH”
C_{10}	/	/	/	/	/	/	/	/	/	/

The determination of criteria weights was accomplished by applying Eqs. (1)-(6), as delineated in the methodology. This process resulted in both intermediary and final criteria weights, which are comprehensively presented in Table 3.

Table 3. Potential impact, total impact and fuzzy weights of criteria

	$\tilde{I}$	$\tilde{I}_j$	$\tilde{w}_j$
C_1	(3.4, 5.9, 8.9)	(75.4, 86.9, 98.9)	(0.52, 0.869, 1.34)
C_2	(37, 46, 55)	(109, 127, 145)	(0.752, 1.27, 1.965)
C_3	(7.4, 10.8, 15.1)	(79.4, 91.8, 105.1)	(0.547, 0.919, 1.424)
C_4	(22.6, 29.8, 37.5)	(94.6, 110.8, 127.5)	(0.652, 1.109, 1.728)
C_5	(2.6, 4, 6)	(74.6, 85, 96)	(0.514, 0.85, 1.301)
C_6	(25.3, 33.5, 42)	(97.3, 114.5, 132)	(0.671, 1.145, 1.789)
C_7	(15.3, 21.2, 27)	(87.3, 102.2, 117)	(0.602, 1.022, 1.586)
C_8	(10.3, 14.8, 20.2)	(82.3, 95.8, 110.2)	(0.568, 0.959, 1.494)
C_9	(15.9, 21.3, 28.3)	(87.9, 102.3, 118.3)	(0.606, 1.023, 1.604)
C_{10}	(1.8, 2.3, 3.7)	(73.8, 83.3, 93.7)	(0.509, 0.834, 1.27)

The same panel of logistics experts proceeded to analyze key performance indicators and other pertinent information related to the CCLSPs. This analysis was conducted in the context of the established set of criteria. Subsequently, these experts evaluated the CCLSPs, employing linguistic evaluations against each criterion. The outcomes of these evaluations are systematically presented in Table 4.

Upon the application of Eqs. (7)-(26), as outlined in the methodology, the values corresponding to each CCLSP were computed. These calculations led to the final ranking of the CCLSPs. The results, including both the individual values and the overall rankings, are systematically tabulated and presented in Table 5.

The results, as delineated in Table 5, reveal that the top-ranked CCLSP is CCLSP10. This is closely followed by CCLSP1 and CCLSP4, which occupy the second and third positions, respectively, in the ranking hierarchy.

Table 4. Evaluation of CCLSPs

	$CCLSP_1$	$CCLSP_2$	$CCLSP_3$	$CCLSP_4$	$CCLSP_5$	$CCLSP_6$	$CCLSP_7$	$CCLSP_8$	$CCLSP_9$	$CCLSP_{10}$
C_1	“M”	“N”	“H”	“L”	“H”	“FL”	“VL”	“N”	“VL”	“VH”
C_2	“M”	“VH”	“N”	“H”	“L”	“L”	“L”	“N”	“L”	“EH”
C_3	“FH”	“VH”	“N”	“EH”	“VL”	“L”	“VL”	“FL”	“L”	“VH”
C_4	“VH”	“L”	“N”	“VH”	“VL”	“VL”	“FL”	“N”	“L”	“EH”
C_5	“VH”	“L”	“N”	“M”	“EH”	“VH”	“FL”	“N”	“L”	“FH”
C_6	“FL”	“VH”	“N”	“H”	“M”	“M”	“VL”	“VH”	“VH”	“M”
C_7	“EH”	“FL”	“VL”	“M”	“N”	“L”	“FH”	“FL”	“L”	“VH”
C_8	“FH”	“H”	“N”	“H”	“L”	“N”	“FH”	“VH”	“EH”	“FL”
C_9	“FH”	“FL”	“N”	“VL”	“VL”	“FH”	“EH”	“FL”	“FH”	“VH”
C_{10}	“FH”	“VL”	“N’	“L”	“H”	“M”	“L”	“VL”	“H”	“M”

Table 5. Ranking of CCLSPs

	$CCLSP_1$	$CCLSP_2$	$CCLSP_3$	$CCLSP_4$	$CCLSP_5$	$CCLSP_6$	$CCLSP_7$	$CCLSP_8$	$CCLSP_9$	$CCLSP_{10}$
Crisp	0.361	0.346	0.324	0.354	0.340	0.341	0.343	0.340	0.349	0.363
Rank	2	5	10	3	8	7	6	9	4	1

4.3 Sensitivity Analysis

This section delves into a sensitivity analysis, conducted to gauge the robustness and stability of the solution obtained from the CCLSP evaluation process. This analysis predominantly concentrated on the three most critical criteria identified in the evaluation. Various scenarios were methodically crafted, wherein the weights of these key criteria were successively adjusted by reductions of 25%, 50%, 75%, and 100%. The outcomes of these sensitivity tests have been meticulously compiled, with numerical data presented in Table 6 and graphical illustrations of the variations provided in Figure 1.

Table 6. Sensitivity analysis results

Rank	$CCLSP_1$	$CCLSP_2$	$CCLSP_3$	$CCLSP_4$	$CCLSP_5$	$CCLSP_6$	$CCLSP_7$	$CCLSP_8$	$CCLSP_9$	$CCLSP_{10}$
Sc.0	2	5	10	3	8	7	6	9	4	1
Sc.1	2	5	10	3	8	7	6	9	4	1
Sc.2	2	5	10	3	8	7	6	9	4	1
Sc.3	2	5	10	3	8	7	6	9	4	1
Sc.4	2	5	10	3	8	7	6	9	4	1
Sc.5	2	5	10	3	8	7	6	9	4	1
Sc.6	2	5	10	3	8	7	6	9	4	1
Sc.7	2	5	10	3	8	7	6	9	4	1
Sc.8	2	4	10	3	8	7	6	9	5	1
Sc.9	2	5	10	3	9	7	6	8	4	1
Sc.10	1	5	10	3	9	7	6	8	4	2
Sc.11	1	5	10	3	9	7	6	8	4	2
Sc.12	1	5	10	3	9	7	6	8	4	2

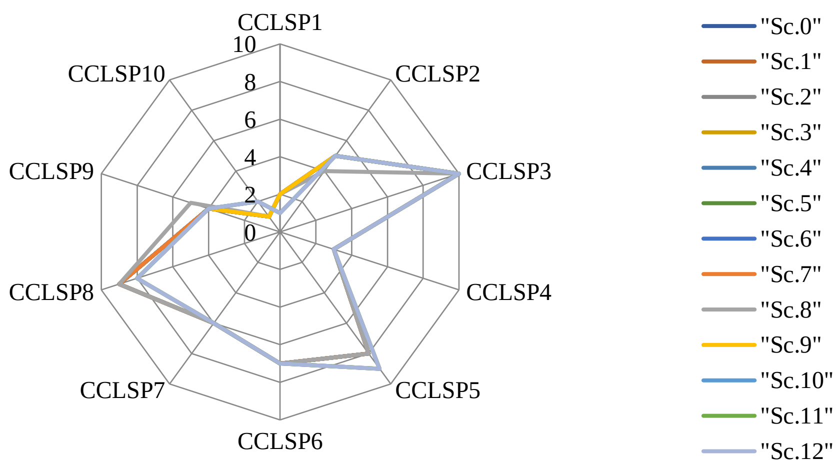

Figure 1. Sensitivity analysis

A remarkable finding from this sensitivity analysis is the consistent ranking of the alternatives, even with deliberate variations in the weights of the key criteria. This steadfast consistency across various scenarios significantly attests to the robustness and stability of the results obtained in the baseline scenario. Notably, the absence of significant fluctuations in the rankings implies that the identified solution upholds its integrity and reliability, irrespective of changes in the weighting configurations. Such resilience is critical, as it reinforces the credibility of the initial findings, affirming the proposed solution's capacity to withstand alterations in the significance attributed to the critical evaluation criteria.

This thorough examination serves to enhance the transparency of the study's findings. It offers crucial insights into the solution's resilience under varying weighting conditions, thereby cementing the reliability of the results across diverse decision-making contexts.

4.4 Validation of Results

In this section, a thorough validation process is detailed, undertaken to ascertain the robustness and validity of the results derived from the fuzzy ADAM method. This validation involved a comparative analysis of the CCLSP rankings obtained using fuzzy ADAM against those acquired through several other well-established MCDM methods. Notable among these methods were fuzzy VIKOR, fuzzy TOPSIS, fuzzy COBRA, and fuzzy CODAS, with the comparative outcomes depicted in Figure 2. The primary objective of this validation exercise was to evaluate the consistency and reliability of the results generated by the fuzzy ADAM method. This was achieved by analyzing the extent of correlation between the fuzzy ADAM outcomes and those produced by the alternative MCDM methodologies.

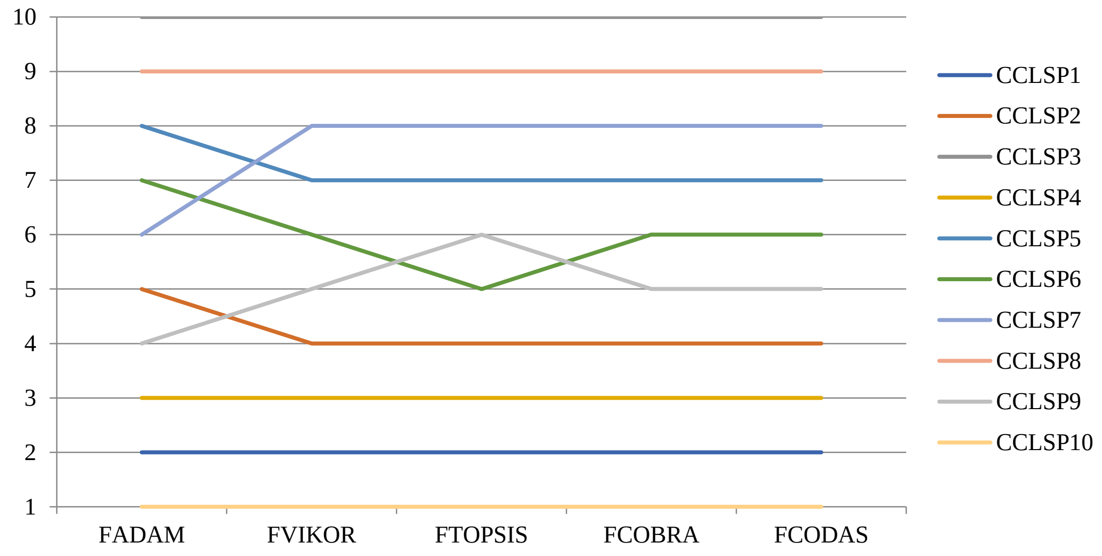

Figure 2. Comparison of rankings obtained by various MCDM methods

In the course of the validation process, the Spearman Correlation Coefficient (SCC) was utilized as the metric to measure the similarity between the rankings generated by the fuzzy ADAM method and those derived from other MCDM methods. The results, as documented in Table 7, revealed an exceptionally high degree of conformity. Specifically, the average correlation value stood at 0.942, denoting a substantial alignment between the outcomes of the fuzzy ADAM method and the comparative MCDM methodologies. This rigorous validation, underscored by the high SCC value, serves to bolster the credibility of the rankings derived from the fuzzy ADAM method. It highlights the strength and consistency of the proposed CCLSP selection framework, particularly in the context of cold chain logistics. The robustness of this framework is thus reinforced, affirming its effectiveness and reliability in facilitating informed decision-making within this specialized domain.

Table 7. SSC values for the comparisons of rankings obtained by various MCDM methods

	FVIKOR	**FTOPSIS**	**FCOBRA**	**FCODAS**	**Average SSC**
FADAM	0.951515	0.915152	0.951515	0.951515	0.942

5. Discussion

This study critically discusses the significant contributions and implications of this study in the field of supply chain management, particularly focusing on the selection of CCLSPs. The research introduces a pioneering standardized and comprehensive framework for evaluating potential CCLSPs, addressing a vital need in the management of temperature-sensitive goods supply chains. The cornerstone of this study is the establishment of a robust evaluation framework, underpinned by a meticulously defined set of criteria. This framework not only equips decision-makers with a systematic and transparent method to assess CCLSPs but also provides a navigational tool for the complexities inherent in the selection process. Thus, the research extends beyond academic enrichment to offer a practical utility for businesses where maintaining the cold chain's integrity is crucial. The holistic framework developed here is designed to empower decision-makers to make informed choices that bolster the reliability and efficiency of their cold chain logistics operations.

The study unfolds with extensive theoretical and practical implications, transcending the confines of cold chain logistics research. Theoretically, it contributes significantly to the evolving methodologies in supply chain management, enhancing the understanding of decision-making processes in the transportation and storage of temperature-sensitive goods. Practically, the framework serves as a vital tool for businesses facing the challenges of CCLSP selection. It offers a systematic approach to risk mitigation, resource optimization, and overall supply chain efficiency enhancement. This equips decision-makers with a clear and standardized methodology, facilitating the seamless flow of temperature-sensitive products. As industries dependent on cold chain logistics continue to expand, the study's practical implications become even more vital, leading to enhanced operational reliability, cost reduction, and improved product quality.

However, it is essential to acknowledge the potential limitations of the study. The framework is developed within a specific regional context, which may limit its direct applicability to other regions without adjustments. The accuracy of data and subjectivity in criteria weighting introduce potential biases, impacting the study's reliability. The dynamic nature of the logistics industry, including changes in regulations, technological advancements, and market dynamics, may affect the framework's effectiveness. Additionally, the model's assumption of independence among criteria does not account for possible interdependencies in real scenarios. Recognizing these limitations is vital for a balanced interpretation of the findings and prompts future research to refine and expand the proposed framework.

6. Conclusion

This research was dedicated to addressing the intricate challenge of selecting CCLSP by developing a structured framework based on a hybrid Multi-Criteria Decision-Making model. The central aim was to provide decision-makers with a systematic approach to navigate the complexities of evaluating competing providers in the temperature-sensitive goods supply chain. This study's significant contributions encompass the establishment of a detailed set of criteria within the proposed framework, thereby facilitating both theoretical advancements in supply chain management methodologies and offering practical tools for industries dependent on cold chain logistics.

The practical implications of this research are considerable, equipping decision-makers with a transparent and standardized methodology to improve operational reliability, cost efficiency, and product quality. On a theoretical level, the study enhances the understanding of decision-making processes, particularly in the context of CCLSP selection.

Future research opportunities include further refinement and validation of the proposed framework across various regional contexts, taking into account the impact of regional specificities. Additionally, future studies should aim to continuously adapt the framework to align with the evolving regulations and market dynamics in the logistics industry. This ongoing adaptation will be crucial to maintain the framework's relevance and efficacy in the ever-changing landscape of cold chain logistics.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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