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Integrated BWM–QFD–MARCOS Framework for Strategic Decision-Making in Cold Chain Logistics

Milan Andrejić, Vukašin Pajić*

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

* Correspondence: Vukašin Pajić (v.pajic@sf.bg.ac.rs)

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Abstract: Ensuring the integrity of goods during cold chain transportation remains a critical challenge in logistics, as it is essential to preserve product quality, freshness, and compliance with stringent safety standards. Strategic decision-making in this context requires the prioritization of customer requirements and the optimal allocation of limited operational resources. In response to these demands, an integrated Multi-Criteria Decision-Making (MCDM) model was developed by combining the Best-Worst Method (BWM), Quality Function Deployment (QFD), and Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) approach. Within this framework, BWM was utilized to determine the relative importance of user requirements, which were then mapped onto specific operational resources through QFD to identify critical resource elements and derive their corresponding weights. These weights, subsequently treated as evaluation criteria in the MARCOS method, were applied to assess the performance of Third-Party Logistics (3PL) providers. The proposed methodology was validated through a case study involving eight user requirements and seven key resources. The findings indicated that precise temperature control and delivery speed were the most critical user requirements, whereas advanced temperature sensors and vehicles with cooling systems were identified as the most significant resources. Based on the MARCOS evaluation, Provider 1 emerged as the most optimal 3PL alternative. This integrated decision-making model offers a systematic and data-driven approach for aligning customer priorities with resource capabilities, thereby enabling logistics providers to enhance service quality, operational efficiency, and strategic competitiveness in temperature-sensitive supply chains. The model also demonstrates practical scalability and adaptability across diverse cold chain scenarios.

Keywords: Cold chain; QFD; BWM; Quality; Improvement; Logistics; Temperature-controlled

1 Introduction

In today's highly competitive market, companies are compelled to earn the trust of a growing customer base to enhance their market position. A pivotal strategy for achieving this is through the continuous improvement and innovation of services, with customer satisfaction serving as a cornerstone of organizational success. Quality management stands as a fundamental process within any business system. This is particularly evident in the case of the cold chain, where maintaining the freshness and quality of transported goods is crucial. The reason lies in the fact that proper temperature control helps preserve the quality of fresh food and prolong its shelf life [1]. It is also important to note that managing the logistics of temperature-sensitive products is significantly more complex than handling dry cargo due to their unique requirements. These include the necessity of maintaining high product quality, using specialized transport vehicles, and meeting increased energy demands for storage, handling, and transportation [2]. Among the various methodologies employed, QFD is prominent for translating customer needs into specific product or service requirements. The primary outcome of implementing QFD is attaining a quality level that aligns with customer expectations. This method encompasses distinct phases and implementation procedures, the execution of which directly contributes to quality enhancement.

The initial sections of this study provide a foundational definition of QFD, accompanied by a brief overview of its historical development. Subsequently, this study delineates the implementation phases of the method, highlighting the commonly utilized tool known as the "House of Quality (HOQ)." This study also discusses the advantages and limitations of QFD. Emphasis is placed on the practical application of QFD across various logistics processes, particularly within temperature-controlled transport logistics. In addition, BWM was applied beforehand to determine the weights of the user requirements, which were then used to implement the QFD method. Based on these two phases, the resources required for the company to meet customer demands were identified. These resources, which were determined through the application of the QFD method, became the criteria used to rank six 3PL providers offering cold chain services using the MARCOS method.

QFD has been effectively applied in the development of sustainable supply chains, with relevant case studies illustrating the procedures and steps involved in its implementation. For instance, a study by Lam [3] demonstrates the integration of QFD in designing a sustainable maritime supply chain by focusing on customer requirements. Additionally, QFD has played a significant role in identifying human errors in warehouse processes, as evidenced by case studies that detail its application. Furthermore, QFD has been instrumental in pinpointing strategic actions for 3PL providers to enhance service quality. Specifically, in the context of cold supply chains, the application of QFD has facilitated the identification of common customer requirements and the resources necessary to meet these expectations. This study aims to explore the application of QFD within temperature-controlled transport logistics, examining how this methodology can be leveraged to meet stringent quality standards and fulfill specific customer demands inherent in cold chain operations.

The remainder of this study is organized below. Section 2 provides the background and literature review. The methodology of the proposed model is presented in Section 3, while the numerical example and results of the application are described in Section 4. Finally, Section 5 presents the concluding remarks.

2 Background and Literature Review

In today's highly competitive business environment, companies are compelled to continuously improve the quality of their services to meet customer demands and enhance their market position. Customer satisfaction has become a critical success factor, and quality management is essential for any business system. QFD is recognized as an effective tool for achieving a high level of quality that meets user needs. It is a methodology that enables the translation of customer requirements into technical specifications through structured phases and implementation procedures, directly impacting the enhancement of product and service quality. The application of QFD in logistics, particularly in cold supply chains, shows significant potential in identifying and addressing key challenges in providing quality services. A lot of studies deal with QFD in logistics.

QFD implementation requires collaboration among teams from different departments. There are four key phases, each utilizing matrices that translate initial customer requirements into production control and planning activities:

a) Product planning: This phase documents customer requirements, defines the company's technical capabilities, and assesses market competition.

b) Product design: This phase involves creativity and innovation in defining crucial product aspects for customer satisfaction.

c) Process planning: This phase monitors production processes, documents key parameters, and ensures target values are met.

d) Process control: This phase uses performance indicators to monitor and control product/service execution, assessing risks and defining control procedures.

After defining primary product characteristics, the "what" from the HOQ is followed by the "how" – the necessary actions to meet customer expectations. This iterative process ensures the customer's voice is carried through from concept to realization.

Implementing the QFD method helps companies position their products or services by integrating customer needs from the initial development stages. By continuously engaging with customers, businesses can enhance efficiency and cost-effectiveness. However, QFD implementation requires significant resources, particularly human capital, fostering teamwork and alignment around shared organizational goals. Some disadvantages include potential disruptions in companies focused primarily on cost reduction and profitability. While QFD ensures customer satisfaction and long-term profitability, some organizations may resist change, particularly if they believe their current approach is already effective.

Davoudi et al. [4] analyzed advancements in cold chain logistics over the past two decades, focusing on reducing food waste in the meat industry. Their study emphasizes the role of QFD in identifying factors that affect quality and resilience in cold supply chains and gives brief insights for theory and practice. Khan and Ali [5] investigated the enhancement of resilience and quality in cold supply chains during the COVID-19 pandemic. Their analysis indicates that QFD can play a key role in identifying and resolving issues in the supply chain during crisis periods. Pajić et al. [6] also used Failure Modes and Effects Analysis (FMEA)-QFD for assessment of risks in distribution of products in order to improve efficiency. Lukale and Hairui [7] applied QFD and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for the provider selection problem and solved the problem of 3PL provider selection for e-commerce activities. Shan et al. [8] presented an optimization design framework that combines quantitative Kano and fuzzy QFD to effectively align express service elements with complex and fluctuating customer demands. An empirical study confirms the framework's ability to prioritize service elements, enhance customer satisfaction, and provide a budget allocation strategy, offering valuable insights for express enterprises and potentially other service industries.

Cheng et al. [9] developed a quality control system for agricultural cold chain logistics by utilizing QFD technology, grounded in customer demand. By employing the Kano model to analyze customer satisfaction and mapping the relationship between customer demands and logistics quality control elements, the research established improvement goals and validated the effectiveness of the method through empirical analysis in specific agricultural enterprises. Nguyen et al. [10] evaluated and selected the most suitable cold chain logistics service providers (CLPs) by proposing an MCDM framework that integrates the grey analytic hierarchy process (G-AHP) and grey complex proportional assessment (G-COPRAS) methodologies, utilizing grey numbers for expert evaluations.Through this framework, the research identified key sustainability performance criteria, with findings highlighting product quality and logistics costs as crucial factors, ultimately determining that Yoshida Saigon Cold Logistics is the best-performing CLP in Vietnam, thereby providing insights for managers and stakeholders to enhance sustainable practices in cold supply chains. Arslan et al. [11] proposed a novel approach for risk evaluation in cold supply chains based on the FMEA approach. Mao et al. [12] developed a novel QFD approach improved with the Criteria Importance Through Intercriteria Correlation (CRITIC) method as well as linguistic distribution assessments.

Chaudhuri et al. [13] presented a literature review regarding decision-making in the cold chain. The results showed that there is a need to understand how continuous monitoring of conditions, such as temperature, humidity, and vibration, can be translated to support real-time assessment of quality, determination of actual remaining shelf life of products and use of those for decision-making in cold chains. Firms across the cold chain need to adopt appropriate technologies suited to the specific contexts to capture data across the cold chain. Ren et al. [14] confirmed the importance of control within the cold chain and concluded that optimizing packaging materials and incorporating dynamic quality perception are essential for maintaining meat quality and safety throughout the entire cold chain. These requirements drive the need for digitalization and intelligent development of the meat cold chain. A major insight from the review is that integrated packaging solutions, along with smart quality assessment and monitoring systems, play a crucial role in transforming the traditional meat cold chain into a more intelligent, sustainable, and efficient cold logistics system, enabling advanced management and control across all stages.

Wang [15] presented the use of QFD as a method for evaluating the service quality of cold chain logistics for fresh products. The approach aimed to better align logistics services with customer expectations. The first step involved identifying customer requirements using the Analytic Hierarchy Process (AHP). Next, an index system for service technologies was developed, based on the internal operations of the enterprise. Finally, a HOQ was constructed by creating a correlation matrix that links customer requirements with the identified service technologies. Similarly, Wang and Hao [16] implemented QFD for improving logistics service quality. Ayağ et al. [17] proposed a fuzzy QFD methodology aimed at identifying key factors and enhancing customer satisfaction. The process began by converting qualitative information into quantitative parameters. These values were then integrated with additional quantitative data to develop two multi-objective mathematical programming models. A combination of QFD and AHP was proposed by Upveja et al. [18] for ranking companies in cold chain. The QFD methodology showed significant potential in logistics and cold supply chains, allowing companies to enhance their services through precise mapping of customer requirements to technical characteristics. Its integration with fuzzy logic and AHP further improved its effectiveness, leading to better results in the implementation of quality improvement strategies.

Fazeli and Peng [19] proposed an approach based on BWM-QFD and Full Consistency Method (FUCOM)-QFD to determine the importance levels of technical measures within the relationship matrix of HOQ. Gunduz et al. [20] presented an innovative hybrid methodology that integrates the BWM and QFD to evaluate the maturity level of supply chain smartness and sustainability by assigning weights to key supply chain management functions. The primary aim of the study conducted by Goel et al. [21] was to identify the key sustainability criteria that align with stakeholder expectations and support the transition toward sustainable product manufacturing. To achieve this, a fuzzy BWM was applied in combination with a QFD model to determine the relative importance of these sustainability criteria in meeting stakeholder needs.

3 Methodology

The QFD method is used for planning new products and services or modifying existing ones to better meet customer needs. To maintain market competitiveness, companies must understand the factors influencing customers' perception of quality. This includes defining characteristics, such as reliability, speed of execution, and other performance metrics that shape consumer perception. The application of the QFD method involves translating customer requirements into concrete actions across all stages of product or service development.

For a product or service to meet the required standards, development teams must clearly define the subject of development and understand customer expectations.QFD provides a systematic approach to development and improvement, integrating customer awareness with functional company elements. The method translates customer desires into quality characteristics of products or services, making QFD synonymous with the ”voice of the customer.”

QFD ensures that customer needs and expectations are heard and implemented into technical product/service characteristics or process stages. Various departments, such as sales, marketing, production, and planning, contribute to developing technical features that align with customer needs. Due to its adaptability, QFD is applicable at all company levels and in various operational conditions. The goal of the QFD method is to translate subjective quality criteria into objective, quantifiable parameters used in product or service creation. It prioritizes where and how to focus development efforts. The primary objectives of QFD implementation include:

a) Prioritizing customers' expressed and unexpressed needs.

b) Converting defined desires into technical, measurable specifications.

c) Developing and delivering high-quality products or services with a focus on customer satisfaction.

The QFD method can be implemented whenever customer needs are identified and quantified. It is most effective when applied throughout the entire lifecycle and across all processes, ensuring continuous attention to the "voice of the customer."

3.1 BWM

To determine the weights of customer requirements, BWM was applied as the initial phase of the methodology, following the steps outlined by Rezaei [22] and further refined by Andrejić and Pajić [23].

Step 1: Defining decision criteria. A finite set of decision criteria $\{c_1, c_2, \ldots, c_n\}$ was first identified based on the specific context of the analysis.

Step 2: Identifying key criteria. The most important (best) and the least important (worst) criteria were selected according to their relevance in the decision-making process.

Step 3: Best-to-others comparison. The best criterion was compared with each of the remaining criteria using a scale from 1 to 9. This generated the best-to-others vector $A_B = (a_{B1}, a_{B2} \ldots, a_{Bn})$, where each element reflects the preference of the best criterion over others. By definition, the best criterion was assigned a value of 1, as shown in Eq. (1).

$$A_B = (a_{B1}, a_{B2} \ldots, a_{Bn}) \tag{1}$$

Step 4: Others-to-worst comparison. Each criterion was then compared against the worst criterion using the same 1 to 9 scale. This resulted in the others-to-worst vector $A_W = (a_{1W}, a_{2W} \ldots, a_{nW})^T$, where the value for the worst criterion is always 1, as shown in Eq. (2).

$$A_W = (a_{1W}, a_{2W} \ldots, a_{nW})^T \tag{2}$$

Step 5: Deriving optimal weights. The final step involved solving an optimization model to derive the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$, as shown in Eq. (3).

$$\begin{aligned} &\text{Min} \cdot \xi \\ &s.t. \\ &\left|\frac{w_B}{w_j} - a_{Bj}\right| \le \xi, for\ all\ j \\ &\left|\frac{w_j}{w_W} - a_{jw}\right| \le \xi, for\ all\ j \\ &\sum_j w_j = 1 \\ &w_i \ge 0, for\ all\ j \end{aligned} \tag{3}$$

3.2 QFD

Along with the "customer's voice," HOQ is another essential component of the QFD method. HOQ includes user requirements (WHATs), resources (HOWs), and a matrix that defines the relationships between the user requirements and the available resources. It also incorporates the roof (representing resource correlations), competition analysis, as well as the prioritization of both user requirements and resources, culminating in a final evaluation.The implementation of the QFD method and the formation of HOQ involve several steps [24, 25].

Step 1: Development of the user requirements list. This step focuses on defining the user requirements related to the quality of a particular logistics service.

Step 2: Development of the resource list. This identifies the necessary resources to meet the defined user requirements.

Step 3: Determining the connection between user requirements and resources. This step establishes appropriate connections (represented by symbols, which are later converted into values) between the requirements and the resources.

Step 4: Resource correlation. This step involves determining the internal correlations between available resources by assigning symbols that reflect the strength of each connection.

Step 5: Prioritizing user requirements and prioritizing resources.

3.3 Marcos

The MARCOS method evaluates alternatives by comparing them with both ideal and anti-ideal reference points. Each alternative's utility is calculated according to its proximity to these two benchmarks. A final ranking is then derived based on these utility scores. This method helps identify the most favorable option by measuring how close each alternative is to the ideal, while also considering its distance from the least desirable (anti-ideal) option. A distinguishing feature of MARCOS is its incorporation of both ideal and anti-ideal solutions at the very beginning of the decision matrix formulation. This enables a more accurate assessment of utility and ensures a balanced comparison between all alternatives. Moreover, the method introduces a new way of defining and aggregating utility functions, allowing it to handle complex decision problems involving many alternatives and criteria without compromising stability. The implementation of MARCOS follows these steps [26].

Step 1: Creating the decision-making matrix containing m alternatives and n criteria.

Step 2: Extending the matrix by including the ideal (AI) and anti-ideal (AAI) solutions as follows:

$$\begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{matrix} C_1 & C_2 & \dots & C_n \end{matrix} \\ \begin{bmatrix} x_{aa1} & x_{\text{aa2}} & \dots & x_{\text{aan}} \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \\ x_{\text{ai1}} & x_{\text{ai2}} & \dots & x_{\text{ain}} \end{bmatrix} \end{array} \tag{4}$$

The ideal solution represents the best case, and the anti-ideal the worst. They can be calculated as follows:

$$AAI = \min_i x_{ij} \; if \; j \in B \, and \, \max_i x_{ij} \; if \; j \in C \tag{5}$$

$$AI = \max_i x_{ij} \; if \; j \in B \, and \, \min_i x_{ij} \; if \; j \in C \tag{6}$$

where, B denotes the beneficial criteria, and C denotes the cost criteria.

Step 3: Normalizing the extended matrix as follows:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \, if \; j \in C \tag{7}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \, if \; j \in B \tag{8}$$

Step 4: Forming the weighted decision matrix using the normalized values and corresponding weights.

$$v_{ij} = n_{ij} \times w_j \tag{9}$$

Step 5: Calculating the utility degrees K_i^- and K_i^+, which measure each alternative's position relative to AAI and AI.

$$K_i^- = \frac{S_i}{S_{aai}} \tag{10}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{11}$$

where, S_i is the sum of weighted values for alternative i.

$$S_i = \sum_{i=1}^{n} V_{ij} \tag{12}$$

Step 6: Computing the utility function for each alternative $f(Ki)$, which reflects its compromise level between AI and AAI.

$$f\left(K_i\right)=\frac{K_i^{+}+K_i^{-}}{1+\frac{1-f\left(K_i^{+}\right)}{f\left(K_i^{+}\right)}+\frac{1-f\left(K_i^{-}\right)}{f\left(K_i^{-}\right)}} \tag{13}$$

The component utility functions are defined as follows:

$$f\left(K_i^{-}\right)=\frac{K_i^{+}}{K_i^{+}+K_i^{-}} \tag{14}$$

$$f\left(K_i^{+}\right)=\frac{K_i^{-}}{K_i^{+}+K_i^{-}} \tag{15}$$

Step 7: Ranking the alternatives in descending order according to the values of their utility functions $f(Ki)$. Figure 1 shows the steps of the proposed method.

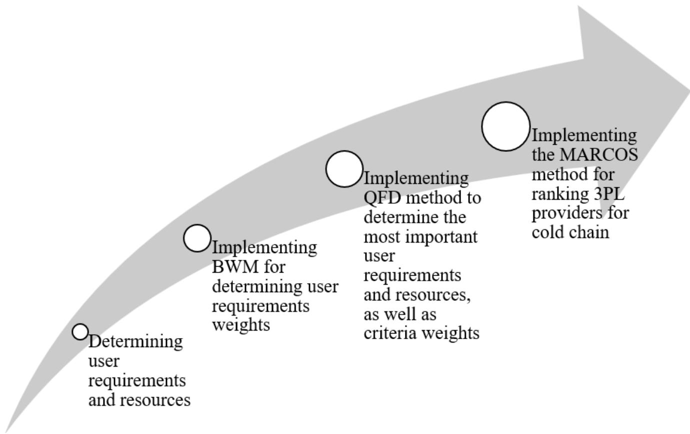

Figure 1. Steps of the proposed method

4 Numerical Example

The cold supply chain plays a crucial role in the transportation of temperature-sensitive goods, such as pharmaceutical products, fresh food items, and biological materials. Given the strict requirements for maintaining a constant temperature, it is essential to implement methods that enable optimal control and monitoring of transport conditions. In this context, a case study was conducted on a company operating within the cold chain logistics sector, with the objective of enhancing service quality through a structured methodological framework.

4.1 Defining User Requirements and Importance Assessment

User requirements were identified based on surveys conducted among logistics industry experts, as well as an analysis of market standards for the cold supply chain. The key user requirements are summarized in Table 1.

Table 1. User requirements

User Requirement	Code
Precise temperature control	UR1
Delivery speed	UR2
Minimal transportation costs	UR3
Packaging integrity maintenance	UR4
Availability of transport units	UR5
Digital shipment tracking	UR6
Environmentally sustainable-logistics	UR7
Route planning flexibility	UR8

The first step in applying the proposed methodology involved determining the best and worst user requirements in order to conduct BWM. Precise temperature control was identified as the best, while availability of transport units

Table 2. BtO matrix

Best to others	UR1	UR2	UR3	UR4	UR5	UR6	UR7	UR8
UR1	1	2	3	4	9	5	8	5

Table 3. OtW matrix

Others to the Worst	UR5
UR1	9
UR2	8
UR3	7
UR4	6
UR5	1
UR6	6
UR7	2
UR8	3

was considered the worst. The Best-to-Others (BtO) and Others-to-Worst (OtW) matrices are presented in Tables 2 and 3, respectively.

Based on the evaluation of these matrices and after applying BWM, the weights of the user requirements were obtained, as shown in Table 4 below. The input-based consistency ratio (CR) had a value of 0.291666667, indicating that the pairwise comparison consistency level is acceptable.

Table 4. User requirement weights

UR1	UR2	UR3	UR4	UR5	UR6	UR7	UR8
0.3232	0.2020	0.1347	0.1010	0.0269	0.0808	0.0505	0.0808

An analysis of user requirements showed that the most important user requirements are precise temperature control and delivery speed, as they directly impact the quality of delivered products.

4.2 Identifying Resources and Their Connection to Requirements

The following key resources, according to logistics specialists and literature, were defined to support meeting user requirements (Table 5).

Table 5. Resources for fulfilling requirements (demands)

Resource	Code	Description
Advanced temperature sensors	RS1	Real-time temperature monitoring
Optimized delivery routes	RS2	Route optimization software
Efficient packaging insulation	RS3	High-quality thermal insulation
Automated tracking and alert systems	RS4	IoT-enabled shipment monitoring
Vehicles with specialized cooling systems	RS5	Precise refrigeration mechanisms
Use of renewable energy sources	RS6	Solar and alternative energy integration
Cost optimization software	RS7	Algorithms for balancing cost and service quality

The relationship between user requirements and resources was established through a relationship matrix, allowing for a clearer identification of the most crucial requirements and resources.

4.3 Result Analysis

To establish the relationship between user requirements (UR) and technical resources (RS), three levels of correlation were defined as follows:

- Strong (9): The resource is essential to fulfilling the requirement.
- Medium (3): The resource significantly contributes but is not the sole solution.
- Weak (1): The resource has a minor impact.

Based on the established QFD matrix in Table 6, the multiplication of the user requirements weights and the strength of the relationships between UR and RS was performed, as shown in Table 7.

Table 6. QFD matrix

	Weight	RS1	RS2	RS3	RS4	RS5	RS6	RS7
UR1	0.3232	9		3		9		
UR2	0.2020		9			3		
UR3	0.1347							9
UR4	0.1010	3		9	3	9		
UR5	0.0269					3		
UR6	0.0808				9			
UR7	0.0505						9	3
UR8	0.0808		3					3

Table 7. QFD matrix after evaluation

	RS1	RS2	RS3	RS4	RS5	RS6	RS7	Σ
UR1	2.9088		0.9696		2.9088			6.7872
UR2		1.818			0.606			2.424
UR3							1.2123	1.2123
UR4	0.303		0.909	0.303	0.909			2.424
UR5					0.0807			0.0807
UR6				0.7272				0.7272
UR7						0.4545	0.1515	0.606
UR8		0.2424					0.2424	0.4848
Σ	3.2118	2.0604	1.8786	1.0302	4.5045	0.4545	1.6062	

After applying the method, it can be concluded based on Table 7 that the most significant user requirement is UR1, followed by UR2, UR4, UR3, etc. On the other hand, when examining the resources, it can be concluded that the most important resources are RS5, RS1, RS2, RS3, etc.

Based on the findings, it is evident that advanced temperature sensors (RS1) and vehicles with cooling systems (RS5) are the most critical elements. These should be the primary investment focus. Optimized delivery routes (RS2) and packaging insulation (RS3) are next when considering importance due to their direct impact on temperature control and product integrity. Cost optimization software (RS7) ranks high, indicating that balancing cost and quality is a significant concern. Automated tracking and alert systems (RS4), though necessary, are less critical than other resources. Finally, renewable energy (RS6) has the lowest priority but is important for long-term sustainability.

The third phase of the proposed model involves the application of the MARCOS method to rank 3PL providers engaged in cold chain operations. To achieve the defined objective, the resources (RS) previously evaluated through the QFD method were redefined as decision-making criteria. Thus, RS1 was mapped to criterion 1 (C1), RS2 to C2, and so forth. In this study, six alternatives (3PL providers) were evaluated and ranked. The evaluation was conducted using a 1–10 scale, based on assessments provided by three domain experts. To derive a single representative value for each alternative, the average score across all criteria was calculated and used as the final input (Table 8).

Table 8. Input data for the MARCOS method

Alternative	C1	C2	C3	C4	C5	C6	C7
A1	8	6	7	6	7	4	9
A2	5	8	6	7	6	6	7
A3	7	5	8	6	8	4	6
A4	6	7	5	8	6	7	5
A5	5	7	7	5	8	5	8
A6	8	7	6	6	6	7	6

On the other hand, in order to determine the criteria weights required for applying the MARCOS method, the total significance of each resource (i.e., the column sums from the QFD matrix) was used in the calculation. The weight of the first criterion was obtained as follows: $w_1 = 3.2118/14.7462 = 0.2178$. Using the same approach, the weights for the remaining criteria were calculated as well (Table 9).

After determining the criteria weights, the MARCOS method was applied following the steps previously outlined in the methodology section. The process began with identifying the ideal and anti-ideal solutions for each criterion (Table 10).

Table 9. Criteria weights

C1	C2	C3	C4	C5	C6	C7
0.2178	0.1397	0.1274	0.0699	0.3055	0.0308	0.1089

Table 10. Ideal and anti-ideal solutions

	C1	C2	C3	C4	C5	C6	C7
AAI	5.00	5.00	5.00	5.00	6.00	4.00	5.00
AI	8.00	8.00	8.00	8.00	8.00	7.00	9.00

In this way, the extended decision-making matrix was obtained and subsequently normalized (Table 11).

Table 11. Normalized matrix

	C1	C2	C3	C4	C5	C6	C7
AAI	0.63	0.63	0.63	0.63	0.75	0.57	0.56
A1	1.00	0.75	0.88	0.75	0.88	0.57	1.00
A2	0.63	1.00	0.75	0.88	0.75	0.86	0.78
A3	0.88	0.63	1.00	0.75	1.00	0.57	0.67
A4	0.75	0.88	0.63	1.00	0.75	1.00	0.56
A5	0.63	0.88	0.88	0.63	1.00	0.71	0.89
A6	1.00	0.88	0.75	0.75	0.75	1.00	0.67
AI	1.00	1.00	1.00	1.00	1.00	1.00	1.00

In the next step, the criteria weights were applied to generate the weighted decision-making matrix (Table 12).

Table 12. Weighted decision matrix

	C1	C2	C3	C4	C5	C6	C7
AAI	0.14	0.09	0.08	0.04	0.23	0.02	0.06
A1	0.22	0.10	0.11	0.05	0.27	0.02	0.11
A2	0.14	0.14	0.10	0.06	0.23	0.03	0.08
A3	0.19	0.09	0.13	0.05	0.31	0.02	0.07
A4	0.16	0.12	0.08	0.07	0.23	0.03	0.06
A5	0.14	0.12	0.11	0.04	0.31	0.02	0.10
A6	0.22	0.12	0.10	0.05	0.23	0.03	0.07
AI	0.22	0.14	0.13	0.07	0.31	0.03	0.11

To determine the utility degree values for each alternative, the S_i values were calculated (Table 13).

Table 13. S_i values and utility degree of alternatives

Alternatives	S_i		
S_{aai}	0.65	K_i^-	K_i^+
A 1	0.88	1.35	0.88
A 2	0.77	1.18	0.77
A 3	0.85	1.30	0.85
A 4	0.76	1.16	0.76
A 5	0.84	1.28	0.84
A 6	0.82	1.25	0.82
S_{ai}	1.00		

Finally, based on the values from Table 13, the utility function values were calculated for each alternative (Table 14), and the alternatives were ranked accordingly (Figure 2).

The results showed that the best alternative was A1, followed by A3, A5, A6, A2, and finally A4 as the lowest-ranked alternative. Based on these results, it can be concluded that the company should opt for the first 3PL provider.

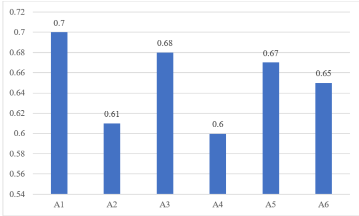

Figure 2. Alternative ranking

Table 14. Utility function of alternatives

Alternatives	$f\left(K_i^-\right)$	$f\left(K_i^+\right)$	$f\left(K_i\right)$	Ranking
A1	0.40	0.60	0.70	1
A2	0.40	0.60	0.61	5
A3	0.40	0.60	0.68	2
A4	0.40	0.60	0.60	6
A5	0.40	0.60	0.67	3
A6	0.40	0.60	0.65	4

5 Conclusions

Cold chain logistics plays a vital role in ensuring the quality, safety, and efficiency of distributing temperature-sensitive products, particularly within the food, pharmaceutical, and chemical industries. This study addressed the key challenges in cold chain logistics management, with a special focus on maintaining the quality and freshness of perishable goods throughout transportation. The application of decision-making methodologies, such as BWM, QFD and MARCOS, proved to be essential for identifying and prioritizing both user requirements and the corresponding resources, as well as for evaluating and ranking 3PL providers. By determining the relative importance of user requirements and mapping them to the necessary resources, the proposed model provides valuable insights for enhancing logistics performance. The case study results highlighted precise temperature control and delivery speed as the most critical user requirements, while advanced temperature sensors and refrigerated vehicles emerged as the most significant resources.

The integration of BWM and QFD demonstrated their effectiveness as a comprehensive decision-support tool, offering a structured and systematic approach to complex planning processes. This framework ensures that logistics solutions are aligned with customer needs and market expectations, leading to improved operational efficiency, reduced losses, and higher service quality. The findings of this study underscore the importance of continuous innovation and improvement in cold chain logistics to meet rising customer demands and sustain competitive advantage. Based on the application of the QFD method, the resources evaluated through this method became the criteria in the final phase of the model, which involved the application of the MARCOS method to rank the 3PL providers. The results of applying the proposed model indicated that the company should choose the first provider.

Future research should aim to further refine prioritization techniques and explore the integration of emerging technologies that can support the evolution of smart, resilient, and sustainable cold chains.

Moreover, subsequent studies may expand the application of this methodological framework to other segments of the cold chain, incorporating additional criteria, such as environmental sustainability, energy efficiency, and the effects of climate change. The use of hybrid models, combining BWM, QFD, and other MCDM approaches, could offer deeper insights into the critical interplay between user needs and resource allocation.

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