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A Novel Approach Based on CRITIC-MOOSRA Methods for Evaluation and Selection of Cold Chain Monitoring Devices

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Abstract: The cold chain industry plays a pivotal role in ensuring the quality and safety of temperature-sensitive products throughout their journey from production to consumption. Central to this process is the effective monitoring of temperature fluctuations, which directly impacts product integrity. With an array of temperature monitoring devices available in the market, selecting the most suitable option becomes a critical task for organizations operating within the cold chain. This paper presents a comprehensive analysis of seven prominent temperature monitoring devices utilized in the cold chain industry. Through a systematic evaluation process, each device is rigorously assessed across six key criteria groups: price, accuracy, usability, monitoring and reporting capabilities, flexibility, and capability. A total of 23 independent metrics are considered within these criteria, providing a holistic view of each device's performance. Building upon this analysis, a robust decision support model is proposed to facilitate the selection process for organizations. The model integrates the findings from the evaluation, allowing stakeholders to make informed decisions based on their specific requirements and priorities. Notably, the Chemical Time Temperature Integrators (CTTI) emerge as the top-ranked device, demonstrating superior performance across multiple criteria. The implications of this research extend beyond device selection, offering valuable insights for enhancing cold chain efficiency and product quality. By leveraging the decision support model presented in this study, organizations can streamline their temperature monitoring processes, mitigate risks associated with temperature excursions, and ultimately optimize their cold chain operations. This study serves as a foundation for further research in the field of cold chain management, paving the way for advancements in temperature monitoring technology and strategies. Future studies may explore additional criteria or expand the analysis to include a broader range of devices, contributing to ongoing efforts aimed at improving cold chain sustainability and reliability.

Keywords: Cold chain; Logistics; Sensors; Monitoring devices; Tracking; MCDM; CRITIC; MOOSRA

1 Introduction

The basic prerequisite for implementing the cold chain is ensuring the appropriate temperature within the transportation vehicles. If the temperature is compromised at any point in the cold chain, it leads to permanent changes in the properties of the goods and consequences that cannot be rectified. The specificity of such chains lies in the sensitivity of all their parts and their susceptibility to easy interruption or disruption.

Currently, there is a wide variety of temperature monitoring devices available on the market for cargo spaces in transportation vehicles. Each of them has certain advantages and disadvantages. Additionally, the prices of these devices vary significantly in the market. There is a gap in the literature regarding the systematization of all characteristics of different devices and the selection of the most suitable ones. Therefore, the aim of this paper is to develop a model to support decision-making in choosing temperature monitoring devices in the cold chain.

On one hand, the paper systematizes all the characteristics of the most commonly used devices, while on the other hand, it develops a completely new methodology for their evaluation and final selection. The paper is based on the CRITIC-MOOSRA approach. The CRITIC method was used for determining criteria weights since comparative analysis with other sets of objective weights indicates that this method achieves a more balanced compromise among the assessed criteria, highlighting its effectiveness in decision-making processes [1]. On the other hand, the MOOSRA method was used for alternative ranking since when comparing the MOOSRA method to the MOORA method, it's observed that the MOORA method does not exhibit negative performance scores, whereas the MOOSRA method shows reduced sensitivity to significant variations in the criteria values [2].

In this paper seven devices were analyzed using 23 criteria grouped into six categories. Price, accuracy, usability, monitoring and reporting capabilities, flexibility, and capability are the most important criteria identified in this paper. Devices observed in this paper are: TCI (Threshold Chemical Indicator); PCI (Progressive Chemical Indicator); CTTI (Chemical Time Temperature Integrators); ETI (Electronic Temperature Indicator); EDLM (Electronic Data Logging Monitor); EDI (Electronic Data Integrator), and TMEL (Electronic Temperature Monitoring and Event Logger System). The results show the great applicability of the proposed approach.

The paper is structured as follows. Following the introduction, section two provides a literature review. The proposed approach is outlined in section three. Results are presented in section four, while section five is dedicated to sensitivity analysis. Finally, concluding remarks and directions for future research are provided in the last section.

2 Literature Review

A review of the literature indicates a notable absence of studies specifically addressing the evaluation and selection of cold chain monitoring devices. Existing research predominantly focuses on topics such as the selection of logistics service providers (LSPs) within the cold chain, the implementation of blockchain technology in cold chain management, establishing traceability in cold chains, monitoring tools and systems, and the associated risks of cold chain operations, etc. For example, Dai et al. [3] conducted research on service innovation among LSPs in China. Based on the results it was concluded that service innovation is very important for LSPs' competitiveness in cold chains. Nguyen et al. [4] in their paper proposed a model for cold chain LSP selection based on the grey analytic hierarchy process (G-AHP) and grey complex proportional assessment (G-COPRAS) methods. In the first phase, the G-AHP method was used to determine criteria weights, while on the other hand, in the second phase, the G-COPRAS method was applied to rank the alternatives. Similarly, Krstić and Tadić [5] proposed a novel model based on Fuzzy FActor RElationship (Fuzzy FARE) and Fuzzy Axial Distance based Aggregated Measurement (Fuzzy ADAM) methods for selecting cold chain LSPs. Fuzzy logic was used in order to tackle the uncertainty that is present during subjective evaluation. Zhang et al. [6] examined how the digital transition based on blockchain will affect a cold chain consisting of manufacturer, retailer and LSP. On the other hand, Hu [7] examined how blockchain and the Internet of Things (IoT) can be combined for monitoring cold chains in real-time. Based on the results of the research it was concluded that the proposed combination can improve transportation efficiency and can have an additional effect on monitoring the transportation process. Bai et al. [8] presented an overview of food preservation and traceability technology for cold chains. New trends regarding monitoring applications in cold chains were examined in a review paper by Badia-Melis et al. [9]. Criteria selection used for planning cold food chain traceability technology was a subject of the paper [10]. Namely, the authors identified 17 selection criteria, such as: cost effectiveness, waterproof capability, flexibility, accuracy, reading range, data transfer speed, multi-tag readability, identification capacity, tag writing cycle, memory capacity, environmental parameters recording, real-time location recording, real-time alert, data carrier durability, world-wide standard, data security, and minimum hardware requirements for readability. Aung and Chang [11] examined the cold chain monitoring tools which can be categorized into one of the following groups: thermometers, chart recorders, temperature indicator labels, data loggers, IoT devices (such as radio frequency identification (RFID), wireless sensor network (WSN), etc.). Tsang et al. [12] examined how IoT-based systems for monitoring cargo can affect operational effectiveness in a cold chain. A fuzzy AHP was used by Özkan and Başligil [13] for the evaluation of vaccine temperature monitoring systems. The authors took into consideration 4 alternatives and 14 criteria (divided into 4 main groups). Based on the results, it was concluded that a cloud-based data logger stood out as the best-ranked alternative. Kartoglu and Ames [14] examined the role of temperature monitoring in ensuring the quality and integrity of vaccines in cold chains. Tsang et al. [15] proposed a route planning system based on IoT for designing a multi-temperature packaging model, developing real-time product monitoring during transportation, and for optimizing routing solutions.

3 Methodology

The proposed model for evaluation and selection of cold chain monitoring devices consists of three phases. In the first phase, a detailed review of the literature and available information was conducted to define the criteria that will be used in evaluating alternatives. In the second phase, the CRITIC method was applied to determine the criteria weights, which were then utilized in the third phase, employing the MOOSRA method to rank the alternatives. The proposed methodology is illustrated in Figure 1.

Figure 1. Methodology for selecting cold chain monitoring devices

3.1 CRITIC Method

CRITIC method incorporates the intensity of contrast and conflict within the decision-making problem structure, as well as employs correlation analysis to identify contrasts among criteria. Implementation steps of this method are as follows [16, 17].

Step 1. Determining initial decision-making matrix $X = [x_{ij}]_{mxn}$ with m alternatives and n criteria, where x_{ij} represents the value of an alternative according to a specific criterion.

Step 2. Normalization of the decision-making matrix using Eq. (1).

$$x_{ij}^* = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{1}$$

Step 3. Determining criteria weights by taking into account standard deviation of the criterion as well as its correlation between other criteria, using Eq. (2).

$$w_j = \frac{C_j}{\sum_{i=1}^{m} C_i} \tag{2}$$

where, C_j represents the quantity of information contained in j^{th} criterion as is calculated using Eq. (3).

$$C_j = \sigma_j \sum_{i=1}^{m} (1 - r_{ij}) \tag{3}$$

where, σ_j represents standard deviation of the j^{th} criterion, while r_{iji} is the correlation coefficient between the j^{th} and i^{th} criteria. The relative significance of the criterion is determined based on the value of C_j since higher value of this coefficient implies a greater amount of information obtained from certain criterion.

3.2 MOOSRA Method

In order to perform alternative ranking using the MOOSRA method, the following steps should be conducted [2].

Step 1. Initial decision-making matrix construction.

$$X_{ij} = \begin{bmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix} \tag{4}$$

Step 2. Normalization of the decision-making matrix using Eq. (5).

$$X_{ij}^* = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^2}} \tag{5}$$

where, X_{ij}^* represents the normalized value and $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$.

Step 3. Calculating performance of the alternatives (Y_i) (Eq. (6)).

$$Y_i = \frac{\sum_{j=1}^{g} w_j X_{ij}^*}{\sum_{j=g+1}^{n} w_j X_{ij}^*} \tag{6}$$

where, g represents the count of attributes intended for maximization, while $(n-g)$ denotes the count of attributes meant for minimization. The w_j signifies the associated weight of the j^{th} criterion.

In certain instances, when we assume that all attributes hold equal importance, the optimization formula is modified as follows (Eq. (7)):

$$Y_i = \frac{\sum_{j=1}^{g} X_{ij}^*}{\sum_{j=g+1}^{n} X_{ij}^*} \tag{7}$$

Step 4. Alternatives ranking by taking into account the value of Y_i (the higher the value the better).

4 Results

As previously mentioned, there is a noticeable gap in existing literature addressing the evaluation and selection of cold chain monitoring devices. Consequently, during the literature review, explicit criteria for evaluation were not identified. To address this deficiency, the authors scrutinized the features, benefits, and limitations associated with each type of device, as outlined in the WHO report [18]. Subsequently, six criteria were formulated: price, accuracy, usability, monitoring and reporting, flexibility, and capability.

Price represents the cost of a device within a specific category, with alternatives rated on a scale of 1-5 based on their respective prices. Under the accuracy criterion, the following characteristics were considered: responsiveness to temperature threshold breaches, accuracy within ±0.5℃, multiple temperature alarm threshold capabilities, potential impact of human factors on the interpretation of color change, and variation in temperature accuracy across the operating range. Usability was evaluated in terms of irreversible changes, responsiveness to a single event, visual indications such as color change, color development, diffusion, graphical representation, absence of additional equipment needed to interpret results, and the restriction of alarm parameter programmability to the manufacturer. Monitoring and reporting were assessed based on the device's potential use as an analytical tool, capability to generate graphs, numerical data, and summary reports, the requirement of using two indicators to monitor upper and lower limits simultaneously, and the absence of time-specific traceability. Flexibility was examined through considerations such as calibration by the manufacturer for single-use devices, user activation and deactivation requirements, standard time and temperature limits (with some customization available for high-volume applications), regular calibration needs, and the necessity of professional installation. The capability criterion was evaluated by considering characteristics like recording frequency and time linked to device memory size, the potential need for additional proprietary hardware, software applications, or licensing for data downloading. Similar to the cost, all other criteria were rated on a scale of 1-5, with a value of 1 assigned to each characteristic a device possesses and 0 if the device lacks that particular characteristic. In the case of features indicating inferior performance, the ratings were inverted (i.e., devices with such features were assigned values of 0, while devices lacking those features were assigned values of 1), as presented in Table 1. The results of this evaluation also established the initial decision matrix.

Devices that were observed as alternatives are thoroughly outlined in the paper [19], and consequently, they will not be exhaustively described here. Therefore, the considered alternatives include:

- A1 - TCI (Threshold Chemical Indicator),
- A2 - PCI (Progressive Chemical Indicator),
- A3 - CTTI (Chemical Time Temperature Integrators),
- A4 - ETI (Electronic Temperature Indicator),
- A5 - EDLM (Electronic Data Logging Monitor),
- A6 - EDI (Electronic Data Integrator),
- A7 - TMEL (Electronic Temperature Monitoring and Event Logger System).

The alternatives were subsequently evaluated for each criterion based on the previously described methodology to establish the initial decision-making matrix, which was utilized both in the application of the CRITIC method and the MOOSRA method (Table 2).

After defining the initial decision-making matrix, the next step involved determining the criteria weights using the CRITIC method, employing Eqs. (1)-(3). In this manner, the proposed model's first phase established the criteria weights (Table 3), which were subsequently utilized in the MOOSRA method to rank the alternatives.

Since the initial decision matrix was established during the application of the CRITIC method, the normalization process was directly initiated when implementing the MOOSRA method. Normalization was carried out using Eq. (5), resulting in the values presented in Table 4.

Table 1. Evaluation of monitoring devices

Criteria	TCI	PCI	CTTI	ETI	EDLM	EDI	TMEL
Price (C1)	2	2	1	3	4	4	5
Accuracy (C2)							
Responds when a temperature threshold has been exceeded	1	1		1			
Accuracy of ±0.5°C				1	1	1	1
Multiple temperature alarm threshold capabilities				1	1	1	1
Interpretation of color change may be affected by human factors	1			1	1	1	1
Temperature accuracy varies over operating range	1	1	1				
Total - C2	3	2	1	4	3	3	3
Usability (C3)							
Irreversible change					1	1	1
Responds to a single event		1	1		1	1	1
Visual indication: Color change, color development, diffusion, graphical indication	1	1	1	1			
No additional equipment needed to read results	1	1	1	1			
Alarm parameters programmable by manufacturer only					1	1	1
Total – C3	2	3	3	2	3	3	3
Monitoring and reporting (C4)							
Can be used as an analytical tool			1		1	1	1
Capable of producing graphs, numerical data and summary reports					1	1	1
Monitoring upper and lower limits at the same time requires use of two indicators				1	1	1	1
No time-specific traceability					1	1	1
Total – C4	0	0	1	1	4	4	4
Flexibility (C5)							
Single use devices are calibrated by manufacturer prior to use				1		1	
User activation required		1		1	1	1	1
User deactivation required					1	1	1
Standard time and temperature limits (some customization available for high volume applications)		1			1		1
Requires regular calibration	1	1	1	1			
Requires professional installation	1	1	1	1	1	1	
Total – C5	2	4	2	4	4	4	3
Capability (C6)							
Recording frequency and recording time tied to size of device memory	1	1	1	1		1	
Additional proprietary hardware, software application or licensing may be required for downloading data	1	1	1				1
Total – C6	2	2	2	1	0	1	1

Table 2. Initial decision-making matrix

Alternative	C1	C2	C3	C4	C5	C6
A1	2	3	2	0	2	2
A2	2	2	3	0	4	2
A3	1	1	3	1	2	2
A4	3	4	2	1	4	1
A5	4	3	3	4	4	0
A6	4	3	3	4	4	1
A7	5	3	3	4	3	1

Table 3. Criteria weights obtained using CRITIC method

Criteria	C1	C2	C3	C4	C5	C6
Weights	0.1064	0.1275	0.1970	0.1525	0.1630	0.2536

Table 4. Normalized decision-making matrix obtained using MOOSRA method

Alternative	C1	C2	C3	C4	C5	C6
A1	0.230940108	0.397359707	0.274721128	0.287000457	0.222222222	0.446278100
A2	0.230940108	0.264906471	0.412081692	0.287000457	0.444444444	0.446278100
A3	0.115470054	0.132453236	0.412081692	0.328812558	0.222222222	0.446278100
A4	0.346410162	0.529812943	0.274721128	0.328812558	0.444444444	0.340363282
A5	0.461880215	0.397359707	0.412081692	0.454248859	0.444444444	0.234448463
A6	0.461880215	0.397359707	0.412081692	0.454248859	0.444444444	0.340363282
A7	0.577350269	0.397359707	0.412081692	0.454248859	0.333333333	0.340363282

The normalized values were then multiplied by the criterion weights to obtain the weighted normalized decision-making matrix (Table 5).

In the next step, the calculation of the performance of the alternatives (Y_i) was carried out using Eq. (6). In the final step, based on the values from Table 6, the alternatives were ranked.

Table 5. Weighted normalized decision-making matrix obtained using MOOSRA method

Alternative	C1	C2	C3	C4	C5	C6
A1	0.024575492	0.050680052	0.054110996	0.043761543	0.036226000	0.113166754
A2	0.024575492	0.033786701	0.081166495	0.043761543	0.072452000	0.113166754
A3	0.012287746	0.016893351	0.081166495	0.050137010	0.036226000	0.113166754
A4	0.036863237	0.067573402	0.054110996	0.050137010	0.072452000	0.086308981
A5	0.049150983	0.050680052	0.081166495	0.069263412	0.072452000	0.059451207
A6	0.049150983	0.050680052	0.081166495	0.069263412	0.072452000	0.086308981
A7	0.061438729	0.050680052	0.081166495	0.069263412	0.054339000	0.086308981

Table 6. Alternative ranking using MOOSRA method

Alternative	$\sum_{j=1}^{g} w_j X_{ij}^*$	$\sum_{j=g+1}^{n} w_j X_{ij}^*$	$Y_i = \frac{\sum_{j=1}^{g} w_j X_{ij}^*}{\sum_{j=g+1}^{n} w_j X_{ij}^*}$	Rank
A1	0.2979	0.0246	12.1237	3
A2	0.3443	0.0246	14.0113	2
A3	0.2976	0.0123	24.2184	1
A4	0.3306	0.0369	8.9678	4
A5	0.3330	0.0492	6.7753	6
A6	0.3599	0.0492	7.3217	5
A7	0.3418	0.0614	5.5626	7

Based on the results, it can be concluded that alternative A3 is the highest-ranked, while alternative A7 is the worst-ranked. The ranking of alternatives can also be expressed as follows: A3 > A2 > A1 > A4 > A6 > A5 > A7.

5 Sensitivity Analysis

To confirm the robustness of the model, sensitivity analysis and model validation were performed. Sensitivity analysis involved defining two scenarios. In the first scenario, criteria weights were determined using the Entropy method, while in the second scenario, the IDOCRIW (Integrated Determination of Objective Criteria Weights) method was employed for obtaining criteria weights. The objective of the sensitivity analysis was to determine whether there would be changes in the ranking of alternatives if the weights of criteria were altered. The weights obtained using the Entropy and IDOCRIW methods are presented in Table 7.

Table 7. Criteria weights in different scenarios

Criteria	C1	C2	C3	C4	C5	C6
Entropy	0.1104	0.0653	0.0160	0.5375	0.0420	0.2288
IDOCRIW	0.0473	0.0773	0.0388	0.3205	0.0678	0.4482

After calculating the criteria weights, the MOOSRA method was applied in both scenarios to rank the alternatives (Table 8).

Table 8. Alternative ranking after conducting sensitivity analysis

Scenarios	Alternative	$\sum_{j=1}^{g} w_j X_{ij}^*$	$\sum_{j=g+1}^{n} w_j X_{ij}^*$	$Y_i = \frac{\sum_{j=1}^{g} w_j X_{ij}^*}{\sum_{j=g+1}^{n} w_j X_{ij}^*}$	Rank
Scenario 1	A1	0.2961	0.0255	11.6138	3
	A2	0.2989	0.0255	11.7263	2
	A3	0.3034	0.0127	23.8060	1
	A4	0.3123	0.0382	8.1664	4
	A5	0.3490	0.0510	6.8453	6
	A6	0.3732	0.0510	7.3207	5
	A7	0.3686	0.0637	5.7834	7
Scenario 2	A1	0.3485	0.0109	31.8845	3
	A2	0.3586	0.0109	32.8140	2
	A3	0.3467	0.0055	63.4483	1
	A4	0.3397	0.0164	20.7221	4
	A5	0.3275	0.0219	14.9842	6
	A6	0.3750	0.0219	17.1561	5
	A7	0.3675	0.0273	13.4490	7

Based on the sensitivity analysis results, it can be asserted that the model's robustness has been confirmed, as there were no changes in the ranking of alternatives in either scenario. In addition to sensitivity analysis, model validation was performed to determine whether there would be a change in the ranking of alternatives when using other MCDM methods. For this purpose, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and MABAC (Multi-attributive Border Approximation Area Comparison) methods were applied [20] (Table 9).

Table 9. Alternative ranking using TOPSIS and MABAC methods

Alternative	TOPSIS Ranking	MABAC Ranking
A1	4	7
A2	3	2
A3	1	5
A4	6	6
A5	7	4
A6	2	1
A7	5	3

After applying the aforementioned methods, the ranking results, in the case of the TOPSIS method, align with the outcomes of the MOOSRA method (with A3 remaining the highest-ranked alternative). However, there have been changes in the ranking of other alternatives. On the other hand, after employing the MABAC method, alternative A6 emerged as the top-ranked, while A1 was ranked the lowest. The validation results indicate that, in certain cases, the choice of the MCDM method can impact the ranking of alternatives.

6 Conclusions

In summary, the effective maintenance of temperature control throughout the entire cold chain process is essential for preserving product integrity and ensuring consumer safety. This study represents a significant advancement in the field by providing a thorough analysis of temperature monitoring devices and proposing a novel methodology for their evaluation and selection.

The practical implications of our research are substantial. By identifying the Chemical Time Temperature Integrators (CTTI) as the optimal device in this study, we offer valuable guidance to industry practitioners seeking to enhance their cold chain operations. Moreover, our decision support model provides a systematic framework for navigating the complexities of device selection, enabling practitioners to make informed decisions based on their specific needs and priorities.

Looking ahead, there are several promising directions for further research. Firstly, the application of simulation techniques and advanced modeling approaches could enrich our understanding of temperature monitoring device performance in dynamic real-world scenarios. Additionally, engaging with industry professionals will facilitate the collection of firsthand insights and practical considerations, ultimately enhancing the relevance and applicability of future research findings. Furthermore, conducting extensive field tests across diverse operational settings and geographical regions will validate the robustness and efficacy of the proposed methodology. This multifaceted approach will not only enhance the generalizability of our findings but also provide valuable insights into the unique challenges and opportunities faced by different segments of the cold chain industry.

Lastly, expanding our analysis to include additional evaluation criteria and stakeholder perspectives will further enrich our understanding of temperature monitoring device selection. By incorporating factors such as cost-effectiveness, scalability, and compatibility with existing infrastructure, future research can offer a more comprehensive framework for decision-making in the cold chain domain.

In conclusion, this study represents a significant step forward in the quest to optimize cold chain management practices. By combining rigorous analysis with practical insights, this paper aims to empower industry stakeholders with the knowledge and tools needed to safeguard product quality and integrity throughout the cold chain.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] D. Diakoulaki, G. Mavrotas, and L. Papayannakis, "Determining objective weights in multiple criteria problems: The critic method," *Computers Ops. Res.*, vol. 22, no. 7, pp. 763–770, 1995. https://doi.org/10.1016/0305-0548(94)00059-H

[2] J. A. Ray, "Green cutting fluid selection using moosra method," *Int. J. Res. Eng. Technol.*, vol. 3, no. 15, pp. 559–563, 2014. https://doi.org/10.15623/ijret.2014.0315105

[3] J. Dai, W. Che, J. J. Lim, and Y. Shou, "Service innovation of cold chain logistics service providers: A multiple-case study in China," *Ind. Mark. Manag.*, vol. 89, pp. 143–156, 2020. https://doi.org/10.1016/j.indmarman.2019.08.002

[4] N. A. T. Nguyen, C. N. Wang, L. T. H. Dang, L. T. T. Dang, and T. T. Dang, "Selection of cold chain logistics service providers based on a grey AHP and grey COPRAS framework: A case study in Vietnam," *Axioms*, vol. 11, no. 4, p. 154, 2022. https://doi.org/10.3390/axioms11040154

[5] M. Krstić and S. Tadić, "Hybrid multi-criteria decision-making model for optimal selection of cold chain logistics service providers," *J. Organ. Technol. Entrep.*, vol. 1, no. 2, pp. 77–87, 2023. https://doi.org/10.56578/jote010201

[6] X. Zhang, Z. Li, and G. Li, "Impacts of blockchain-based digital transition on cold supply chains with a third-party logistics service provider," *Transp. Res. E: Logist. Transp. Rev.*, vol. 170, p. 103014, 2023. https://doi.org/10.1016/j.tre.2023.103014

[7] X. Hu, "Cold chain logistics model of agricultural products based on embedded system and blockchain," *Prod. Plan. Control*, 2022. https://doi.org/10.1080/09537287.2022.2101939

[8] L. Bai, M. Liu, and Y. Sun, "Overview of food preservation and traceability technology in the smart cold chain system," *Foods*, vol. 12, no. 15, p. 2881, 2023. https://doi.org/10.3390/foods12152881

[9] R. Badia-Melis, U. Mc Carthy, L. Ruiz-Garcia, J. Garcia-Hierro, and J. I. Robla Villalba, “New trends in cold chain monitoring applications - A review,” *Food Control*, vol. 86, pp. 170–182, 2018. https://doi.org/10.1016/j.foodcont.2017.11.022

[10] S. Islam, L. Manning, and J. M. Cullen, “Selection criteria for planning cold food chain traceability technology enabling industry 4.0,” *Procedia Comput. Sci.*, vol. 200, pp. 1695–1704, 2022. https://doi.org/10.1016/j.procs.2022.01.370

[11] M. M. Aung and Y. S. Chang, “Cold chain monitoring tools,” in *Cold Chain Management*. Cham: Springer, 2023. https://doi.org/10.1007/978-3-031-09567-2_5

[12] Y. P. Tsang, K. L. Choy, C. H. Wu, G. T. S. Ho, H. Y. Lam, and P. S. Koo, “An IoT-based cargo monitoring system for enhancing operational effectiveness under a cold chain environment,” *Int. J. Eng. Bus. Manag.*, vol. 9, 2017. https://doi.org/10.1177/1847979017749063

[13] B. Özkan and H. Başligil, “Evaluating vaccine temperature monitoring systems via fuzzy analytic hierarchy process,” *İstanbul Üniversitesi İşletme Fakültesi Dergisi*, vol. 45, no. 1, pp. 2–11, 2016.

[14] U. Kartoglu and H. Ames, “Ensuring quality and integrity of vaccines throughout the cold chain: The role of temperature monitoring,” *Expert Rev. Vaccines*, vol. 21, no. 6, pp. 799–810, 2022. https://doi.org/10.1080/14760584.2022.2061462

[15] Y. P. Tsang, K. L. Choy, C. H. Wu, G. T. S. Ho, H. Y. Lam, and V. Tang, “An intelligent model for assuring food quality in managing a multi-temperature food distribution centre,” *Food Control*, vol. 90, pp. 81–97, 2018. https://doi.org/10.1016/j.foodcont.2018.02.030

[16] M. Madić and M. Radovanović, “Ranking of some most commonly used nontraditional machining processes using rov and critic methods,” *U.P.B. Sci. Bull., Series D*, vol. 77, no. 2, pp. 193–204, 2015.

[17] E. A. Adali and A. T. Isik, “Critic and maut methods for the contract manufacturer selection problem,” *Europ. J. Multidiscip. Stud.*, vol. 2, no. 5, pp. 88–96, 2017. https://doi.org/10.26417/ejms.v5i1.p93-101

[18] “Temperature and humidity monitoring systems for transport operations,” World Health Organization, 2015. https://www.who.int/docs/default-source/medicines/norms-and-standards/guidelines/distribution/trs961-annex9-supp15.pdf?sfvrsn=cd633a05_2

[19] V. Pajić, M. Andrejić, and P. Chatterjee, “Enhancing cold chain logistics: A framework for advanced temperature monitoring in transportation and storage,” *Mechatron. Intell Transp. Syst.*, vol. 3, no. 1, pp. 16–30, 2024. https://doi.org/10.56578/mits030102

[20] J. Wang, J. Wen, V. Pajić, and M. Andrejić, “Optimizing cross-dock terminal location selection: A multi-step approach based on CI-DEA–IDOCRIW–MABAC for enhanced supply chain efficiency—A case study,” *Mathematics*, vol. 12, no. 5, p. 736, 2024. https://doi.org/10.3390/math12050736