International Journal of Management Economics and Business, Vol. 22, No. 1, 2026
Uluslararası Yönetim İktisat ve İşletme Dergisi, Cilt 22, Sayı 1, 2026

Research Article / *Araştırma Makalesi*

CLUSTER ANALYSIS AND HYBRID MCDM-BASED ASSESSMENT OF LOGISTICS PERFORMANCE IN OECD COUNTRIES

Burcu KEKLİK[1], Najibul KASHEM[2], Esra AYDIN ÜNAL[3]

ABSTRACT

The Logistics Performance Index (LPI), published biennially by the World Bank, is a key tool used to assess countries' logistics systems based on six criteria: customs, infrastructure, international shipments, logistics service quality, tracking and tracing, and timeliness. A higher LPI score is associated with stronger trade capacity, economic development, and global competitiveness. This study analyzes the 2023 LPI scores of Organization for Economic Co-operation and Development (OECD) countries, aiming to classify them into groups and evaluate their internal rankings. Using the K-means clustering method, 38 countries were grouped into four clusters. The relative importance of logistics criteria within each group was determined using the Method based on the Removal Effects of Criteria (MEREC) and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) methods. A joint weighting approach was then applied, and countries were ranked using the MOORA Importance Coefficient method. Findings show that Logistics Services Quality and International Shipping are consistently ranked among the most influential criteria. MEREC tends to highlights Logistics Service Quality, while LOPCOW prioritizes Tracking and Tracing. In all clusters, Logistics Services Quality, International Shipping, and Infrastructure stand out as key determinants of performance. According to the results, the top-performing countries in each cluster were Australia (Group 1), the Czech Republic (Group 2), Chile (Group 3), and Australia again (Group 4). Sensitivity analysis confirmed the robustness of the model.

Keywords: *OECD Countries, Clustering Method, MEREC, LOPCOW, MOORA*

JEL Classification Codes: *$C0_2$, C60, C61, M11, L91*

1 Sivas Cumhuriyet University Social Sciences Institute, Sivas, Türkiye, *keklikburcu9@gmail.com*

2 Sivas Cumhuriyet University Social Sciences Institute, Sivas, Türkiye, *najibul.kashem@gmail.com*

3 Asst. Prof., Sivas Cumhuriyet University, Zara Veysel Dursun School of Applied Sciences, Sivas, Türkiye *eaunal@cumhuriyet.edu.tr*

Cite this article as: Keklik, B., Kashem, N., Aydın Ünal, E. (2026). Cluster analysis and hybrid mcdm-based assessment of logistics performance in oecd countries. *International Journal of Management Economics and Business*, 22(1), 239-270. https://doi.org/10.17130/ijmeb.1678425

ISSN:2147-9208 E-ISSN:2147-9194
http://dx.doi.org/10.17130/ijmeb.1678425
Received: 17.04.2025, Accepted: 22.09.2025

OECD ÜLKELERİNİN LOJİSTİK PERFORMANSININ KÜMELEME TABANLI VE HİBRİT ÇOK KRİTERLİ KARAR VERME YÖNTEMLERİ İLE DEĞERLENDİRİLMESİ

ÖZET

Dünya Bankası tarafından iki yılda bir yayımlanan Lojistik Performans Endeksi (LPI), ülkelerin lojistik sistemlerini altı kriter temelinde değerlendirmek için kullanılan önemli bir araçtır: gümrük, altyapı, uluslararası taşımacılık, lojistik hizmet kalitesi, izlenebilirlik ve zamanında teslimat. Yüksek bir LPI skoru, güçlü bir ticaret kapasitesi, ekonomik kalkınma ve küresel rekabet gücü ile ilişkilendirilmektedir. Bu çalışma, Ekonomik Kalkınma ve İşbirliği Örgütü (OECD) ülkelerinin 2023 yılına ait LPI puanlarını analiz ederek, ülkeleri kümelere ayırmayı ve her küme içindeki sıralamalarını değerlendirmeyi amaçlamaktadır. K-means kümeleme yöntemi kullanılarak 38 ülke dört kümeye ayrılmıştır. Her bir gruptaki lojistik kriterlerin göreli önemi, Kriterlerin Etki Ortadan Kaldırma Yöntemi (MEREC) ve Logaritmik Yüzde Değişim Temelli Objektif Ağırlıklandırma (LOPCOW) yöntemiyle belirlenmiştir. Daha sonra ortak ağırlıklandırma yöntemi uygulanmış ve ülkeler MOORA Önem Katsayısı yöntemi ile sıralanmıştır. Bulgular, Lojistik Hizmet Kalitesi ve Uluslararası Taşımacılığın en etkili kriterler arasında sürekli olarak ön plana çıktığını göstermektedir. MEREC yöntemi genellikle Lojistik Hizmet Kalitesini öne çıkarırken, LOPCOW yöntemi İzlenebilirlik kriterine öncelik vermektedir. Tüm kümelerde Lojistik Hizmet Kalitesi, Uluslararası Taşımacılık ve Altyapı, performansı belirleyen temel göstergeler olarak öne çıkmaktadır. Sonuçlara göre, her bir kümede en yüksek lojistik performansa sahip ülkeler sırasıyla Avustralya (1. grup), Çek Cumhuriyeti (2. grup), Şili (3. grup) ve tekrar Avustralya (4. grup) olmuştur. Duyarlılık analizi, modelin sağlamlığını doğrulamıştır.

Anahtar Kelimeler: *OECD Ülkeleri, Kümeleme Yöntemi, MEREC, LOPCOW, MOORA*

JEL Sınıflandırması: *$C0_2$, C60, C61, M11, L91*

1. Introduction

In the realm of globalization, the importance of cost reduction has been acknowledged as a pivotal element for competitiveness in international trade. The increased competitiveness and globalization have made logistics a cornerstone of trade. Efficient logistics services have facilitated the movement of products, resulting in faster and more secure services and ultimately contributing to decreased costs in international trade (Çiftçi & Aydın, 2024).

Logistics, in general, refers to the activities carried out in the process of producing or procuring the necessary goods or services. The logistics sector necessitates the coordinated execution of activities such as transportation, storage, customs clearance, insurance, packaging, value-added services, order and inventory management, and inspection activities (Karabacak & Kutlu, 2024). In recent years, the industry has witnessed the implementation of solutions encompassing mixed transportation (multimodal, intermodal, and combined), modern warehouse investments, and a rise in the variety and quality of services. Logistics not only plays a crucial role in global growth but is also gaining prominence on a global scale. This is predominantly attributed to the escalating global activities in the supply chain. An ineffective logistics framework that hampers trade leads to both time and cost losses. The existence of top-notch logistics services aids in cutting down transportation costs, ultimately boosting the competitiveness of the countries (Yildiz, 2023).

Logistics performance is a key factor in attracting international investors, playing a crucial role for countries. When multinational companies consider investing in a country, they often base their decisions on its Logistics performance index (LPI) values. To assess countries' logistics performance, the World Bank publishes the Logistics Performance Index (LPI) every two years, based on survey data collected across multiple countries. In this survey, participants evaluate logistics performance using six main dimensions, assigning scores on a scale from 1 to 5. A score closer to 5 indicates higher logistics performance compared to other countries (Karakoy & Ölmez, 2019). Countries are ranked based on the simple arithmetic average of the scores obtained from the survey. The six LPI dimensions defined by the World Bank are as follows: customs, infrastructure, international transportation, logistics service quality, traceability, and on-time delivery.

OECD nations are renowned for their superior logistical capabilities, showcasing cutting-edge infrastructure and effective transportation systems. Supply chain management is further improved by digital technologies and contemporary customs procedures, which lower costs and increase dependability. As a result, these nations frequently have strong rankings in international trade and robust economic growth in global LPI (World Bank , 2023).

According to the LP index, countries are ranked solely based on average scores, with equal weighting of criteria. However, in reality, LPI dimensions can have varying degrees of importance. Because it comprises six independent dimensions and these dimensions have different impacts on logistics performance, using MCDM methods instead of the current evaluation method would provide a more realistic and precise ranking. In addition, the OECD countries vary greatly in terms of their economies, locations, and levels of development. Ranking countries at similar levels to each other will allow them to assess themselves and increase their competitiveness.

For these reasons, a new approach has been proposed to evaluate countries' logistics performance. The aim of the study is to group OECD countries according to their similarity levels and to rank the countries within each group using objective MCDM methods. Firstly, 38 OECD countries were grouped using the K-means method. Then, for each group, the weights of the criteria were calculated using two objective criteria weighting methods, LOPCOW and MEREC. The results obtained from both methods were combined using a joint weighting method, resulting in more stable weighting results. The MOORA Importance Coefficient method was used to rank the logistics performances. Sensitivity analyses were conducted to verify the validity and reliability of the proposed approach. The ranking results were compared with other methods. Finally, sensitivity was analyzed in scenarios where the criteria had different weights.

The key contributions of this study are as follows: Cluster analysis allows the identification of similar logistics profiles, while MCDM methods assess the importance of dimensions that impact logistics performance. This will enable countries to prioritize their policies and strategies. This study provides more realistic ranking results, enabling countries to compare their logistics performance with others. Considering these aspects, the study is regarded as original and as a contribution to the existing literature.

The research is divided into four parts. The next section features a literature review aimed at pinpointing research deficiencies within this area. A thorough examination of current studies was performed, and the literature review extensively addresses findings from studies related to LPI, the Clustering technique, MEREC, LOPCOW, and the MOORA Importance Coefficient approach. The methods employed in this research are outlined in Section 2. Section 3 includes the dataset, the ranking outcomes of the applied methods, and the results of sensitivity analyses. The concluding section of the study summarizes and assesses the findings, offering recommendations for future research.

2. Literature Review

When we look at the current literature on this subject, it is observed that MCDM methods are frequently used in evaluating the LPI of country groups or countries. In addition, there are many studies available where various country groups' LPI are analyzed using the Clustering method. In this study literature review is divided into three parts. The initial part focuses on research related to implementing clustering methods for measuring the LPI. The second part encompasses various studies utilizing LOPCOW and MEREC methods, while the third section pertains to performance ranking, applying the method. MOORA Importance Coefficient.

Çakır (2017) proposed hybrid technique is a mixture of CRITIC, SAW, and Peters` FLR techniques to determine the logistics overall performance of 34 OECD member nations in 2014. Additionally, the consequences acquired from the proposed technique have been in comparison with the TOPSIS, VIKOR, and SAW techniques. The consequences acquired display that the rating of Peters' FLR version isn't just like the rating of the corresponding MCDM techniques.

Kısa et al. (2019) used integrated decision-making methods, the OECD aims to evaluate the logistics performance of countries. Obtained from field logistics performance indicators. The importance of field logistics performance criteria was determined using the SWARA method and the logistics performance of the countries was analyzed using the EDAS method. According to the application results, the most important criteria are logistics services, defined as quality, infrastructure, and international transportation. Logistics The best performing countries were Germany, the Netherlands, and Sweden.

Özmen (2019) applied a new approach to assess the logistics competitiveness of countries, taking into account both the sector of logistics activities and the volume of logistics transport. The TODIM (Portuguese acronym for Interactive and Multi-Criteria Decision Making) method based on Mahala Nobis Distance has been developed and improved for OECD countries. It is used to evaluate the competitiveness of logistics. The results show that the proposed model is effective in assessing the logistics competitiveness of countries even with interactive and interdependent criteria.

Anuşlu et al. (2019) explored the significance of Industry 4.0 in addressing challenges related to energy, resources, and sustainability. By utilizing modern technologies, Industry 4.0 accelerates innovation, enhances flexibility in global supply chains, and mitigates current manufacturing challenges. The research employs clustering analysis with global indices like Global Innovation, Sustainable Development Goals, Logistics Performance, and Environmental Performance to group countries based on their impact areas within Industry 4.0.

Yıldırım & Mercangöz (2020) proposed a model for evaluating the LPI of OECD countries from 2010 to 2018. Utilizing the fuzzy analytical hierarchy method, the model calculates LPI based on six indicators, assigning weights differently from the WB survey. The grey additive ratio assessment (ARAS-G) method is then applied to assess the logistics performances of

OECD countries annually. Spearman ϱ and Kendall's Tau correlation methods are employed to scrutinize relationships within yearly rankings and those spanning the 2010–2018 period. Results indicate that ARAS-G rankings exhibit the strongest correlation with time. This study showcases a novel application of the ARAS-G method, providing unique insights into the evolving logistics performances of OECD countries.

Eren & Ömürbek (2021) discussed the increasing importance of the logistics sector due to its impact on national economies and competitiveness. Using the World Bank's LPI criteria, the study clusters OECD countries based on their logistics performance, revealing significant differences among clusters through the Canopy algorithm and Kruskal-Wallis Test.

Rađenović (2021) investigated the crucial role of transportation management systems in enhancing supply chain efficiency and reducing costs. Kahreman (2023) focused on the performance ranking of G20 countries was analyzed between 2006 and 2015, including the 2008 crisis. An integrated model consisting of LOPCOW and COCOSO methods was used to evaluate the economic performance of G20 countries. According to the results of the LOPCOW method, the importance level of the criteria considered, that is, the criteria that affect the economic performance the most, are exchange rate, unemployment rate, and inflation variables. According to the results of the COCOSO method, the best performing countries were the USA, Germany, and Korea, while the worst economic performing countries were Indonesia, Argentina, and South Africa. In addition, it was determined that there was a decline in the general situation of the USA and EU countries after the 2008 crisis.

Bakır & Çakır (2021) evaluated the innovation performance of 23 EU and OECD countries using MCDM methods with 2019 data from the Global Competitiveness Index, Global Innovation Index, and European Innovation Scoreboard. According to the Borda method, which combines all MCDM results, Sweden ranked first.

Yürüyen et al. (2023) evaluated the 2021 performance of Turkish logistics companies listed on the "Fortune 500 Turkey" website by integrating MCDM methods. SV, MEREC, CRITIC, and LOPCOW methods were applied to determine the objective weights of the criteria. The alternatives were ranked by applying the MACONT method. According to the results of the study, the logistics company with the best performance was determined as Lİ7, and the logistics company with the lowest performance was determined as Lİ3.

Miskiç et al. (2023) developed an integrated evaluation model for the LPI of European Union (EU) countries, emphasizing sensitivity analysis. Utilizing the MEREC method for weight calculation and MARCOS for ranking, Germany emerges as the top-ranked country in LPI. The sensitivity analysis highlights the impact of the criteria weight values on EU country rankings, advocating for a modified LPI evaluation considering criteria importance and countries' real needs.

In the study conducted by Pehlivan (2024), a novel approach was introduced by combining Fuzzy C-Means clustering and fuzzy multi-criteria decision-making (FMCDM) methods to evaluate the logistics performance indices of countries. The analysis considered the gross domestic product (GDP) and six sub-indicators of the Logistics Performance Index (LPI) for 160 countries. Countries were clustered according to income groups using the Fuzzy C-Means method. These country groups were then ranked using FMCDM methods such as SAM, TOPSIS, MOORA, and ARAS. The ranking results were found to be consistent with the 2018 LPI rankings. It was observed that the top 10 countries generally had high levels of welfare, while the bottom 10 countries were those affected by war, natural disasters, and poverty.

Özekenci (2025), the logistics performance of OECD countries for the year 2023 was evaluated by integrating various multi-criteria decision-making methods. The weights of the criteria were determined using SD, CRITIC, LOPCOW, and MEREC methods. These weights, derived from different techniques, were then aggregated using the Combined Weighting Method. The LPI values of OECD countries were ranked using the CRADIS method, a comprehensive MCDM technique. Among the OECD countries, Finland was identified as having the highest logistics performance, while Costa Rica ranked the lowest.

Stević et al. (2024) examined the World Bank's LPI rankings from a methodological perspective and proposed an alternative decision support framework. The weights of the criteria for evaluating the logistics performance efficiency of 118 countries were determined using the Entropy method. The countries were ranked using MCDM methods including MCRAT, SAW, TOPSIS, and FUCA. By employing various sensitivity analyses, the study assessed the impact of weighting techniques across more than 2,500 different MCDM outcomes, and demonstrated that the FUCA method should be recommended to decision-makers for computing LPI rankings.

Yılmaz (2025) analyzed the digitalization levels of leading countries in the Logistics Performance Index using 2023 data. The top 23 countries in the LPI were included as alternatives to assess the relationship between their digitalization indices and logistics performance. The CRITIC method was used to obtain the weights of the criteria, and the alternatives were ranked using the TOPSIS method. The findings revealed that the three countries with the highest level of digitalization were Singapore, the United States, and the Netherlands.

Kartal et al. (2024) analyzed the financial performance of 25 companies in the BIST Sustainability 25 Index using data from 2014–2022. TTRAK led between 2014–2017, while FROTO ranked highest from 2017–2022.

Teker et al. (2024) compared the energy sustainability of 36 OECD countries based on 15 criteria. Solar electricity consumption was the most critical factor. Switzerland ranked highest according to PROMETHEE, GIA, and Copeland, whereas Germany ranked first with the VIKOR method.In their study,

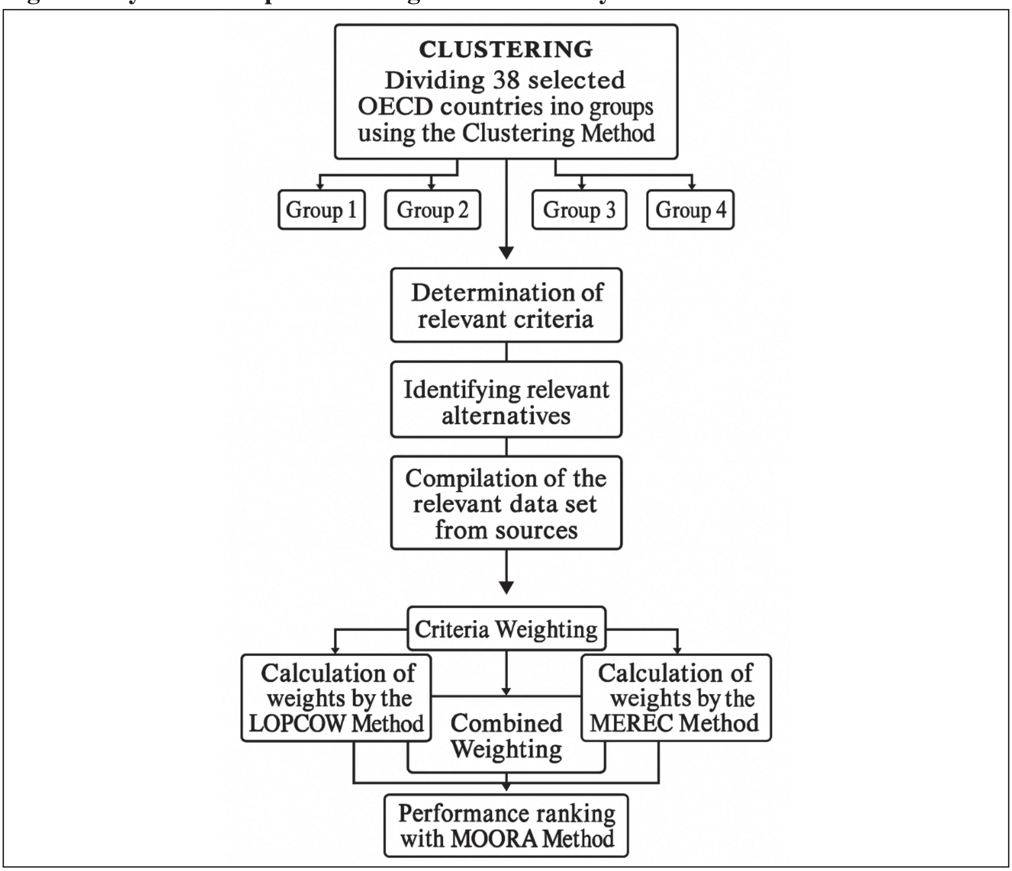
Topal & Ulutaş (2024) evaluated the logistics performance of G8 countries using multi-criteria decision-making methods. The Standard Deviation (SD) method was applied to determine the weights of the criteria, while the AROMAN method was used to assess the performance of the countries. According to the analysis results, Germany emerged as the top-performing country in terms of logistics performance among the G8 nations.

3. Data and Methodology

3.1. Data

In this part of the study, the analysis of OECD countries 2023 LPI data sets using hybrid MCDM methods is discussed. The reason for focusing solely on the OECD countries in our analysis is due to their relatively comparable levels of economic development and institutional capacity in logistics infrastructure, digitalization, and policy implementation. This selection allows for a more homogeneous group comparison and ensures more meaningful interpretation of the results. Moreover, OECD countries are major actors in global supply chains, making their logistics performance particularly relevant. Thus, the scope of the study was deliberately limited to the 38 OECD member countries to ensure analytical consistency and practical relevance. Since the data in the report published by the World Bank was used, the variables in this report were taken as the criteria of the MCDM analysis. Thus, it will be possible to compare the results obtained with the results in the report. The analytical part of the study consists of three sections. In the first section, the 38 OECD countries were divided into clusters using the cluster analysis K-means method. In the second section, LPI criteria weights obtained from the MEREC and LOPCOW methods are combined using a joint weighting approach, resulting in more stable and consistent criterion weights. In the final section, performance ranking was carried out using the MOORA Importance Coefficient method. The overall framework of these sections is illustrated in Figure 1.

Figure 1: Systematic Operation Diagram of the Study



The objective of this study is to assess and rank the performance of the selected 38 OECD countries using the

LPI for the year 2023. Six criteria have been identified for LPI ranking, obtained from the World Bank database. The criteria are as follows: Infrastructure, International shipping, Quality of logistics services, Tracking, On-time delivery, and Customs (Sharawi, 2025; Arvis et al., 2018). The six LPI dimensions defined by the World Bank are as follows:

Infrastructure: This refers to the quality of the physical and technological infrastructure necessary for the effective execution of logistics operations. It includes road, rail, port, and airport infrastructure, as well as information and communication technology infrastructure (e-logistics systems).

International Shipping: This dimension measures how easily and competitively a country can arrange international shipments. It evaluates the ease of organizing import and export operations, access to international transportation services, price competitiveness, and frequency of shipments.

Quality of logistics services: This assesses the competence and performance of logistics providers, including freight forwarders, transport operators, and other logistics service providers. It takes into account their reliability, the quality of freight transportation, warehousing, distribution services, and supply chain management expertise.

Tracking and Tracing: This dimension measures the ability to track shipments throughout the entire logistics process and the quality of information provided to customers. It includes tracking capabilities at each stage, customer updates on shipment status, and the use of digital tracking technologies.

On time delivery: This refers to the frequency with which shipments reach their destinations within the scheduled or expected timeframes. Key factors include the rate of delivery delays, consistency in transit times, and the frequency of delays caused by customs and transportation processes

Customs: This dimension evaluates the speed, transparency, and predictability of customs procedures at a country's border crossings. It also assesses the efficiency of import and export procedures.

Table 1 presents the relevant criterias and details.

Table 1: Performance Indicators and Details Used in the Study

Sequence	Criterion Name	Code	Aspect
1	Infrastructure	K1	Maximum (Max)
2	International shipping	K2	Maximum (Max)
3	Quality of logistics services	K3	Maximum (Max)
4	Tracking and Tracing	K4	Maximum (Max)
5	On time delivery	K5	Maximum (Max)
6	Customs	K6	Maximum (Max)

Note: Max: beneficial feature, Min: cost-oriented feature.

The selection of the above criteria is grounded in the works of by Brauers (2008), Zavadskas (2016), Çakır (2017), Anuşlu (2019), Ulkhaq (2023), and Stević et al. (2024). The data for these indicators, presented in Table 1, were collected from the World Bank website.

3.2. K-Means Clustering Analysis Method.

The Clustering method involves categorizing data with similar characteristics into distinct groups, aiming to achieve homogeneity within each group while ensuring diversity between groups (Özekes, 2003; Cengiz & Öztürk, 2012; Çolak et al., 2016).

In clustering, when the distance between objects within a cluster is very small, and the distance between clusters is substantial (Ünal et al., 2011). The widely used unsupervised learning method, the K-means algorithm, is a sharp clustering algorithm that allows each data point to belong to only one cluster (Sariman, 2011).

The general logic of the K-means algorithm is to partition a dataset consisting of n data objects into k clusters, where k represents the number of input parameters. The objective is to ensure that, after the partitioning process, the clusters exhibit maximum intra-cluster similarity and minimum inter-cluster similarity. As an iterative algorithm falling under divisive clustering methods, the K-means algorithm continuously updates clusters in a cyclical manner until reaching the optimal solution (Demiralay & Çamurcu, 2005; Silahtaroğlu, 2008).

The processing steps of the K-means algorithm are as follows:

Step 1: Randomly select k objects. The chosen k objects represent cluster centers, denoted as M_1, M_2 ,..., M_k. The sample midpoint is calculated as equation 1 presented below (Gersho & Gray, 2012).

$$\boldsymbol{M_k = \frac{1}{n_k}\sum_{i=1}^{n_k} x_{ik}} \tag{1}$$

Step 2: Intra-cluster variations are provided in equation (2). The Mean Squared Error Formula is calculated as per the formula, denoted as e_1, e_2 ,..., e_k. (Linde et al., 2023).

$$\boldsymbol{e_i^2 = \sum_{i=1}^{n_k}(x_{ik} - M_k)^2} \tag{2}$$

For the space encompassing all clusters in set K, the sum of squared errors represents the total intra-cluster variations. Therefore, the square error value is calculated as per equation (3):

$$\boldsymbol{E_k^2 = \sum_{K=1}^{K} e} \tag{3}$$

Step 3: Assign each data point to its closest cluster.

Step 4: Recalculate the centers for k clusters when all data points are assigned to their closest clusters.

Step 5: Repeat Steps 2 and 3 until there is no change in the cluster centers.

3.3. MEREC Method

MEREC method, one of the objective criterion weighting methods, was developed by (Ghorabaee et al., 2019). It was recommended by MCDM methods literature in 2021. In determining the criterion weight, the method in question considers the removal effects of the criteria, in other words, when calculating the importance weight for any criterion, the criterion whose weight is calculated is disabled and the change in the total criterion weight is taken into account. This method differs from other objective MCDM criterion weighting methods, such as CRITIC and ENTROPY. In contrast to alternative weighting techniques, the MEREC approach identifies the weights by removing the influence of each criterion on the ranking. This ensures a more objective and dependable outcome.

The MEREC method consists of six steps (Ghorabaee et al., 2019).

Step 1: Creating the Decision Matrix

In the first step, a decision matrix consisting of n alternatives and m criteria is created.

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & & x_{2m} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{4}$$

Step 2: Creating the Normalized Decision Matrix

The decision matrix is normalized using Equation (5) and (6).

$$n_{ij}^{x} = \left\{ \frac{minx_{ij}}{x_{ij}} \text{ if j} \in \textbf{ Maximize } \boldsymbol{criter} \right. \tag{5}$$

$$n_{ij}^{x} = \left\{ \frac{x_{ij}}{maksx_{ij}} \text{ if j} \in \textbf{ Minimize } \boldsymbol{criter} \right. \tag{6}$$

Step 3: Finding the Total Performance Value (S_j)

The total performance value (S_j) of each alternative is calculated using Equation (7).

$$S_i = ln\left(1 + \left(\frac{1}{m}\sum j\,|ln(n_{ij}^{x})|\right)\right) \tag{7}$$

Step 4: Determining the Performance of Alternatives $S_i{}'$

The performance of the alternatives is $S_{ij}{}'$ determined by removing each criterion separately. Equation (8) is used for this calculation.

$$S'_{ij} = ln\left(1 + \left(\frac{1}{m}\sum k, k \neq j\,|ln(n_{ik}^{x})|\right)\right) \tag{8}$$

Step 5: Determination of the Total Deviations (E_j) In this step, the total of the absolute deviations (E_j) is calculated. (E_{ij}) based on the values obtained from steps 1-3 and steps 1-4 to show the effect of removing the criterion. The effect of removing the criterion is determined.

$$E_J = \sum_i |S'_{ij} - S_i| \tag{9}$$

Step 6: Calculation of Criterion Weights In this step, the objective weight (W_j) of each criterion is calculated using the subtraction effects (E_j) of Steps 1-5.

$$W_{jmerec} = \frac{E_j}{\sum_k E_k} \tag{10}$$

3.4. LOPCOW Method

The LOPCOW method, introduced to the literature by Ecer & Pamucar (2022), is a very new method that falls into the objective criterion weighting group. This method offers appropriate solutions for benefit and cost-oriented criteria without any criterion limitations. The difference of the method is objective group can be expressed as the percentage of standard deviations of the mean square values of the series, eliminating the difference (gap) caused by the size of the data. The LOPCOW method is not affected by negative raw data, in other words, negative values. The LOPCOW method consists of four stages (Ecer & Pamucar, 2022).

Step 1: Creating the Decision Matrix

In order to identify and solve the decision problem, it is first necessary to create an internal decision matrix (IDM) consisting of m alternatives and n criteria. Decision matrix as expressed in Equation (4) is created.

Step 2: Creating the Normalized Decision Matrix

Using the linear normalization technique (max min), the elements of the decision matrix (IDM) are subjected to normalization through Equation (11) and (12). If the criteria are cost-oriented, in other words minimum-oriented, it is calculated with the help of Equation (11). If the criteria are maximum-oriented, in other words benefit-oriented, it is calculated with the help of Equation (12).

$$r_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \tag{11}$$

$$r_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \tag{12}$$

Step 3: In this step, the Percentage Value PV_{ij} matrix is constructed to normalize the scale differences among criteria. For each criterion, the PV_{ij} value for each alternative is calculated using Equation (13), which considers the mean squared value in relation to the standard deviation. This transformation helps eliminate scale imbalances and ensures comparability among criteria by expressing each value as a percentage relative to its variability.

$$PV_{ij} = \left| ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^2}{m}}}{\sigma}\right).100\right| \tag{13}$$

Step 4: Calculation of Objective Weights (W_j)

Finally, the objective importance weight for each criterion is calculated via Equation (14).

$$W_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}} \tag{14}$$

3.5. Aggregated Weighting Method

In decision-making problems, determining criterion weights plays a critical role in determining the outcome. Objective weighting methods generally rely on data-driven analysis, independent of decision-makers’ own experiments. However, due to the diverse perspectives and breadth of scope offered by each method, weighting based on a single method can be dependent on specific details. Therefore, a more reliable analysis model can be created using the joint weighting method in MCDM problems. By applying the proposed method, more appropriate objective weights for the criteria were calculated. More precisely, the weights obtained from the MEREC and LOPCOW methods were combined with Equation (15), and objective weights for each criterion were calculated (Zavadskas & Podvezko, 2016).

$$W_{j\,ortak} = \frac{W_{j\,merec} \cdot W_{jlopcow}}{\sum_{j=1}^{m} W_{j\,merec} \cdot W_{j\,lopcow}} \tag{15}$$

This approach is a normalized combined weighting method based on geometric multiplication. The weights obtained for each criterion are integrated by multiplying the outputs of the MEREC and LOPCOW methods and then normalized by dividing by the total value. This allows both the average impact (MEREC) and the sensitivity-based variability (LOPCOW) of the criteria to be considered simultaneously.

3.6. MOORA Method

The MOORA method, developed by (Brauers, 2013), is a method for complex decision-making. It is a multi-purpose tool that can be used to solve problems using extremely simple computational steps. It is an optimization technique (Chakraborty et al., 2023). Also referred to as multi-feature optimization, this technique allows for the simultaneous optimization of two or more conflicting features, subject to certain restrictions (Gadakh et. al., 2013). The application steps of the method are summarized below (Brauers, 2008):

Step 1: Decision matrix as expressed in Equation (4) is created.

Step 2: The decision matrix is normalized using equation (16).

$$x_{ij}^{*} = \frac{X_{ij}}{\sqrt{\sum_{J=1}^{m} x_{ij}^{2}}} \tag{16}$$

Step 3: Using the ratio approach, evaluation scores are calculated, and alternatives are sorted. This is

presented in Equation 17.

$$y_j^{*} = \sum_{i=1}^{i=g} w_j x_{ij}^{*} - \sum_{i=g+1}^{i=n} w_j x_{ij}^{*} \tag{17}$$

In this context, the objective is to maximize the points assigned to each item, with the index $i = 1, 2, ..., g$ The scores g are collected while minimization is being carried out. The scores $i = g+1, g+2, ..., n$ are then subtracted. The alternative with the highest value is then preferred y_j^{*}.

4. Results

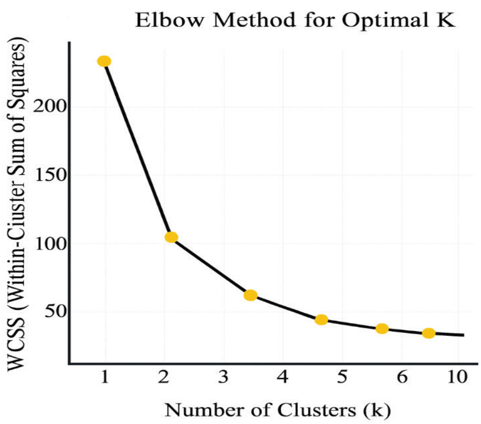
This section provides a comparative analysis of the outcomes derived from the categorization of countries based on the applied clustering method. Following this, the results of the analysis of the relative importance of the criteria are presented. Finally, the performance evaluation and ranking analyses are presented in tabular form. The sequence begins with the presentation of the country clustering results, continues with the findings of the criteria importance weighting analysis, and concludes with the performance evaluation and ranking results.

4.1. Cluster Analysis Results

This study aimed to cluster OECD countries based on their similarities using LP scores. The number of clusters was determined visually using the elbow method and the rule of thumb method (Di Lascio et al., 2018), using Equation (18).

$$k = \sqrt{n/2} \tag{18}$$

Figure 2: Elbow Method for Determining Optimal Number of Clusters



According to Figure 2 and rule of thumb methods, considering the LPI data, countries with the highest similarity are grouped together, resulting in a total of 4 clusters among the 38 OECD countries. The following table presents the mean scores of each LPI indicator for the four identified clusters. Additionally, the number of countries in each cluster is also provided. Table 3 displays the clustering results of the countries.

Table 2: Mean Scores of each LPI Indicator

Cluster	Customs Score	Infrastructure Score	International Shipments Score	Logistics Competence and Quality Score	Timeliness Score	Tracking and Tracing Score	Number of Countries
1	3.51	3.71	3.38	3.75	3.81	3.81	15
2	3.1	3.36	3.3	3.44	3.56	3.24	7
3	2.7	2.8	2.82	3.02	3.28	3.02	5
4	3.9	4.12	3.67	4.12	4.15	4.13	11

Table 3: Country Groups

Cluster	Country
Cluster 1	Australia, Estonia, France, Greece, Iceland, Ireland, Israel, Italy, Korea Republic, Luxembourg, New Zealand, Norway, Poland, United Kingdom, United States
Cluster 2	Czech Republic, Latvia, Lithuania, Portugal, Slovak Republic, Slovenia, Türkiye
Cluster 3	Chile, Colombia, Costa Rica, Hungary, Mexico
Cluster 4	Austria, Belgium, Canada, Denmark, Finland, Germany, Japan, Netherlands, Spain, Sweden, Switzerland

According to the results, the LPI data analysis has led to the classification of 38 OECD countries into four distinct clusters. When Table 2 is examined, it is seen that 15 countries are included in Cluster 0. These are developed countries such as the USA, Australia, France, and the United Kingdom. On the other hand, it is noteworthy that the income and welfare levels of these countries are high. Cluster 1 includes the Czech Republic, Latvia, Lithuania, Portugal, Slovak Republic, Slovenia, and Turkey. It is observed that developing countries are included in this cluster. They belong to the upper and middle-income groups. Additionally, their foreign trade volumes are at moderate levels. Countries with coastlines such as Turkey, Slovenia, Portugal, Latvia, and Lithuania are also included in this cluster. In Cluster 2, includes Chile, Colombia, Costa Rica, Hungary, and Mexico are upper-middle-income, each with unique economic characteristics. The countries in this cluster can be described as having a moderate level of economic prosperity compared to Clusters 0 and 1. Furthermore, in terms of foreign trade volume, these countries can be at an upper-middle level. Cluster 3 comprises Austria, Belgium, Canada, Denmark, Finland, Germany, Japan, the Netherlands, Spain, Sweden, and Switzerland. These countries exhibit a similar level of development to those in Cluster 0, with notably high levels of foreign trade. Furthermore, all 9 countries in these clusters (France, Spain, Italy, Norway, Sweden, Canada, Germany, the Netherlands, and Denmark) have coastlines.

4.2. Results of the MEREC-LOPCOW Methods

Criterion weights were determined separately for each of the four groups formed as a result of the cluster analysis using the MEREC and LOPCOW methods. The process for the MEREC method began with the creation of the decision matrix. Following this, the elements of the decision matrix were normalized according to Equations (5) and (6). Then, the values for each alternative were calculated using Equation (7). In the next step, the S_{ij}^{I} values for all alternatives were derived by sequentially removing each criterion using Equation (8). Then, the sum of the deviations for each alternative was calculated by applying Equation (9). Following this, the weights of the criteria were determined using Equation (10).

In the initial step of the LOPCOW method, the decision matrix underwent normalization through Equations (11) and (12). Subsequently, using the relevant steps of Equation (13), the percentage values PV_{ij} for each criterion were computed in the next stage. Following this, the weights of the criteria were obtained through Equation (14).

To obtain more appropriate objective weights, the criterion weights obtained through the MEREC method for assessment criteria were combined with the weights obtained through the LOPCOW method using Equation (15). All results obtained for each group are shown in Table 4-Table 7, respectively.

Table 4 : Criterion Weights (W_j) Obtained from all Methods for the First group of Countries

Method	**MEREC**			**LOPCOW**		**Joint Weighting**	
Criteria	E_j	W_j	**Ranking**	W_j	**Ranking**	W_j	**Ranking**
K1	0.224	0.181	2	0.148	5	0.160	3
K2	0.153	0.124	6	0.114	6	0.084	6
K3	0.295	0.238	1	0.183	2	0.259	1
K4	0.159	0.129	5	0.204	1	0.156	5
K5	0.211	0.170	3	0.181	3	0.183	2
K6	0.195	0.158	4	0.170	4	0.159	4

In the first group of countries, the results obtained from the MEREC method indicate that the most significant criterion is Logistics Services Quality (K3), followed by Infrastructure (K1), and On-time Delivery (K5), respectively. In contrast, the LOPCOW method identifies Tracking and Tracing (K4) as the most influential criterion, with Logistics Services Quality (K3) and On-time Delivery (K5) ranked second and third, respectively. According to the Common Weighting procedure, the three most impactful criteria influencing LPI performance are determined to be Logistics Services Quality (K3), On-time Delivery (K5), and Infrastructure (K1), in that order. These findings reflect a consistent emphasis on the quality and timeliness of logistics services across methods in evaluating the logistics performance of the first group of countries.

Table 5: Criterion Weights (W_j) Obtained from all Methods for the Second Group of Countries

Method	**MEREC**			**LOPCOW**		**Joint Weighting**	
Criteria	E_j	W_j	**Ranking**	W_j	**Ranking**	W_j	**Ranking**
K1	0.064	0.117	6	0.136	6	0.094	6
K2	0.130	0.238	1	0.204	1	0.284	1
K3	0.093	0.170	3	0.177	3	0.176	2
K4	0.071	0.131	5	0.184	2	0.142	4
K5	0.091	0.168	4	0.136	5	0.134	5
K6	0.097	0.177	2	0.164	4	0.094	6

For the second group of countries, obtained from the MEREC method indicate that International Shipping (K2) emerges as the most influential criterion, followed by Customs (K6) in the second position, and Logistics Services Quality (K3) in the third. According to the

LOPCOW method identifies an alternative assessment, International Shipping (K2) again ranks as the most critical factor, while Tracking and Tracing (K4) and Logistics Services Quality (K3) occupy the second and third positions, respectively. As presented in Table 6, the findings obtained through the Joint Weighting Procedure indicate that the three most significant indicators affecting LPI performance are International Shipping (K2), Logistics Services Quality (K3), and Customs (K6), in that order.

Table 6: Criterion Weights (W_j) Obtained from all Methods for the Third Group of Countries

Method	MEREC			LOPCOW		Joint Weighting	
Criteria	E_j	W_j	**Ranking**	W_j	**Ranking**	W_j	**Ranking**
K1	0.059	0.208	2	0.148	4	0.188	3
K2	0.044	0.153	4	0.172	3	0.161	5
K3	0.063	0.222	1	0.129	5	0.175	4
K4	0.037	0.128	5	0.277	1	0.218	1
K5	0.050	0.177	3	0.175	2	0.190	2
K6	0.032	0.112	6	0.098	6	0.067	6

For the third group of countries, the results of the MEREC method indicate that Logistics Services Quality (K3) is the most influential criterion, followed by Infrastructure (K1) in the second position, and On-time Delivery (K5) in the third. According to the LOPCOW method, Tracking and Tracing (K4) ranks first, while On-time Delivery (K5) and International Shipping (K2) are ranked second and third, respectively. Furthermore, based on the results obtained through the Common Weighting procedure, the three primary indicators influencing LPI performance in the third group are identified as Tracking and Tracing (K4), On-time Delivery (K5), and Infrastructure (K1), respectively.

Table 7: Criterion Weights (W_j) Obtained from all Methods for the Fourth Group of Countries

Method	MEREC			LOPCOW		Joint Weighting	
Criteria	E_j	W_j	**Ranking**	W_j	**Ranking**	W_j	**Ranking**
K1	0.144	0.205	3	0.188	2	0.225	3
K2	0.152	0.216	2	0.184	3	0.232	1
K3	0.178	0.253	1	0.157	4	0.231	2
K4	0.104	0.148	4	0.197	1	0.170	4
K5	0.061	0.086	6	0.140	5	0.071	6
K6	0.065	0.092	5	0.134	6	0.072	5

Based on the results obtained using the MEREC method for the fourth group of countries, Logistics Services Quality (K3) emerges as the most critical criterion, followed by International Shipping (K2) in the second position, and Infrastructure (K1) in the third. In contrast, the results derived from the LOPCOW method indicate that Tracking and Tracing (K4) is the most influential factor, with Infrastructure (K1) ranked second and International Shipping (K2) ranked third. To obtain more appropriate objective weights, the criterion weights calculated through the MEREC method were combined with those obtained from the LOPCOW method using Equation (15). As shown in Table 7, the three most influential indicators affecting LPI performance for this group are International Shipping (K2), Logistics Services Quality (K3), and Infrastructure (K1), respectively.

4.3. MOORA Method Results

Once the weights of the criteria have been determined using the MEREC and LOPCOW methods, the country of each groups will be ranked according to their logistics performance using the MOORA Importance Coefficient method. The ranking of the countries for four clusters is calculated using the MOORA Importance Coefficient method. The decision matrix is then normalized by Equation (16), after which the evaluation scores y_{ij}^* are determined by Equation (17). The calculated values, y_{ij}^* values and rankings are presented in Table 8 for reference.

Table 8 illustrates that, according to the MOORA Importance Coefficient method for cluster first, France, the United States and South Korea are in the first three positions, with Iceland occupying the last position.

Table 8: Evaluation Scores (y_{ij}^*) and Final Standings MOORA Importance Coefficient Method for 1 Cluster Countries

Country	y_{ij}^*	Rank	Country	y_{ij}^*	Rank
Australia	0.0182	7	Korea, Rep.	0.0187	3
Estonia	0.0180	11	Luxembourg	0.0181	9
France	0.0192	1	New Zealand	0.0177	14
Greece	0.0186	4	Norway	0.0180	12
Iceland	0.0177	15	Poland	0.0178	13
Ireland	0.0180	10	United Kingdom	0.0183	5
Israel	0.0181	8	United States	0.0188	2
Italy	0.0183	6			

Table 9: Evaluation Scores (y_{ij}^*) and Final Standings MOORA Importance Coefficient Method for 2nd Cluster Countries

Country	y_{ij}^*	Rank
Czechia	0.0409	6
Latvia	0.0433	1
Lithuania	0.0426	2
Portugal	0.0424	4
Slovakia	0.0408	7
Slovenia	0.0420	5
Turkiye	0.0425	3

Table 9 illustrates the results of the MOORA Importance Coefficient method for cluster second, which indicate that Latvia, Lithuania and Turkey are in the first three positions, respectively, while the Slovak Republic is in the last position.

Table 10: Evaluation Scores (y_{ij}^*) and Final Standings MOORA Importance Coefficient Method for 3rd Cluster Countries

Country	y_{ij}^*	Rank
Chile	0.0676	2
Colombia	0.0670	3
Costa Rica	0.0652	5
Hungary	0.0721	1
Mexico	0.0657	4

Table 10 illustrates the results of the MOORA Importance Coefficient method for cluster third, which indicate that Hungary, Chile and Colombia are in the first three positions, respectively, while Costa Rica is in the last position.

Table 11: Evaluation Scores (y_{ij}^*) and Final Standings MOORA Importance Coefficient Method for 4th Cluster Countries

Country	y_{ij}^*	Rank
Austria	0.0224	9
Belgium	0.0230	5
Canada	0.0230	4
Denmark	0.0229	7
Finland	0.0238	1

Table 11. continue

Germany	0.0231	3
Japan	0.0221	10
Netherlands	0.0229	6
Spain	0.0218	11
Sweden	0.0226	8
Switzerland	0.0234	2

Table 11 demonstrates that, according to the MOORA Importance Coefficient method for cluster fourth, Finland, Switzerland and Germany are in the first three positions, respectively, while Spain is in the last position.

5. Sensitivity Analysis

In this study, the suitability of the proposed approach for evaluating logistics performance across countries and the reliability and stability of the results were verified through sensitivity analysis. Sensitivity analysis can be conducted in two different ways. In the first method, the ranking results of the proposed approach can be compared with various MCDM approaches (Isık et al., 2024). In the second method, the impact of changes in criterion weights on the ranking results of alternatives can be evaluated (Mukhametzyanov & Pamucar, 2018). In this study, sensitivity analysis was conducted in two ways: examining the changes in ranking results by changing the criterion weights and comparing the obtained ranking results with the ranking results of different MCDM methods (MAIRCA, WASPAS, TOSPIS, EDAS).

5.1. The Effect of Changes in Criteria Weights on Alternative Rankings

In the second stage of the sensitivity analysis, the impact of varying criterion weights on alternative rankings was examined. It is of great importance to investigate the effect of changes in criterion weights on alternative rankings to ensure the robustness and reliability of the proposed model (Korucuk et al., 2022; Ecer, 2021). This analysis is recommended by numerous researchers in the literature (Aytekin et al., 2023).

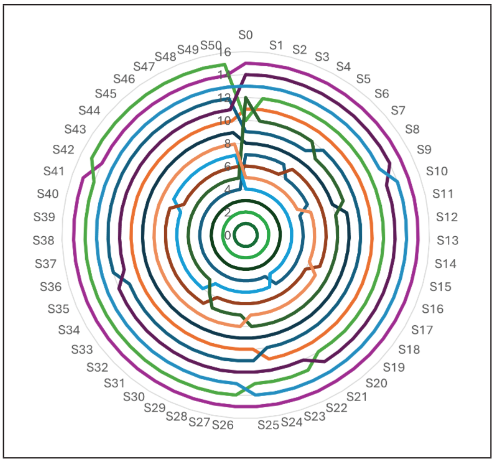
The purpose of this sensitivity analysis is to evaluate the effect of the most effective criterion on the ranking performance of the proposed model. The weight of the most important criterion is reduced in small proportions and since the total weight must be equal to 1, the weights of other criteria are also increased in certain proportions. Thus, in the final case, the importance of the most important criterion decreases while the importance of other criteria increases. If there are no changes in the ranking results despite this change, it turns out that the proposed approach is appropriate, reliable and correct.

For the sensitivity analysis performed by changing the weight coefficients, 50 scenarios were developed. The weight of the criterion with the highest weight was reduced by 2% in each scenario. The weights of the remaining criterias were adjusted proportionally with the help of Equation (19) so that the sum of the weights is equal to 1. The cluster was formed on a separate basis for each of the following categories: one, two, three and four. The alterations to each scenario are illustrated in Figures 3.

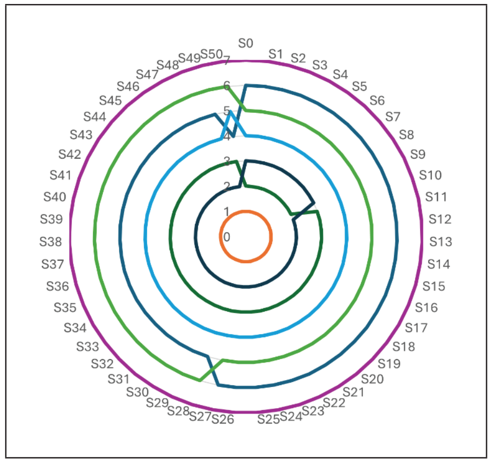
$$\boldsymbol{w_i^*} = \frac{\boldsymbol{w_i(1-w_{C_3}^*)}}{\boldsymbol{(1-w_{C_3})}} \tag{19}$$

Here w_{C3} represents the original weight of the criterion with the highest weight, $w_{C3}{}^*$ represents the corrected value of the C_B criterion, w_i represents the original value of the considered criterion, and $w_i{}^*$ represents the corrected value of the weight coefficient of the considered criterion.

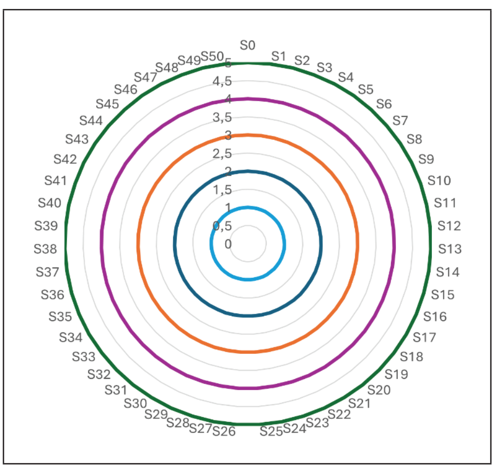
Figure 3: Scenario Results for All Clusters



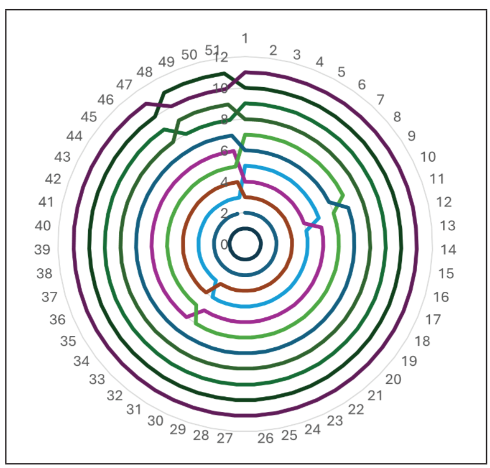
a) 1.Cluster



a) 2.Cluster



a) 3.Cluster



b) 4.Cluster

The scenarios for 2023 are analyses separately for each cluster (see Figure 3). In the context of Cluster 1, France is positioned at the top of the ranking in all scenarios, while Iceland occupies the lowest position. Upon analysis of Cluster 2, it is evident that Latvia consistently occupies the top position, while the Slovak Republic consistently occupies the lowest. In Cluster 3, the performance ranking remains consistent across all scenarios. Hungary was ranked first. Costa Rica is positioned at the lowest rank. Finally, an analysis of Cluster 4 reveals that Finland consistently ranks first, while Spain is consistently ranked last, with only minor deviations. While there are minor discrepancies in the performance rankings contingent on the scenarios, except for Cluster 2, the results are largely analogous. At this juncture of the sensitivity analysis, it was discerned that the outcomes yielded by disparate scenarios are proximate. Despite the existence of minor discrepancies in the results due to the scenarios, the general ranking remains unaltered. Consequently, the study model is deemed to be stable and consistent.

5.2. Results of Ranking Consistency Across Methods

The MOORA Importance Coefficient method represents a relatively recent contribution to the field of MCDM methodologies. Consequently, in order to guarantee the reliability of the findings, similar methodologies have been selected for comparison with the results of the initial analyses, which were conducted using alternative MCDM methods. The rationale for the selection of these methods is that the utilization of disparate normalization techniques in studies employing multi-criteria techniques may result in the distortion of data, which could potentially lead to erroneous decisions. Accordingly, in order to obtain accurate and consistent results, methods that take into account the effects of normalization techniques were preferred (Ecer & Pamucar, 2022). In multi-criteria decision-making (MCDM) studies, correlation analysis is commonly employed to evaluate the degree of agreement between the rankings produced by different methods. This comparison is essential for assessing the consistency and robustness of the results. If a high correlation is observed—particularly using Spearman's rank correlation coefficient—it suggests that the methods generate similar rankings, indicating that the decision outcomes are not overly sensitive to the choice of method. Such consistency enhances the credibility and reliability of the model.

Moreover, correlation analysis helps determine whether the results are method-dependent or generalizable across techniques. A strong correlation (e.g., between MOORA and TOPSIS) may indicate that these methods share similar underlying principles (e.g., normalization-based scoring), while low correlation values may reflect structural differences or sensitivity to criteria weighting schemes.

Therefore, analyzing correlations between methods supports the methodological rigor of the study and provides decision-makers with greater confidence in the stability of the results. This approach is widely adopted in the literature to validate ranking outcomes across MCDM techniques (Pamučar et al., 2017; Więckowski & Sałabun, 2023).

For comparison purposes, the WASPAS, TOPSIS, MAIRCA and EDAS methods were used for each cluster alone. The results of cluster 1 methods are presented in Table 12.

Table 12: Ranking Values According to Different MCDM Methods for First Cluster Countries

Country	MOORA	WASPAS	TOPSİS	MAIRCA	EDAS
Australia	7	7	11	5	7
Estonia	11	11	10	11	10
France	1	1	1	1	1
Greece	4	4	2	4	4
Iceland	15	15	13	15	15
Ireland	10	12	6	13	11
Israel	8	8	8	9	8
Italy	6	6	9	6	6
Korea, Rep.	3	3	4	3	3
Luxembourg	9	9	7	10	9
New Zealand	14	14	15	12	14
Norway	12	10	14	8	12
Poland	13	13	12	14	13
United Kingdom	5	5	5	7	5
United States	2	2	3	2	2

Upon analysis of Table 12, it becomes evident that the performance ranking outcomes of the disparate MCDM methods and MOORA Importance Coefficient method for cluster first exhibit a high degree of similarity.

To ascertain the relationship between the results obtained from the various methods, a Spearman's correlation test was conducted on the MCDM methods. The results of this test are presented in Table 13 for the reader's convenience.

Table 13: Spearman Correlation Test Results for First Cluster Countries

	WASPAS	TOPSİS	MAIRCA	EDAS
MOORA	0.986**	0.889**	0.929**	0.996**

Note: **: 0.01; *:0.05 significance level.

As indicated in Table 13, the mean Spearman correlation value of the MOORA Importance Coefficient method in relation to alternative techniques for cluster first is 0,950. It can be observed that the MOORA Importance Coefficient method produces consistent results when compared with other MCDM methods, as indicated by the values.

Table 14: Ranking Values According to Different MCDM Methods for Second Cluster Countries

Country	MOORA	WASPAS	TOPSİS	MAIRCA	EDAS
Czechia	6	6	7	6	6
Latvia	1	1	1	1	1
Lithuania	2	2	3	2	2
Portugal	4	4	2	4	4
Slovakia	7	7	6	7	7
Slovenia	5	5	5	5	5
Turkiye	3	3	4	3	3

Table 14 demonstrates that the performance rankings of the various MCDM methods and the MOORA Importance Coefficient method for the initial cluster exhibit a notable degree of similarity. The results of the four methods are perfectly aligned with one another.

To ascertain the relationship between the results obtained from the various methods, a Spearman correlation test was conducted on the MCDM methods. The results of this test are presented in Table 15 for the reader's convenience.

Table 15: Spearman Correlation Test Results for Second Cluster Countries

	WASPAS	TOPSİS	MAIRCA	EDAS
MOORA	1.000**	0.857*	1.000**	1.000**

Note: **: 0.01; *:0.05 significance level.

As indicated in Table 15, the mean Spearman correlation value of the MOORA Importance Coefficient method in relation to alternative techniques for cluster first is 0,964. It can be observed that the MOORA Importance Coefficient method produces consistent results when compared with other MCDM methods, as indicated by the values.

Table 16: Ranking Values According to Different MCDM Methods for Third Cluster Countries

Country	MOORA	WASPAS	TOPSİS	MAIRCA	EDAS
Chile	2	2	2	2	3
Colombia	3	3	3	3	2
Costa Rica	5	5	4	5	5
Hungary	1	1	1	1	1
Mexico	4	4	5	4	4

Table 16 demonstrates that the performance rankings of the various MCDM methods and the MOORA Importance Coefficient method for the second cluster are strikingly similar. The results obtained from the five methods are in complete agreement with one another.

A Spearman correlation test was conducted to ascertain the relationship between the results obtained from the various MCDM methods. The results of this test are presented in Table 17 for the reader's convenience.

Table 17: Spearman Correlation Test Results for Third Cluster Countries

	WASPAS	TOPSİS	MAIRCA	EDAS
MOORA	1.000**	0.900*	1.000**	0.900*

Note: **: 0.01; *:0.05 significance level.

As indicated in Table 17, the mean Spearman correlation value of the MOORA Importance Coefficient method in relation to alternative techniques for cluster second is 0,950. It can be observed that the MOORA Importance Coefficient method produces consistent results when compared with other MCDM methods, as indicated by the values.

Table 18: Ranking Values According to Different MCDM Methods for Fourth Cluster Countries

Country	MOORA	WASPAS	TOPSIS	MAIRCA	EDAS
Austria	9	9	8	9	9
Belgium	5	5	4	7	5
Canada	4	4	6	4	4
Denmark	7	7	7	5	6
Finland	1	1	1	1	1
Germany	3	3	3	3	3
Japan	10	10	10	10	10
Netherlands	6	6	5	6	7
Spain	11	11	11	11	11
Sweden	8	8	9	8	8
Switzerland	2	2	2	2	2

Table 18 illustrates that the performance rankings of the various MCDM methods and the MOORA Importance Coefficient method for the third cluster are strikingly similar.

A Spearman correlation test was conducted to ascertain the relationship between the results obtained from the various MCDM methods. The results of this test are presented in Table 26 for the reader's convenience.

Table 19: Spearman Correlation Test Results for Fourth Cluster Countries

	WASPAS	TOPSİS	MAIRCA	EDAS
MOORA	1.000**	0.964**	0.964**	0.991**

Note: **: 0.01; *:0.05 significance level.

As indicated in Table 19, the average Spearman correlation value of the MOORA Importance Coefficient method with respect to alternative techniques for the third cluster is 0,980 is. As evidenced by the data, the MOORA Importance Coefficient method yields results that are moderately consistent in comparison to other MCDM methods.

6. Discussion and Conclusion

The growth of international trade and the economic advancement of nations are inextricably linked to the expansion of their logistics infrastructure. However, for countries to reap the benefits of globalization, access to global markets and technological superiority, it is essential that they provide logistics services in an efficient manner and adhere to established rules governing international trade processes. The strategic decisions taken in the logistics sector, which play a pivotal role in the global and national economies, are of paramount importance for sustainable development. The activities of the logistics sector exert a significant influence on national economies, given the interconnectivity between the various economic sectors. One of the most significant factors that facilitate trade is international logistics. The performance of logistics is a significant determinant of international trade. An enhancement in logistics performance has a beneficial impact on international trade, leading to an increase in the volume of international trade. In this regard, it is crucial for countries to monitor the outcomes of the LPI, identify areas of deficiency, and enhance their logistics performance through the implementation of studies in the pertinent domain.

The objective of this study is to evaluate the logistics performance of 38 OECD countries in accordance with the logistics performance criteria published by the World Bank for 2023. In order to achieve this objective, the clustering method and the MCDM method were employed. The OECD countries were initially divided into clusters based on their respective logistics performance, with each cluster subsequently evaluated using the LOPCOW, MEREC and MOORA Importance Coefficient methods. A Spearman correlation analysis was conducted to assess the reliability and stability of the proposed approach by comparing the results obtained with those obtained from other MCDM methods. Furthermore, sensitivity analysis was conducted to assess the impact of varying weightings for the criteria. The results of the analysis led to the division of the 38 OECD countries into four clusters based on the LPI data (Eren & Ömürbek, 2021). Upon analysis of the clusters, it becomes evident that the countries in question are predominantly situated within the same cluster, exhibiting a tendency to cluster with other countries exhibiting similar income levels. The results of the common importance weighting method indicate that logistics service quality, on-time delivery and customs criteria are the most significant factors influencing the countries in Cluster first. An evaluation of the most important criteria reveals that countries with high logistics performance also have very high scores for these criteria. This indicates that these countries have high-quality logistics services, developed logistics infrastructures and are effective in organizing international shipments. The United States of America, Australia, France, and Italy, which are situated within Cluster 1, are home to the largest and most powerful ports in the world. France and Italy have a high level of railway infrastructure, which is conducive to the efficient movement of goods. In Cluster 1, the most significant factors are international dispatch, logistics service quality, and customs. Upon evaluation of the existing criteria, it becomes evident that the majority of countries in Cluster 2 are positioned at the lowest ranks across all criteria. The cluster comprises two Baltic states, namely Latvia and Lithuania. Furthermore, the countries within this cluster demonstrate a moderate performance in foreign trade. The proportion of road and railway lines in Latvia and Lithuania, which are both situated within the cluster, is relatively low. In terms of air transport, Slovakia is deficient in terms of infrastructure. In Cluster 3, the most significant criteria are monitoring and follow-up, timely delivery, and infrastructure. The foreign trade volumes of the countries in Cluster 3 are considerable. These countries are characterized by a high level of economic and social development. It is notable that several Latin American countries, including Chile, Colombia, and Costa Rica, are included in this group. In Cluster 4, the most significant criteria are international transportation, the quality of logistics services, and customs clearance. Canada, Sweden, and Spain are home to the largest and most powerful ports in the world. The Scandinavian countries, including Denmark, Sweden, and Finland, it is evident that Germany's railway and aviation infrastructure is of a considerably higher standard than that of other countries.

According to the MOORA Importance Coefficient method, countries were ranked within each cluster based on their logistics performance. In Cluster 1, France, the United States, and South Korea demonstrated the highest performance, while Ireland ranked lowest. France functions as a key logistics hub in Europe, supported by major ports (e.g., Le Havre, Marseille), high-speed rail, and advanced road networks. The United States maintains one of the world's largest logistics markets, benefiting from technological infrastructure, automation, and its strategic role in global trade. South Korea's highly integrated logistics system, anchored by the ports of Incheon and Busan, offers fast and efficient multimodal transport. Ireland, despite its strategic transatlantic position, faces logistical complexity due to post-Brexit regulations and cross-border trade issues (SLAM, 2025).

In Cluster 2, Latvia, Turkey, and Lithuania lead the group, while Slovakia is positioned at the bottom. Latvia leverages its Baltic Sea access and rail infrastructure. Turkey's strategic location enables connectivity between Europe, Asia, and the Middle East, though bureaucratic and geographic challenges persist (Arun & Özmutlu, 2023). Lithuania's logistical strength lies in its regional integration, but climatic and market limitations remain. Slovakia, constrained by a small domestic market and terrain-related difficulties, exhibits the lowest performance in the group.

Cluster 3 includes the Netherlands, Chile, and Colombia as top performers, with Costa Rica ranked lowest. The Netherlands benefits from highly modernized logistics infrastructure and strategic distribution centers. Chile has capitalized on technological advancements, such as 5G, to enhance e-commerce and transport systems. Colombia's dual-ocean access and regional position provide strong logistics potential. Costa Rica, despite a relatively developed road network, struggles with infrastructure modernization and climate-related disruptions.

In Cluster 4, Finland, Switzerland, and Belgium rank highest, while Japan is placed at the bottom. Finland and Switzerland maintain high-efficiency multimodal logistics systems, with Finland serving as a transit bridge between Northern Europe and Asia. Despite being landlocked, Switzerland is well-connected to major European ports. Belgium's central location, advanced port facilities, and investment in innovation strengthen its logistics capacity. While Japan's logistics sector is technologically advanced and globally integrated, its vulnerability to natural disasters poses ongoing operational risks. Increasing the efficiency of logistics activities and ensuring that processes are carried out on a regular basis are also very cost effective. In this way, high costs can be brought under control. Strict and costly trade regulations that cause time losses have a negative impact on competition. In this case, countries that want to participate in the global economy should review customs regulations, reduce long waiting times at ports, reduce unnecessary physical inspections, and eliminate bureaucracy and unnecessary procedures (World Bank, 2023).

The findings of this study are broadly aligned with existing research in the logistics performance literature. Similar to the results reported by Stević et al. (2024), countries with well-developed logistics infrastructure—such as the United States, France, South Korea, and the Netherlands—consistently appear at the top of performance rankings. In both studies, key criteria such as *logistics service quality*, *international shipment capacity*, and *customs efficiency* emerge as dominant factors influencing logistics performance. This consistency reinforces the view that infrastructure quality and service reliability are fundamental determinants of logistics efficiency.

The clustering results obtained through K-means reveal that countries tend to group according to income levels and development status, which echoes the observations made in prior studies that employed similar classification techniques using LPI data (e.g., Clustering Countries According to the Logistics Performance Index, 2018). Particularly, Baltic countries such as Latvia and Lithuania, and lower-income countries like Costa Rica and Slovakia, appear in clusters characterized by lower performance across all criteria—most notably in infrastructure and tracking capability. Furthermore, the strong correlation between the MOORA-based rankings and those obtained from other MCDM techniques is consistent with the methodological robustness demonstrated in Stević et al. (2024). The Spearman correlation results confirm that MOORA delivers stable and coherent rankings, validating its use in comparative evaluations. Overall, the results of this study confirm prior research findings that improvements in logistics performance are closely tied to enhanced international trade capacity, technological advancement, and efficient customs operations (World Bank, 2023). Therefore, countries aiming to strengthen their global logistics standing must prioritize regulatory simplification, infrastructure modernization, and service quality improvements.

The study has several limitations. First, the study focused only on OECD countries and ignored the performance of non-OECD countries. Future research could analyze the logistics performance of different groups of countries such as the EU, ASEAN and BRICS. Second, although the integrated approach has produced consistent results, further validation through real data and case studies could improve the robustness of the model. Although only the year

2023 is considered, detailed analysis can be carried out using data from earlier years. Furthermore, given the dynamic nature of the logistics sector, continuous monitoring, and updating of the criteria and methodology is necessary to maintain the validity and accuracy of the model over time.

In future studies, it is planned to extend the scope of the analysis to include non-OECD countries. Additionally, incorporating multi-year data may provide insights into performance trends over time. Further research could also integrate sustainability-related indicators into the logistics performance framework to reflect emerging global priorities.

Contrubution Rate Declaration

The authors have equal contribution at all stages of the study.

Conflict of Interest Declaration

We declare that there is no conflict of interest between the authors.

References

Aytekin, A., Görçün, Ö. F., Ecer, F., Pamucar, D., & Karamaşa, Ç. (2023). Foreign market selection of suppliers through a Novel REF-Sort technique. *Kybernetes*, *52*(11), 4958-4992. HYPERLINK "https://doi.org/10.1108/K-03-2022-0459" \t "_blank" https://doi.org/10.1108/K-03-2022-0459

Anuşlu, M. D., & Fırat, S. Ü. (2019). Clustering analysis application on Industry 4.0-driven global indexes. *Procedia Computer Science, 158*, 145-152. HYPERLINK "https://doi.org/10.1016/j.procs.2019.09.037" \t "_blank" \o "Persistent link using digital object identifier" https://doi.org/10.1016/j.procs.2019.09.037

Arun, K., & Yıldırım Özmutlu, S. (2023). Evaluation of Turkey's logistics performance index with a strategic perspective. *Nevşehir Hacı Bektaş Veli Üniversitesi SBE Dergisi*, *13*(3), 1315–1327. HYPERLINK "https://doi.org/10.30783/nevsosbilen.1228917" \t "_new" https://doi.org/10.30783/nevsosbilen.1228917

Arvis, J. F., Ojala, L., Wiederer, C., Shepherd, B., Raj, A., Dairabayeva, K., Kiiski, T. (2018). *Connecting to compete 2018: Trade logistics in the global economy-The logistics performance index and its indicators* (No. 128355).

Bakır, S., & Çakır, S. (2021). Seçilmiş ülkelerin yenilik performanslarının çok kriterli karar verme teknikleriyle ölçümü. *Uluslararası Yönetim İktisat ve İşletme Dergisi, 17*(4)*, 971-992*.

Brauers, W. K. (2008). Multi-Objective contractor's ranking by applying the MOORA Method. *Journal of Business Economics and Management*, *9*(4), 245-255.

Brauers, W. K. (2013). Optimization methods for a stakeholder society: A revolution in economic thinking by multi-objective optimization. *Springer Science & Business Media*. https://link.springer.com/book/10.1007/978-1-4419-9178-2

Cengiz, D., & Öztürk, F. (2012). The study of the cities in Turkey with cluster analysis according to their education levels. *Trakya Üniversitesi Sosyal Bilimler Dergisi* , *14*(1), 69-84.

Chakraborty, S., Datta, H. N., Kalita, K., & Chakraborty, S. (2023). A narrative review of multi-objective optimization on the basis of ratio analysis (MOORA) method in decision making. *Opsearch, 60*(4), 1844-1887 doi: 10.1007/s12597-023-00676-7.

Çiftçi, B., & Aydın, U. (2024). OECD ülkelerinde lojistik performans ve küresel yetenek rekabet gücü: Entegre Merec-Ahp-Topsis yaklaşımıyla bir analiz. *International Journal of Advances in Engineering and Pure Sciences*, *36*(4), 367-395.

Çakır, S. (2017). Measuring logistics Performance of OECD countries via fuzzy linear regression. *Journal of Multi-Criteria Decision Analysis, 24*(3-4), 177-186.

Çolak, B., Durdağ, Z., & Erdoğmuş, P. (2016). K-Means algoritması ile otomatik kümeleme. *El-Cezerî Fen ve Mühendislik Dergisi, 3*(2), 315-323. HYPERLINK "https://doi.org/10.31202/ecjse.264195" https://doi.org/10.31202/ecjse.264195

Demiralay, M., & Çamurcu., A. Y. (2005). Cure, Agnes ve K-Means algoritmalarındaki kümeleme yeteneklerinin karşılaştırılması. *İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi, 4*(8), 1-18.

Ecer, F. (2021). FUCOM sübjektif ağırlıklandırma yöntemi ile rüzgâr çiftliği yer seçimini etkileyen faktörlerin analizi. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, *27*(1), 24-34.

Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. *Omega*, *112*(102690), 1-18.

Eren, H., & Ömürbek, N. (2021). OECD Ülkelerinin Lojistik Performansları Açısından Kümelenmesi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *26*(2), s. 153-166.

Gadakh, V. S., Shinde, V. B., & Khemnar, N. (2013). Optimization of welding process parameters using MOORA method. *The International Journal of Advanced Manufacturing Technology, 69*(9-12), 2031-2039.

Gersho, A., & Gray, R. M. (2012). *Vector Quantization and Signal Compression* (Cilt 159). USA: Springer Science & Business Media.

Ghorabaee, M. K., Govindan, K., Amiri, M., Zavadskas, E. K., & Antuchevičienė, J. (2019). An integrated type-2 fuzzy decision model based on WASPAS and SECA for evaluation of sustainable manufacturing strategies. *Journal of Environmental Engineering and Landscape Management*, *27*(4), 187-200.

Işık, Ö., Çalık, A., & Shabir, M. (2024). A consolidated MCDM framework for overall performance assessment of listed insurance companies based on ranking strategies. *Computational Economics*, 1-42.

Kahreman, Y. (2023). G20 Ülkelerinin Ekonomik Performanslarının 2008 Krizi Döneminde LOPCOW-COCOSO Yöntemi İle Değerlendirilmesi. *İzmir Journal of Economics*, *38*(3), s. 786-803.

Karabacak, E., & Kutlu, H. A. (2024). Evaluating the efficiencies of logistics centers with fuzzy logic: The case of Turkey. *Sustainability. 16*(1), 438.

Karaköy, Ç. & Ölmez, U. (2019). *Balkan Ülkelerinde Lojistik Performans Endeksi Değerlendirilmesi*. Uluslararası Sosyal, Beşeri ve İdari Bilimlerde Yenilikçi Yaklaşımlar Sempozyumu'nda sunulmuş bildiri, (s. 178-180).

Kartal, C., Özdil, Z., & Acar Karaboğa, M. (2024). BIST sürdürülebilirlik 25 endeksi firmalarinin çok kriterli karar verme yöntemleri ile finansal performans analizi. *Uluslararası Yönetim İktisat Ve İşletme Dergisi*, 20(ICMEB'24 Özel Sayı), 79-100.

Kısa, A., Gök, C., & Ayçin, E. (2019). OECD ülkelerinin lojistik performanslarinin swara tabanli edas yöntemi ile değerlendirilmesi. *Çankırı Karatekin Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi* , *9*(1), 301-325.

Korucuk, S., Aytekin, A., Ecer, F., Karamaşa, Ç., & Zavadskas, E. K. (2022). Assessing green approaches and digital marketing strategies for twin transition via fermatean fuzzy swara-copras. *Axioms, 11*(12), 1-25.

Mukhametzyanov, I., & Pamucar, D. (2018). A sensitivity analysis in MCDM problems: A statistical approach. *Decision Making: Applications in Management and Engineering*, *1*(2), 51-80.

Di Lascio, F. M. L., Giammusso, D., & Puccetti, G. (2018). A clustering approach and a rule of thumb for risk aggregation. *Journal of Banking & Finance*, *96*, 236-248.

Linde, Y., Buzo, A., & Gray, R. (2023). An algorithm for vector uantizer design. *IEEE Transactions on Communications* , *28*(1), 84-95.

Miskiç, S., Stević, Z., Tadiç, S., Elhayyat, A., & Krstić, M. (2023). Assessment of the lPI of the eu countries using mcdm model with an emphasis on the importance of criteria. *World Review of Intermodal Transportation Research, 11*(3), 258-279.

Özekenci, E. K. (2025). Evaluation of the logistics performance index of OECD countries based on hybrid MCDM methods. *Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi*, *47*(1), 47-76.

Özekes, S. (2003). Veri madenciliği modelleri ve uygulama alanlari. *İstanbul Ticaret Üniversitesi Dergisi, 3*, 65-82.

Özmen, M. (2019). Logistics competitiveness of OECD countries using an improved TODIM method. *Sādhanā, 44*, 1-11.

Pamučar, D., Stević, Ž., & Sremac, S. (2017). A new model for determining weight coefficients of criteria in MCDM models: Full Consistency Method (FUCOM). *Symmetry*, *9*(12), 1–27.

Pehlivan, N. Y. (2024). A novel integrated FCM/MCDM methodology for evaluating logistic performance index. In *Data-Driven Modelling with Fuzzy Sets* (pp. 305-328). CRC Press.

Rađenović, Ž. (2021). Transportation management systems: Logistics performance index approach. *Challenges of Tourism and Business Logistics in the 21st Century*, *4(1)*, 100-108.

Sariman, G. (2011). Veri madenciliğinde kümeleme teknikleri üzerine bir çalışma: K-means ve k-medoids kümeleme algoritmalarının karşılaştırılması. *Süleyman Demirel Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 15*(3), 192-202.

Sharawi, H. (2025). *The impact of LPIs' indicators on the global logistics performance index: Global perspective*. Available at SRN: HYPERLINK "https://ssrn.com/abstract=5101068" \t "_blank" https://ssrn.com/abstract=5101068 , Accessed 17.01.2025.

Silahtaroğlu, G. (2008). Veri madenciliği. İstanbul: Papatya Yayınları.

Stević, Ž., Ersoy, N., Başar, E. E., & Baydaş, M. (2024). Addressing the global logistics performance index rankings with methodological insights and an innovative decision support framework. *Applied sciences*, *14*(22), 10334

Swiss Life Asset Managers. *France's hidden strengths in logistics real estate*. Retrived from HYPERLINK "https://www.swisslife-am.com/en/home/hub/2025/q1/logistics-real-estate-france.html" \t "_new" https://www.swisslife-am.com/en/home/hub/2025/q1/logistics-real-estate-france.html , Accessed 06.03.2025.

Teker, S., Azkeskin, S. A., & Aladağ, Z. (2024). Enerji sürdürülebilirliğinin çok kriterli karar verme yöntemleri ile ölçülmesi ve Copeland yöntemi ile bütünleştirilmesi: OECD ülkeleri üzerine bir çalışma. *Uluslararası Yönetim İktisat ve İşletme Dergisi*, *20*(4), 871-895.

Topal, A., & Ulutaş, A. (2024). Evaluating the logistics performance of g8 nations using multi-criteria decision-making models. *J. Intell. Manag. Decis, 3*, 150-158.

Ünal, Y., Ekim, U., & Köklü, M. (2011). Üniversite öğrencilerin ortak zorunlu derslerdeki başarilarinin k-means algoritmasi ile incelenmesi. *Engineering Sciences, 6*(1)*,* 342-347.

Yıldırım, B. F., & Mercangöz., B. A. (2020). Evaluating the logistics performance of OECD countries by using fuzzy AHP and ARAS-G. *Eurasian Economic Review, 10*(1), 27-45.

Yılmaz, B. (2025). Determining The Digitalization Levels of Leading Countries in Logistics Performance Index: An Application with CRITIC-TOPSIS Approach. Verimlilik Dergisi, *59*(2), 431-450.

Yildiz, T. (2023). *Logistics and supply chain management: Fundamentals and strategies*. Independently published. ISBN 979-8375061962.

Yürüyen, A. A., Ulutaş, A., & Özdağoğlu, A. (2023). Lojistik işletmelerinin performansının bir hibrit ÇKKV modeli ile değerlendirilmesi. *Business & Management Studies: An International Journal, 11*(3), 731-751.

Zavadskas, K. E., & Podvezko, V. (2016). Integrated determination of objective criteria weights in MCDM. *International Journal of Information Technology & Decision Making, 15*(2), 267-283.

Więckowski, J., & Sałabun, W. (2023). Sensitivity analysis in multiple-criteria decision-making methods: A systematic literature review. Applied Soft Computing, *138*, 110261.

World Bank. (2023). *Connecting to compete 2023: Trade logistics in an uncertain global economy*. Retrived from https://lpi.worldbank.org, Accessed 21.04.2024