SCIENTIFIC OASIS

Journal of Intelligent Decision Making and Granular Computing

Journal homepage: www. jidmag.org
ISSN: 3042-3759

A Multi-Criteria Decision-Making Framework for the Adoption of Emerging Technologies in Cold Chain Management

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ARTICLE INFO

Article history:
Received 27 August 2025
Received in revised form 30 September 2025
Accepted 19 October 2025
Available online 23 October 2025

Keywords:
Cold Chain, Logistics, Technology selection, SITDE, RAM, p, q-Quasirung Orthopair Fuzzy Sets, Industry 4.0.

ABSTRACT

The fact that operations and business models in cold chain logistics have become more complex than in the past due to digital transformation, disruptive developments in the industry 4.0 process, and increasing pressures in the context of sustainability and green policies necessitates the use of advanced technologies to ensure efficiency, transparency, and sustainability. This study developed a multi-criteria decision-making-based framework to evaluate the adoption of new and advanced technologies related to cold chain logistics. In this context, four alternative solutions—IoT-based sensor systems, blockchain-based traceability platforms, cloud-based management software, and AI/machine learning-supported forecasting and optimization tools—were examined within the framework of eleven criteria. These criteria include installation cost, data security, traceability capability, ease of use, integration potential, energy consumption, system reliability, compliance with standards, scalability, environmental impact, and stakeholder acceptance. While the findings show that C10 Environmental Impact, C8 Compliance and Standards, and C9 Flexibility and Scalability criteria are the prominent criteria for determining the most appropriate technology, A1 IoT Sensor Systems have been chosen as the top priority alternative that should be adopted and integrated into business models. Ultimately, a thorough robustness check was conducted to verify the validity and reliability of the model proposed in this study.

1. Introduction

Cold chain operations are one of the most critical components of modern supply chains and logistics processes to ensure food safety and protect pharmaceuticals, medical supplies, and sensitive products against adverse situations such as spoilage and waste. In this scope, insufficient food

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https://doi.org/10.31181/jidmgc11202521

transport and warehousing operations, interruptions in the cold chain [1], unsuccessful planning processes, and mistakes of the last users are the leading reasons for the food lost and waste (FLW) [2] Effective and efficient structuring and management of cold chains guarantees the quality and safety of food products and greatly influences and shapes cost optimization, environmental impact on operations, and customer satisfaction [3]. Each perishable product has a certain optimal storage temperature; whether it is too high or too low will affect its safety and quality [4]. Especially in food and pharmaceutical logistics, changes and fluctuations in ambient temperatures or operational errors can cause millions of dollars in losses for businesses and their stakeholders. In that regard, the correct choice, prioritization, and integration of technological applications into the system have become a critical and strategic necessity regarding operational efficiency and effectiveness, and their environmental and social impacts.

Depending on the disruptive technologies emerging in the Industry 4.0 process and the increasingly prominent concept of digital transformation, IoT-based sensor systems, blockchain solutions, cloud-based management software, and artificial intelligence/machine learning-supported optimization tools have become more prominent as advanced and innovative technologies that can be used in cold chain operations. The adoption of these technologies and their integration into the business models of logistics businesses conducting cold chain operations make it necessary to consider multidimensional criteria such as cost, safety, sustainability, ease of integration, and stakeholder acceptance, as well as the technical performance of these technologies. In this direction, determining and prioritizing the most appropriate technology is a highly complex decision-making problem considering the non-linear relationships between the criteria, the multidimensional, contradictory and complex nature of the criteria, as well as the uncertainties, ambiguities and decision-maker hesitations inherent like the cold chain logistics industry, and to solve this problem reasonably, in addition to addressing the criteria in a balanced and reasonable manner, A strong and reliable decision-making framework is needed to enable effective modeling and management of uncertainties.

Although technology selection and adoption have been discussed from different perspectives in the literature on cold chain applications, the studies have primarily focused on certain factors and discussed the benefits of technologies to be used in cold chain applications with their qualitative dimensions. Decision-making tools and models are mostly neglected in the literature, and there is no adequate relationship and integration between expert evaluations and systematic and data-based approaches. Due to these research gaps in literature, decision-makers often make choices based on their intuitive and limited knowledge, leading to erroneous investment decisions and increased operational costs and uncertainties.

This study develops an integrated decision-making model consisting of Subjective & SITDE and RAM methods with the help of p, q-Quasirung Orthopair Fuzzy Sets (p, q-QROFS) to fill these research gaps and eliminate theoretical evaluation inadequacies. By applying this model, advanced technology alternatives that can be used in cold chain operations, such as IoT sensor systems, blockchain-based platforms, cloud-based software, and AI/ML solutions, were analyzed in the light of the evaluations made by four professionals who are experts in the fields of logistics, informatics, food safety and sustainability, taking into account eleven basic criteria.

The decision-making model used in this study provides significant advantages. Foremost, p, q-Quasirung Orthopair Fuzzy Sets capture and process uncertainty and ambiguity much more effectively than traditional fuzzy sets [5]. Recognizing the dynamic nature of decision-makers' criteria, this framework enhances the applicability of decision-making processes by analyzing point values tied to different parameters, enabling the realistic modeling of decision scenarios and ensuring that the model effectively reflects the complexities involved in real-world decision-making processes [5].

At the same time, the ability to adjust the parameters in the p and q aggregation operators by decision-makers in line with the specific requirements and preferences of the scenario injects a high level of adaptability into the decision process, enhancing its applicability to a wide range of real-world situations that consider different degrees of membership and non-membership [6].

Subjectively process linguistic evaluations of decision-makers using mathematical operations of the fuzzy set preferred in this study to determine criterion weightings, which are integrated with the SITDE method, an objective weighting approach developed by Gopisetty and Sama [7]. This approach integrates subjective and objective information, resulting in more balanced results. The RAM method, which was ultimately chosen for ordering alternatives, is highly understandable, practical, and flexible, as well as a compelling and consistent sorting approach. Based on these advantages, the proposed p, q-QROF Subjective – SITDE & RAM integrated methodological framework stands out as a potent and robust decision-making tool compared to traditional decision-making approaches, as it digitizes expert opinions in a rational context by considering cost and benefit criteria together, and allows multidimensional, transparent, flexible, and reproducible analyses.

The innovations provided by this study can be summarized in three dimensions: (i) it combines the criteria that are discussed in the literature in a holistic structure, (ii) it reduces subjectivity by integrating expert opinions with a strong mathematical infrastructure, (iii) technologies are evaluated not only in terms of their operational benefits but also in terms of environmental and stakeholder dimensions, and (iv) p, q-QROFS-based Subjective & SITDE and RAM methods are proposed. Thus, the study both provides a methodological and contextual contribution to the academic literature and develops an applicable roadmap for the strategic decision processes of enterprises.

The rest of the paper is structured as follows: Section 2 describes the methodological framework used and the theoretical background of the MCDM approach. Section 3, the research design, criteria, alternatives, and the characteristics of the expert group are introduced in detail. Section 4 presents the findings regarding the implementation of the proposed model and discusses the results. Section 5 discussion 6 concludes the study, discusses theoretical and practical contributions, and indicates suggestions for future research.

2. Methodology

This study proposes a Subjective – SITDE & RAM integrated decision-making model based on p, q-QROF sets to eliminate the research gaps and theoretical evaluation deficiencies discussed above. The proposed model is designed to capture the multidimensional and complex nature of decision-makers' evaluations in the context of modeling and managing uncertainties, ambiguities, expert hesitations, and evaluating and prioritizing innovative technologies that have the potential to be used in cold supply chains. Beyond decision-making approaches that are often one-dimensional and have methodological deficiencies, it offers a holistic, flexible, and robust structure that can reflect the complexities of decision-making in real-world conditions within supply chain and logistics management. By integrating subjective and objective weighting approaches, sequencing alternatives, and modeling highly complex uncertainties, the decision-making framework offers theoretical contributions and improves practical and reliable applicability for decision-makers and practitioners.

2.1 Preliminary information on p, q – QOFS

This section illustrates the evolution of p, q – QOFS, summarizing its key definitions and characteristics. Let, Ξ is the universe of discourse containing the elements of the p, q – QOF sets.

Definition 1. Intuitionistic Fuzzy Set (IFS): An IFS can be described as follows [8].

$$\tilde{I} = \left\{ x, \left\langle \mu_I(x), \vartheta_I(x) \right\rangle : x \in \Xi \right\} \tag{1}$$

The membership and non-membership degrees, such as $\mu_I(x) \to [0,1]$ and $\vartheta_I(x) \to [0,1]$ are affixed with the following condition: $0 \le \mu_I(x) + \vartheta_I(x) \le 1; \forall x \in \Xi$

Definition 2. Pythagorean Fuzzy Set (PFS): A PFS is defined as follows:

$$P = \{x, \langle \mu_P(x), \vartheta_P(x) \rangle : x \in \Xi\} \tag{2}$$

The condition fulfilled by the membership and non-membership values is represented by $0 \le \mu_P(x)^2 + \vartheta_P(x)^2 \le 1; \forall x \in \Xi$.

To enhance decision-makers' flexibility by extending the definitions, q-ROFS was introduced by researchers [9-11]. The definition is given below.

Definition 3. Rung Orthopair Fuzzy Set (q-ROFS)

$$Q = \{x, \langle \mu_Q(x), \vartheta_Q(x) \rangle : x \in \Xi\} \tag{3}$$

A natural integer q is utilized in q-ROFS as the exponent to express the inequality in the following form $0 \le \mu_Q(x)^q + \vartheta_Q(x)^q \le 1; \forall x \in \Xi; q \ge 1$. The degree of indeterminacy is given as: $\pi_Q = \sqrt[q]{1 - (\mu_Q(x))^q - (\vartheta_Q(x))^q}; \forall x \in \Xi$

Seikh and Mandal [12] expanded q-ROFS into a more generalized and flexible form to better capture vagueness, which resulted in the definition of p, q-QOFS as follows.

Definition 4. Quasirung Orthopair Fuzzy Set (p, q-QOFS)

$$\wp = \{x, \langle \mu_\wp(x), \vartheta_\wp(x) \rangle : x \in \Xi\} \tag{4}$$

Differing from q-ROFS, p, q-QOFS applies two natural integers, p and q, as powers to uphold the condition: $0 \le \mu_\wp(x)^p + \vartheta_\wp(x)^q \le 1; \forall x \in \Xi$. The degree of indeterminacy is provided as:

$$\pi_\wp = \sqrt[\varepsilon]{1 - (\mu_\wp(x))^p - (\vartheta_\wp(x))^q}; \forall x \in \Xi; \varepsilon = L.C.M(p,q)$$

Different values of the natural integers p and q characterize the p, q-QOFS in terms of other types of fuzzy numbers, such as IFS ($p = q = 1$), PFS ($p = q = 2$), q-ROFS ($p = q$) and so on.

Introducing the *p, q* Quasirung Orthopair Fuzzy Number (p, q-QOFN) allows us to preserve the basic definition and characteristics of *p, q*-QOFS while proceeding with further definitions.

Definition 5. Operation on p, q-QOFNs: Let, $\wp = (\mu, \vartheta)$, $\wp_1 = (\mu_1, \vartheta_1)$ and $\wp_2 = (\mu_2, \vartheta_2)$ are any three p, q-QOFNs. Then the following operations are defined.
operations are defined

5a. $\wp_1 \le \wp_2$ iff $\mu_1 \le \mu_2$ and $\vartheta_1 \ge \vartheta_2$

5b. $\wp_1 = \wp_2$ iff $\mu_1 = \mu_2$ and $\vartheta_1 = \vartheta_2$

5c. $\wp_1 \oplus \wp_2 = \left(\sqrt[p]{\mu_1^p + \mu_2^p - \mu_1^p \mu_2^p}, \vartheta_1 \vartheta_2 \right)$

5d. $\wp_1 \otimes \wp_2 = \left(\mu_1 \mu_2, \sqrt[q]{\vartheta_1^q + \vartheta_2^q - \vartheta_1^q \vartheta_2^q} \right)$

5e. $\alpha \wp = (\sqrt[p]{1 - (1 - \mu^p)^\alpha}, \vartheta^\alpha)$, where $\alpha \ge 0$ is a real number used as a scalar multiplier.

5f. $\wp^\alpha = (\mu^\alpha, \sqrt[q]{1 - (1 - \vartheta^q)^\alpha})$, where α is used as a power.

5g. $\wp^c = (\vartheta, \mu)$ (Complement of $\wp$)

Definition 6. Score and Accuracy function: The score function can be defined as follows:

$$\Diamond(\wp) = \frac{1+\mu^{p} - \vartheta^{q}}{2};\ 0 \le \Diamond(\wp) \le 1 \tag{5}$$

It may be noted that $\Diamond(\wp)$ increases monotonically while μ increases and monotonically decreases as ϑ increases.

The accuracy function is obtained as

$$\Lambda(\wp) = \mu^{p} + \vartheta^{q};\ 0 \le \Lambda(\wp) \le 1 \tag{6}$$

The p, q-QOFNs are compared according to the following rules

i) If $\Diamond(\wp_1) < \Diamond(\wp_2)$ then $\wp_1 \prec \wp_2$

ii) If $\Diamond(\wp_1) > \Diamond(\wp_2)$ then $\wp_1 \succ \wp_2$

iii) If $\Diamond(\wp_1) = \Diamond(\wp_2)$ then

$\Lambda(\wp_1) < \Lambda(\wp_2) \Rightarrow \wp_1 \prec \wp_2$

$\Lambda(\wp_1) > \Lambda(\wp_2) \Rightarrow \wp_1 \succ \wp_2$

$\Lambda(\wp_1) = \Lambda(\wp_2) \Rightarrow \wp_1 = \wp_2$

Definition 7. Aggregation

Let, $\wp_k = (\mu_k, \vartheta_k);\ \mathrm{k} = 1, 2 \ldots k$ is a series of p, q-QOFNs with corresponding weight values denoted by ω_k such that $\omega_k > 0; \sum_{k=1}^{k} \omega_k = 1$. Then, the definitions of the p, q-QOF weighted averaging (p, q-QOFWA) and p, q-QOF weighted geometric (p, q-QOFWG) aggregations are given below.

$$p,q-QOFWA(\wp_1,\wp_2,\ldots\wp_k) = \mathop{\oplus}_{k=1}^{k} \omega_k \wp_k = \begin{pmatrix} \sqrt[p]{1-\prod_{k=1}^{k}(1-\mu_k^{p})^{\omega_k}}, \\ \prod_{k=1}^{k} \vartheta_k^{\omega_k} \end{pmatrix} \tag{7}$$

$$p,q-QOFWG(\wp_1,\wp_2,\ldots\wp_k) = \mathop{\otimes}_{k=1}^{k} \wp_k^{\ \omega_k} = \begin{pmatrix} \prod_{k=1}^{k} \mu_k^{\omega_k}, \\ \sqrt[q]{1-\prod_{k=1}^{k}(1-\vartheta_k^{q})^{\omega_k}} \end{pmatrix} \tag{8}$$

Definition 8. Interaction operations for p, q-QOFNs: The definitions proposed by Riaz et al., [13] for q-ROFNs can be extended to derive the interactive operations for p, q-QOFNs as follows:

8a. $\wp_1 \mathop{\oplus}_{\text{int}} \wp_2 = \left(\sqrt[p]{\mu_1^p + \mu_2^p - \mu_1^p \mu_2^p}, \sqrt[q]{\vartheta_1^q + \vartheta_2^q - \vartheta_1^q \vartheta_2^q - \vartheta_1^q \mu_2^p - \mu_1^p \vartheta_2^q} \right)$

8b. $\wp_1 \mathop{\otimes}_{\text{int}} \wp_2 = \left(\sqrt[p]{\mu_1^p + \mu_2^p - \mu_1^p \mu_2^p - \vartheta_1^q \mu_2^p - \mu_1^p \vartheta_2^q}, \sqrt[q]{\vartheta_1^q + \vartheta_2^q - \vartheta_1^q \vartheta_2^q} \right)$

8c. $\lambda \wp = \left(\sqrt[p]{1-(1-\mu^p)^{\lambda}}, \sqrt[q]{(1-\mu^p)^{\lambda} - (1-\mu^p-\vartheta^q)^{\lambda}} \right); \lambda > 0$

8d. $\wp^{\lambda} = \left(\sqrt[p]{(1-\vartheta^q)^{\lambda} - (1-\mu^p-\vartheta^q)^{\lambda}}, \sqrt[q]{1-(1-\vartheta^q)^{\lambda}} \right); \lambda > 0$

Definition 9. p, q-QOF interaction weighted averaging: By generalizing the definitions of Riaz et al., [13], the p, q-QOF interaction weighted averaging (p, q-QOFIWA) and p, q-QOF interaction weighted geometric averaging (p, q-QOFIWG) operators can be defined as follows:

$$p,q-QOFIWA(\wp_1,\wp_2,....\wp_k)=\overset{k}{\underset{s=1}{\oplus}}\omega_s\wp_s$$
$$=\left(\begin{array}{l}\sqrt[p]{1-\prod_{s=1}^{k}(1-\mu_s^p)^{\omega_s}},\\ \sqrt[q]{\prod_{s=1}^{k}(1-\mu_s^p)^{\omega_s}-\prod_{s=1}^{k}(1-\mu_s^p-\vartheta_s^q)^{\omega_s}}\end{array}\right) \tag{9}$$

$$p,q-QOFIWG(\wp_1,\wp_2,....\wp_k)=\overset{k}{\underset{s=1}{\otimes}}\wp_s^{\;\omega_s}$$
$$=\left(\begin{array}{l}\sqrt[p]{\prod_{s=1}^{k}(1-\vartheta_s^q)^{\omega_s}-\prod_{s=1}^{k}(1-\mu_s^p-\vartheta_s^q)^{\omega_s}},\\ \sqrt[q]{1-\prod_{s=1}^{k}(1-\vartheta_s^q)^{\omega_s}}\end{array}\right) \tag{10}$$

2.2 The Suggested Model

In this section, the mathematical notion of the Subjective & SITDE integrated weighting approach used for weighting the criteria and the RAM method used for the ranking of the alternatives is shown.

2.2.1 Subjective approach using mathematical notion of the p, q-QROF sets

Step 1. Computing the subjective weights of the criteria: In this step, subjective weights of the criteria are calculated following the mathematical notions of the p, q – QOFSs.

Step 1(a). At this stage, experts evaluate each criterion based on their knowledge, experience, and expertise regarding their impact and importance. Experts consider the linguistic assessment scale given in Table 1.

Table 1
Linguistic assessment scales and their corresponding p, q – QOFNs

Level	Linguistic description	p, q - QOFN	
		μ	ϑ
9	Extremely Good (EG)	0.9	0.1
8	Very Very Good (VVG)	0.8	0.2
7	Very Good (VG)	0.7	0.3
6	Medium Good (MG)	0.6	0.4
5	Medium (M)	0.5	0.5
4	Medium Bad (MB)	0.4	0.6
3	Bad (B)	0.3	0.7
2	Very Bad (VB)	0.2	0.8
1	Very Very Bad (VVB)	0.1	0.9

Step 1(b). In the second step of subjective weighting, the experts' evaluations are collected and the p, q – QOFNs corresponding to Table 1 are converted. Then these numbers are aggregated with the help of Eqs (7) and (8).

Step 1(c). The score function values for p, q – QOFNs combined in the next step are calculated using Eq. (5).

Step 1(d). The score function values obtained in the last step are normalized, and the subjective weight values of the criteria are calculated. For this, Eq. (11) is employed.

$$w_{ij}^{SUB} = \frac{\Diamond(\wp)}{\sum_{i=1}^{n} \Diamond(\wp)} \tag{11}$$

2.2.2 p, q – QOF-SITDE algorithm for identifying the objective weights of the criteria

Step 2. The SITDE approach, developed by Gopisetty and Sama [7], provides a novel framework for objective weighting in MCDM. Unlike classical methods like Entropy, CRITIC, or MEREC, which rely on the assumption of symmetric distributions, SITDE incorporates skewness to directly handle distributional asymmetry.

Step 2(a). Generation of the decision matrix: The process begins with collecting responses from experts $E_g\ (g = 1,2,....,r)$, who evaluate the alternatives $A_i\ (i = 1,2,...,m)$ with respect to various criteria $C_j\ (j = 1,2,....,n)$.

$\beta_{ij}^{g} = \left(\mu_{ij}^{g}, \vartheta_{ij}^{g}\right)$ is the assessment of the i^{th} alternative subject to j^{th} criterion as opined by the g^{th} specialist. The experts perform these linguistic appraisals considering linguistic terms given in Table 1.

Step 2(b). Aggregation of the individual ratings using p, q-QOFIWA operation: the aggregation operations are performed using Eq. (9).

Step 2(c). Deriving the score values for constructing the decision matrix: Eq. (5) is employed to calculate the score values. Consequently, we derive the crisp decision matrix, which is given as follows:

$$\Delta = \begin{array}{c} \\ A_1 \\ A_2 \\ .. \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & ...... & C_j \end{array} \\ \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{pmatrix} \end{array} \tag{12}$$

Step 3. Once the initial decision matrix is obtained, the basic algorithm of the SITDE method is followed for the determination of objective criterion weights.

Step 3(a). Construct the initial performance matrix, as presented in Eq. (12). This matrix consists of *m* alternatives, denoted as $A_i\ (i = 1,2,...,m)$, and *n* criteria, represented as $C_j\ (j = 1,2,....,n)$.

In Eq. (12), y_{pq} denotes the performance value of the i^{th} alternative against the j^{th} criterion.

Step 3(b). In this step, the normalized performance matrix is created. This process is mandatory for the criteria to become comparable because they have different qualities. The SITDE approach considers the criteria according to whether they are cost or benefit criteria, and these normalization processes are conducted with the help of Eq. (13).

$$r_{ij} = \begin{cases} \dfrac{\min y_{ij} \left| i = 1,2,...,m \right.}{y_{ij}}, \ if \ i \in B \\ \dfrac{y_{ij}}{\max y_{ij} \left| i = 1,2,...,m \right.}, \ if \ i \in C \end{cases} \tag{13}$$

In Eq. (13), *B* symbolizes the beneficial, and *C* denotes the cost criteria.

Step 3(c). Calculate the standard deviation of each criterion within the normalized performance matrix. The standard deviation corresponding to the i^{th} criterion, denoted by σ_i is computed as follows:

$$\sigma_j = \left[\frac{\sqrt{\sum_{i=1}^{m} \left(r_{ij} - \bar{r}_j \right)^2}}{m} \right] \tag{14}$$

Here, the term $\bar{r}_q$ depicts the arithmetic mean of the normalized values corresponding to criterion j, and with the help of Eq. (15) are identified as follows:

$$\bar{r}_j = \left[\frac{\sqrt{\sum_{i=1}^{m} r_{ij}}}{m} \right] \tag{15}$$

Step 3(d). In this step, the coefficients of skewness, indicating the asymmetry in each criterion's score distribution, is computed for each normalized criterion employing Eq. (16).

$$s_i = \left[\frac{m}{(m-1)(m-2)} \sum_{i=1}^{m} \left(\frac{r_{ij} - \bar{r}_j}{\sigma_j} \right)^3 \right] \tag{16}$$

Step 3(e). Standardize the calculated skewness values. At this stage, the skewness coefficients obtained from the distribution of each criterion are normalized by applying the transformation procedure given in Eq. (17).

$$ls_i = \left| \left((s_i + 1) + \left(\left| \min(s_i) \right| + 1 \right) \right) \right| \tag{17}$$

Step 3(f). The preliminary objective weight values assigned to each criterion are computed.

$$w_j^{OBJ} = \frac{ls_i}{\sum_{j=1}^{n} ls_i} \tag{18}$$

Step 4. The application of multiple MCDM algorithms to determine criterion weights may lead to slight inconsistencies in the resulting coefficients. These variations primarily arise from the methodological diversity of the techniques, each relying on distinct computational frameworks and evaluation logics. To overcome this issue and enhance the robustness of the weighting process, this study employs a non-linear weight integration-based aggregation operator [14-15]. This approach consolidates the outcomes of different MCDM methods, thereby ensuring a more coherent, stable, and representative allocation of criterion weights. By jointly incorporating the insights of multiple weighting techniques, the proposed operator produces optimized coefficients that provide a more balanced and objective assessment of criterion importance. Specifically, the weights obtained through Subjective and SITDE are integrated using the non-linear aggregation formula presented below:

$$w_j^{\text{int}} = \frac{\left(w_j^{SUBJ} \right)^{\xi} \left(w_j^{OBJ} \right)^{\varphi}}{\sum_{j=1}^{n} \left(w_j^{SUBJ} \right)^{\xi} \left(w_j^{OBJ} \right)^{\varphi}} \tag{19}$$

Here, w_j^{int} denotes the integrated weight of the j^{th} criterion, while $\left(w_j^{SUBJ}\right)^{\xi}$ and $\left(w_j^{OBJ}\right)^{\varphi}$ represent the individual weights of the criterion C_j as computed via the SITDE and subjective procedures, respectively. The parameters ξ and φ, where ξ, $\varphi \in [0, 1]$, serve as priority factors, reflecting the relative emphasis assigned to the SITDE and subjective methodologies within the integration framework. Eq. (19) is structured to support decision makers (DMs) in articulating their relative preference for either weighting procedure through prioritization parameters. For instance, to reflect a stronger methodological preference for the SITDE than the subjective procedure, the DM can increase the value of ξ within the interval [0, 1], amplifying its influence in the final weight computation. Lastly, it is worth noting that, in generating the initial solution, both prioritization parameters were assigned a value of 0.5, thereby ensuring equal contribution from the SITDE and subjective procedures within the integrated weighting structure.

2.2.3 p, q – QOF-RAM algorithm for identifying the ranking performance of the alternatives

Step 5. At this stage, the Root Assessment Method (RAM) approach, a ranking method developed by Sotoudeh-Anvari [16], is used to determine the relative importance of alternatives and rank them. There are some main reasons for choosing this method. Firstly, unlike traditional decision-making approaches, this approach uses a different degree of balance and compensation between cost and benefit criteria. In addition, the process does not bother to make pairwise comparisons, and parameter changes do not affect the results. At the same time, the RAM method resists the rank reversal problem compared to traditional ranking approaches. In addition, this approach was expanded with the help of p, q – QOF sets in this study, and the method was given the ability to manage uncertainties, ambiguities, and expert hesitations more effectively.

Step 5(a). The first step of the RAM method is the same as the first step of the SITDE method. The first decision matrix obtained from the calculations performed in Step 2 by following the mathematical notion of p, q – QOF sets is used in the same way in this step.

Step 5(b). Apply the linear sum normalization formula given in Eq. (20) to standardize the decision matrix.

$$r_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}, \ \left(j = 1, 2, ..., n\right) \tag{20}$$

Step 5(c). The weighted normalized decision matrix is derived through the application of Eq. (21).

$$x_{ij} = r_{ij} w_j^{int}, \ \left(j = 1, 2, ..., n\right) \tag{21}$$

Step 5(d). The sums of the weighted normalized scores associated with beneficial and non-beneficial criteria for the i^{th} alternative are obtained through Eqs. (22) and (23).

$$s_{+i} = \sum_{i=1}^{n} x_{+ij} \tag{22}$$

$$s_{-i} = \sum_{i=1}^{n} x_{-ij} \tag{23}$$

In the above equations, s_{+i} represents the sum of the weighted normalized values for the beneficial criteria, while s_{-i} denotes the sum of the weighted normalized values for the non-beneficial criteria.

Step 5(e). The overall score for each alternative is determined using the aggregation function below:

$$RI_i = \sqrt[2+S_{-i}]{2 + s_{+i}}, \ \left(j = 1, 2, ..., n\right) \tag{24}$$

Step 5(f). The ranking of alternatives is determined by the magnitude of their RI_i values. A higher RI_i value indicates a greater priority for the alternative A_i. In other words, alternatives with larger RI_i values are considered superior options.

Before delving further into the details of RAM, it is important to clarify the role of the constant value "2" in the radicand and index of Formula (4). The sums of the weighted normalized scores for beneficial criteria (s_{+i}) and cost criteria (s_{-i}) for each alternative is typically less than one. This arises because normalization constrains the elements of the decision matrix to the range [0, 1], and these normalized values are subsequently multiplied by the criteria weights, which are themselves less than one, to produce the weighted normalized scores. As a result, the raw radical expression, $\sqrt[s_{-i}]{s_{+i}}$, can yield unreliable or undefined results.

In certain cases, all decision criteria may be cost-type, resulting in $s_{+i} = 0$. To address this, a constant value of +2 is added to the radicand to ensure a meaningful outcome. Similarly, when all criteria are benefit-type, $s_{-i} = 0$ may be zero. Again, adding the same constant (+2) prevents the calculation from involving a 0^{th} root, which is mathematically undefined. This adjustment guarantees that the RAM formula produces distinct and valid results across all scenarios.

3. A Numerical Illustration

In this section, the integrated decision-making model introduced above has been applied to the decision-making problem related to the determination of advanced technology, which is the top priority in adopting and integrating into cold chains, and the results obtained have been summarized and discussed.

3.1 The Preparation Process

Before proceeding to the proposed model's mathematical operations and implementation steps, a preparation process was designed in which applications such as defining the research problem, forming the expert board, determining the criteria and alternatives, and collecting linguistic data related to them were carried out.

3.1.1 Problem description

This study aims to identify advanced technologies from Industry 4.0 (IoT sensor systems; blockchain-based traceability platforms; cloud-based management software; AI/ML-powered forecasting and optimization tools) as a multi-criteria, ambiguous, and expert-based decision problem that should be adopted and integrated into business processes as a result of operational, environmental, regulatory, and stakeholder-oriented multi-criteria-based evaluation. The decision problem includes the following components: (*i*) multiple performance metrics of advanced technologies (cost of installation, data security, traceability, ease of use, integration potential, energy consumption, system reliability, compliance with standards, scalability, environmental impact, stakeholder acceptance), (*ii*) linguistic and hesitant evaluations of decision makers, (*iii*) contradictions between criteria and skewness of distributions, and (*iv*) parametric modeling of uncertainty.

The solution objective is to rank the alternatives by considering these structural uncertainties and contradictions, and to provide a transparent technology selection guide that can be applied at the enterprise level. For this purpose, the study was based on uncertainty-based assessment expressed with p, q-Quasirung Orthopair Fuzzy Sets; non-linear integration of subjective (expert linguistic) and SITDE weighting approaches; and RAM-based sequencing.

3.1.2 Construction of the Experts Panel

A committee of experts was formed to reflect the multidimensional structure of the study's research problem. In this context, people with expertise in logistics, information technologies, food safety, and sustainability were identified, and a candidate pool was created. Nine candidates were selected, and the four experts who best met the determined criteria preferred participation on the board. The candidates' academic qualifications, professional experience, field suitability, and multifaceted perspectives were considered during the selection process. Regarding scholarly competence, having at least a master's degree and at least ten years of professional experience were among the basic conditions. In addition, the priority evaluation factors were that the candidates specialized in a field directly related to the criterion set of the study and had both academic and sectoral experience.

As a result of this process, U1 (Logistics and Supply Chain, 16 years of experience, PhD) for its contributions to the integration of logistics processes and cost management; U2 (Information and Communication Technologies, 12 years of experience, Master's Degree) thanks to its expertise in digital infrastructures, data security and blockchain technologies; U3 (Food Safety and Cold Storage, 18 years of experience, PhD) due to its knowledge in quality management, cold storage and traceability of food products; U4 (Sustainability and Industry 4.0, 10 years of experience, PhD) was included in the board with his studies on environmental impact, energy consumption and Industry 4.0 perspective. Thus, the board is structured to cover technological, operational, food safety, and sustainability dimensions in a balanced manner.

3.1.3 Identification of the Criteria and Alternatives

The criteria and alternatives used in this study were determined systematically to holistically evaluate the selection process of advanced technologies in cold chain logistics. First, a literature review was conducted, sectoral reports were examined, and expert opinions were obtained. Since operational, environmental, and regulatory dimensions come to the fore due to the nature of the cold chain, a set of criteria has been created to reflect this multidimensionality. In this context, Installation Cost is an economic factor that directly affects the applicability of technologies, since Data Security is one of the most critical risk areas of digital solutions; Traceability Capability, product safety, and regulation compliance to ensure compliance; Ease of Use has been chosen to increase the effectiveness of the application processes. Integration Potential represents the ability to adapt with existing supply chain infrastructures; Energy Consumption and Environmental Impact criteria have enabled sustainability-oriented evaluation. System Reliability ensures the sustainability of uninterrupted operations; Compliance and Standards ensure compliance with regulatory frameworks; Flexibility and Scalability are the ability of technologies to adapt to the future; Customer/Supplier Acceptance is included to measure stakeholders' approach to technology and willingness to adopt it (Table 2).

Table 2
The identified criteria set

Code	Criteria	Code	Criteria
C1	Installation Cost	C7	System Reliability
C2	Data Security	C8	Compatibility and Standards
C3	Traceability	C9	Flexibility and Scalability
C4	Ease of Use	C10	Environmental Impact
C5	Integration Potential	C11	Customer/Supplier Acceptance
C6	Energy Consumption		

In selecting alternatives (Table 3), technologies that stand out in cold chain logistics today and have a high potential for transformation were considered. IoT Sensor Systems are essential as they allow real-time monitoring of critical parameters such as temperature and humidity. Blockchain platforms have been considered to provide transparent and reliable traceability of products throughout the supply chain. Cloud Software has been among the alternatives due to its ease of data storage, sharing, and management, and its potential to increase operational efficiency. Finally, AI/ML Solutions were evaluated for their contribution to intelligent decision-making processes, including demand forecasting, routing optimization, and risk management.

Table 3
The determined advanced technologies for cold chains

Code	Criteria
A1	IoT Sensor Systems
A2	Blockchain Platforms
A3	Cloud Software
A4	AI/ML Solutions

The criteria and alternatives determined within this framework reflect the scope of the research problem holistically, allowing the study to analyze technologies comparatively with a multi-criteria decision-making approach.

3.1.4 Collecting p, q – QOF Data regarding the Criteria and Alternatives

The study collected expert opinions on evaluating criteria and alternatives in two separate stages. In the first stage, experts were brought together to determine the importance of the criteria used in the research problem. In this process, each expert evaluated the relative importance of the criteria in the context of the situation through the statements in the linguistic assessment scale in Table 1. Thus, the importance levels of the criteria were obtained based on the experts' linguistic preferences.

In the second stage, the performance of the alternatives against the determined criteria was evaluated. The experts expressed the level at which each alternative meets each criterion, again based on the linguistic terms given in Table 1. In this way, the strengths and weaknesses of the other options were revealed through linguistic expressions, and the evaluations obtained were then converted into numerical form and included in the analysis process. In both stages, the experts' evaluations were made by considering the linguistic scales defined in Table 1, so that both the weights of the criteria and the performance values of the alternatives were obtained consistently and comparably.

3.2 Calculation of the Weights of the Criteria

At this stage, in order to determine the weights of the Criteria, first the subjective criterion weights were calculated by using the mathematical applications of the p, q – QOF sets, then the objective weights of the Criteria were calculated by following the basic algorithm of the p, q – QOF based SITDE approach, and then the final criterion weight values were obtained by combining these subjective and objective weights.

3.2 Calculation of the subjective weights of the criteria

At this stage, in order to determine the weights of the Criteria, first the subjective criterion weights were calculated by using the mathematical applications of the p, q – QOF sets, then the objective weights of the Criteria were calculated by following the basic algorithm of the p, q – QOF based SITDE approach, and then the final criterion weight values were obtained by combining these subjective and objective weights.

Step 1. The subjective weights of the criteria were calculated following the mathematical definitions of p, q – QOFSs. Accordingly, the experts evaluated each criterion based on their knowledge, experience, and expertise about the impact and importance of the criteria. The linguistic scale given in Table 1 was considered in the evaluations. Table 4 shows the linguistic assessments of the experts.

Table 4
Linguistic assessment of the experts

Codes	Criteria	DM1	DM2	DM3	DM4
C1	Installation Cost	VG	M	MG	MG
C2	Data Security	MG	EG	VVG	VG
C3	Traceability	VVG	VVG	EG	VVG
C4	Ease of Use	MG	VG	MG	MG
C5	Integration Potential	VVG	EG	VG	VVG
C6	Energy Consumption	VG	MG	MG	VVG
C7	System Reliability	EG	VVG	VVG	VG
C8	Compatibility and Standards	VG	VG	EG	VVG
C9	Flexibility and Scalability	EG	VVG	VG	VG
C10	Environmental Impact	MG	M	VVG	EG
C11	Customer/Supplier Acceptance	VVG	VG	VG	VVG

Then, in the second stage of subjective weighting, the experts' evaluations were collected and converted into p, q – QOFN values corresponding to Table 1. Later, these values were concatenated with the help of Eqs. (7) and (8). The score function values of the combined p, q – QOFNs were calculated using Eq. (5). The score function values obtained in the last step were normalized, and the subjective weights of the criteria were calculated. Eq. (11) was used for this operation. As a result, the subjective weight values of the criteria were reached by systematically following the steps. Table 5 shows the combined p, q – QOFNs, score function values, and final weights of the criteria obtained after the calculations.

Table 5
The final results of the computations

Codes	Criteria	μ	ϑ	Score Val.	Weight
C1	Installation Cost	0.6118	0.6249	0.4192	0.0824
C2	Data Security	0.7879	0.7409	0.4701	0.0924
C3	Traceability	0.8333	0.7801	0.4851	0.0953
C4	Ease of Use	0.6299	0.6251	0.4296	0.0844
C5	Integration Potential	0.8174	0.7648	0.4807	0.0944
C6	Energy Consumption	0.6936	0.6627	0.4473	0.0879
C7	System Reliability	0.8174	0.7648	0.4807	0.0944
C8	Compatibility and Standards	0.7996	0.7481	0.4758	0.0935
C9	Flexibility and Scalability	0.7996	0.7481	0.4758	0.0935
C10	Environmental Impact	0.7670	0.7334	0.4566	0.0897
C11	Customer/Supplier Acceptance	0.7570	0.7043	0.4689	0.0921

3.3 Calculation of the objective weights of the criteria

At this stage, the objective weights of the criteria were calculated by following the basic algorithm of the p, q – QOF-based SITDE approach. The results obtained are shown below.

Step 2. At this stage, the experts were asked to evaluate the performance of the alternatives against various criteria, and the experts made their evaluations using the linguistic terms given in

Table 1. Then, individual evaluations were aggregated with the p, q–QOFIWA process. This process was carried out with the help of Eq. (9). Score values were obtained to create the decision matrix. As a result of these score values calculated using Eq. (5), the first decision matrix shown in Table 6 was obtained.

Table 6
The initial decision matrix

Codes	A1	A2	A3	A4
C1	0.6363	0.4375	0.6037	0.5545
C2	0.6574	0.8595	0.7119	0.7360
C3	0.8073	0.8595	0.7119	0.7119
C4	0.6574	0.5280	0.7744	0.6037
C5	0.6858	0.6858	0.8354	0.7360
C6	0.6574	0.5337	0.6363	0.5545
C7	0.7360	0.6574	0.7360	0.6265
C8	0.7314	0.7383	0.7119	0.6858
C9	0.7360	0.6265	0.7538	0.8354
C10	0.6889	0.7146	0.6141	0.7146
C11	0.7119	0.6037	0.7360	0.6574

For example, the element value in cell C1-A1 is calculated as follows.

$$\Diamond(\wp)_{A1-C1} = \frac{1+\left(1-\left(\left(\left(0.8^3\right)\left(0.6^3\right)\left(0.7^3\right)\left(0.7^3\right)\right)^{0.25}\right)^{\frac{1}{3}}\right)^{\frac{1}{3}} - \left(\left(\left(\left(0.8^3\right)\left(0.6^3\right)\left(0.7^3\right)\left(0.7^3\right)\right)^{0.25}\right)-\left(\left(\left(\left(0.8^3-0.2^2\right)\left(0.6^3-0.4^2\right)\left(0.7^3-0.3^2\right)\left(0.7^3-0.3^2\right)\right)^{0.25}\right)^{\frac{1}{2}}\right)\right)^2}{2} = 0.6363$$

Step 3. Once the initial decision matrix was obtained, the basic algorithm of the SITDE method was applied to determine the objective weights of the criteria. First, the performance matrix was created as shown in Eq. (12). This matrix consisted of m alternatives and n criteria. Here, each matrix element shows the performance value of alternative i against criterion j. Then, with the help of Eq. (13), the normalized performance matrix was obtained (Table 7).

Table 7
The normalized decision matrix

Codes	A1	A2	A3	A4
C1	1.0000	0.6876	0.9488	0.8715
C2	1.0000	0.7648	0.9234	0.8931
C3	0.8818	0.8283	1.0000	1.0000
C4	0.8032	1.0000	0.6818	0.8746
C5	1.0000	1.0000	0.8208	0.9318
C6	1.0000	0.8120	0.9679	0.8435
C7	0.8512	0.9531	0.8512	1.0000
C8	0.9377	0.9288	0.9633	1.0000
C9	0.8512	1.0000	0.8311	0.7499
C10	0.8915	0.8594	1.0000	0.8594
C11	0.8480	1.0000	0.8202	0.9184

Then, the standard deviation for each criterion was calculated using Eq. (14). Immediately afterwards, the arithmetic mean of each criterion was determined with the help of Eq. (15). Table 8 shows the standard deviation and arithmetic mean values for the criteria.

Table 8
σ_j and $\bar{r}_j$ values for the criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
σ_j	0.1369	0.0979	0.0865	0.1331	0.0846	0.0921	0.0748	0.0319	0.1043	0.0667	0.0803
r_j	0.8770	0.8953	0.9275	0.8399	0.9381	0.9059	0.9139	0.9574	0.8581	0.9026	0.8966

In the following substep, the coefficients of skewness, indicating the asymmetry in each criterion's score distribution, was computed for each normalized criterion employing Eq. (16). Then, skewness values were normalized using Eq. (17). In the last step, criterion weights were determined with the help of Eq. (18) using these values. Table 9 shows the results obtained.

Table 9
Final weight values of the criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	0.7267	1.2205	-0.1475	-0.0209	0.3913	1.0698	-0.5867	-0.2379	-0.0003	-0.0046	-0.2224
A2	-2.6494	-2.3660	-1.5108	1.7385	0.3913	-1.0616	0.1435	-0.7209	2.5223	-0.2714	2.1296
A3	0.1445	0.0234	0.5883	-1.6748	-2.6694	0.3068	-0.5867	0.0061	-0.0172	3.1175	-0.8604
A4	-0.0001	0.0000	0.5883	0.0177	-0.0004	-0.3104	1.5239	2.3724	-1.1162	-0.2714	0.0198
s_i	-1.1855	-0.7481	-0.3212	0.0403	-1.2582	0.0031	0.3293	0.9465	0.9257	1.7134	0.7111
ls_i	0.7288	0.9203	1.0774	1.1935	0.6931	1.1821	1.2775	1.4362	1.4312	1.6037	1.3786
w_j^{OBJ}	0.0564	0.0712	0.0834	0.0924	0.0536	0.0915	0.0989	0.1111	0.1108	0.1241	0.1067

Step 4. Then, subjective and objective criterion weights were combined using equation 19, and ζ and φ parameters were used for this, and both were taken as 0.5 in this study (Table 10).

Table 10
Subjective, objective, and integrated criteria weights

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
w_j^{sub}	0.0824	0.0924	0.0953	0.0844	0.0944	0.0879	0.0944	0.0935	0.0935	0.0897	0.0921
w_j^{obj}	0.0564	0.0712	0.0834	0.0924	0.0536	0.0915	0.0989	0.1111	0.1108	0.1241	0.1067
w_j^{int}	0.0687	0.0817	0.0898	0.0890	0.0717	0.0903	0.0974	0.1027	0.1025	0.1063	0.0999
Rank	11	9	7	8	10	6	5	2	3	1	4

According to the results, C10 Environmental Impact has been determined as the most critical and influential criterion for selecting and prioritizing advanced technologies for cold chains. This is followed by C8 Compliance and Standards and C9 Flexibility and Scalability criteria, respectively. The rest are listed as C11 Customer/Supplier Acceptance > C7 System Reliability > C6 Energy Consumption > C3 Traceability Capability > C4 Ease of Use > C2 Data Security > C5 Integration Potential > C1 Installation Cost.

3.3 Identification of the Advanced Technology Alternatives

Step 5. At this stage, the relative importance of the alternatives was determined, and their ranks were established using the Root Assessment Method (RAM) approach, a ranking method developed by Sotoudeh-Anvari [16]. The first step of the RAM method was the same as the first step of the SITDE method. In the second step, the first decision matrix obtained following the mathematical structure of p,q–QOF sets was used similarly in this stage.

Then, the linear sum normalization formula given in Eq. (20) was applied to standardize the first decision matrix. Table 11 shows the normalized decision matrix with normalized values.

Table 11
The normalized decision matrix

Codes	A1	A2	A3	A4
C1	0.0000	1.0000	0.1640	0.4114
C2	0.0000	1.0000	0.2700	0.3890
C3	0.6464	1.0000	0.0000	0.0000
C4	0.5249	0.0000	1.0000	0.3072
C5	0.0000	0.0000	1.0000	0.3356
C6	0.0000	1.0000	0.1705	0.8321
C7	1.0000	0.2818	1.0000	0.0000
C8	0.8675	1.0000	0.4977	0.0000
C9	0.5241	0.0000	0.6092	1.0000
C10	0.7438	1.0000	0.0000	1.0000
C11	0.8180	0.0000	1.0000	0.4056

The weighted normalized decision matrix was obtained using Eq. (21) in the next step. Afterwards, the sums of the weighted normalized scores associated with the benefit and cost criteria of the alternatives were calculated using Eqs. (22) and (23). The integration function given in Eq. (24) determined the total score for each alternative. The order of the options was made according to the magnitude of the values obtained. A higher value indicates that the relevant alternative is more prioritized. Therefore, alternatives with great value have been considered superior options. Table 12 shows the results obtained regarding the ranking of the alternatives.

Table 12
The weighted normalized matrix and the obtained results

Codes	A1	A2	A3	A4
C1	0.0000	1.0000	0.1640	0.4114
C2	0.0000	1.0000	0.2700	0.3890
C3	0.6464	1.0000	0.0000	0.0000
C4	0.5249	0.0000	1.0000	0.3072
C5	0.0000	0.0000	1.0000	0.3356
C6	0.0000	1.0000	0.1705	0.8321
C7	1.0000	0.2818	1.0000	0.0000
C8	0.8675	1.0000	0.4977	0.0000
C9	0.5241	0.0000	0.6092	1.0000
C10	0.7438	1.0000	0.0000	1.0000
C11	0.8180	0.0000	1.0000	0.4056
S_{+1}	0.5057	0.4080	0.4935	0.3325
S_{-i}	0.0000	0.1590	0.0267	0.1034
RI_i	1.5829	1.5024	1.5696	1.4958
Rank	1	3	2	4

The ranking results obtained show that the most prioritized advanced technology that should be prioritized is A1 IoT Sensor Systems, which is consistent with prior research emphasizing the role of wireless sensor-based IoT architectures in ensuring product safety and compliance in cold chains. This was followed by A3 Cloud Software, A2 Blockchain Platforms ranked third, and A4 AI/ML Solutions ranked last.

4. Robustness and Validity Check

A comprehensive soundness check was carried out at this stage. For this, firstly, the effect of the change in criterion weights on the ranking results was examined. Then, the values of the ξ and ϕ parameters were changed, and their impact on the results was observed. In the third stage, the resistance of the proposed model to the rank reversal problem was tested. In the first stage, the criteria weights were changed in 110 scenarios following the basic algorithm proposed by Görçün et al. [17]. Varying weight values in each scenario were included in the evaluation process, and the effect of these different weight values on the ranking results was observed. Figure 1 shows the impact of the changed weight values on the ranking results in 110 scenarios.

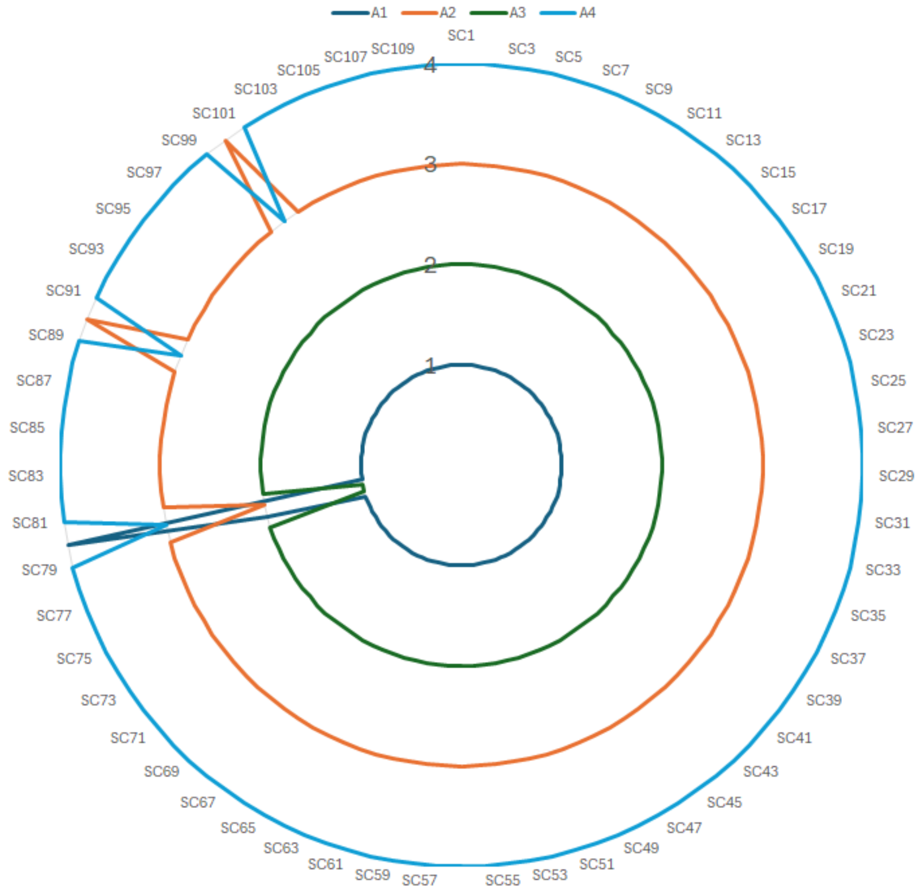

Fig. 1. New ranking results for 110 scenarios

As shown in Figure 1, when the weight values of the most effective criteria were changed by 80% or more, some changes were observed in the ranking results for the alternatives. On the other hand, it is not obvious that the weight value of a criterion decreases to this extent in real life conditions. While the ranking results of A1 and A3 changed in only two scenarios, the ranking results of A2 and A4 differed in 3 scenarios. In addition, the average similarity rate is calculated to be 97.7%, which is quite high if bird. These findings show that the proposed model is maximally resistant to changes in criterion weights.

In the second stage, the values of ξ and ϕ parameters were changed from 0 to 1, and ten scenarios were prepared for this. In each scenario where the values of these parameters were changed, the application of the sorting method used in this study was repeated. Figure 2 shows the results of this analysis.

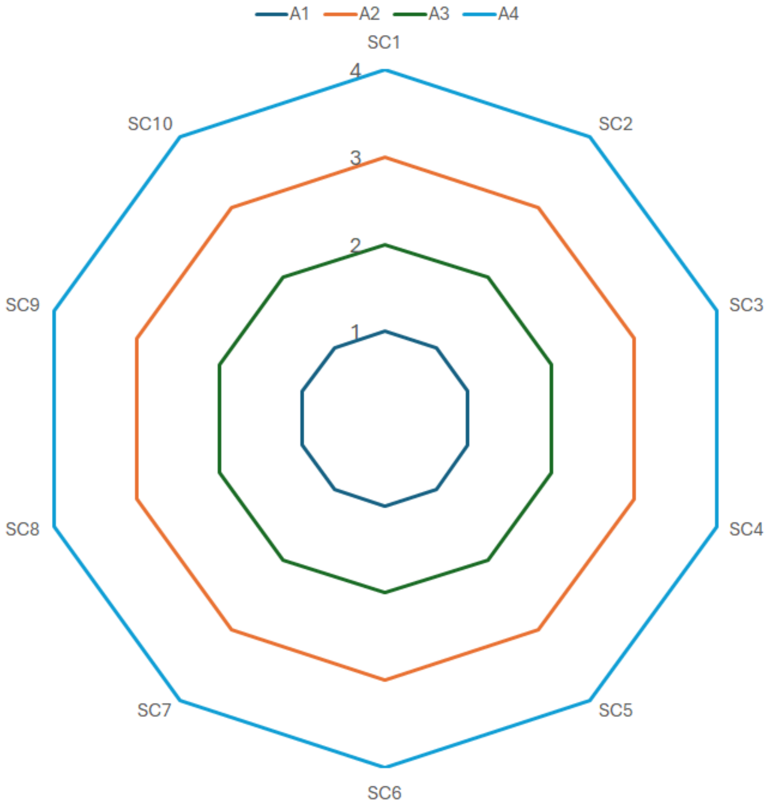

Fig. 2. Ranking results for ten scenarios

As can be seen in Figure 2, when the parameter values were changed, there was no change in the ranking results for the alternatives.

In the last stage, to measure the resistance of the proposed model to the rank reversal problem, the worst and next alternative in each scenario was extracted [18], the ranking methodology was applied again for the rest and the results obtained were examined. Table 13 presents the results of the rank reversal test.

Table 13
The results of the rank reversal test

Codes	Scenarios
Original	A1 >A3 >A2 > A4
SC2	A1 >A3 >A2
SC2	A1 >A3
SC3	A1

As shown in Table 13, although the worst alternative was extracted in each scenario, the ranking result did not change. This finding proves that the proposed model is resistant to the rank reversal problem.

5. Results

The findings of this study provide several noteworthy insights into the adoption of advanced technologies in cold chain logistics. Based on the integrated weighting approach, the most critical evaluation criterion was identified as environmental impact (C10), followed by compliance with standards (C8) and flexibility and scalability (C9). These results indicate that decision-makers in cold chain operations place greater emphasis on sustainability, regulatory alignment, and adaptability to future demands, rather than solely focusing on cost efficiency or ease of use. Such prioritization reflects the increasing pressures of environmental regulations, corporate sustainability strategies, and the dynamic nature of logistics infrastructures. In contrast, installation cost (C1) and integration potential (C5) were ranked lowest, suggesting that while economic considerations remain relevant, they are no longer the dominant drivers of technology adoption decisions in this sector.

Regarding technological alternatives, the results of the RAM method show that IoT-based sensor systems (A1) emerged as the most suitable solution for integration into cold chain business models. This finding underscores the pivotal role of real-time monitoring of temperature, humidity, and other critical parameters in ensuring product quality [19] and compliance. IoT sensors not only provide operational transparency but also directly support sustainability objectives by reducing spoilage and waste [20]. Cloud-based software (A3) ranked second, highlighting the importance of digital platforms for centralized data storage, accessibility, and process optimization. Meanwhile, blockchain platforms (A2) secured the third rank, indicating their growing but still secondary relevance compared to real-time monitoring tools. Finally, AI/ML solutions (A4), while recognized for their potential in forecasting and optimization, were ranked lowest—likely due to their higher complexity, implementation challenges, and the need for extensive data maturity.

The outcomes offer significant implications for both practitioners and policymakers:

Logistics firms should prioritize IoT sensor deployment as the foundational step in digital transformation. Once real-time monitoring and traceability are achieved, subsequent integration of cloud platforms and blockchain can further strengthen supply chain transparency and compliance.

The predominance of environmental criteria suggests that investments in technology are no longer just about efficiency but also about meeting sustainability goals. This aligns with global green policies, such as carbon neutrality commitments and waste reduction targets. The high ranking of compliance and standards highlights the need for policymakers to design clearer guidelines and incentive mechanisms. Governments can accelerate technology adoption by offering tax incentives or subsidies for firms adopting environmentally friendly and regulatory-compliant technologies.

Customer and supplier acceptance ranked relatively high (C11), signaling that successful adoption requires not only technological readiness but also stakeholder trust and willingness. Firms should, therefore, implement awareness and training programs to ensure smoother adoption.

This study reveals that the cold chain industry is undergoing a paradigm shift: firms increasingly perceive sustainability and compliance as sources of competitive advantage rather than constraints. Additionally, the relatively lower ranking of cost-related factors shows a broader acceptance that long-term benefits—such as reduced spoilage, compliance with green regulations, and enhanced reputation—outweigh short-term financial burdens. Importantly, the robustness analysis confirmed that the proposed framework maintains stable rankings even under significant changes in weights, ensuring reliability for real-world decision-making.

This study provides several methodological and theoretical innovations: By combining subjective (expert-driven) and objective (SITDE) weighting with RAM, the model bridges the gap between expert judgment and systematic data-driven approaches. The use of p, q-Quasirung Orthopair Fuzzy Sets enhances the capacity to model uncertainty, vagueness, and decision-maker hesitation more effectively than classical fuzzy sets. Unlike previous studies that focus narrowly on cost or technical performance, this framework incorporates sustainability, regulatory, and stakeholder dimensions, providing a comprehensive decision-making tool. The results remained highly stable across multiple scenarios, demonstrating the model's resistance to rank reversal and its suitability for complex real-world applications. Beyond theoretical contributions, the framework offers an actionable roadmap for logistics companies, policymakers, and supply chain managers seeking structured guidance in technology adoption.

In summary, the study demonstrates that IoT-based monitoring systems are the cornerstone of sustainable and resilient cold chain management, while complementary technologies such as cloud platforms, blockchain, and AI/ML play supporting but progressively important roles. By integrating advanced MCDM techniques, the proposed framework ensures a balanced and reliable evaluation that reflects the complexity of real-world logistics systems.

Ultimately, the findings underscore that the future of cold chain logistics lies in green, transparent, and digitally enabled systems. Firms that prioritize sustainability and compliance-driven technology adoption will not only enhance their operational efficiency but also secure long-term resilience in an increasingly competitive and regulated market environment. The methodological rigor and robustness of the proposed approach ensure that it can serve as a replicable template for decision-making in other domains of logistics and supply chain management, marking both a theoretical advancement and a practical contribution to the field.

6. Discussion

The findings of this research reveal a critical paradigm shift in the adoption of cold chain technology. In contrast to earlier studies, which, for example, Liang et al., [3] and East et al., [4] virtually solely emphasized economic or technical efficiency drivers, our outcomes demonstrate that today, sustainability and compliance drivers dominate decision-making. This aligns with subsequent research [4, 19] that also placed particular stress upon environmental pressures and regulatory regimes as deciding forces of supply chain digitalization. Our contribution extends these perspectives by combining both subjective expert information and objective distribution-based weighting (SITDE) in a formal fashion, guided through powerful sequencing with RAM.

Compared with well-known MCDM approaches such as AHP–TOPSIS or fuzzy DEMATEL, the proposed framework more accurately captures uncertainty, asymmetry, and expert hesitance. For instance, earlier research based on entropy- or CRITIC-based weighting often made symmetric distribution assumptions and could thus not reflect extreme evaluations from heterogeneous experts. Our SITDE-p,q-QROFS overcomes this limitation directly by offering a more robust and versatile modeling framework.

The role of IoT-based sensing systems as the most relevant technology is underpinned by existing literature [19] that cited the inherent significance of real-time monitoring. Nonetheless, our model also captures that cloud software is more relevant than blockchain use in current cold chain contexts. This departure from some past research highlights the fact that while blockchain is promising, its adoption is also hindered by integration complexity and high implementation cost.

Managerially, the results provide an adoption blueprint in a step-by-step manner:

i. Begin with IoT deployment for traceability and monitoring,
ii. Deploy cloud platforms for centralized data and operational effectiveness,
iii. Deploy blockchain for compliance and transparency,
iv. Incrementally explore AI/ML as data maturity and expertise develop.

This approach is especially applicable for companies in emerging economies, where limitations in resources and low digital maturity can hinder the parallel adoption at scale of all Industry 4.0 technologies.

7. Conclusion

This study developed and applied an integrated multi-criteria decision-making framework based on p, q-Quasirung Orthopair Fuzzy Sets, SITDE, and RAM to evaluate and prioritize advanced technology alternatives for cold chain logistics. The findings revealed that environmental impact, compliance with standards, and flexibility and scalability are the most influential criteria shaping technology adoption decisions. This reflects the growing importance of sustainability, regulatory alignment, and adaptability in an era where logistics operations face increasing pressures from green policies and dynamic supply chain demands. Among the alternatives, IoT-based sensor systems were identified as the most suitable technology, followed by cloud-based management software and blockchain platforms, while AI/ML solutions ranked lowest due to implementation challenges and data maturity requirements.

The study offers important managerial implications by demonstrating that logistics firms should strategically prioritize IoT-based solutions as a foundation for digital transformation and subsequently integrate cloud and blockchain platforms to build more transparent, sustainable, and resilient supply chains. At the policy level, the results highlight the need for supportive regulatory frameworks, incentives, and clear compliance standards to accelerate the adoption of environmentally friendly and innovative technologies. The framework also underscores the importance of stakeholder acceptance, signaling that successful adoption requires not only technical readiness but also social and organizational alignment.

From a theoretical and methodological perspective, the proposed framework contributes to the literature by integrating subjective and objective weighting methods, employing a novel uncertainty-handling mechanism, and ensuring robust and stable results across multiple scenarios. It not only advances academic discussions on decision-making in logistics but also provides a practical and replicable roadmap for real-world applications.

Despite these contributions, the study is not without limitations. The evaluation was based on the judgments of a limited number of experts, which may restrict the generalizability of the results. Moreover, the analysis focused on a specific set of technologies and criteria, which, although comprehensive, may not fully capture all potential technological innovations or context-specific considerations in diverse supply chains.

Future research can address these limitations by expanding the expert pool to include a wider range of stakeholders from different regions and industries, thereby enhancing the robustness and representativeness of the findings. Additionally, subsequent studies could explore dynamic decision-making models that account for the evolving nature of technological adoption over time, integrating longitudinal data and scenario-based simulations. Another promising avenue lies in testing the proposed framework across different sectors of logistics and supply chain management, such as last-mile delivery, maritime transport, or warehousing, to validate its adaptability and scalability. Furthermore, combining this model with real-world performance data and life-cycle assessments could provide deeper insights into the environmental and economic impacts of emerging technologies.

In conclusion, this research provides both theoretical advancements and practical guidance for decision-makers navigating the complexities of technology adoption in cold chain logistics. By emphasizing sustainability, compliance, and adaptability, and by offering a rigorous yet flexible decision-making tool, the study lays the foundation for further exploration and innovation in building smarter, greener, and more resilient supply chains for the future.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

This research received no external funding.

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