INTERNATIONAL JOURNAL OF AUTOMOTIVE SCIENCE AND TECHNOLOGY

2025, VOL. 9, NO:2, 230-240 www.ijastech.org e-ISSN: 2587-0963

Prioritization of Digital Technology Applications in Intermodal Freight Transport using CRITIC-based Picture Fuzzy TOPSIS Method

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Research Article

Abstract

Recent advancements in digitalization have transformed the logistics sector by introducing innovative solutions that enhance efficiency, sustainability, and decision-making. In intermodal freight transport, the adoption of digital technologies offers significant potential to optimize operations, reduce costs, and improve environmental performance. However, prioritizing these technologies is crucial for ensuring strategic investments and maximizing their impact. This study proposes a hybrid multi-criteria decision-making (MCDM) framework that integrates Criteria Importance Through Intercriteria Correlation (CRITIC) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) within a Picture Fuzzy environment to evaluate and rank digital technology applications in intermodal freight transport. The findings indicate that "Artificial Intelligence (AI) for Optimization" is the most critical digital technology, followed by "Cloud Computing and Big Data Analytics" and "Internet of Things (IoT) for Asset Tracking". Additionally, Operational Efficiency and Economic Efficiency emerged as the most influential evaluation criteria for digital adoption. To validate the reliability and consistency of the proposed methodology, a sensitivity analysis was conducted by modifying the weight values of the criteria, with robustness tested across 15 different scenarios. The results provide logistics managers with a structured approach for selecting and implementing the most impactful digital technologies to improve efficiency, cost-effectiveness, and supply chain resilience. Furthermore, the study offers insights for the automotive industry to integrate smart vehicle technologies and AI-driven solutions, increasing connectivity, automation, and sustainability in intermodal logistics. Future research can extend this framework by incorporating additional MCDM methods and real-world case studies to further refine digital transformation strategies in freight transport.

Keywords: CRITIC; Digital Technology; Intermodal Freight Transport; Picture Fuzzy Sets; TOPSIS

History
Received 14.02.2024
Revised 05.04.2024
Accepted 10.05.2025

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To cite this paper: Bakioğlu, G., Prioritization of Digital Technology Applications in Intermodal Freight Transport using CRITIC-based Picture Fuzzy T OPSIS Method. International Journal of Automotive Science and Technology. 2025; 9 (2): 230-240. https://doi.org/10.30939/ijastech..1639635

1. Introduction

Intermodal freight transport refers to the movement of goods using multiple modes of transportation—such as railroad, road, sea, and air- without the need to handle the cargo itself when the modes change [1]. By shifting long-haul freight from road to rail, this approach significantly lowers carbon emissions and alleviates congestion, contributing to improved environmental sustainability [2]. Additionally, intermodal transport is prioritized in national and international policies as a means to mitigate negative externalities such as traffic accidents and infrastructure strain, reinforcing its role in the transition towards more sustainable freight systems [3].

Intermodal freight transport enhances efficiency by combining the flexibility of road transport with the cost-effectiveness of rail and maritime transport, allowing for optimized logistics operations and reduced overall costs [4]. According to Cryns et al. [5], maritime transport accounted for 67.8% of freight transport in the EU in 2022, followed by road transport at 24.9%, collectively representing 92.7% of total freight movement. Rail transport comprised 5.5%, inland waterways 1.6%, and air freight 0.2%. Figure 1 shows the Modal distribution of EU freight transportation between 2018 and 2022. Maritime transport remained the dominant mode, though its share gradually declined from 69.6% in 2018 to 67.8% in 2022, while road transport increased steadily from 22.8% to 24.9%, highlighting its growing role in freight movement. Rail transport fluctuated slightly but remained relatively stable at around 5.5%, whereas inland waterways slightly declined from 1.7% to 1.6%. Air transport consistently accounted for only 0.2%, reflecting its minimal contribution to overall freight transport.

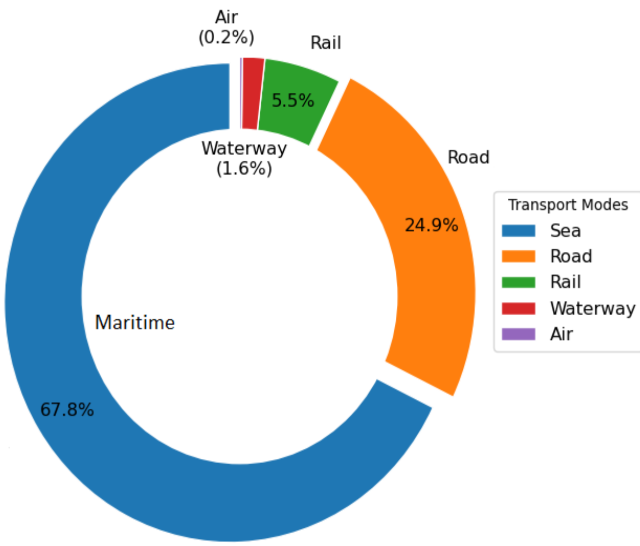

Figure 1. Modal distribution of EU freight transportation between 2018 and 2022.

Despite its advantages, intermodal freight transport faces several challenges that hinder its full adoption. These include high transshipment costs, complex coordination among multiple stakeholders, inefficiencies in terminal operations, and the lack of real-time visibility across transport networks [4]. Additionally, the reliance on different transport infrastructures, each governed by its own set of regulations and operational standards, can lead to bottlenecks and delay. To overcome these challenges, digitalization has emerged as a key enabler in transforming intermodal freight transport by improving connectivity, automation, and data-driven decision-making. The integration of advanced digital technologies—such as the blockchain, artificial intelligence (AI), Internet of Things (IoT), and cloud computing—has revolutionized intermodal logistics by enabling real-time cargo tracking, dynamic route optimization, and enhanced coordination among supply chain actors [6]. For instance, IoT-based sensors, GPS tracking, and blockchain technology enhance real-time cargo visibility, security, and transparency, reducing uncertainties, paperwork, and delays while improving trust in logistics.

Prioritizing digital technology applications in intermodal freight transport is essential for enhancing efficiency, sustainability, and competitiveness, as different solutions offer distinct benefits. Given their interdependencies and varying impacts on cost, operations, and the environment, a structured decision-making approach is crucial for effective implementation. Various studies have demonstrated the effectiveness of multi-criteria decision-making (MCDM) methods in optimizing intermodal transport systems. Zecevic et al. [7] applied a fuzzy Delphi-based Analytic Network Process (ANP) and fuzzy Delphi Vlse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) to select intermodal transport terminal locations. Uyanık et al. [8] integrated the Decision-Making Trial and Evaluation Laboratory (DEMATEL) with the Intuitionistic Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to determine logistics center locations in Istanbul. Gandhi et al. (2024) employed an integrated approach using spherical fuzzy sets to prioritize solutions for mitigating risks associated with intermodal railroad freight transportation in alignment with sustainable development goals. Similarly, Krstic et al. [9] utilized combined fuzzy MCDM methods for selecting intermodal terminal subsystem technologies.

The comprehensive literature review identifies a critical gap in establishing a complete list of digital technology applications in intermodal freight transport and the evaluation criteria for assessing alternatives. While existing research has primarily applied MCDM methods to transportation-related problems, such as intermodal terminal location and subsystem technology selection, this study addresses a key gap by focusing on digitalized intermodal freight transport. Additionally, no prior studies have explored the integration of the CRITIC and TOPSIS methods within the transportation sector. The novelty of this research lies in the application of Picture Fuzzy Sets with these methods, providing a more effective approach to handling the ambiguity inherent in real-world decision-making.

This study aims to address the identified knowledge gap by defining key evaluation criteria and providing a systematic decision-making framework for intermodal freight transport. To achieve this, the research integrates the Criteria Importance Through Intercriteria Correlation (CRITIC) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methods within a Picture Fuzzy environment to prioritize digital technology applications in intermodal freight transport. The key contributions of this study are as follows:

- Identifying digital technology applications in intermodal freight transport through an extensive survey, incorporating insights from a comprehensive literature review and expert consultations.
- Developing an integrated CRITIC-TOPSIS model under a Picture Fuzzy framework to evaluate and prioritize digital tools for intermodal freight transport.
- Utilizing the CRITIC method to determine the relative importance of evaluation criteria for assessing smart applications in intermodal freight logistics.
- Applying the TOPSIS method to rank technological applications based on their suitability and effectiveness in intermodal freight transport.
- Conducting a sensitivity analysis by varying the weight of each criterion to assess their influence on the final prioritization and validate the robustness of the proposed methodology.

This research offers decision-makers a systematic framework to evaluate and prioritize digital technologies, enabling data-driven choices that enhance efficiency and sustainability in intermodal freight transport. For policymakers, the findings provide valuable insights to support the development of regulations and investment strategies that facilitate digital transformation in the sector.

2. Methodology

The evaluation and prioritization of digital technology applications in intermodal freight transport involve multiple, often conflicting criteria, requiring a systematic decision-making approach. Traditional assessment methods may struggle to handle the inherent uncertainty and subjectivity in expert opinions. Therefore, this study employs a multi-criteria decision-making (MCDM) framework, integrating CRITIC and TOPSIS methods within a Picture Fuzzy environment to ensure a more robust and reliable evaluation process. The CRITIC method is utilized to determine the objective weights of evaluation criteria by considering both the contrast intensity and correlation among them, eliminating potential bias in expert judgments. TOPSIS, on the other hand, ranks digital technology applications based on their closeness to the ideal solution, effectively distinguishing the most suitable alternatives. The integration of Picture Fuzzy Sets enhances this framework by incorporating positive, negative, neutral, and refusal degrees, allowing for a more comprehensive representation of expert uncertainty. This combined approach provides greater accuracy and consistency in prioritizing digital transformation strategies in intermodal freight transport, ensuring informed decision-making for both industry stakeholders and policymakers.

The methodology employed in this study consists of three stages. In the first stage, potential criteria and alternatives are identified, and a hierarchical structure is developed to systematically organize the decision framework. The second stage involves the integration of two multi-criteria decision-making (MCDM) approaches. The CRITIC method is applied to determine the objective weights of the evaluation criteria, which are then used to assess the alternatives. Subsequently, single-valued Picture Fuzzy TOPSIS is implemented using the weights derived from the CRITIC method, generating a ranking of digital technology applications for intermodal freight transport. In the third stage, validation tests are conducted to ensure the robustness and reliability of the proposed model. A sensitivity analysis is performed by altering the weight values of criteria obtained from the CRITIC method and recalculating the revised closeness values using the Picture Fuzzy TOPSIS approach. The detailed integration and flow of the suggested methodology are depicted in the schematic design in Figure 2.

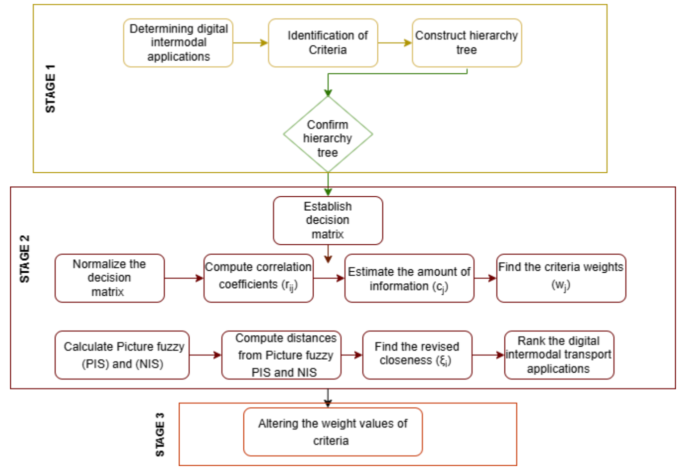

Figure 2. Flowchart of methodology

2.1. Picture Fuzzy Sets

In the evaluation of digital technologies in intermodal freight transport, decision-making often relies on the personal experiences and intuition of experts. However, such subjective approaches may be limited due to uncertainties and incomplete information. This necessitates the use of fuzzy logic and its derived methods to ensure a more consistent and reliable assessment of digital technologies.

Zadeh [10] introduced the concept of fuzzy sets to handle uncertainties in real-world applications, where each element is assigned a membership value between 0 and 1, representing its degree of belonging to a set. Over time, various extensions of fuzzy sets have emerged to address different decision-making scenarios. Atanassov [11] proposed intuitionistic fuzzy sets, which incorporate both membership and non-membership values, with the constraint that their sum must not exceed one. However, intuitionistic fuzzy sets may be insufficient in situations requiring more nuanced assessments, such as cases involving acceptance, rejection, neutrality, and hesitation.

To address these limitations, Cuong and Kreinovich [12] developed the Picture Fuzzy Set (PFS) theory, which defines each element with four parameters: positive membership, negative membership, neutrality, and rejection. The sum of these four values must not exceed one. Picture fuzzy sets provide a more comprehensive modeling framework for decision-makers by capturing uncertainty and reflecting human reasoning more effectively. This extension is particularly useful in preventing information loss and analyzing complex decision-making environments.

Given the inherent uncertainties in evaluating digital technologies for intermodal freight transport, this study employs Picture Fuzzy Sets to model expert preferences more effectively. The fundamental definitions of Picture Fuzzy Sets are presented in the following section:

Definition 1: Let x be an element of the universal set X and belong to a Picture Fuzzy Set denoted by $\tilde{P}$. The Picture Fuzzy Set $\tilde{P}$ within the set X is defined as given in Equation 1 [12]**:**

$$\tilde{P} = \{\langle x, \mu_P(x), \eta_P(x), v_P(x)\rangle | x \in X\} \quad (1)$$

Here, $\mu_P(x)$ ϵ [0,1] represents the positive membership degree**,** $v_P(x)$ ϵ [0,1] denotes the negative membership degree**,** and $\eta_P(x)$ ϵ [0,1] corresponds to the neutral membership degree**.** These membership degrees satisfy the condition specified in Equation 2**.**

$$0 \leq \mu_P(x) + \eta_P(x) + v_P(x) \leq 1 \quad \forall\ x \in X \tag{2}$$

In picture fuzzy sets, the decision-makers whose opinions are consulted are classified into four groups: those who vote "yes" μ_P, those who vote "no" v_P, those who abstain η_P, and those who vote "reject" π_P. Here, π_P represents the membership degree of rejection, which is calculated using Equation 3:

$$\pi_P(x) = 1 - (\mu_P(x) + \eta_P(x) + v_P(x) \quad \forall\ x \in X \tag{3}$$

Definition 2: Let $\tilde{P}_1 = (\mu_{P_1}, \eta_{P_1}\ v_{P_1})$ and $\tilde{P}_2 = (\mu_{P_2}, \eta_{P_2}\ v_{P_2})$ be two picture fuzzy numbers, and λ be a positive number. The fundamental mathematical operations on picture fuzzy sets are expressed as follows [12]:

$$\tilde{P}_1 \oplus \tilde{P}_2 = \{\mu_{P_1} + \mu_{P_2} - \mu_{P_1}\mu_{P_2}, \eta_{P_1}\eta_{P_2}, v_{P_1}v_{P_2}\} \tag{4}$$

$$\tilde{P}_1 \otimes \tilde{P}_2 = \{\mu_{P_1}\mu_{P_2}, \eta_{P_1} + \eta_{P_2} - \eta_{P_1}\eta_{P_2}, v_{P_1} + v_{P_2} - v_{P_1}v_{P_2}\} \tag{5}$$

$$\lambda\tilde{P}_1 = \left\{\left(1 - \left(1 - \mu_{P_1}\right)^{\lambda}, {\eta_{P_1}}^{\lambda}, {v_{P_1}}^{\lambda}\right)\right\}, \lambda > 0, \tag{6}$$

$$\left(\tilde{P}_1\right)^{\lambda} = \left\{{\mu_{P_1}}^{\lambda}, \left(1 - \left(1 - \eta_{P_1}\right)^{\lambda}\right), \left(1 - \left(1 - v_{P_1}\right)^{\lambda}\right)\right\}, \quad \lambda > 0. \tag{7}$$

Definition 3: $\tilde{P}_i = P(\mu_i, \eta_i, v_i)$, $i = (1,2,\dots,n)$, is defined as a group of picture fuzzy sets. The aggregation of this set is performed using the picture fuzzy weighted average (PFWA) formula, as expressed in Equation 8.

$$\text{PFWA}\ (\tilde{P}_1, \tilde{P}_2, \dots . \tilde{P}_n) = \left((1 - \textstyle\prod_{i=1}^{n}(1 - \mu_i)^{w_i}), (\prod_{i=1}^{n}(\eta_i)^{w_i}), (\prod_{i=1}^{n}(v_i)^{w_i})\right) \tag{8}$$

Here, w_i = (w$_1$, w$_2$, …,w$_n$), represents the weight vector, and these vectors are defined as $w_i \in [0, 1]$. Additionally, the condition $\sum_{i=1}^{n} w_i = 1$ is satisfied.

Definition 4: $\tilde{P}_1 = (\mu_{P_1}, \eta_{P_1}\ v_{P_1})$ ve $\tilde{P}_2 = (\mu_{P_2}, \eta_{P_2}\ v_{P_2})$ be two picture fuzzy numbers. Score functions are utilized to rank and compare these two image fuzzy numbers. The mathematical expression of this function is given in Equation 9 [13]:

$$S(\tilde{P}_1) = \mu_{P_1} - \eta_{P_1} - v_{P_1} \qquad S(\tilde{P}_2) = \mu_{P_2} - \eta_{P_2} - v_{P_2} \tag{9}$$

Here, the S (P) function takes values in the range of [-1, 1].

2.2. CRITIC Method

The CRITIC method, short for "CRiteria Importance Through Intercriteria Correlation," is a robust decision-making technique designed for multi-criteria analysis. Introduced by Diakoulaki et al. in 1995, this approach aims to objectively determine the relative importance of criteria in decision-making processes. It evaluates the significance of each criterion by considering the contrast intensity, represented through the standard deviation, and the interrelations among criteria, expressed as the correlation coefficient. By integrating these two factors, the CRITIC method calculates weights that reflect both the variability and the level of interdependence among criteria. This methodology is widely used in Multiple Attribute Group Decision Making (MAGDM) scenarios, offering a systematic way to assess and prioritize criteria based on their contribution to the overall decision-making framework. The procedural steps of CRITIC method are given as follows:

Step 1: Establish decision matrix $D = \left(C_j(x_i)\right)_{m\times n}$ using Eq. (10), where $C_j (j = 1,2, \dots, n)$ and $x_i (i = 1,2, \dots, m)$ be the criteria and alternatives respectively.

$$D = \left(C_j(x_i)\right)_{m\times n} = \begin{array}{c c} & \begin{array}{ccc} C_1 & \cdots & C_n \end{array} \\ \begin{array}{c} x_1 \\ \vdots \\ x_m \end{array} & \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{m1} & \cdots & P_{mn} \end{bmatrix} \end{array} \tag{10}$$

Step 2: Normalize the decision matrix N = $(n_{ij})_{m\times n}$; where N is structured using Eq. (11) where ${X_{ij}}^{+} = \max_i X_{ij}$, ${X_{ij}}^{-} = \min_i X_{ij}$.

$$n_{ij} = \begin{cases} \dfrac{X_{ij} - {X_{ij}}^{-}}{{X_{ij}}^{+} - {X_{ij}}^{-}} & if\ j \in C_b, \\ \dfrac{{X_{ij}}^{+} - X_{ij}}{{X_{ij}}^{+} - {X_{ij}}^{-}} & if j \in C_c \end{cases} \tag{11}$$

here C$_b$ and C$_c$ show the benefit criteria and cost criteria, respectively.

Step 3: Compute the correlation coefficients between criteria pairs. Correlation coefficient (r_{jt}) between the pair of criteria j and t is calculated using Eq. (12):

$$r_{jt} = \frac{\sum_{i=1}^{m}(n_{ij} - \overline{n_j})(n_{ij} - \overline{n_t})}{\sqrt{\sum_{i=1}^{m}(n_{ij} - \overline{n_j})^2 (n_{ij} - \overline{n_t})^2}} \tag{12}$$

Step 4: Estimate the amount of information (c_j) for each criterion is calculated using Eq. (13):

$$c_j = \varphi_j \sum_{t=1}^{n}(1 - r_{jt}) \tag{13}$$

Step 5: Find the criteria weights (w_j) using Eq. (14):

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} \tag{14}$$

2.3. Picture Fuzzy TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang and Yoon (1981), is a widely used approach for solving multi-criteria decision-making (MCDM) problems. It identifies the best alternative by calculating the geometric distances of each option from two benchmark solutions: the positive ideal solution (PIS) and the negative ideal solution (NIS). The optimal alternative is the one closest to the PIS and farthest from the NIS. To enhance its ability to manage uncertainty and vagueness, the TOPSIS method has been extended to incorporate Picture Fuzzy Sets, resulting in the Picture Fuzzy TOPSIS (PF-TOPSIS) approach. This extension integrates Picture Fuzzy Sets to effectively handle imprecise information, enabling the PF-TOPSIS method to prioritize alternatives in complex decision-making scenarios with greater reliability. The steps of PF-TOPSIS are as follows:

Step 1: Construct Picture fuzzy decision matrix $D = \left(C_j(x_i)\right)_{m\times n}$ using Eq. (15), where $C_j(j = 1,2,\ldots,n)$ and $x_i(i = 1,2,\ldots,m)$ be the criteria and alternatives respectively.

$$D = \left(C_j(x_i)\right)_{m\times n} = \begin{array}{c c} & \begin{array}{ccc} C_1 & \cdots & C_n \end{array} \\ \begin{array}{c} x_1 \\ \vdots \\ x_m \end{array} & \begin{bmatrix} P\left(\mu_{P_{11}}, \eta_{P_{11}} \ \ v_{P_{11}}\right) & \cdots & P\left(\mu_{P_{1n}}, \eta_{P_{1n}} \ \ v_{P_{1n}}\right) \\ \vdots & \ddots & \vdots \\ P\left(\mu_{P_{m1}}, \eta_{P_{m1}} \ \ v_{P_{m1}}\right) & \cdots & P\left(\mu_{P_{mn}}, \eta_{P_{mn}} \ \ v_{P_{mn}}\right) \end{bmatrix} \end{array} \quad (15)$$

Step 2: Aggregate the picture fuzzy decision matrix utilizing picture fuzzy weighted average (PFWA) which was given in Eq. (8).

Step 3: Utilizing Equations (16) and (17), compute the Picture fuzzy positive ideal solution (PIS) and negative ideal solution (NIS):

$$x^{+} = \left\{\max_i \langle s\left((x_i)\right)\rangle \middle| j = 1,2,\cdots,n\right\} = \left\{\langle P\left(\mu_{P_1}{}^{+}, \eta_{P_1}{}^{+}, v_{P_1}{}^{+}\right)\rangle, \cdots, \langle P\left(\mu_{P_n}{}^{+}, \eta_{P_n}{}^{+}, v_{P_n}{}^{+}\right)\rangle\right\} \quad (16)$$

$$x^{-} = \left\{\min_i \langle s\left((x_i)\right)\rangle \middle| j = 1,2,\cdots,n\right\} = \left\{\langle P\left(\mu_{P_1}{}^{-}, \eta_{P_1}{}^{-}, v_{P_1}{}^{-}\right)\rangle, \cdots, \langle P\left(\mu_{P_n}{}^{-}, \eta_{P_n}{}^{-}, v_{P_n}{}^{-}\right)\rangle\right\} \quad (17)$$

Step 4: Compute distances from Picture fuzzy PIS and NIS with normalized Euclidean distance using Eqs. (18) and (19):

$$D(x_i, x^{+}) = \sum_{j=1}^{n} w_j d\left(C_j(x_i), C_j(x^{+})\right) = \sqrt[2]{\frac{1}{n}\sum_{j=1}^{n} w_j \left(\left|(\mu_{ij})^2 - (\mu_j^{+})^2\right| + \left|(\eta_{ij})^2 - (\eta_j^{+})^2\right| + \left|(v_{ij})^2 - (v_j^{+})^2\right|\right)}, \quad i = 1,2,\cdots,m, \quad (18)$$

$$D(x_i, x^{-}) = \sum_{j=1}^{n} w_j d\left(C_j(x_i), C_j(x^{-})\right) = \sqrt[2]{\frac{1}{n}\sum_{j=1}^{n} w_j \left(\left|(\mu_{ij})^2 - (\mu_j^{-})^2\right| + \left|(\eta_{ij})^2 - (\eta_j^{-})^2\right| + \left|(v_{ij})^2 - (v_j^{-})^2\right|\right)}, \quad i = 1,2,\cdots,m. \quad (19)$$

Step 5: Determine the revised closeness $\xi(x_i)$ of the alternative x_i using Eq. (20):

$$\xi(x_i) = \frac{D(x_i,x^{-})}{D_{max}(x_i,x^{-})} - \frac{D(x_i,x^{+})}{D_{min}(x_i,x^{+})} \quad (20)$$

Step 6: Identify the optimal ranking of alternatives, where the best option is the one with the highest adjusted closeness value $\xi(x_i)$.

3. Results and Discussion

Digital technologies such as blockchain, AI, IoT, and big data analytics have the potential to transform intermodal freight transport by enhancing efficiency, transparency, and operational coordination. However, the complex nature of intermodal systems requires a thorough evaluation of these technologies to guide their effective implementation and address challenges like inefficiencies, environmental concerns, and high costs.

This study aims to evaluate and prioritize digital technology applications in intermodal freight transport using multi-criteria decision-making approaches. By assessing their economic, environmental, and operational impacts, the research provides a framework to help stakeholders identify and implement the most impactful solutions, ensuring a sustainable and efficient freight system. The primary digital technology applications in intermodal freight transport are identified through a literature review and consultations with experts as follows:

Blockchain for Logistics Management (A1): Blockchain technology creates a secure, decentralized ledger for storing and sharing information among multiple stakeholders in the logistics chain. This ensures transparency, immutability, and traceability of transactions and documents [14]. By replacing traditional, often error-prone methods, blockchain streamlines operations such as order tracking, payment processing, and compliance with international trade regulations.

Artificial Intelligence (AI) for Optimization (A2): Artificial Intelligence (AI)-powered systems and automation technologies significantly enhance operational efficiency in ports and warehouses by automating complex tasks such as container management, scheduling, and predictive maintenance. Additionally, AI plays a pivotal role in demand forecasting, fraud detection, and dynamic pricing, thereby optimizing decision-making processes and resource allocation [15]. These capabilities collectively contribute to a more resilient and adaptive logistics ecosystem, ensuring competitiveness in dynamic market conditions.

Internet of Things (IoT) for Asset Tracking (A3): It involves using interconnected sensors and devices to monitor the location, status, and condition of goods and equipment in real-time throughout the supply chain. IoT devices, such as GPS trackers and environmental sensors, collect and transmit data on key metrics like location, temperature, humidity, and vibration. This data enables stakeholders to ensure the safety and quality of goods, proactively address potential issues, and streamline operations. IoT-based tracking improves supply chain transparency, reduces losses and delays, and facilitates efficient decision-making by providing actionable insights across every stage of intermodal freight transport [16].

Cloud Computing and Big Data Analytics (A4): Cloud computing and big data analytics are transformative technologies that enable the storage, processing, and analysis of vast amounts of logistics and transportation data in real time. Cloud platforms offer scalable infrastructure for storing and sharing data across stakeholders in the supply chain, ensuring seamless collaboration and accessibility. Big data analytics processes this data to extract actionable insights, such as demand patterns, fleet performance, and risk forecasts, supporting informed decision-making [15]. Together, these technologies optimize resource allocation, enhance operational efficiency, and improve the resilience and adaptability of intermodal freight transport systems in dynamic market conditions.

Geographic Information Systems (GIS) for Strategic Planning (A5): GIS uses spatial data and advanced mapping tools to optimize the logistics network, determining efficient intermodal connections, and minimizing environmental impact. By integrating geographic and economic data, GIS aids in strategic decision-making, improves infrastructure utilization, and ensures sustainable transport solutions across the supply chain [17].

Table 1. Detailed overview of criteria.

Criteria	**#**	**Description**	**Criteria Type**
Economic Aspect	C1	Economic Aspect evaluates the financial implications associated with the implementation, maintenance, and operational costs of a solution. It reflects how cost-effective a particular application is in terms of resource allocation and long-term affordability.	Cost
Technological Feasibility	C2	Integration challenges, compatibility with existing systems, and scalability are considered when assessing the practicality of adopting a technology. This criterion evaluates the readiness of an application to handle technical demands and support operational goals.	Benefit
Environmental Sustainability	C3	The potential to reduce emissions, conserve energy, and minimize waste plays a critical role in evaluating applications. This highlights each technology's contribution to sustainable logistics practices and its alignment with environmental objectives.	Benefit
Operational Efficiency	C4	Improvements in processes, reliability, and response times are key metrics for assessing performance. This criterion measures an application's ability to streamline operations and ensure a more productive intermodal freight system.	Benefit
Security and Data Protection	C5	Security and data protection examine the technology's effectiveness in safeguarding data and systems against cyber threats, breaches, and operational disruptions. Each application is evaluated based on its ability to ensure confidentiality, integrity, and availability of critical logistics information.	Benefit
Scalability and Adaptability	C6	Scalability and adaptability focus on how easily the technology can be extended to larger operations or adapted to future demands and challenges. This criterion evaluates whether the application can handle growth in logistics requirements and maintain efficiency in dynamic environments.	Benefit

In this study, digital technology applications in intermodal freight transport are prioritized as the primary focus. To evaluate these applications effectively, six distinct criteria have been defined, derived from a comprehensive literature review and expert consultations. These criteria aim to encompass various factors influencing the effectiveness and implementation of digital technologies within the context of intermodal freight transport. Table 1 presents a detailed overview of these criteria, listing their corresponding numbers, descriptions, and relevant references.

The hierarchy tree is used in this study to visually represent the decision structure for evaluating digital technology applications in intermodal freight transport. At the top level of the tree, the main objective, which is the evaluation of digital technology applications in this field, is placed. The second level contains the defined criteria that will be used to assess these applications, and at the final level, the various digital applications for intermodal freight transport are listed, forming a clear structure for evaluation. Figure 3 indicates the hierarchy tree of this study.

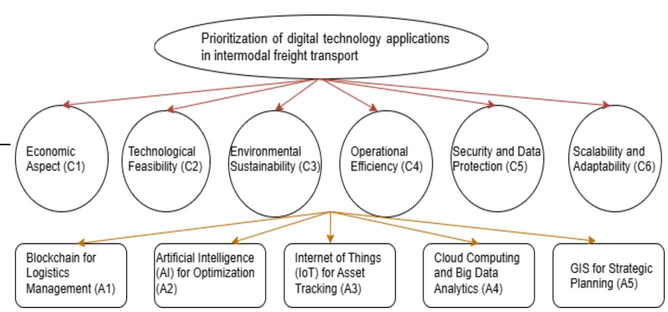

Figure 3. Hierarchy tree of this study.

3.1. Application

This study employs an integrated CRITIC-TOPSIS methodology within a picture fuzzy environment to assess digital technology applications in intermodal freight transport. In the first phase, a decision matrix must be constructed to implement the proposed approach. To achieve this, linguistic variables represented by picture fuzzy numbers, as presented in Table 2, were utilized.

Table 2. Picture Fuzzy Number Linguistic Variables.

Linguistic terms	**Picture fuzzy numbers**
Very good (VG)	(0.9, 0.0, 0.05)
Good (G)	(0.75, 0.05, 0.1)
Moderate good (MG)	(0.6, 0.0, 0.3)
Fair (F)	(0.5, 0.1, 0.4)

Moderate poor (MP)	(0.3, 0.0, 0.6)
Poor (P)	(0.25, 0.05, 0.6)
Very Poor (VP)	(0.1, 0.0, 0.85)

Decision-makers and experts from the Turkish State Railways and academia used linguistic terms to construct the decision matrix, which is provided in Table 3. The criteria for evaluating digital technology applications in intermodal freight transport were then weighted using the CRITIC approach.

Table 3. Decision matrix.

Alternatives/Criteria	Economic Efficiency (C1)	Technological Feasibility (C2)	Environmental Sustainability (C3)	Operational Efficiency (C4)	Security and Data Protection (C5)	Scalability and Adaptability (C6)
Blockchain for Logistics Management (A1):	P	G	MG	G	VG	G
Artificial Intelligence (AI) for Optimization (A2):	MP	VG	G	VG	G	VG
Internet of Things (IoT) for Asset Tracking (A3):	P	G	MG	VG	MG	G
Cloud Computing and Big Data Analytics (A4):	P	VG	G	VG	G	G
Geographic Information Systems (GIS) for Strategic Planning (A5):	MP	G	G	G	G	G

Following the construction of the decision matrix, normalization was performed using Eq. (11). Subsequently, the correlation coefficient (r_{jt}) matrix between pairs of criteria was established using Eq. (12), as shown in Table 4. The amount of information (c_j) was then estimated using Eq. (13).

The final criterion weights are presented in Figure 4. "Operational Efficiency," with a weight of 0.274, was identified as the most important criterion for assessing digital solutions in intermodal freight transport. "Economic Efficiency" (0.170) ranked second, followed by "Technological Feasibility" (0.165). Meanwhile, "Security and Data Protection" (0.147), "Scalability and Adaptability" (0.135), and "Environmental Sustainability" (0.109) were identified as the least influential criteria.

Table 4. Correlation coefficients matrix.

Criteria	Economic Efficiency (C1)	Technological Feasibility (C2)	Environmental Sustainability (C3)	Operational Efficiency (C4)	Security and Data Protection (C5)	Scalability and Adaptability (C6)
Economic Efficiency (C1)	1.000	0.389	0.345	-0.389	0.953	0.068
Technological Feasibility (C2)	0.389	1.000	0.763	0.667	0.408	0.612
Environmental Sustainability (C3)	0.345	0.763	1.000	0.313	0.551	0.766
Operational Efficiency (C4)	-0.389	0.667	0.313	1.000	-0.408	0.408
Security and Data Protection (C5)	0.953	0.408	0.551	-0.408	1.000	0.250
Scalability and Adaptability (C6)	0.068	0.612	0.766	0.408	0.250	1.000

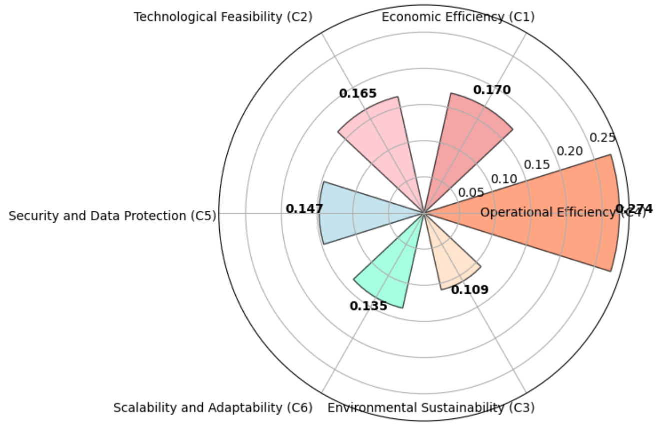

Figure 4. Final criterion weights.

In the second phase, single-valued picture fuzzy TOPSIS method is applied with using the weight obtained from first phase. After constructing decision matrix, Picture fuzzy positive ideal solution (PIS) and negative ideal solution (NIS) were computed using Eqs. (16) and (17). The results are shown as follows:

x^{+} = {P(0.50, 0.1, 0.40), P(0.90, 0, 0.05), P(0.90, 0, 0.05), P(0.90, 0, 0.05), P(0.75, 0.05, 0.10), P(0.90, 0, 0.05)}

x^{-} = {P(0.25, 0.05, 0.60), P(0.75, 0.05, 0.10), P(0.60, 0, 0.30), P(0.75, 0.05, 0.10), P(0.60, 0, 0.30), P(0.75, 0.05, 0.10)}.

The distances from the Pythagorean fuzzy Positive Ideal Solution (PIS) and the Pythagorean fuzzy Negative Ideal Solution (NIS), along with the revised closeness $\xi(x_i)$, are calculated using Eqs. (18), (19), and (20), as presented in Table 5.

Table 5. Distances from Picture fuzzy PIS and NIS, and revised closeness coefficients.

Alternatives	**Picture fuzzy PIS, $D(x_i, x^{+})$**	**Picture fuzzy NIS, $D(x_i, x^{-})$**	**Revised closeness, $\xi(x_i)$**
Blockchain for Logistics Management (A1):	0.087	0.034	-1.681
Artificial Intelligence (AI) for Optimization (A2):	0.042	0.084	0.000
Internet of Things (IoT) for Asset Tracking (A3):	0.070	0.062	-0.946
Cloud Computing and Big Data Analytics (A4):	0.060	0.072	-0.581
Geographic Information Systems (GIS) for Strategic Planning (A5):	0.081	0.047	-1.395

Based on the revised closeness values, Artificial Intelligence (AI) for Optimization (A2) emerges as the most favorable digital technology application in intermodal freight transport, with a revised closeness value of 0.000. This is followed by Cloud Computing and Big Data Analytics (A4) (-0.581), indicating its relative importance. The Internet of Things (IoT) for Asset Tracking (A3) ranks third with a revised closeness value of -0.946, followed by Geographic Information Systems (GIS) for Strategic Planning (A5) (-1.395). Blockchain for Logistics Management (A1) ranks the lowest, with a revised closeness value of -1.681, suggesting it is the least preferable among the evaluated alternatives. Figure 5 demonstrates the ranking results of proposed methodology.

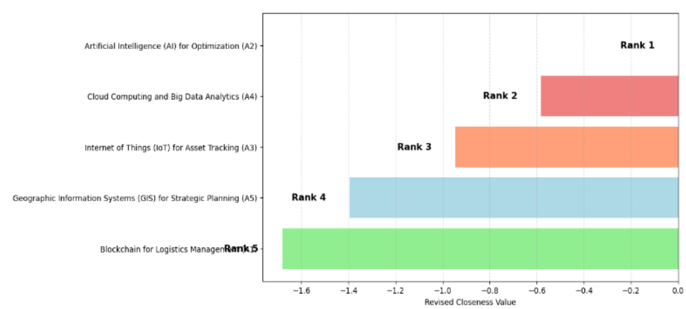

Figure 5. Ranking results of methodology.

3.2. Sensitivity Analysis

Sensitivity analysis is a technique used to assess the robustness of a decision-making model by examining how variations in input parameters influence the final outcomes. It helps determine the extent to which changes in criteria weights affect the ranking of alternatives, ensuring the reliability and stability of the proposed methodology. The result is deemed sensitive when a change in a criterion's weight causes a change in the ranking order, showing that the weights assigned have a substantial influence on the decision-making process. Conversely, if the ranking remains unchanged despite modifications in weight values, the result is deemed robust, signifying that the priority of alternatives is stable regardless of precise weight assignments. Sensitivity analysis is used to make sure the decision model is consistent across all weighting scenarios by identifying how changes in the weight of each criterion impact the ranking of digital technology applications in intermodal freight transport.

In this study, sensitivity analysis is conducted by altering the weight values of criteria derived from the CRITIC methodology and recalculating the revised closeness values using the Picture fuzzy TOPSIS approach. A total of 15 scenarios are considered, each involving the exchange of weight values between two criteria. The notation ξ1-2 represents a scenario where the weight of Criterion 1 is changed with Criterion 2. Figure 6 presents the heatmap of revised closeness (ξ) values across 15 scenarios.

These scenarios introduce various criterion importance configurations, allowing decision-makers to observe the impact of weight changes on the ranking of digital technology applications. This analysis provides valuable insights for policymakers and automotive industry stakeholders by ensuring that the selection of digital solutions is based on a stable and well-founded decision-making framework.

Figure 7 shows the ranking results across 15 scenarios. The ranking results for the digital technology applications in intermodal freight transport show the following trends. Artificial Intelligence (AI) for Optimization (A2) consistently ranks first across all scenarios, highlighting its strong perceived importance in the digitalization of intermodal freight transport. Cloud Computing and Big Data Analytics (A4) holds the second position in every scenario, supporting its significant role in the process. Internet of Things (IoT) for Asset Tracking (A3) is predominantly ranked third, although there is a slight variation in Scenario 3-4, where it drops to fourth place. Geographic Information Systems (GIS) for Strategic Planning (A5) holds the fourth position in most scenarios, but it rises to third in Scenarios 3-4 and 4-6, indicating some shifting perspectives on its importance. Finally, Blockchain for Logistics Management (A1) is ranked fifth in all scenarios, positioning it as the least important application for digitalizing intermodal freight transport. Overall, while most rankings remain stable, the minor shifts in the positions of IoT and GIS highlight variations in their perceived significance across different scenarios. The sensitivity analysis results show that, despite changes in the weight of criteria across 15 scenarios, the ranking results remained largely consistent. This demonstrates that the methodology provides reliable outcomes, validating the stability of the priority of digital technology applications for intermodal transport.

Figure 6. Heatmap of revised closeness values across 15 scenarios.

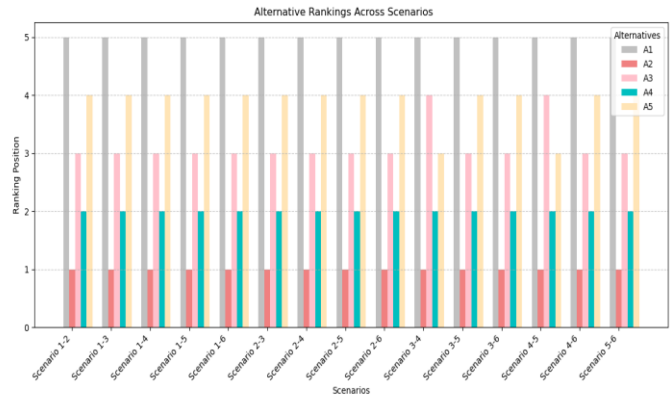

Figure 7. Ranking results across 15 scenarios.

3.3. Discussion

This study is crucial for advancing digital transformation in intermodal freight transport by providing a structured framework to enhance efficiency, reduce costs, and improve sustainability. By integrating CRITIC and TOPSIS within a Picture Fuzzy environment, it offers a novel approach to handling uncertainty in technology evaluation. The findings aid decision-makers in selecting optimal digital solutions and guide policymakers in shaping strategic investments and regulations, ensuring a more resilient and adaptive freight transport system.

As a result of the computations, "Artificial Intelligence (AI) for Optimization" emerges as the top-ranked digital technology application in intermodal freight transport due to its ability to enhance operational efficiency, optimize resource allocation, and improve decision-making. AI-driven systems enable predictive analytics, real-time data processing, and automated decision support, which are critical for managing complex intermodal logistics networks. Kine et al. [15] highlighted that AI, combined with big data, plays a crucial role in processing vast amounts of collected and stored data to support planning and decision-making in intermodal transport. To implement this technology effectively, logistics managers should invest in AI-powered platforms for demand forecasting, route optimization, and automated scheduling while ensuring staff training for seamless integration. Policymakers must support AI adoption by developing regulatory frameworks that promote data standardization, cybersecurity, and collaboration among stakeholders. Additionally, incentives for AI-driven innovation and infrastructure modernization will be crucial in accelerating the digital transformation of intermodal logistics.

As a result of the computations, "Cloud Computing and Big Data Analytics" and "Internet of Things (IoT) for Asset Tracking" rank as the second and third most critical digital technology applications in intermodal freight transport. Cloud computing enables seamless data integration, real-time information sharing, and improved collaboration among stakeholders, making it essential for optimizing logistics operations. Similarly, big data analytics enhances decision-making by analyzing vast amounts of transport data to predict demand, optimize routes, and reduce delays. Medic et al. [18] highlighted that emerging technologies such as IoT, cloud computing, and big data play a vital role in transforming manufacturing and logistics environments by enhancing automation and connectivity. Meanwhile, IoT-based asset tracking improves cargo visibility, enhances security, and minimizes losses by providing real-time location and condition monitoring of freight. Kim et al. [19] reviewed the competitiveness of IoT in multimodal transport, emphasizing its potential to enhance decision-making systems and enable machine-to-machine interaction. To successfully implement these technologies, logistics managers should invest in cloud-based logistics platforms, IoT-enabled tracking systems, and advanced data analytics tools while ensuring cybersecurity measures and workforce training. Policymakers must establish regulations for secure data sharing, incentivize digital infrastructure investments, and promote industry-wide adoption of standardized IoT and cloud solutions to facilitate a smooth digital transition in intermodal logistics.

In the prioritization of evaluation criteria for digital technology applications in intermodal transport, Operational Efficiency ranks first, followed by Economic Efficiency as the second most critical criterion. Operational efficiency is essential as it directly impacts service reliability, cargo handling speed, and overall logistics performance by minimizing delays, optimizing routes, and ensuring seamless coordination across different transport modes. Digital technologies such as AI, cloud computing, and IoT enhance operational efficiency by enabling automation, real-time tracking, and predictive analytics, ultimately improving supply chain resilience. Economic efficiency, ranked second, is crucial for cost reduction, resource optimization, and long-term financial sustainability in intermodal logistics. By leveraging digital solutions, companies can lower transportation costs, reduce empty trips, and maximize asset utilization, leading to improved profitability. To effectively apply these criteria, logistics managers should integrate performance-based assessments when adopting digital tools, focusing on reducing lead times, increasing cargo throughput, and optimizing costs. Policymakers should support this transformation by developing financial incentives for technology adoption, establishing performance benchmarks, and promoting industry-wide standards that ensure both operational and economic benefits in digitalizing intermodal freight transport.

The findings of this study provide valuable insights for policymakers and the automotive industry in advancing digital transformation in intermodal freight transport. Policymakers should develop regulatory frameworks that promote the adoption of digital technologies by ensuring data interoperability, cybersecurity, and standardized communication protocols across transport networks. Additionally, financial incentives such as tax reductions, subsidies, and public-private partnerships can encourage investment in AI, IoT, and cloud-based logistics solutions. The automotive industry, as a key stakeholder in intermodal transport, should focus on integrating smart vehicle technologies, such as connected and autonomous trucks, with intermodal systems to enhance operational efficiency and reduce emissions.

4. Conclusion

This study is crucial as it addresses the growing need for digital transformation in intermodal freight transport by providing a structured approach to prioritizing digital technology applications. With increasing complexity in logistics networks, integrating advanced technologies such as AI, IoT, and cloud computing is essential for enhancing efficiency, reducing costs, and improving sustainability. While previous research has explored various multi-criteria decision-making (MCDM) methods in transportation, a comprehensive evaluation framework for prioritizing digital solutions in intermodal logistics has been lacking.

This study fills this gap by integrating CRITIC and TOPSIS within a Picture Fuzzy environment, offering a novel methodology to assess digital applications objectively. The results of the CRITIC method revealed that Operational Efficiency is the most critical evaluation criterion for assessing digital technology applications in intermodal freight transport, followed by Economic Efficiency. These findings are essential for decision-makers, as they provide a data-driven basis for selecting technologies that enhance logistics performance and cost-effectiveness. For the automotive and logistics industry, the emphasis on operational and economic efficiency highlights the need for investments in smart vehicle technologies, connected systems, and automation to improve integration with intermodal transport networks. By prioritizing these criteria, both sectors can make informed decisions that drive digital transformation and improve the overall sustainability and competitiveness of freight transport.

The outcome of the Picture Fuzzy TOPSIS approach identified "Artificial Intelligence (AI) for Optimization" as the top-ranked digital technology application in intermodal freight transport, followed by "Cloud Computing and Big Data Analytics" and "Internet of Things (IoT) for Asset Tracking" as the second and third most critical applications. These results provide valuable insights for decision-makers, guiding them in prioritizing investments in technologies that enhance operational efficiency, data-driven decision-making, and real-time cargo tracking. By focusing on these high-impact solutions, policymakers and industry leaders can accelerate the digital transformation of intermodal freight transport, improve supply chain resilience, and drive sustainability in logistics operations [20].

Sensitivity analysis was also performed by modifying the weight values of criteria obtained through the CRITIC method and recalculating the closeness values using the Picture Fuzzy TOPSIS approach. A total of 15 scenarios were analyzed, each involving an exchange of weight values between two criteria. The results indicate that, despite these variations, the ranking of digital technology applications remained largely stable, confirming the robustness and reliability of the proposed methodology. This validation ensures that the prioritization of digital solutions for intermodal freight transport remains consistent, increasing confidence in the decision-making framework.

Future research can expand this study by incorporating additional criteria and stakeholder perspectives to refine the prioritization of various decision-making problems, such as selecting optimal practices for reverse logistics and sea freight logistics. Enhancing the methodology with alternative MCDM techniques, such as Best-Worst Method (BWM) or Decision-Making Trial and Evaluation Laboratory (DEMATEL), could offer deeper insights into the interrelationships between evaluation criteria. Additionally, exploring different fuzzy set extensions, such as q-rung orthopair sets and spherical fuzzy sets, may further enhance the robustness and flexibility of the decision-making framework in future studies.

Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

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