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Analysis of Logistics 4.0 Service Provider Alternatives with CRITIC-Based WASPAS Method

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ABSTRACT

Purpose: This study aims to evaluate and identify the most suitable logistics service providers within the framework of Logistics 4.0, shaped by digital transformation and Industry 4.0 technologies. Logistics 4.0 seeks to optimize logistics processes using innovative technologies such as smart systems and big data analytics. In this context, selecting the right service provider is of strategic importance for businesses. This study intends to assist companies in making accurate decisions in this complex process.

Method: The CRITIC (Criteria Importance Through Intercriteria Correlation) based WASPAS (Weighted Aggregated Sum Product Assessment) method was employed. The CRITIC method was used to determine the objective weights of the criteria, while the WASPAS method utilized these weights to calculate the overall performance scores of the alternatives.

Findings: The results of the study reveal the key criteria that businesses should consider when selecting Logistics 4.0 service providers and identifying the top-performing service providers.

Originality: This study highlights the advantages and effectiveness of using the combined CRITIC and WASPAS methods in the selection of service providers in the logistics sector. Additionally, it contributes to the literature on the selection of Logistics 4.0 service providers.

Keywords**:** Logistics 4.0, Multi-Criteria Decision Making, CRITIC, WASPAS.
JEL Codes: C44, M10, D70.

Lojistik 4.0 Hizmet Sağlayıcı Alternatiflerinin CRITIC tabanlı WASPAS Yöntemi ile Analizi

ÖZET

Amaç: Bu çalışmanın amacı, dijital dönüşüm ve Endüstri 4.0 teknolojileriyle şekillenen Lojistik 4.0 kavramı çerçevesinde, lojistik hizmet sağlayıcılarının değerlendirilmesi ve en uygun hizmet sağlayıcının belirlenmesidir. Lojistik 4.0, akıllı sistemler ve büyük veri analitiği gibi yenilikçi teknolojileri kullanarak lojistik süreçleri optimize etmeyi hedefler. Bu bağlamda, doğru hizmet sağlayıcıyı seçmek, işletmeler için stratejik bir öneme sahiptir. Çalışma, işletmelerin bu karmaşık süreçte doğru kararlar almasına yardımcı olmayı amaçlamaktadır.

Yöntem: CRITIC (Criteria Importance Through Intercriteria Correlation) tabanlı WASPAS (Weighted Aggregated Sum Product Assessment) yöntemi kullanılmıştır. CRITIC yöntemi ile kriterlerin objektif ağırlıkları belirlenmiş, WASPAS yöntemi ise bu ağırlıkları kullanarak alternatiflerin genel performans skorlarını hesaplamıştır.

Bulgular: Çalışma sonuçları, işletmelerin Lojistik 4.0 hizmet sağlayıcılarını seçerken dikkat etmeleri gereken önemli kriterleri ve en iyi performans gösteren hizmet sağlayıcıları ortaya koymuştur.

Özgünlük: Bu çalışma, CRITIC ve WASPAS yöntemlerinin birlikte kullanımının, lojistik sektöründe hizmet sağlayıcı seçiminde sağladığı avantajları ve yöntemlerin etkinliğini vurgulamaktadır. Ayrıca, lojistik sektöründe Lojistik 4.0 hizmet sağlayıcılarının seçimi konusunda literatüre katkı sağlamaktadır.

Anahtar Kelimeler: Lojistik 4.0, Çok Kriterli Karar Verme, CRITIC, WASPAS.
JEL Kodları: C44, M10, D70.

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1. INTRODUCTION

The logistics sector is undergoing a significant transformation driven by digitalization and the integration of Industry 4.0 technologies. This new paradigm has given rise to the concept of Logistics 4.0, which aims to make logistics processes more efficient, flexible, and sustainable. Logistics 4.0 involves the integration of innovative technologies such as smart systems, big data analytics, the Internet of Things (IoT), artificial intelligence, and automation technologies (Wang et al., 2020; Hofmann & Rüsch, 2017). The adoption of these technologies not only optimizes traditional logistics operations but also creates new opportunities for enhancing the entire supply chain. Consequently, the selection of suitable logistics service providers becomes a critical strategic decision for businesses seeking to leverage the full potential of Logistics 4.0.

The criteria for evaluating logistics service providers in the context of Logistics 4.0 are diverse and multifaceted. Key criteria include cost, service quality, technology utilization, flexibility, and sustainability. Each of these criteria plays a crucial role in determining the overall effectiveness and competitiveness of a logistics service provider (Govindan et al., 2018; Büyüközkan & Göçer, 2018). For instance, the cost criterion evaluates the financial implications of choosing a particular provider, while service quality assesses the reliability and performance of logistics services. Technology utilization examines the extent to which providers integrate advanced technologies into their operations, and flexibility measures their ability to adapt to changing conditions. Finally, sustainability considers the environmental and social impacts of logistics activities (Kannan et al., 2020).

In this context, Multi-Criteria Decision Making (MCDM) methods have emerged as valuable tools for evaluating and selecting logistics service providers. Among these methods, the CRITIC (Criteria Importance Through Intercriteria Correlation) and WASPAS (Weighted Aggregated Sum Product Assessment) techniques have gained prominence due to their robust analytical capabilities. The Criteria Importance Through Intercriteria Correlation (CRITIC) method helps in determining the objective weights of various criteria, while the Weighted Aggregated Sum Product Assessment (WASPAS) method utilizes these weights to calculate the overall performance scores of alternatives (Zavadskas et al., 2012; Yazdani et al., 2019). By combining these methods, decision-makers can achieve a more comprehensive and accurate assessment of logistics service providers. This integrated approach addresses the complexity and multi-dimensionality of the decision-making process in the Logistics 4.0 environment. One of the central aims of Logistics 4.0 is to optimize operational efficiency through the use of smart technologies, data-driven decision-making, and automation. In this context, the selection of service providers that can deliver efficient logistics solutions is critical for businesses seeking competitive advantage. This study not only identifies the best-performing service providers but also focuses on how these providers contribute to improved efficiency in logistics operations.

This study aims to contribute to the decision-making process for selecting Logistics 4.0 service providers by offering a systematic approach for identifying the most efficient providers. A review of the existing literature reveals a lack of objective and systematic MCDM methods specifically tailored to Logistics 4.0 service provider selection. This study fills that gap by integrating the CRITIC and WASPAS methods, providing a comprehensive and objective evaluation framework. The original contribution of this research lies in its proposal of a hybrid approach that addresses the complexity of decision-making in Logistics 4.0.

The rest of the study is organized as follows. In the second section, the concept of Logistics 4.0 is explained in detail. In the third section, the methods used in the study are presented. In the fourth section, the application area of the study is given. In the last section, the results obtained in the study are interpreted.

LOGISTICS 4.0

Industry 4.0 represents the digital transformation of manufacturing processes, encompassing automation, data exchange, smart systems, and the integration of advanced manufacturing techniques. This paradigm shift has brought about revolutionary changes across a wide range of areas, from production lines to supply chains. Key technologies driving Industry 4.0 include the IoT, cyber-physical systems, big data analytics, and Artificial Intelligence (AI). These technologies enable real-time monitoring, predictive maintenance, and enhanced decision-making capabilities, significantly improving operational efficiency and flexibility (Hofmann & Rüsch, 2017; Wang et al., 2020). As a result, companies adopting Industry 4.0 principles can achieve higher levels of productivity and competitiveness in the global market.

Logistics 4.0, a subset of Industry 4.0, specifically focuses on the logistics and supply chain sectors. It aims to optimize logistics processes using advanced technologies and digital innovations. Logistics 4.0 leverages IoT to connect various components of the supply chain, enabling real-time tracking and monitoring of goods and assets. This connectivity enhances transparency, reduces delays, and improves overall supply chain efficiency (Barreto et al., 2017). Moreover, big data analytics plays a crucial role in Logistics 4.0 by providing insights into patterns and trends, helping companies make data-driven decisions and anticipate potential disruptions. By integrating these technologies, Logistics 4.0 seeks to create a more responsive and agile supply chain.

One of the fundamental aspects of Logistics 4.0 is the use of autonomous vehicles and drones for transportation and delivery. Autonomous trucks and drones equipped with advanced sensors and navigation systems can operate with minimal human intervention, reducing labor costs and increasing delivery speed and accuracy. These autonomous systems can optimize delivery routes in real time, avoiding traffic congestion and minimizing fuel consumption. Additionally, warehouses are becoming increasingly automated with the use of robotic systems for sorting, picking, and packing goods (Saarikko et al., 2020; Fottler et al., 2020: 38). This automation not only enhances efficiency but also reduces the risk of human error, ensuring a more reliable logistics operation.

The integration of AI and machine learning in Logistics 4.0 further enhances decision-making and operational efficiency. AI algorithms can analyze vast amounts of data from various sources, such as weather conditions, traffic patterns, and inventory levels, to optimize logistics processes. For instance, predictive analytics can forecast demand and adjust inventory levels accordingly, reducing the risk of stockouts or overstocking. Machine learning models can also identify patterns in transportation data to improve route planning and delivery schedules (Ivanov et al., 2019; Choi et al., 2019). By utilizing these advanced technologies, companies can achieve greater operational efficiency, cost savings, and improved customer satisfaction.

Sustainability is another critical aspect of Logistics 4.0. The integration of green technologies and practices aims to reduce the environmental impact of logistics operations. Electric and hybrid vehicles, for instance, are being adopted to lower carbon emissions. Additionally, smart logistics systems can optimize energy consumption in warehouses and transportation networks. The use of recyclable and biodegradable packaging materials is also being promoted to minimize waste (de Oliveira and Handfield, 2019; Agyabeng-Mensah et al., 2020). By focusing on sustainability, Logistics 4.0 not only addresses environmental concerns but also enhances the corporate social responsibility of businesses.

Logistics 4.0 represents a significant evolution in the logistics and supply chain sectors, driven by the integration of advanced digital technologies. By leveraging IoT, AI, autonomous systems, and sustainable practices, Logistics 4.0 aims to create more efficient, agile, and environmentally friendly logistics operations. This transformation offers numerous benefits, including cost savings, improved customer satisfaction, and a reduced environmental footprint. As businesses continue to adopt and integrate these technologies, the logistics industry is poised for a future of increased innovation and competitiveness (Wang et al., 2020; Hofmann and Rüsch, 2017).

3. CRITIC and WASPAS METHODS

3.1 CRITIC Method

The CRITIC method is an MCDM technique used to determine the objective weights of evaluation criteria. Developed by Diakoulaki et al. (1995), the CRITIC method is particularly useful in scenarios where subjective judgments might introduce biases, as it relies on the intrinsic properties of the data to assign weights to criteria. This method considers both the contrast intensity of each criterion and the conflict or correlation between criteria, thus providing a comprehensive approach to weight determination. The CRITIC method involves several steps:

1. Normalization: The first step in the CRITIC method is to normalize the decision matrix. This is done to bring all the criteria to a comparable scale. The normalized value r_{ij} of each element is calculated using Equation 1.

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

2. Standard Deviation Calculation: The standard deviation σ_j of each criterion is then calculated using Equation 2. This measures the contrast intensity or the degree of differentiation of each criterion.

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_{ij} - \bar{r}_j)^2} \tag{2}$$

3. Correlation Coefficient Calculation: The correlation coefficient ρ_{jk} between criteria j and k is calculated via Equation 3 to assess the degree of conflict between criteria.

$$\rho_{jk} = \frac{\sum_{i=1}^{n}(r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{n}(r_{ij} - \bar{r}_j)^2 (r_{ik} - \bar{r}_k)^2}} \tag{3}$$

4. Information Content Calculation: The amount of information provided by each criterion C_j is then determined (Equation 4). This considers both the standard deviation and the correlation with other criteria.

$$C_j = \sigma_j \sqrt{\sum_{k=1}^{m}(1 - p_{jk})} \quad (4)$$

5. Weight Calculation: Finally, the weight W_j of each criterion is calculated by normalizing the information content values (Equation 5).

$$W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \quad (5)$$

The CRITIC method is particularly advantageous because it provides an objective way to determine the weights of criteria, eliminating potential biases associated with subjective weight assignment. It considers both the variability of criteria and their interrelationships, ensuring that the final weights reflect the true importance of each criterion in the decision-making process (Diakoulaki et al., 1995; Zavadskas et al., 2012).

By integrating the CRITIC method with other MCDM techniques, such as the WASPAS, decision-makers can achieve more accurate and reliable evaluations of alternatives. This integrated approach leverages the strengths of both methods, providing a robust framework for complex decision-making scenarios in various fields, including logistics, supply chain management, and beyond (Yazdani et al., 2019; Zavadskas et al., 2012).

The CRITIC method has been widely applied in MCDM problems across various domains. Ahmad et al. (2023) integrated the CRITIC method with the MABAC method for identifying occupational hazards using q-rung picture fuzzy sets. Taletović (2023) reviewed the application of MCDM methods in warehouse management, highlighting the effectiveness of the CRITIC method. Lai and Liao (2021) employed the CRITIC method in the DNMA approach to evaluate blockchain platforms, emphasizing the method's ability to reflect criteria correlations. Zhang et al. (2023) introduced the Cloud-CRITIC-PDR method, combining the CRITIC method with a cloud model and probabilistic dominance relations for hybrid MCDM. Abouhawwash and Jameel (2023) applied the CRITIC method to evaluate solar power installations under a Neutrosophic MCDM model.

Nabavi et al. (2024) assessed the sensitivity of MCDM methods, including CRITIC, in chemical engineering optimization applications. Hassan et al. (2023) used the CRITIC method to determine factor weights for evaluating solar PV plant sites. Sarucan et al. (2024) ranked BSECO member countries using CRITIC, COPRAS, and Borda Count methods, with Albania ranked first. Al-Hchaimi et al. (2022) applied the CRITIC method to evaluate DoS countermeasure techniques on MPSoC-based IoT platforms. Kumar et al. (2022) utilized the CRITIC method for ranking solid-state drives in a MCDM framework. Ulutas and Karaköy (2019) analyze the performance of a cargo company from 2011 to 2017 using the CRITIC and ROV methods. Krishankumar et al. (2023) assessed zero-carbon measures in sustainable transportation within smart cities using a CRITIC-MARCOS framework based on q-rung fuzzy preferences. Günay and Ecer (2022) conducted a comparative analysis of Türkiye's real sector from both economic and financial perspectives using the CRITIC-MAIRCA method.

Yilmaz and Burdurlu (2023) prioritized criteria for selecting wooden furniture joints using the CRITIC method and ARAS method, identifying strength as the top criterion. Özekenci (2023) evaluated the export performance of Turkish metropolitan cities, ranking them using integrated MCDM methods including CRITIC. Shao et al. (2023) suggested a value index system for energy storage systems based on the CRITIC model and MCDM models. Pala (2023) compared the financial performance of technology and information sector companies using the CRITIC method for criteria weighting. Mohamed et al. (2024) used the CRITIC method to select the optimal Internet of Energy platforms for smart cities. As seen in the above studies, the CRITIC method has not been used in the Logistics 4.0 field before.

3.2 WASPAS Method

WASPAS methodology is an MCDM technique that combines the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to improve decision-making accuracy. Below are the detailed steps, explanations, and formulas (Zavadskas and Turskis, 2012):

1. Construct the Decision Matrix: The decision matrix $X = [x_{ij}]$ is formed (Equaiton 6) where x_{ij} represents the performance of alternative A_i with respect to criterion C_j.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \cdots & x_{1m} \\ x_{21} & x_{22} & x_{23} & x_{2m} \\ \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} \cdots & x_{mn} \end{bmatrix} \quad (6)$$

2.Normalize the Decision Matrix: Normalization is performed to transform the criteria values into a comparable scale (Equation 7 and 8).

For benefit criteria,

$$\overline{x_{ij}} = \frac{x_{ij}}{\max_i(x_{ij})} \qquad i = 1,2,\dots,m \qquad j = 1,2,\dots,n \quad (7)$$

For cost criteria,

$$\overline{x_{ij}} = \frac{\min_i(x_{ij})}{x_{ij}} \qquad i = 1,2,\dots,m \qquad j = 1,2,\dots,n \quad (8)$$

3. Construct the Weighted Normalized Decision Matrix: The normalized values are then multiplied by the respective weights of the criteria (Equation 9).

$$v_{ij} = w_j . r_{ij} \quad (9)$$

where w_j is the weight of criterion C_j.

4. Calculate the Overall Performance Scores Using WSM and WPM: The WSM score for each alternative A_i is calculated using Equation 10 and the WPM score for each alternative A_i is calculated using Equation 11.

$$Q_i^{(1)} = \sum_{j=1}^{n} \overline{x_{ij}} w_j \quad (10)$$

$$Q_i^{(2)} = \prod_{j=1}^{n} \overline{x_{ij}}^{w_j} \quad (11)$$

5. Combine WSM and WPM Scores: The final WASPAS score for each alternative is a combination of the WSM and WPM scores (Equaiton 12), adjusted by the parameter λ ($0 \le \lambda \le 1$), which balances the influence of WSM and WPM.

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)} = \lambda \sum_{j=1}^{n} (X_{ij})\, w_j + (1-\lambda) \prod_{j=1}^{n} (X_{ij})^{w_j} \quad (12)$$

The WASPAS method has been extensively applied in various MCDM problems. Handayani et al. (2023) employed the WASPAS method to select online English courses, determining that the British Council obtained the highest score. Abualkishik and Almajed (2023) utilized WASPAS for ranking Intelligent Transportation Systems alternatives. Ahmad and Ozcek (2023) used WASPAS to solve sustainable crop selection problems using neutrosophic type 2 data. Barbara et al. (2023) developed an internet tool for decision-makers based on WASPAS, called waspasWEB. Arisantoso et al. (2023) implemented WASPAS in a decision support system for selecting webcams. Alharbi et al. (2024) assessed leadership management challenges in the energy sector using WASPAS. Mayatopani (2023) applied WASPAS for selecting corn seeds. Do (2021) optimized surface roughness and material removal rate in grinding processes using WASPAS. Narayanamoorthy et al. (2021) combined WASPAS with fuzzy set theory to select hair mask products. Taletović (2023) reviewed WASPAS among other methods for warehouse management practices.

Rastpour et al. (2022) used WASPAS to evaluate companies' greenness in the dairy industry. Akpınar (2021) used the same method to evaluate third-party logistics providers. Khalilzadeh et al. (2024) employed fuzzy WASPAS for project risk management. Zaher and Eldakhly (2023) integrated WASPAS with trapezoidal neutrosophic sets for failure mode risk evaluation. Abdelhafeez et al. (2024) ranked optimal livestock locations using WASPAS. Dahooie et al. (2022) used WASPAS for selecting solar power plant locations in Iran. Sharma et al. (2022) applied WASPAS to select lightweight materials for railway vehicles. Özekenci (2023) evaluated export performance of Turkish metropolitan cities using WASPAS. Gökkuş et al. (2023) ranked Çanakkale districts in terms of rangeland quality using WASPAS among other methods. Pala (2023) compared the financial performance of technology companies using WASPAS. Akmermer and Çelik (2021) evaluated the contribution of fishery products to Turkish foreign trade using WASPAS. Aytekin et al. (2023) evaluated pharmaceutical distribution and warehousing companies using a combined Fermatean fuzzy Entropy-WASPAS approach. Karaca and Ulutaş (2018) use Entropy and WASPAS methods to select the most suitable renewable energy source for Türkiye. By analyzing multiple energy alternatives, the study provides a comprehensive evaluation model that ranks energy sources based on various criteria. As seen in the above studies, the WASPAS method has not been used in the Logistics 4.0

field before, too. Therefore, this study plans to take its place in the literature as the first study in which the CRITIC and WASPAS methods are used as a hybrid in the field of Logistics 4.0.

The CRITIC and WASPAS methods were specifically chosen for this study due to their unique advantages in MCDM. The CRITIC method allows for the determination of objective weights for criteria, minimizing the potential biases associated with subjective judgments. The WASPAS method, which combines the WSM and WPM, enhances decision accuracy by considering both additive and multiplicative factors. These methods were deemed particularly suitable for Logistics 4.0 service provider evaluation, where multiple interrelated criteria must be considered. Compared to alternative methods, the integration of CRITIC and WASPAS offers a more comprehensive and reliable approach for addressing the complexity of Logistics 4.0 decision-making.

4. PROBLEM STATEMENT USING MCDM

With the emergence of the concept of Logistics 4.0, businesses are turning to work with companies that have proven themselves in this field and to increase their collaborations. This situation necessitates the transformation of many logistic companies in this field. In this study, the problem of a company deciding on the most suitable among alternative companies that have implemented Logistics 4.0 among logistics service providers and proven themselves in this field was addressed. In the problem addressed, five alternative logistics companies were determined by the purchasing experts of the company. Ten criteria were determined for the evaluation of these alternatives. The criteria used in this study, such as operational efficiency, technological infrastructure, and real-time monitoring, are directly related to improving logistics efficiency. The integration of these criteria into the CRITIC-WASPAS framework ensures that the selected service providers are those most capable of optimizing logistical processes and achieving higher levels of efficiency. The evaluation criteria used in this study were selected based on a comprehensive review of the relevant literature in the field of Logistics 4.0 and MCDM. Key criteria, such as technological infrastructure, operational efficiency, and sustainability, were chosen because they are critical success factors in the implementation of Logistics 4.0 systems. Moreover, expert consultations with industry professionals ensured that the selected criteria reflect the most important aspects of logistics service provider performance in today's digital and automated environments. According to the criteria addressed, the alternative that best provides the Logistics 4.0 transformation was selected. The problem hierarchy is provided in Figure 1. The criteria used in the study are as follows:

Technological Infrastructure (TI): The level of IoT, big data analytics, artificial intelligence, and automation systems that the company possesses.

Integration Capability (IC): The company's ability to integrate with existing supply chain and logistics processes. This includes compatibility with ERP (Enterprise Resource Planning) and other logistics software.

Data Security and Privacy (DSP): The company's data security policies and measures are taken to ensure data privacy.

Real-Time Monitoring and Visibility (RTMV): The company's ability to provide real-time monitoring and visibility at every stage of logistics process and the supply chain.

Adaptability and Flexibility (AF): The company's capacity to quickly adapt to changing market conditions and customer demands.

Operational Efficiency (OE): How efficiently the company manages its processes, its success in reducing costs, and optimizing operations.

Customer Service and Support (CSS): The quality of the company's customer service and technical support.

Logistics Network and Coverage (LNC): The company's logistics network and coverage area, including which regions it serves and its performance in those regions.

Environmental Sustainability (ES): The company's environmental sustainability policies and practices.

References and Reputation (RR): The company's reputation in the industry, customer references, and past performance.

The decision matrix was created after the decision-makers determined the criteria mentioned above. The decision matrix used in the study is given in Table 1. Normalized decision matrix is provided in Table 2 while a correlation matrix is provided in Table 3. Standard deviation, information content calculation, and weight results are provided in Table 4.

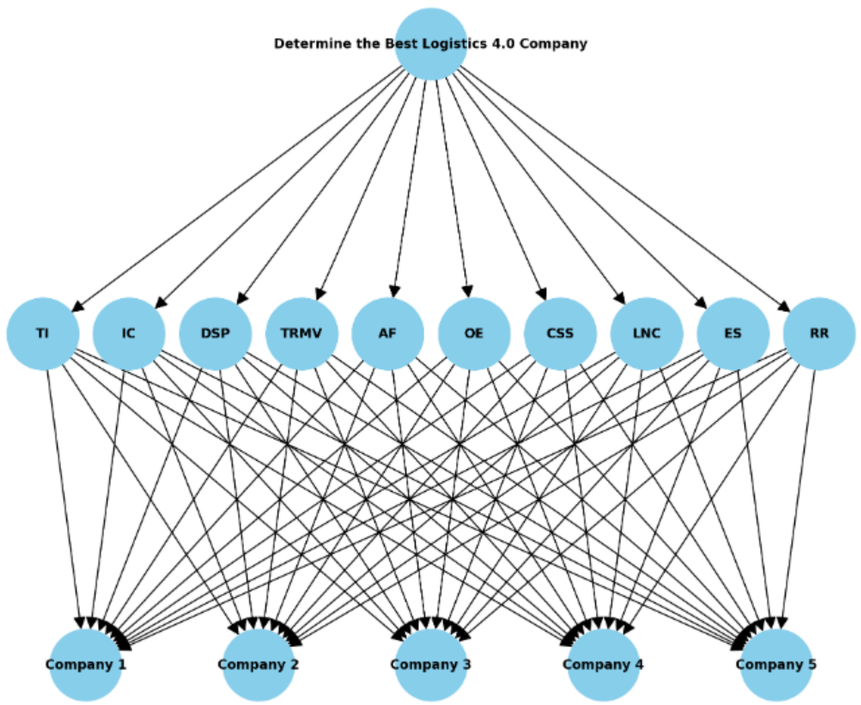

Figure 1: The hierarchical structure of the problem

Table 1. Decision matrix of the problem

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	45	55	40	40	60	55	50	45	90	60
Company 2	55	35	45	30	45	75	35	30	40	50
Company 3	85	80	80	75	85	70	70	90	85	25
Company 4	80	85	75	90	80	95	90	85	65	20
Company 5	65	70	65	70	75	60	55	60	70	40

Table 2. Normalized matrix

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.000	0.400	0.000	0.167	0.375	0.000	0.273	0.250	1.000	0.000
Company 2	0.250	0.000	0.125	0.000	0.000	0.500	0.000	0.000	0.000	0.250
Company 3	1.000	0.900	1.000	0.750	1.000	0.375	0.636	1.000	0.900	0.875
Company 4	0.875	1.000	0.875	1.000	0.875	1.000	1.000	0.917	0.500	1.000
Company 5	0.500	0.700	0.625	0.667	0.750	0.125	0.364	0.500	0.600	0.500

Table 3. Correlation matrix

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
TI	1.000	0.809	0.981	0.860	0.827	0.595	0.786	0.912	0.095	0.978
IC	0.809	1.000	0.881	0.969	0.978	0.356	0.927	0.960	0.516	0.828
DSP	0.981	0.881	1.000	0.920	0.905	0.491	0.805	0.938	0.196	0.960
TRMV	0.860	0.969	0.920	1.000	0.932	0.508	0.929	0.928	0.291	0.905
AF	0.827	0.978	0.905	0.932	1.000	0.226	0.840	0.960	0.563	0.804
OE	0.595	0.356	0.491	0.508	0.226	1.000	0.633	0.432	-0.469	0.715
CSS	0.786	0.927	0.805	0.929	0.840	0.633	1.000	0.909	0.334	0.857
LNC	0.912	0.960	0.938	0.928	0.960	0.432	0.909	1.000	0.458	0.897
ES	0.095	0.516	0.196	0.291	0.563	-0.469	0.334	0.458	1.000	0.019
EE	0.978	0.828	0.960	0.905	0.804	0.715	0.857	0.897	0.019	1.000

Table 4. Final weights

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
σ_j	0.418	0.406	0.445	0.418	0.409	0.389	0.380	0.427	0.394	0.418
C_j	0.903	0.722	0.857	0.736	0.804	2.146	0.753	0.686	2.755	0.853
W_j	0.081	0.064	0.076	0.066	0.072	0.191	0.067	0.061	0.246	0.076

In the study, the calculation phase of the criteria weights with the CRITIC method was concluded with Table 4. It was seen that the criterion with the highest weight was the ES criterion. The criterion with the lowest level of importance was the LNC criterion. The ranking of the alternatives was made with the WASPAS method. First, the normalized values are shown in Table 5. Total relative importance values are provided in Table 6 while total relative importance by WPM values are provided in Table 7.

Table 5. Normalized matrix

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.529	0.647	0.500	0.444	0.706	0.579	0.556	0.500	1.000	0.333
Company 2	0.647	0.412	0.563	0.333	0.529	0.789	0.389	0.333	0.444	0.400
Company 3	1.000	0.941	1.000	0.833	1.000	0.737	0.778	1.000	0.944	0.800
Company 4	0.941	1.000	0.938	1.000	0.941	1.000	1.000	0.944	0.722	1.000
Company 5	0.765	0.824	0.813	0.778	0.882	0.632	0.611	0.667	0.778	0.500

Table 6. Total relative importance (Q1)

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.043	0.041	0.038	0.029	0.051	0.111	0.037	0.031	0.246	0.025
Company 2	0.052	0.026	0.043	0.022	0.038	0.151	0.026	0.020	0.109	0.030
Company 3	0.081	0.060	0.076	0.055	0.072	0.141	0.052	0.061	0.232	0.061
Company 4	0.076	0.064	0.071	0.066	0.068	0.191	0.067	0.058	0.178	0.076
Company 5	0.062	0.053	0.062	0.051	0.064	0.121	0.041	0.041	0.191	0.038

Table 7. Total relative importance by WPM (Q2)

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.950	0.973	0.949	0.948	0.975	0.901	0.961	0.959	1.000	0.920
Company 2	0.965	0.945	0.957	0.930	0.955	0.956	0.939	0.935	0.819	0.933
Company 3	1.000	0.996	1.000	0.988	1.000	0.943	0.983	1.000	0.986	0.983
Company 4	0.995	1.000	0.995	1.000	0.996	1.000	1.000	0.997	0.923	1.000
Company 5	0.979	0.988	0.984	0.984	0.991	0.916	0.968	0.976	0.940	0.949

Q_i values for Company 1 is 0.635, Company 2 is 0.508, Company 3 is 0.888, Company 4 is 0.911, and Company 5 is 0.719 respectively. Hence the best alternative is Company 4 with the highest score. After, Company 3, Company 5, Company 1, and Company 2 are the other selectable alternatives.

5. DISCUSSION and CONLUSION

Industry 4.0 represents the fourth industrial revolution, marked by the integration of advanced digital technologies into manufacturing processes. It combines the Internet of Things, artificial intelligence, big data analytics, and cyber-physical systems to create smart factories. These technologies are also pivotal in transforming logistics, leading to the emergence of Logistics 4.0. In smart factories, interconnected machines communicate and make autonomous decisions, impacting supply chain logistics by improving efficiency and productivity. Industry 4.0 enhances flexibility and customization in production, which in turn demands more agile and responsive logistics systems. Data-driven decision-making, predictive maintenance, and real-time monitoring are critical components that improve logistics operations. By leveraging cloud computing and edge computing, Industry 4.0 enables seamless data exchange across the entire supply chain, enhancing logistics coordination. The revolution fosters innovation through digital twins, virtual simulations, and augmented reality, which are also applied in logistics for better planning and execution. Cybersecurity becomes crucial to protect interconnected systems, including logistics networks, from potential threats. Overall, Industry 4.0 is transforming traditional manufacturing and logistics into highly automated, intelligent, and adaptive ecosystems.

Logistics 4.0 is the application of Industry 4.0 principles to the logistics and supply chain management sector. It leverages IoT, AI, big data, and automation to streamline logistics operations. Smart logistics systems enable real-time tracking and monitoring of goods, enhancing visibility and transparency. AI algorithms optimize routing and scheduling, reducing delivery times and costs. Autonomous vehicles and drones are increasingly used for transportation and warehousing, minimizing human intervention. Predictive analytics helps in demand forecasting and inventory management, ensuring efficient stock levels. The integration of blockchain technology ensures secure and transparent transactions. Collaborative robots (cobots) assist in warehouse operations, improving accuracy and speed. Logistics 4.0 promotes sustainability by optimizing routes and reducing emissions. It creates interconnected and flexible supply chains that can quickly respond to market demands. The results of this study demonstrate that the selected logistics service providers, particularly those ranked highest, offer significant opportunities for improving operational efficiency. By utilizing advanced technologies and optimizing key performance indicators such as flexibility and adaptability, these providers contribute to more efficient and responsive logistics operations, aligning with the goals of Logistics 4.0.

To select the best Logistics 4.0 service provider, the CRITIC and WASPAS methods were employed in this study. These MCDM methods allowed for a comprehensive evaluation of each company based on the ten criteria. The CRITIC method helped in determining the objective weights of the criteria by considering the contrast intensity of each criterion. The WASPAS method combined the WSM and the WPM, providing a robust framework for ranking the alternatives. Through this approach, the most suitable company was selected based on its overall performance across the evaluated criteria. Finally, this study successfully identified the best company for Logistics 4.0 implementation using a structured and rigorous evaluation process. This study makes significant contributions to the field by introducing the combined use of CRITIC and WASPAS methods in the evaluation of Logistics 4.0 service providers. By integrating these two powerful MCDM techniques, the study fills a notable gap in the literature, where objective and systematic approaches to service provider selection in Logistics 4.0 are limited. The combined methodology offers valuable insights for both academic research and practical applications in the logistics industry, providing a robust framework for more reliable decision-making. Future studies could explore the integration of additional criteria, such as the company's innovation capacity and collaboration with technology partners. Moreover, applying other MCDM methods and comparing their results could provide further insights into the robustness of the selection process. Moreover, longitudinal studies could be conducted to assess the long-term impact of Logistics 4.0 implementation on the selected company's performance.

Conflict of Interest
No potential conflict of interest was declared by the author.

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Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Abdelhafeez, A., Khalil, N. A., Eassa, M., & Elkholy, M. (2024). “Selection Optimal Livestock Location under Multi-Criteria Decision Making Fuzzy Framework”. *Precision Livestock*, *1*, 58-65.

Abouhawwash, M. and Jameel, M. (2023). “Evaluation Factors of Solar Power Plants to Reduce Cost Under Neutrosophic Multi-Criteria Decision Making Model”, *Sustainable Management Journal*, 2(3), 101-114.

Abualkishik, A. and Almajed, R. (2023). “WASPAS Multi-Criteria Decision-Making Method for Assessment Effectiveness and Performance Intelligent Transportation Systems Alternatives”, *Financial Technology & Innovation*, 3(1), 1-12.

Agyabeng-Mensah, Y., Ahenkorah, E., Afum, E., Owusu, L., Agyabeng, C. and Baah, C. (2020). “The Influence of Logistics Outsourcing, Information Technology, and Innovation Capabilities on Supply Chain Sustainability”, *Journal of Cleaner Production*, 258, 120808. https://doi.org/10.1016/j.jclepro.2020.120808

Ahmad, A. and Ozcek, M. (2023). “Multi-Criteria Decision-Making Methodology for Sustainable Crop Selection”, *International Journal of Artificial Intelligence and Computing*, 6(1), 1-15.

Ahmad, U., Khan, A. and Saeid, A. (2023). “Integrated Multi-Criteria Group Decision-Making Methods Based on Q-Rung Picture Fuzzy Sets for the Identification of Occupational Hazards”, *Applied Soft Computing*, 123, 105591.

Akmermer, B., & Çelik, P. (2021). “Contribution of fishery and aquaculture products to Turkish foreign trade: An evaluation by a hybrid multi-criteria decision-making method”. *Ege Journal of Fisheries & Aquatic Sciences (EgeJFAS)/Su Ürünleri Dergisi*, *38*(3).

Akpınar, M. E. (2021). “Third-party logistics (3PL) provider selection using hybrid model of SWARA and WASPAS”. *International Journal of Pure and Applied Sciences*, *7*(3), 371-382.

Alharbi, A.H., Jabali, H.M., Rajan, P. and Salamai, A. (2024). “Evaluation Challenges of Leadership Management in the Energy Sector using Multi-Criteria Decision Making Approach”, *Management Studies*, 4(2), 21-30.

Al-Hchaimi, A.A.J., Sulaiman, N.B., Mustafa, M.A.B, Mohtar, M.N.B, Hassan, S.L.B.M. and Muhsen, Y.R. (2022). “Evaluation Approach for Efficient Countermeasure Techniques Against Denial-of-Service Attack on MPSoC-Based IoT Using Multi-Criteria Decision-Making”, *IEEE Access*, 10, 114569-114585. https://doi.org/10.1109/ACCESS.2022.3232395

Arisantoso, A., Somaida, M.H., Sanwasih, M. and Shalahudin, M.I. (2023). “Multi-Criteria Decision Making Using the WASPAS Method in Webcam Selection Decision Support Systems”, *Indonesian Journal of Computing Science*, 7(1), 1-11.

Aytekin, A., Görçün, Ö.F., Ecer, F., Pamucar, D. and Karamaşa, Ç. (2023). “Evaluation of the Pharmaceutical Distribution and Warehousing Companies through An Integrated Fermatean Fuzzy Entropy-WASPAS Approach”, *Kybernetes*, 52(11), 5561-5592.

Barbara, F., dos Santos, M., Silva, A.S., Moreira, M., Lopes Fávero, L.P., Pereira Júnior, E.L., Carvalho, W.A., Muradas, F., Pereira, D.A. de M. and Portella, A.G. (2023). “Interactive Internet Framework Proposal of WASPAS Method: A Computational Contribution for Decision-Making Analysis”, *Mathematics*, 11(15), 3375.

Barreto, L., Amaral, A. and Pereira, T. (2017). “Industry 4.0 Implications in Logistics: An Overview”, *Procedia Manufacturing*, 13, 1245-1252.

Büyüközkan, G. and Göçer, F. (2018). “Digital Supply Chain: Literature Review and A Proposed Framework for Future Research”, *Computers in Industry*, 97, 157-177. https://doi.org/10.1016/j.compind.2018.02.010

Choi, T.M., Chan, H.K. and Yue, X. (2019). “Recent Development in Big Data Analytics for Business Operations and Risk Management”, *IEEE Transactions on Cybernetics*, 49(1), 36-45.

de Oliveira, U.R. and Handfield, R. (2019). “Analytical Models for Assessing Green Supply Chain Practices in the Brazilian Automotive Industry”, *Resources, Conservation and Recycling*, 145, 269-278. https://doi.org/10.1016/j.resconrec.2019.02.031

Diakoulaki, D., Mavrotas, G. and Papayannakis, L. (1995). “Determining Objective Weights in Multiple Criteria Problems: The CRITIC Method”, *Computers & Operations Research*, 22(7), 763-770. https://doi.org/10.1016/0305-0548(94)00059-H

Do, T. (2021). “The Combination of Taguchi – Entropy – WASPAS - PIV Methods for Multi-Criteria Decision Making When External Cylindrical Grinding of 65G Steel”, *Journal of Manufacturing Engineering*, 14, 1-12.

Fottler, M., Ford, E. and Braunscheidel, M. (2020). “Healthcare Operations Management: A Systems Perspective”, Routledge. https://doi.org/10.4324/9781003046778

Gökkuş, Z., Şentürk, S., & Alatürk, F. (2023). “Ranking Çanakkale Districts in terms of rangeland quality with multi-criteria decision making methods”. *Türk Tarım ve Doğa Bilimleri Dergisi*, *10*(3), 605-614.

Govindan, K., Soleimani, H. and Kannan, D. (2018). “Reverse Logistics and Closed-Loop Supply Chain: A Comprehensive Review to Explore the Future”, *European Journal of Operational Research*, 240(3), 603-626.

Günay, F. and Ecer, F. (2022). "A Comparative Analysis of the Real Sector in Turkey from the Economic and Financial Perspectives with the CRITIC-MAIRCA Method", *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 7(1), 186-219.

Handayani, N., Heriyani, N., Septian, F. and Alexander, A.D. (2023). "Multi-Criteria Decision Making Using the WASPAS Method for Online English Course Selection", *Teknoinfo*, 17(1), 1-10.

Hassan, I., Alhamrouni, I. and Azhan, N.H. (2023). "A CRITIC–TOPSIS Multi-Criteria Decision-Making Approach for Optimum Site Selection for Solar PV Farm", *Energies*, 16(10), 4245.

Heidary Dahooie, J., Husseinzadeh Kashan, A., Shoaei Naeini, Z., Vanaki, A.S., Zavadskas, E.K. and Turskis, Z. (2022). "A Hybrid Multi-Criteria-Decision-Making Aggregation Method and Geographic Information System for Selecting Optimal Solar Power Plants in Iran". *Energies*, *15*(8), 2801.

Hofmann, E. and Rüsch, M. (2017). "Industry 4.0 and the Current Status as well as Future Prospects on Logistics", *Computers in Industry*, 89, 23-34.

Ivanov, D., Dolgui, A. and Sokolov, B. (2019). "The Impact of Digital Technology and Industry 4.0 on the Ripple Effect and Supply Chain Risk Analytics", *International Journal of Production Research*, 57(3), 829-846.

Kannan, D., Govindan, K. and Rajendran, S. (2020). "Fuzzy AHP Integrated with Fuzzy TOPSIS for Analyzing Logistics Service Provider Selection Criteria", *Journal of Cleaner Production*, 106, 256-267. https://doi.org/10.1016/j.jclepro.2014.11.053

Karaca, C. and Ulutaş, A. (2018). "Entropi ve WASPAS Yöntemleri Kullanılarak Türkiye Için Uygun Yenilenebilir Enerji Kaynağının Seçimi", *Ege Academic Review*, 18(3), 483-494.

Khalilzadeh, M., Banihashemi, S.A. and Božanić, D. (2024). "A Step-by-Step Hybrid Approach Based on Multi-Criteria Decision-Making Methods and A Bi-Objective Optimization Model to Project Risk Management", *Decision Making in Manufacturing and Services*, 7(1), 1-15.

Krishankumar, R., Mishra, A.R., Rani, P., Ecer, F. and Ravichandran, K.S. (2023). "Assessment of Zero-Carbon Measures for Sustainable Transportation in Smart Cities: A CRITIC-MARCOS Framework Based on Q-Rung Fuzzy Preferences", *IEEE Internet of Things Journal,* 10(21), 18651-1866. https://doi.org/10.1109/JIOT.2023.3293513

Kumar, R., Goel, P., Zavadskas, E., Stević, Ž. and Vujović, V. (2022). "A New Joint Strategy for Multi-Criteria Decision-Making: A Case Study for Prioritizing Solid-State Drive", *International Journal of Computers Communications & Control*, 17(6), 5010.

Lai, H. and Liao, H. (2021). "A Multi-Criteria Decision Making Method Based on DNMA and CRITIC with Linguistic D Numbers for Blockchain Platform Evaluation", *Engineering Applications of Artificial Intelligence*, 95, 104200.

Mayatopani, H. (2023). "Multi-Criteria Decision Making Using Weighted Aggregated Sum Product Assessment in Corn Seed Selection System", *Cereal International*, 15, 21-31.

Mohamed, M., Ayman, S. and Sleem, A. (2024). "Valuation of Internet of Energy (IoE) Platforms in Smart Cities: A Hybrid Multi-Criteria Decision Making Approach", *Plant Cell Biotechnology and Molecular Biology*, 25(3), 253-264.

Nabavi, S., Wang, Z. and Rangaiah, G.P. (2024). "Sensitivity Assessment of Multi-Criteria Decision-Making Methods in Chemical Engineering Optimization Applications", arXiv preprint.

Narayanamoorthy, S., Brainy, J.V., Manirathinam, T., Kalaiselvan, S., Kureethara, J.V. and Kang, D. (2021). "An Adoptable Multi-Criteria Decision-Making Analysis to Select a Best Hair Mask Product-Extended Weighted Aggregated Sum Product Assessment Method", *Fuzzy Information and Engineering*, 7(1), 1-10.

Özekenci, E.K. (2023). "Evaluation of Export Performances of Metropolitans in Turkey Based on Integrated Multi-Criteria Decision-Making Methods", *Dicle University Journal of Economics and Administrative Sciences*, 14(1), 59-74.

Pala, F. (2023). "Comparison of the Companies Operated for Technology and Information Sector in BIST by Multi-Criteria Decision Making Method and Financial Performance Measurements", *Financial Studies*, 27(1), 117-130.

Rastpour, E., Kayvanfar, V. and Rafiee, M. (2022). Multi-Criteria Decision-Making Methods for the Evaluating of A Real Green Supply Chain in Companies with Fast-Moving Consumer Goods", *International Journal of Production Research*, 1, 1-14.

Saarikko, T., Westergren, U.H. and Blomquist, T. (2020). "Digital Transformation: Five Recommendations for the Digitally Conscious Firm", *Business Horizons*, 63(6), 825-839. https://doi.org/10.1016/j.bushor.2020.07.005

Sarucan, A., Baysal, M.E. and Engin, O. (2024). "Ranking of the Member Countries in the Black Sea Economic Cooperation Organization Using Multi-Criteria Decision-Making Methods", *Journal of Sustainable Development*, 19(1), 101-113.

Shao, C., Wei, B., Liu, W., Yang, Y., Zhao, Y. and Wu, Z. (2023). "Multi-Dimensional Value Evaluation of Energy Storage Systems in New Power System Based on Multi-Criteria Decision-Making", *Processes*, 11(5), 1565.

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2022). "Developing a framework for enhancing survivability of sustainable supply chains during and post-COVID-19 pandemic". *International Journal of Logistics Research and Applications*, *25*(4-5), 433-453.

Taletović, M. (2023). “Application of Multi-Criteria Decision-Making Methods in Warehouse: A Brief Review”, *Studies in Economics and Management*, 11, 31-45.

Ulutaş, A. and Karaköy, Ç. (2019). “CRITIC ve ROV Yöntemleri Ile Bir Kargo Firmasının 2011-2017 Yılları Sırasındaki Performansının Analiz Edilmesi”, *MANAS Sosyal Araştırmalar Dergisi*, 8(1), 223-230.

Wang, G., Gunasekaran, A., Ngai, E.W. and Papadopoulos, T. (2020). “Big Data Analytics in Logistics and Supply Chain Management: Certain Investigations for Research and Applications”, *International Journal of Production Economics*, 176, 98-110.

Yazdani, M., Chatterjee, P., Zavadskas, E.K. and Streimikiene, D. (2019). “A Novel Integrated Decision-Making Approach for the Evaluation and Selection of Sustainable Suppliers in the Power Industry”, *Sustainability*, 10(1), 1-19. https://doi.org/10.3390/su10010015

Yilmaz, K. and Burdurlu, E. (2023). “Selection of Wooden Furniture Joints with Multi-Criteria Decision-Making Techniques”, *International Journal of Computer Integrated Manufacturing*, 36(8), 842-856.

Zaher, M. A., & Eldakhly, N. M. (2023). “An Integrated Framework for Dynamic Resource Allocation in Multi-project Environment”. *Full Length Article*, 10(1), 08-8.

Zavadskas, E.K. and Turskis, Z. (2012). “A New Additive Ratio Assessment (ARAS) Method in Multicriteria Decision-Making”, *Technological and Economic Development of Economy*, 16(2), 159-172.

Zavadskas, E.K., Turskis, Z. and Kildienė, S. (2012). “State of Art Surveys of Overviews on MCDM/MADM Methods”, *Technological and Economic Development of Economy*, 18(4), 672-695.

Zhang, X., Lv, M. and Yuan, X. (2023). “Research on Cloud-CRITIC-PDR Method for Hybrid Multi-Criteria Decision Making”, *Journal of Intelligent & Fuzzy Systems*, 45, 5067-5078.