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EVALUATING THE LOGISTICS PERFORMANCE OF THE EU CANDIDATE AND MEMBER COUNTRIES USING THE WENSLO AND ARTASI METHODS

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Abstract

Recently, important interconnected events experienced around the world, such as COVID-19, the blockage of the Suez Canal, and the decrease in the water level in the Panama Canal, have revealed the importance of logistics activities. This study aimed to evaluate the logistics performances of European Union (EU) candidates and member countries using Multi-Criteria Decision-Making (MCDM) methods. This study applied the six Logistic Performance Index (LPI) criteria, and it utilized a criteria-weighting method known as Weights by ENvelope and SLOpe (WENSLO) and an MCDM method called Alternative Ranking Technique based on Adaptive Standardized Intervals (ARTASI) to assess 8 EU candidates (EUc) and 27 EU members (EUm). The findings are compared with the ANGLE, CRITIC, CVM, ENTROPY, GINI, LOPCOW, MEREC, and SD methods for the WENSLO method, and the MABAC, MARCOS, WASPAS, TOPSIS, CRADIS, PIV, and CoCoSo methods are used for the ARTASI method. Finland, a Northern European high-income economy, was ranked first, and Cyprus, although it is an island country and may have logistical connections with many countries, was ranked last among EU countries. On the other hand, Türkiye, which ranks first among the EUc for the LPI by the MCDM, is in a better situation than some EUm. However, other candidates are ranked after the members. This study addresses a relevant and timely topic in the field of logistics performance. In this regard, the use of innovative methods (WENSLO and ARTASI) sets the paper apart from other studies.

Keywords: *LPI, WENSLO, ARTASI, MCDM, Logistics.*

AB'YE ADAY VE ÜYE ÜLKELERİN LOJİSTİK PERFORMANSLARININ WENSLO VE ARTASI YÖNTEMLERİ KULLANILARAK DEĞERLENDİRİLMESİ

Öz

Son dönemde dünya genelinde yaşanan COVID-19, Süveyş Kanalı'nın tıkanması ve Panama Kanalı'ndaki su seviyesinin düşmesi gibi birbirine bağlı önemli olaylar lojistik faaliyetlerin önemini ortaya koymuştur. Bu çalışma ile Avrupa Birliği'ne (AB) üye ve aday ülkelerin lojistik performanslarının, Çok Kriterli Karar Verme (ÇKKV) yöntemleri kullanılarak değerlendirmesi amaçlanmaktadır. Bu çalışmada altı Lojistik Performans Endeksi (LPI) kriteri uygulanmış ve 8 AB adayı (EUc) ve 27 AB üyesini (EUm) değerlendirmek için Weights by ENvelope and SLOpe (WENSLO) olarak bilinen bir kriter ağırlıklandırma yöntemi ve Alternative Ranking Technique based on Adaptive Standardized Intervals (ARTASI) adı verilen bir ÇKKV yöntemi kullanılmıştır. Bulgular, WENSLO yöntemi için ANGLE, CRITIC, CVM, ENTROPY, GINI, LOPCOW, MEREC ve SD yöntemleri ile karşılaştırılırken, ARTASI yöntemi için MABAC, MARCOS, WASPAS, TOPSIS, CRADIS, PIV ve CoCoSo yöntemleri kullanılmıştır. Araştırma sonuçlarına göre Kuzey Avrupa'nın yüksek gelirli ekonomilerinden Finlandiya ilk sırada yer alırken, bir ada ülkesi olmasına ve birçok ülke ile lojistik bağlantısı bulunmasına rağmen Kıbrıs AB ülkeleri arasında son sırada yer almıştır. Öte yandan, ÇKKV yöntemine göre LPI için EUc arasında ilk sırada yer alan Türkiye, bazı EUm'lerden daha iyi durumdadır. Ancak diğer aday ülkeler, üyelerden sonra sıralanmıştır. Bu çalışma, lojistik performans alanında güncel ve önemli bir konuyu ele almaktadır. Bu bağlamda, yenilikçi yöntemlerin (WENSLO ve ARTASI) kullanılması, çalışmayı diğer çalışmalardan ayırmaktadır.

Anahtar kelimeler: *LPI, WENSLO, ARTASI, ÇKKV, Lojistik.*

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1. INTRODUCTION

Logistics serves as the backbone of global trade, with world merchandise trade volume reaching $23.8 trillion (WTO, n.d.) in 2023. This sector is crucial for both companies and countries, offering a range of complex activities that significantly impact trade and competitiveness. Key logistics functions include transportation, warehousing, brokerage, customs clearance, delivery, operations, and data and information management. Since the importance of developed and emerging markets in global logistics activity continues to increase, logistics plays a key role in the development of the global economy (Isik et al. 2020, Janno et al. 2021, Özekenci 2023). Therefore, these logistics activities must be conducted cautiously, competently, and in a timely manner. In addition to that, it should be backed by the up-to-date infrastructure that ensures the traceability and fast customs procedures during the international transportation of goods. Otherwise, inefficient logistics activities can create disruption and damage across the economy, trade, and supply chains. Thus, companies, policymakers, and academics closely monitor and evaluate the Logistics Performance Index (LPI), which has been published by the World Bank (WB) since 2007. Given these global logistics challenges, it is imperative to evaluate the logistics performance of key players, such as countries, country groups, intergovernmental organizations, and their candidate/member countries.

Among these country groups, the EU holds a very prominent position with an $8,7 trillion merchandise trade volume, representing 36,5% of total trade (WTO, n.d.). The EU's extensive production capacity and its role as a logistics hub bridging East and West further emphasize its importance. Thus, EUm (European Union members) and EUc (European Union candidates) play key roles in international trade, logistics, and the global economy. Hence, measuring and evaluating the LPI of EUm and EUc with different methods is vital. Since the latest LPI ranking was published in 2023, evaluating the latest LPI will have a significant impact on the trade facilitation and supply chain capabilities that lead to achieving a more efficient and competitive economy. It is important to point out that the LPI measures the aforementioned logistics criteria under six dimensions, which consist of customs, infrastructure, ease of arranging shipments, quality of logistics services, tracking and tracing, and timeliness for a broad group of countries. Based on these points, the motivation of this research is both to promote MCDM (Multi-Criteria Decision-Making) methods by applying the recently introduced WENSLO (Weights by ENvelope and SLOpe) and ARTASI (Alternative Ranking Technique based on Adaptive Standardized Intervals) methods and to present the most recently published 2023-LPI dataset in the literature.

This study addresses a relevant and timely topic in the field of logistics performance by the use of innovative methods called WENSLO and ARTASI, which set the paper apart from other studies. In this regard, this research fills the gap not only by comparing the WENSLO and ARTASI methods with their counterparts in the literature but also by comparing EUm and EUc separately with the same dataset that is using the most recent LPI. In light of the literature, this study aimed to propose a new model to evaluate the logistics performances of EUc and EUm countries with up-to-date decision-making methods.

The main contributions of this paper are as follows:

- This is the first paper to use the WENSLO weighted ARTASI method,
- The applied methods are used for the EUm and EUc' LPI-2023,
- The proposed model is compared with various current MCDM methods and shows a high level of robustness.

This study consists of five sections. The rest of the paper is structured as follows: The second section reviews the relevant studies through a literature review; the third section explains the materials and methods used in the study; the fourth section evaluates the EUc and EUm using LPI data and newly introduced methods; finally, the conclusion section underlines an interpretation and criticism of the findings, and the findings are discussed.

2. LITERATURE REVIEW

In recent years, there has been an increasing amount of literature evaluating the logistics performance of countries using MCDM methods (Isik et al. 2020, Kara et al. 2022, Özekenci 2023, Manavgat et al. 2023). These studies related to LPI are focused mainly on trade, competitiveness, and usage of different MCDM methods. Some of the most recent studies, which use MCDM for measuring LPI, are summarized below.

Çakır (2017) proposed a hybrid methodology, which is a combination of SAW, CRITIC, and Peters' FLR methods, for measuring the logistics performance of 34 OECD countries based on the 2014 LPI data. Peters' FLR model ranking is different from other MCDM methods. since it can estimate relationships among variables even if the dataset interacts in a fuzzy, qualitative, and uncertain way. Marti et al. (2017) used data envelopment analysis (DEA) as a tool for MCDM to be able to measure the dimensions of LPI: their findings show that income and geographical area have a strong effect on logistics performance.

Rezaei et al. (2018) used the Best Worst Method (BWM) to measure the relative importance of the LPI indicators and compared the results with the original LPI ranking. A questionnaire was administered among 107 experts and analyzed with BWM to assign weights to the components of LPI. As a result, the most important component of the LPI is infrastructure (0.25), whereas tracking and tracing (0.10) is the least important component. It shed light on which LPI component to focus on for countries to improve their score and rank. Ulutaş and Karaköy (2019) also focused on weighting the LPI dimensions by using two methods called objective (CRITIC) and subjective (SWARA), then ranked its sample EUm by using the PIV method. Isik et al. (2020) used SV (Statistical Variance) and the MABAC methods to analyze and rank the logistics performance index of Central and Eastern European Countries (CEECs). The proposed model was found consistent since the LPI ranking and proposed hybrid model ranking are the same.

Mercangoz et al. (2020) evaluated the LPI of 28 EUm and 5 EUc countries and ranked them by using the COPRAS-Grey method for the selected period (2010, 2012, 2014, 2016, 2018). Instead of a single term, the proposed method represents a wider period of statistics. Likewise, Yildirim and Mercangoz (2020) used AHP and ARAS-G methods to evaluate the LPI of OECD countries for the selected period (2010-2018). Results indicate a strong relationship with the chosen period and rankings calculated by ARAS-G. Furthermore, Senir (2021) also ranked EUm and Türkiye's domestic LPI in 2018 by using CRITIC and COPRAS methods. "Without physical examination" is the most important criterion according to CRITIC, and the Netherlands, Slovenia, and Denmark were, respectively, the top three performing countries according to COPRAS. On the other hand, Mešić et al. (2022) evaluated the 2018-LPI of the Western Balkans by integrating CRITIC and MARCOS methods. Criteria weights were obtained by using the CRITIC method, and Serbia was the best-ranked country according to the MARCOS method.

Çalık et al. (2023) evaluated 2018 LPI by integrating AHP-TOPSIS, AHP-VIKOR, and AHP-CODAS methods in different fuzzy environments. It is found that infrastructure and logistics quality and competence are the most important criteria, while tracking and tracing is the least important criteria. Manavgat et al. (2023) evaluated the LPI-2018, Enabling Trade Index (ETI-2016), Liner Shipping Connectivity Index (LSCI-2021), and Availability and Quality of Transport Infrastructures (AQTI-2016) index data by using the ROC-based WASPAS method and also Moran's I and Local Indicators of Spatial Association (LISA) method for spatial autocorrelation.

Miškić et al. (2023) evaluated the 2018 LPI of the EU countries by using an integrated MEREC-MARCOS method. The MEREC method was used to weight the six criteria of LPI, and the MARCOS method was used for ranking the 27 EUm. Similarly, Yu and Rakshit (2023) used the H-DEA approach to investigate the weight criteria of the 2018 LPI. It has been found that timeliness is the most important sub-indicator of LPI. Gürler et al. (2024) also evaluated the 2018 LPI of EUm by determining criteria weights with a genetic algorithm and some MCDM tools. Likewise, Arman and Organ (2023) focused on evaluating the logistics performance of EUm and EUc countries with 2023 LPI data by using MEREC and CoCoSo methods. As a result of the study, infrastructure and customs are the two most important criteria. Moreover, Türkiye has the highest score among EUc while Finland has the highest score among EUm counties. It was also found that Türkiye performed better than 9 EUm countries. Another study that is using MEREC was conducted by Pala (2023). He evaluated the logistics performance of Türkiye and its competitors such as Poland, Hungary, Czechia and Slovakia by using MEREC-Corr approach. In addition, SAW method is also used for ranking the countries for the LPI data between 2010-2018. One of the most important results of the study indicates that improvements in customs procedures can help Türkiye to reach higher rank in LPI among its rivals. Besides, Alnıpak (2024) used AHP and CoCoSo methods for assessing the logistic performance of APEC (Asia Pacific Economic Cooperation) countries with 2023 LPI. The findings indicate that calculated ranking of countries is slightly different from WB ranking and the most important criterion was "the quality of trade and transport-related infrastructure".

On the other hand, Türkoğlu and Duran (2023) used CRITIC, GIA and WASPAS methods to evaluate the 2018 LPI of Australia, China, Japan, South Korea, India and New Zealand. According to the findings the most important criterion for ranking was the "Customs Management" and Japan performed better in country ranking than others. Another interesting study focused on the logistic performance of Africa published by Mercan and Aydın (2024) in the context of trade relation. 2023 LPI and 2022 trade data were analyzed using integrated Entropy-MOORA Reference Approach. The findings indicates that South Africa ranks first, and Libya was the last in country ranking. Furthermore, no correlation between trade data and LPI was found.

İnce et al. (2023) used MEREC and CODAS methods to be able to measure and compare the logistics performance of G20 countries before and during Covid-19. According to the results of the study, "monitoring and tracing" was the most important criterion before, during, and after Covid-19. The best performing countries among the G-20 before Covid-19 were Germany, Japan, and England, but during Covid-19 this ranking was Germany, Canada, and Japan. Results of the study demonstrate that Covid-19 affected the LPI ranking of many countries. Likewise, Akbulut et al. (2024) evaluated the logistic performance of G-20 countries by using the 2018 LPI data set with SD, PSI-MEREC and MARA methods. As a result, "Customs" seems the most important criterion; Germany was the first and Russia was the last in country ranking among G-20 countries, and these results are consistent with WB ranking. In addition to that, Kale and Tilki (2024) evaluated the 2023 LPI data set by using the ENTROPY-weighted TOPSIS method and compared the ranking with the WB ranking. Results of the analysis are consistent with WB ranking even though there are some differences. Çıray et al. (2024) also evaluated the 2023 LPI data set by using the ENTROPY-based ORESTE method. The main contribution of the study to the literature is to introduce a novel method called ORESTE that is producing accurate ranking results.

Since the LPI ranking by the WB assumes equal weighting when ranking countries, previous researches have focused on weighting the criteria. However, these researches have been conducted with previous data which shows some other conditions before the lastly living hard situations such as Covid-19. As can be seen from these aforementioned studies, analyzing the LPI by using different methods have extended the literature. But none of them have used WENSLO and ARTASI methods in this context. Main purpose of this paper is to apply the WENSLO and ARTASI methods, which are the most recent MCDM methods, and demonstrate the application process steps on the 2023 LPI data for EUm and EUc sample. To be able to present more comprehensive results, findings will also be compared with the results of similar, common, and current ranking methods in the literature, such as ANGLE (Shuai et.al. 2012), CRITIC (CRiteria Importance Through Intercriteria Correlation) (Mesic et.al. 2022), CVM (Coefficient of Variations Method), ENTROPY (Shemshadi et.al. 2011; Kale and Tilki, 2024), GINI (Aggarwal et.al. 2024), LOWCOP (LOgarithmic Percentage Change-driven Objective Weighting) (Ecer and Pamucar, 2022), MEREC (Method based on the Removal Effects of Criteria) (Keshavarz-Ghorabaee et.al. 2021), SD (Standard Deviation) (Nguyen et.al. 2020), MABAC (Multi-Attributive Border Approximation area Comparison) (Pamucar & Cirovic, 2015), MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution) (Stevic et.al., 2020), WASPAS (Weighted Aggregated Sum Product Assessment) (Zavadskas et.al., 2012), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) (Wang and Lee, 2009), CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution) (Ha, 2023), PIV (Proximity Indexed Value) (Ersoy,2021) and COCOSO (COmbined COmpromise SOlution) (Yazdani et al., 2018) methods. In this regards, this research's main contribution to the literature is not only applying the latest hybrid MCDM methods called as WENSLO and ARTASI for weighting and ranking in logistics performance but also using the latest 2023 LPI in the calculations for ranking EUm and EUc.

3. MATERIALS AND METHODS

The WB has been scoring countries by their logistics competence and providing a ranking since 2007 with a 5-point scale. This time, the latest updated LPI ranking was achieved for 139 countries, complemented by the six key performance indicators, and derived from a Big Data approach (Arvis et al., 2023). The indicators used to evaluate countries are selected based on customs, infrastructure and services, cost, reliability, and time indicators, based on theoretical and empirical research and the practical experience of logistics professionals involved in international transportation. The WB has analyzed countries using six LPI components as shown in Table 1 (Isik et al. 2020, Janno et al. 2021, Arvis et al. 2023).

Table 1: Criteria used in LPI calculations

Code	Criteria	Definition
C1	Customs	Efficiency of customs and borders
C2	Infrastructure	Quality of trade and transport infrastructure
C3	International Shipments	Ease of arranging competitively priced shipments
C4	Logistics Competence and Quality	Competence and quality of logistics services
C5	Timeliness	Frequency with which shipments reach consignees within scheduled or expected delivery times
C6	Tracking and Tracing	Ability to track and trace consignments

There are various criteria and alternatives for MCDM, and decision-making can occur at any time in any area of human life. It is a very essential distinction to determine the criteria weights for evaluating the alternatives in MCDM models (Keleş, 2023). However, no weight value is assigned to the indicators in the ranking based on a 5-point Likert scale. MCDM methods are an effective tool used to evaluate multiple alternatives using multiple criteria. In this study, MCDM methods introduced to the literature quite recently and the recently published LPI-2023 edition are highlighted to make a difference. MCDM methods that allow a multidimensional analysis of the problem, objectively considering all criteria, including opposing ones, appear to be a suitable approach to ranking the countries with superior logistics performance (Kizielewicz et al., 2021). The WENSLO method (Pamucar et al., 2023), very recently introduced to the literature, was used to weight the LPI indicators of countries on an objective basis, and the ARTASI method (Pamucar et al., 2024) was used to rank the alternative EUm and EUc countries.

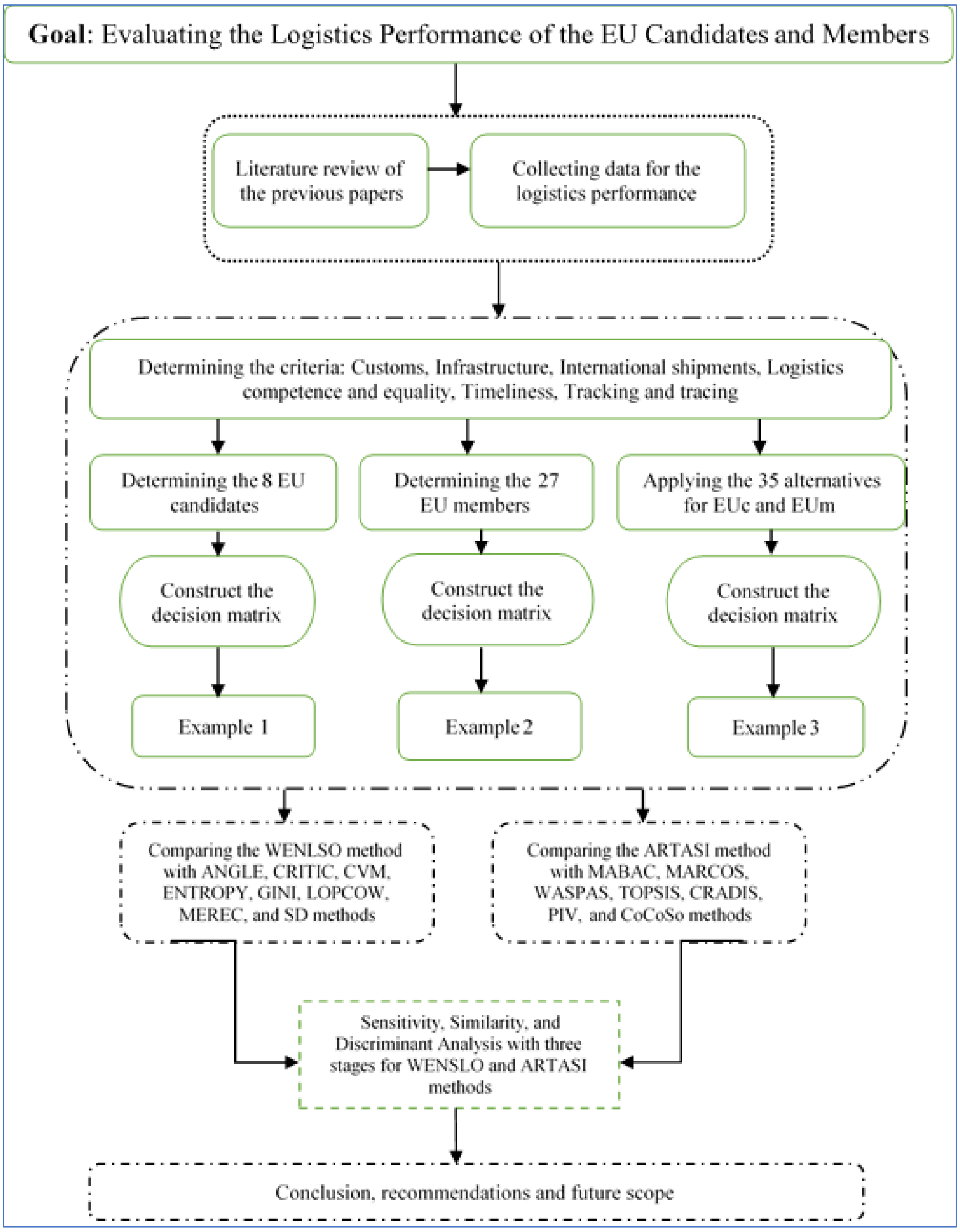

Figure 1: Flowchart for WENSLO-ARTASI Methods

3.1. The WENSLO Method Procedures

The WENSLO- "*Weights by ENvelope and SLOpe*" method was recently introduced to the literature as an objectively criteria-weighting MCDM method in a decision-making problem by Pamucar et al. (2023). The WENSLO method can be used to find the weights of criteria (without benefit or cost criteria tendency) regardless of individual judgments and personal opinions of expert groups. The WENSLO is a promising method and also has an interesting background. It is based on determining the weights of the criteria based on the envelope and slope of the criteria. Another positive side of the WENSLO method is that the calculation process is not influenced by whether the criteria are classified as benefits or costs. The criterion is expected to have a greater weight when the value of the envelope is high while the value of the slope is low using the WENSLO method. The solution stages of the WENSLO method can be explained in seven steps.

Step 1. The decision matrix is created: The decision matrix consists of m alternatives and n criteria. Each criterion is directed max-min target. $A_1, A_2, \dots, A_m$ representing the alternatives, $C_1, C_2, \dots, C_n$ representing the criteria, ζ_{ij} is the estimated value of the ith alternative according to the jth criterion.

$$\left[\zeta_{ij}\right]_{mxn} = \begin{bmatrix} A/C & C_1 & C_2 & \cdots & C_j \\ A_1 & \zeta_{11} & \zeta_{12} & \cdots & \zeta_{1j} \\ A_2 & \zeta_{21} & \zeta_{22} & \cdots & \zeta_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_i & \zeta_{i1} & \zeta_{i2} & \cdots & \zeta_{mn} \end{bmatrix} \tag{1}$$

Step 2. The non-dimensional normalized decision matrix is obtained using max-min (sum-based) linear normalization. This step is shown at the Equation (2):

$$z_{ij} = \frac{\zeta_{ij}}{\sum_{i=1}^{m} \zeta_{ij}} \forall_j \in \left[1, 2, \dots, n\right] \tag{2}$$

Step 3. Criterion class interval is calculated: The value of the jth criterion class interval Δz_j is calculated by Sturges' rule, following Equation (3).

$$\Delta z_j = \frac{\max z_{ij} - \min z_{ij}}{1 + 3.322 \cdot \log(m)} \forall_j \in \left[1, 2, \dots, n\right] \tag{3}$$

Step 4. The criterion envelope is calculated: The criterion envelope is obtained by finding the square root of the squares of two successive normalized criterion values and Δz_j.

$$E_j = \sum_{i=1}^{m-1} \sqrt{(z_{i+1,j} - z_{i,j})^2 + \Delta z_j^{\,2}} \tag{4}$$

Step 5. The criterion slope is calculated: Using the sum of the normalized criterion values, it is divided by one minus the number of alternatives multiplied by Δz_j.

$$\tan \varphi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1) \cdot \Delta z_j} \forall_j \in \left[1, 2, \dots, n\right] \tag{5}$$

Step 6. The envelope–slope ratio is defined: The ratio of the Envelope of the criterion to the slope of the criterion is calculated.

$$q_j = \frac{E_j}{\tan \varphi_j} \forall_j \in [1,2,...,n] \tag{6}$$

Step 7. The criteria weights are calculated: The ratio of total envelope-slope ratio is divided into total ratio; hence each criterion has an objective weight.

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \forall_j \in [1,2,...,n] \tag{7}$$

3.2. The ARTASI Method Procedures

The ARTASI- "*Alternative Ranking Technique based on Adaptive Standardized Intervals*" method was recently introduced to the literature based on distance measure as a ranking MCDM method by Pamucar et al. (2024). The rank reversal problem is eliminated using the ARTASI method. The interval of the normalization/standardization of the criterion can be adjusted with the ARTASI method using various ranges. The solution stages of the ARTASI method can be explained in six steps. Step 1 is the same as all MCDM methods, namely, the decision matrix is created.

Step 2. Absolute minimum and maximum values are defined for all of the criteria based on the initial decision matrix.

$$\zeta_j^{\max} = \max_{1 \le i \le m}(\zeta_{ij}) + \left\{ \max_{1 \le i \le m}(\zeta_{ij}) \right\}^{1/m} \quad \text{for absolute maximum values} \tag{8}$$

$$\zeta_j^{\min} = \min_{1 \le i \le m}(\zeta_{ij}) - \left\{ \min_{1 \le i \le m}(\zeta_{ij}) \right\}^{1/m} \quad \text{for absolute minimum values} \tag{9}$$

Step 3. The initial decision matrix is standardized: Criteria of different dimensions are standardized to a range chosen by the decision maker. Most MCDM methods perform normalization in the range of [0-1]. For instance, ψ(l) represents the first limit of the interval while ψ(u) represents the upper limit of the interval. Another difference of the ARTASI method is that these limits can be changed depending on the decision maker's preference. We used the interval (1, 100) in this example; also, other intervals can be used, such as (1, 10), (0, 1), and (1,1000).

$$\phi_{ij} = \frac{\psi^{(u)} - \psi^{(l)}}{\zeta_j^{\max} - \zeta_j^{\min}} \cdot \zeta_{ij} + \frac{\zeta_j^{\max} \cdot \psi^{(l)} - \zeta_j^{\min} \cdot \psi^{(u)}}{\zeta_j^{\max} - \zeta_j^{\min}} \tag{10}$$

All of the criteria are converted into standardized types in this step, but if the criterion is min type, it is necessary to modify the values max type. By the way, max type criteria are expressed as: $\zeta_{ij} = \phi_{ij}$.

$$\zeta_{ij} = -\phi_{ij} + \max_{1 \le i \le m}(\phi_{ij}) + \min_{1 \le i \le m}(\phi_{ij}) \tag{11}$$

Step 4. The degree of usefulness of alternatives concerning the ideal and anti-ideal values are defined: The standardized value of each criterion is divided by the maximum value of that criterion and multiplied by the weight and the upper limit of the interval to obtain the ideal value.

$$\vartheta_{ij}^{+} = \frac{\zeta_{ij}}{\max_{1 \le i \le m}(\zeta_{ij})} \cdot w_j \cdot \psi^{(u)} \tag{12}$$

The standardized minimum value of each criterion is divided by the standardized value of that criterion and multiplied by the weight and the upper limit of the interval value. Then, the anti-ideal value is obtained with the help of expression (14).

$$\vartheta_{ij} = \frac{\min\limits_{1 \le i \le m}(\zeta_{ij})}{\zeta_{ij}} \cdot w_j \cdot \psi^{(u)} \tag{13}$$

$$\vartheta_{ij}^{-} = -\vartheta_{ij} + \max_{1 \le i \le m}(\vartheta_{ij}) + \min_{1 \le i \le m}(\vartheta_{ij}) \tag{14}$$

Step 5. Aggregated degrees of utility of alternatives are calculated: The aggregate degree of utility of alternatives is calculated for ideal and anti-ideal values.

$$\Im_i^{+} = \sum_{j=1}^{n} \vartheta_{ij}^{+} \text{ for ideal,} \qquad \Im_i^{-} = \sum_{j=1}^{n} \vartheta_{ij}^{-} \text{ for anti-ideal} \tag{15}$$

Step 6. The final utility functions are calculated and alternatives are ranked: The final utility degree is calculated based on ideal, anti-ideal, alfa, and beta parameters.

$$U_i = (\Im_i^{+} + \Im_i^{-})\left\{\alpha \cdot f(\Im_i^{+})^{\beta} + (1-\alpha) \cdot f(\Im_i^{-})^{\beta}\right\}^{1/\beta}; \beta \in [1, +\infty); \alpha \in [0,1] \tag{16}$$

By setting the parameter α = 0.5, the effect of the total benefit levels of the alternatives on the final decision is balanced, simulating an equal influence of the total benefit levels in the decision-making process. If the β parameter represents the stabilization parameter of the aggregation function which is a more straightforward calculation of the final utility functions and is adopted 1 and the α parameter, which represents the influence of the aggregated levels of the alternatives is adopted 0.5, the expression can be transformed as follows.

$$U_i = (\Im_i^{+} + \Im_i^{-})\left\{0.5 \cdot f(\Im_i^{+}) + 0.5 \cdot f(\Im_i^{-})^{\beta}\right\} \tag{17}$$

4. FINDINGS

MCDM is a fundamental and interdisciplinary field that is considered when more than one criterion is involved in decision problems. Many MCDM methods are proposed in the literature for determining criterion weights or selecting/ranking alternatives, which provide processes that result in rational and explainable decisions (Keleş and Pekkaya, 2023:294). This study first compares EUc (to explain more with less data) and EUm separately using LPI data, then EUc and EUm together.

4.1. WENSLO Method for Criteria Weights

Although Entropy, CRITIC, and SD (Standard Deviation) methods are popular objective criterion weighting methods, new methods such as ANGLE, CVM (Coefficient of Variations Method), GINI (Gini coefficient-based weighting), LOPCOW, and MEREC have also been introduced to the literature in recent years. This article initially uses the WENSLO method with a three-stage plan to obtain the LPI criterion weights. In the first stage, the WENSLO method is carried out for EUc. The decision matrix is created and normalized.

Table 2: Decision and Normalized Matrix of EUc

Alternatives	Customs	Infrastructure	International Shipments	Logistics Competence and Quality	Timeliness	Tracking and Tracing	C1	C2	C3	C4	C5	C6
Albania	2.4	2.7	2.8	2.3	2.5	2.3	0.118	0.129	0.120	0.101	0.098	0.097
Ukraine	2.4	2.4	2.8	2.6	3.1	2.6	0.118	0.115	0.120	0.114	0.122	0.110
Moldova	1.9	1.9	2.7	2.8	3.0	2.8	0.094	0.091	0.116	0.123	0.118	0.118
Bosnia and Herzegovina	2.7	2.6	3.1	2.9	3.2	3.2	0.133	0.124	0.133	0.127	0.125	0.135
North Macedonia	3.1	3	2.8	3.2	3.5	3.2	0.153	0.144	0.120	0.140	0.137	0.135
Montenegro	2.6	2.5	2.8	2.8	3.2	3.2	0.128	0.120	0.120	0.123	0.125	0.135
Serbia	2.2	2.4	2.9	2.7	3.4	2.9	0.108	0.115	0.124	0.118	0.133	0.122
Türkiye	3.0	3.4	3.4	3.5	3.6	3.5	0.148	0.163	0.146	0.154	0.141	0.148

Using the normalized decision matrix values, the max-min values of each criterion, and then the criterion class interval Δz_j are calculated by Sturges' rule. The criterion envelope, slope, and ratio values are calculated. Finally, the criteria weights are presented.

Table 3: Calculations and Weights

	C1	C2	C3	C4	C5	C6
Min	0.094	0.091	0.116	0.101	0.098	0.097
Max	0.153	0.163	0.146	0.154	0.141	0.148
Sum	1	1	1	1	1	1
zj	0.015	0.018	0.008	0.013	0.011	0.013
Envelope	0.015	0.023	0.008	0.019	0.026	0.018
	0.029	0.030	0.009	0.016	0.011	0.015
	0.042	0.038	0.019	0.014	0.013	0.021
	0.025	0.026	0.015	0.019	0.016	0.013
	0.029	0.030	0.008	0.022	0.016	0.013
	0.025	0.019	0.009	0.014	0.013	0.018
	0.042	0.051	0.023	0.037	0.013	0.028
Sum	0.206	0.217	0.089	0.140	0.109	0.126
Slope	9.667	7.962	19.021	10.857	13.247	11.286
Ratio	0.021	0.027	0.005	0.013	0.008	0.011
Weights	0.249	0.318	0.055	0.151	0.097	0.130

Calculated values show that C2-Infrastructure-31.8%, followed by C1-Customs-24.9% criteria, were found in the first ranks. On the contrary, C3-International Shipments-5.46% was found to be the lowest. The weights found by the WENSLO method can also be compared with the other weight-finding methods.

Table 4: LPI Criteria Weights of EUc

	WENSLO	ANGLE	CRITIC	CVM	ENTROPY	GINI	LOPCOW	MEREC	SD
C1	0.249	0.203	0.181	0.211	0.236	0.228	0.162	0.207	0.203
C2	0.318	0.220	0.169	0.220	0.273	0.231	0.167	0.229	0.220
C3	0.055	0.102	0.199	0.091	0.057	0.088	0.069	0.052	0.102
C4	0.151	0.166	0.124	0.167	0.154	0.163	0.162	0.153	0.166
C5	0.097	0.140	0.178	0.138	0.114	0.121	0.251	0.177	0.139
C6	0.130	0.170	0.149	0.173	0.166	0.169	0.189	0.182	0.169

The criteria weights obtained from different methods can be compared with the Pearson correlation. In this study, correlations are presented between the WENSLO method and eight other MCDM methods.

Table 5: Correlations of LPI Criteria Weights of EUc

	WENSLO	ANGLE	CRITIC	CVM	ENTROPY	GINI	LOPCOW	MEREC	SD
WENSLO	1								
ANGLE	0.955	1							
CRITIC	-0.110	-0.306	1						
CVM	0.933	0.997	-0.327	1					
ENTROPY	0.977	0.994	-0.216	0.986	1				
GINI	0.952	0.989	-0.245	0.989	0.989	1			
LOPCOW	0.139	0.319	-0.322	0.352	0.261	0.221	1		
MEREC	0.801	0.906	-0.304	0.917	0.883	0.857	0.681	1	
SD	0.956	1.000	-0.304	0.997	0.995	0.989	0.316	0.905	1

The highest correlation (r = 0.977) was observed between the WENSLO and the Entropy methods. Following this, high correlations were found with SD (0.956), ANGLE (0.955), GINI (0.952), and CVM (0.933) methods.

In the first stage, all stages of the decision problem where the number of alternatives is less are shown, and then in the second stage, criterion weights for EUm countries are calculated (Appendix 1) and presented (Fig. 2) by the WENSLO method.

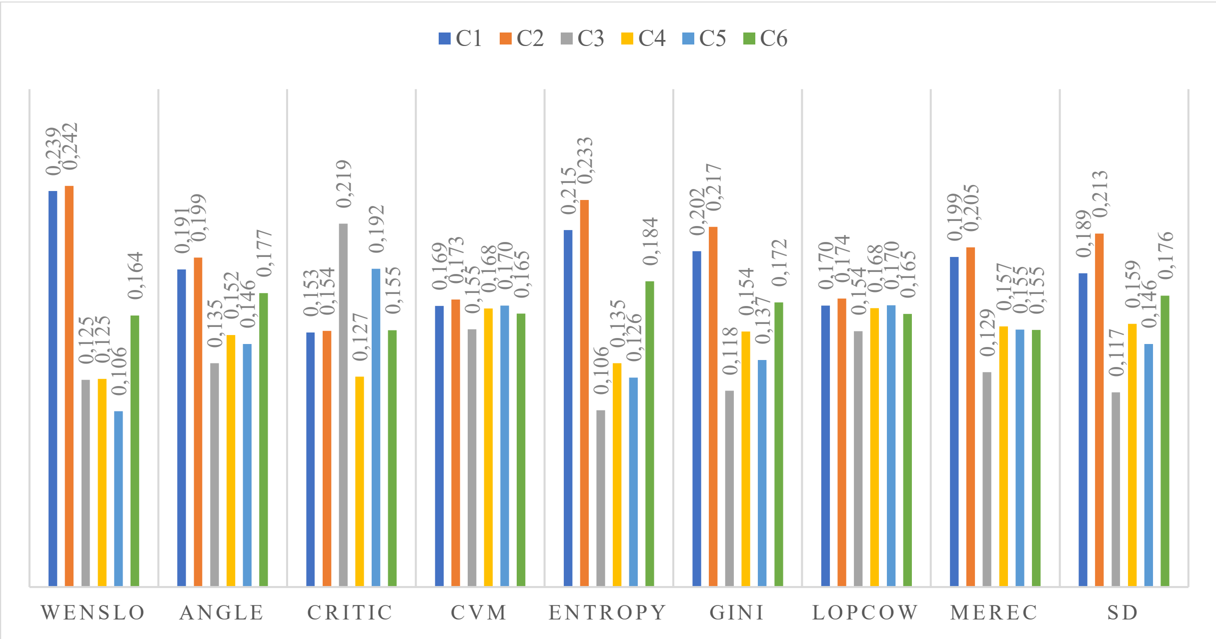

Figure 2: LPI Criteria Weight Values of EUm

Among the LPI criteria calculated for EUm countries, C2-Infrastructure-24.2%, followed by C1-Customs-23.9%, ranked first. On the other hand, C5-Timeliness-10.6% was calculated to have the lowest weight. In Figure 2, the findings of the criterion weights by different methods are presented visually. At first glance, the similarity of WENSLO and ENTROPY shapes is striking. However, for a better analysis, the correlations between the methods were calculated and presented (Appendix 1) for the EUm. Accordingly, WENSLO and ENTROPY correlation (r=0.950) was found to be the highest. Then, high correlation values were again found between the WENSLO method and the ANGLE (0.939) and GINI (0.939) methods.

In the third and final stage, the EUc and the EUm were combined and evaluated in a decision matrix for criterion weights using the WENSLO method. Criteria weights for EUm and candidates are calculated (Appendix 2) and presented (Fig. 3).

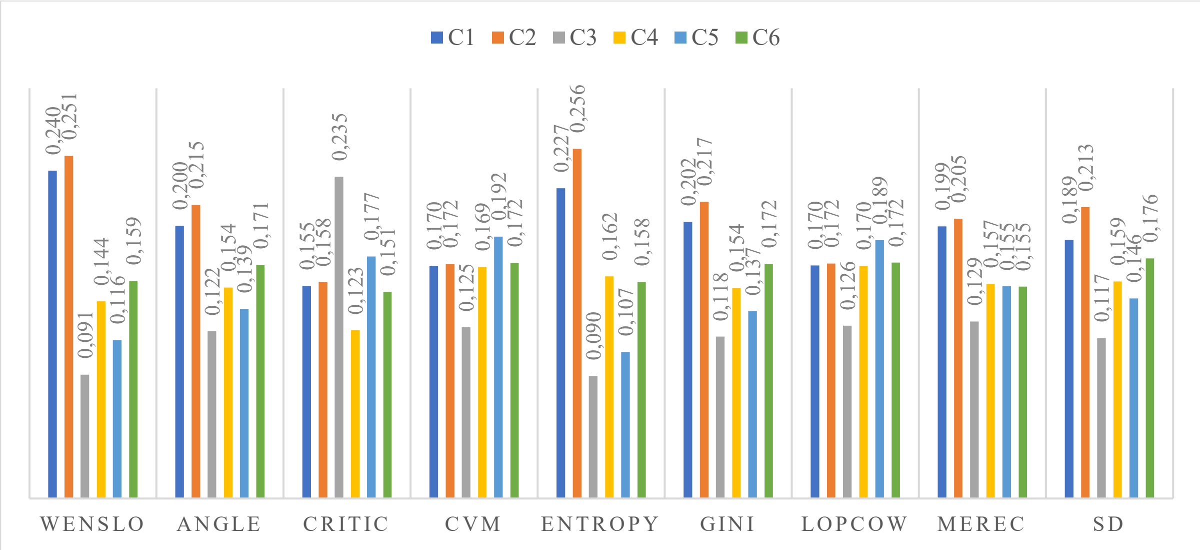

Figure 3: LPI Criteria Weight Values of EUm and Candidates

Figure 3, which presents the criterion weights for EUm and EUc, highlights the similarity between the WENSLO method and the ENTROPY, GINI, and ANGLE methods. On the other hand, remarkable findings can be obtained when the findings are examined statistically with correlation analysis, instead of looking for a similarity only in terms of shape. In the decision matrix where the LPI of EUc and EUm are evaluated together, the WENSLO method and the ANGLE (0.990), GINI (0.990), and ENTROPY (0.986) methods were found to have the highest correlation. Then, MEREC (0.976) and SD (0.951) findings were also quite high. On the contrary, in three different samples, the findings of the WENSLO method and the CRITIC method were negatively correlated.

4.2. ARTASI Method for Ranking of Alternatives

An essential stage of MCDM methods involves evaluating alternatives according to specific goals using the available data (Kizielewicz et al. 2023). In this study, the ARTASI method is employed to rank alternatives in a three-stage approach: first, comparing EUc countries, then EUm countries, and finally, assessing EUc and EUm countries together. The ARTASI method applies the decision matrices created in the previous stage. Absolute minimum and maximum values are calculated for each criterion to produce a standardized decision matrix.

Table 6: Absolute minimum and maximum values and standardization of the decision matrix

	C1	C2	C3	C4	C5	C6
wj	0.249	0.318	0.055	0.151	0.097	0.130
max	4.252	4.565	4.565	4.670	4.774	4.670
min	0.816	0.816	1.568	1.190	1.379	1.190
Albania	46.633	50.741	41.696	32.577	33.699	32.577
Ukraine	46.633	42.818	41.696	41.113	51.196	41.113
Moldova	32.224	29.614	38.394	46.804	48.280	46.804
Bosnia and Herzegovina	55.278	48.100	51.605	49.649	54.112	58.186
North Macedonia	66.805	58.663	41.696	58.186	62.860	58.186
Montenegro	52.397	45.459	41.696	46.804	54.112	58.186
Serbia	40.870	42.818	44.999	43.958	59.944	49.649
Türkiye	63.923	69.227	61.513	66.722	65.776	66.722

The degree of usefulness for EUc' LPI is defined by ideal and anti-ideal solutions. The ideal and non-ideal (after converted) degrees of usefulness are presented together in Table 7.

Table 7: Defining the degree of usefulness of EUc

	C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C5	C6
Albania	17.379	23.343	3.699	7.376	4.946	6.365	19.702	26.884	3.838	7.376	4.946	6.365
Ukraine	17.379	19.698	3.699	9.309	7.514	8.033	19.702	23.445	3.838	10.513	8.245	9.072
Moldova	12.009	13.624	3.406	10.598	7.086	9.145	12.009	13.624	3.406	11.969	7.861	10.328
Bosnia and Herzegovina	20.601	22.128	4.578	11.242	7.942	11.369	22.392	25.863	4.803	12.571	8.588	12.103
North Macedonia	24.897	26.988	3.699	13.175	9.226	11.369	24.897	29.394	3.838	14.026	9.424	12.103
Montenegro	19.527	20.913	3.699	10.598	7.942	11.369	21.594	24.724	3.838	11.969	8.588	12.103
Serbia	15.231	19.698	3.992	9.954	8.798	9.701	17.276	23.445	4.207	11.288	9.173	10.848
Türkiye	23.823	31.847	5.457	15.108	9.654	13.037	24.355	31.847	5.457	15.108	9.654	13.037

The aggregated utility degrees of the alternatives are calculated by adding the ideal and anti-ideal values for each alternative. Then a correction is made. Finally, the final utility functions are calculated and presented, and then alternatives are ranked.

Table 8: Aggregated and final degrees of utility of EUc

Alternatives	Vij+	Vij-	Si+	Si-	Ui	Rank
Albania	63.11	69.11	0.48	0.52	66.11	7
Ukraine	65.63	74.82	0.47	0.53	70.22	6
Moldova	55.87	59.20	0.49	0.51	57.53	8
Bosnia and Herzegovina	77.86	86.32	0.47	0.53	82.09	3
North Macedonia	89.35	93.68	0.49	0.51	91.52	2
Montenegro	74.05	82.82	0.47	0.53	78.43	4
Serbia	67.37	76.24	0.47	0.53	71.81	5
Türkiye	98.93	99.46	0.50	0.50	99.19	1

In the decision problem where 8 EU candidate country alternatives' LPIs are evaluated, the countries are ranked: Türkiye, North Macedonia, Bosnia and Herzegovina, Montenegro, Serbia, Ukraine, Albania, and Moldova, respectively. In addition, the ARTASI method used to rank the alternatives has been compared with the results of similar, common, and current ranking methods in the literature, such as MABAC, MARCOS, WASPAS, TOPSIS, CRADIS, PIV, and CoCoSo methods.

Table 9: LPI Ranks and Scores of the EUc

	ARTASI	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo	ARTASI	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo
Albania	7	7	7	7	5	7	7	7	66.11	-0.19	0.60	0.74	0.43	0.72	0.11	1.49
Ukraine	6	6	6	6	6	6	6	6	70.22	-0.13	0.61	0.75	0.35	0.73	0.11	2.40
Moldova	8	8	8	8	8	8	8	8	57.53	-0.31	0.55	0.67	0.14	0.65	0.14	1.24
Bosnia and Herzegovina	3	3	3	3	3	3	3	3	82.09	0.11	0.68	0.84	0.54	0.82	0.07	3.16
North Macedonia	2	2	2	2	2	2	2	2	91.52	0.32	0.75	0.93	0.78	0.91	0.03	3.77
Montenegro	4	4	4	4	4	4	4	4	78.43	0.03	0.66	0.81	0.47	0.79	0.08	2.91
Serbia	5	5	5	5	7	5	5	5	71.81	-0.09	0.62	0.76	0.34	0.74	0.10	2.53
Türkiye	1	1	1	1	1	1	1	1	99.19	0.51	0.80	0.99	0.96	0.99	0.00	4.32

It is noteworthy that the same rank (except for a small rank change of the TOPSIS method) is found in all ranking methods. This may be explained by the small number of alternatives. For these reasons, it may be more appropriate to solve the problem with different and many alternatives and examine the changes between the rankings. Thus, EUm countries were again examined using the ARTASI method for LPI (Appendix 3). It was observed that the first four ranks in the ranking for EUm countries for LPI were the same for seven different methods. Accordingly, Finland is ranked first, followed by Germany, Denmark, and the Netherlands. However, in later rankings, differences are found in the methods. Correlations between the rankings were examined with Spearman correlation analysis to understand the extent of change. There are very high correlations between the ARTASI method and others; it is the lowest ARTASI-TOPSIS (Spearman r=0.982). This indicates that only 1-2 rank changes were observed overall between the methods.

Following the LPI rankings for EUm in the second stage, the LPI rankings of EUm and EUc were evaluated together in the same decision matrix in the third stage. The LPI ranks of EUm and EUc were also applied using the ARTASI method and are presented (Appendix 4). This time, in the evaluation made using the ARTASI and seven different methods for 35 countries, the first three ranks were found to be the same: Finland, Germany, and Denmark. There are very high correlations between the ARTASI method and the other seven methods; it is the lowest ARTASI-TOPSIS (Spearman r=0.992), and others are quite high. In this assessment, Türkiye draws attention among the candidate countries by getting a better ranking than 2/3 of the member countries. Other candidate countries did not have a better rank than the member states.

4.3. Sensitivity, Similarity and Discriminant Analysis

By using sensitivity analysis, the impact of changes in the existing method on the results can be examined. Given the variety of methods employed in this study, understanding the results through sensitivity analysis will provide valuable insights and contribute to the literature. Sensitivity analysis is presented in three stages since this study is conducted in three parts, such as EUc, Eum, and EUc with Eum. WENSLO-based ARTASI and other WENSLO-based methods were compared for a better understanding of all three parts. This time, the ARTASI method calculations used the ANGLE, CRITIC, CVM, ENTROPY, GINI, LOPCOW, MEREC, and SD methods instead of the WENSLO method. Thus, the effect of different criterion weighting methods is examined for the ARTASI method.

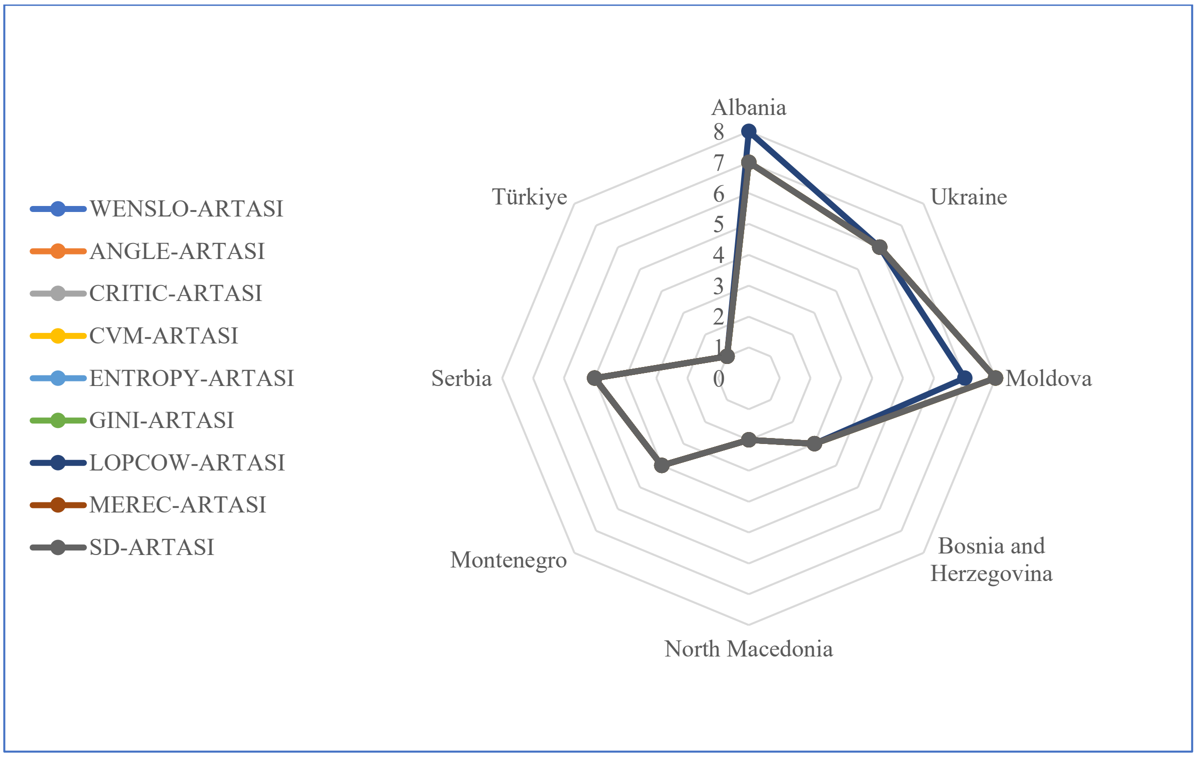

Figure 4: Sensitivity analysis for EUc

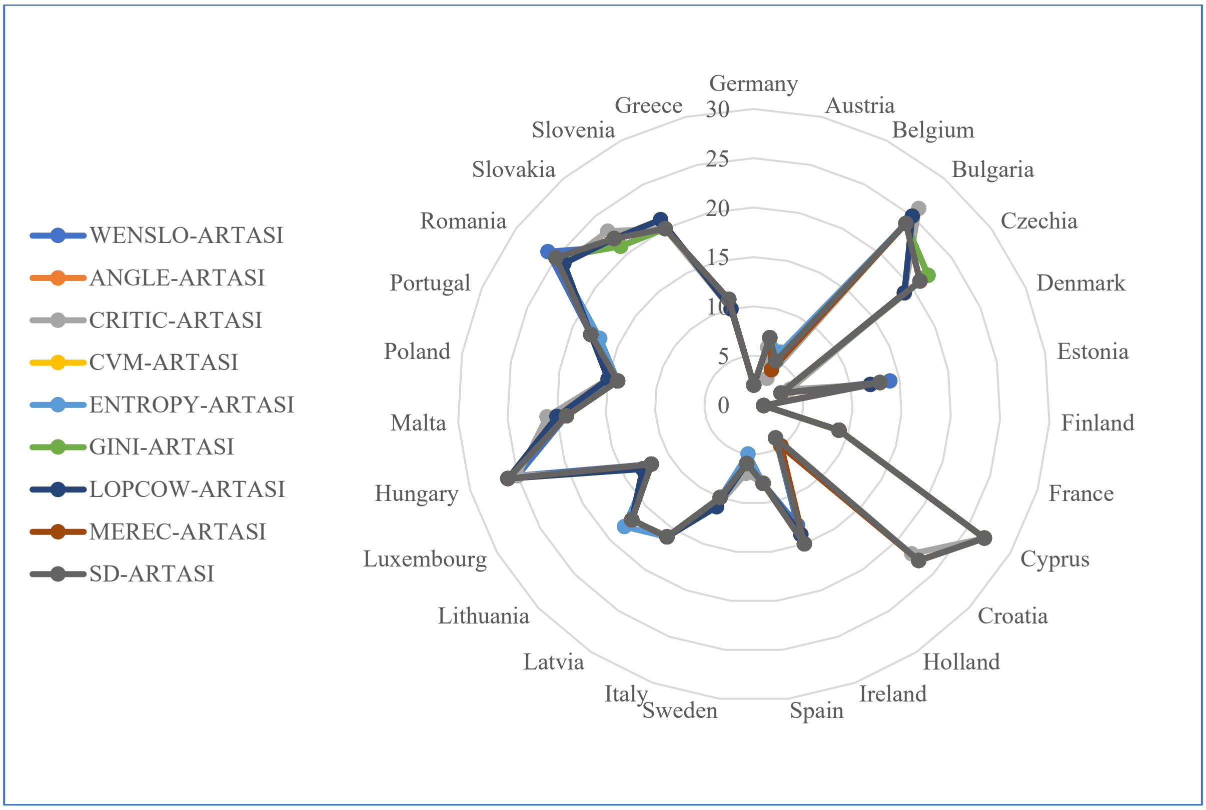

Figure 5: Sensitivity analysis for EUm

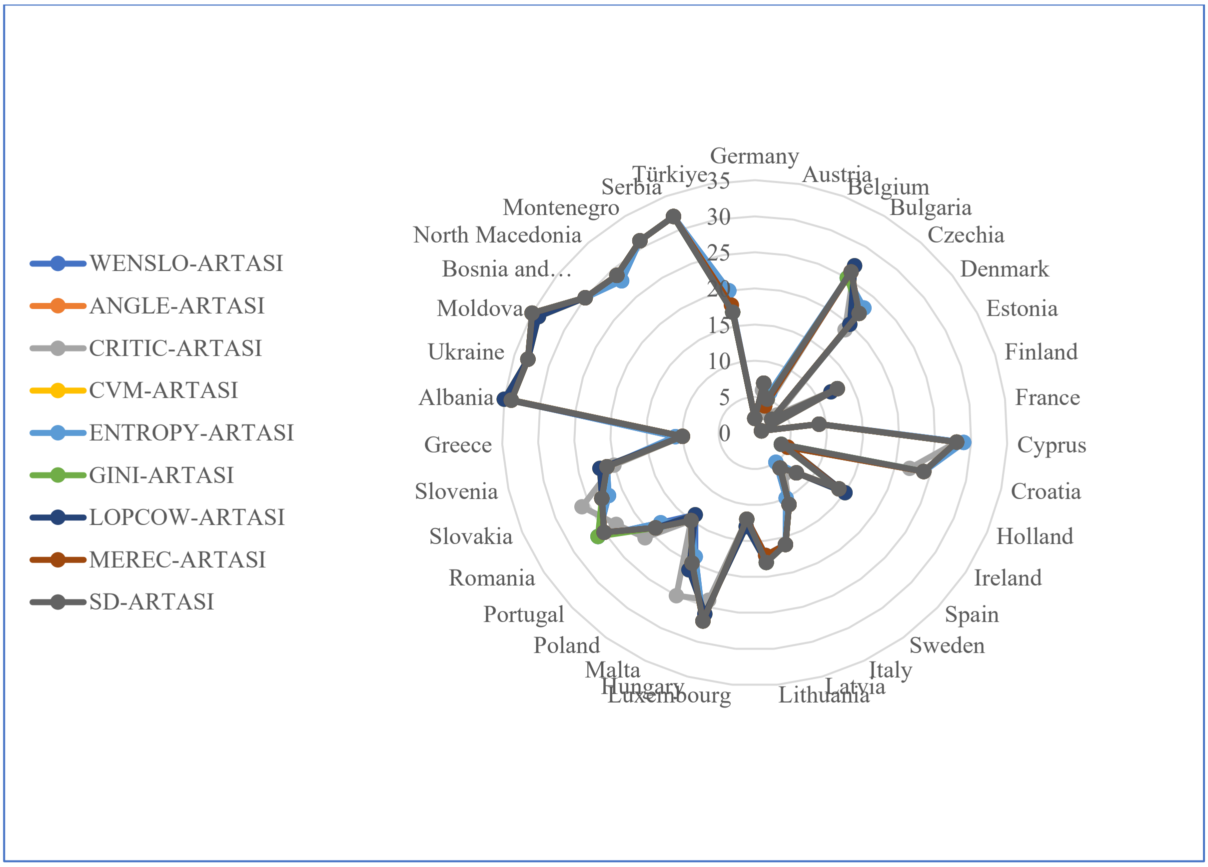

Figure 6: Sensitivity analysis for EUm and EUc

Sensitivity analyses demonstrate that the ARTASI method is a powerful ranking tool, as it generally produced robust and consistent rankings when eight different criterion weights were used as input. Furthermore, the coefficient of variation (Keleş, 2023), calculated using the mean and standard deviation, reveals differences across the existing criteria weighting methods (see Table 10).

Table 10: The coefficient of variations for different weighting methods

	WENSLO	ANGLE	CRITIC	CVM	ENTROPY	GINI	LOPCOW	MEREC	SD
EUc	59.313	25.487	15.968	28.607	47.422	34.004	35.171	37.009	25.700
EUm	35.968	15.568	19.768	3.718	30.995	22.813	4.074	17.458	20.156
EUc and EUm	39.168	21.332	22.703	13.174	38.987	22.813	12.595	17.458	20.156

The coefficients of variation vary depending on the methods used. However, the least variability is observed in the CVM and LOPCOW methods, which rely on the mean and standard deviation. On the other hand, the highest variability in criterion weights is seen in the WENSLO and ENTROPY methods. The WENSLO-ARTASI ranking findings are then compared with those of other weight-based methods, yielding relatively high correlations (see Table 11). The lowest, but still quite high, correlation is observed between the WENSLO-ARTASI and LOPCOW-ARTASI models (r = 0.976).

Table 11: Correlations of the different ARTASI models

	WENSLO-ARTASI	ANGLE-ARTASI	CRITIC-ARTASI	CVM-ARTASI	ENTROPY-ARTASI	GINI-ARTASI	LOPCOW-ARTASI	MEREC-ARTASI	SD-ARTASI
EUc	1.000	1.000	1.000	1.000	1.000	1.000	0.976	1.000	1.000
EUm	1.000	0.996	0.987	0.991	0.996	0.998	0.991	0.996	0.997
EUc and EUm	1.000	0.997	0.981	0.994	1.000	0.997	0.994	0.997	0.997

Weighted similarity coefficient analysis (Sałabun and Urbaniak, 2020) shows that the ARTASI method is a powerful ranking method and can be used instead of similar methods (see Table 12).

Table 12: Weighted similarity for the models

	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo
ARTASI-EUc	1.000	1.000	1.000	0.982	1.000	1.000	1.000
ARTASI-EUm	0.998	0.998	0.998	1.000	0.998	0.998	1.000
ARTASI-EUm and EUc	1.000	0.997	0.997	1.000	0.997	0.997	1.000

Very high similarities are found between the ARTASI method and similar preferred methods in the study, with the lowest but still very high correlations observed between the ARTASI-TOPSIS rankings (r=0.982). Weighted similarity findings are also similar to Spearman rank analysis. The distances of the findings obtained from the methods can be examined using discriminant analysis in the common space (Altıntaş, 2023).

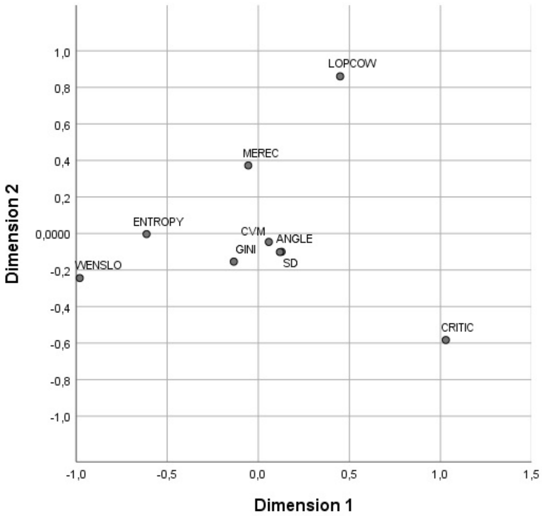

Figure 7a: Discriminant analysis for EUc

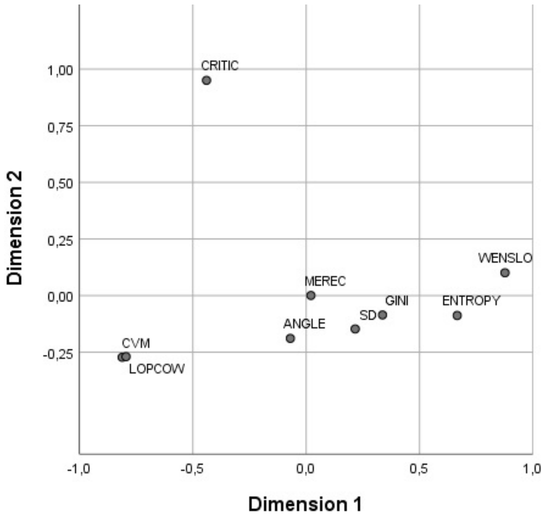

Figure 7b: Discriminant analysis for EUm

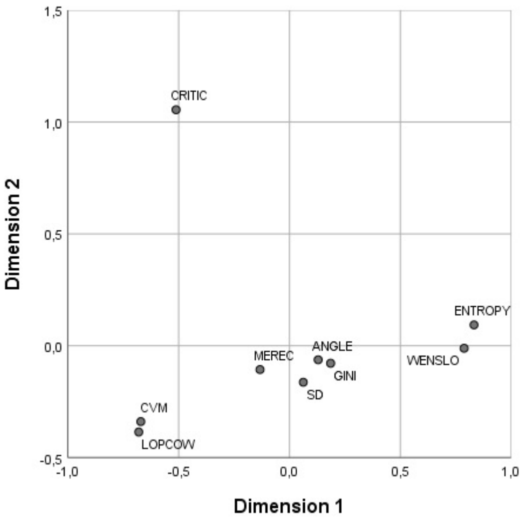

Fig. 7c: Discriminant analysis for EUc with EUm

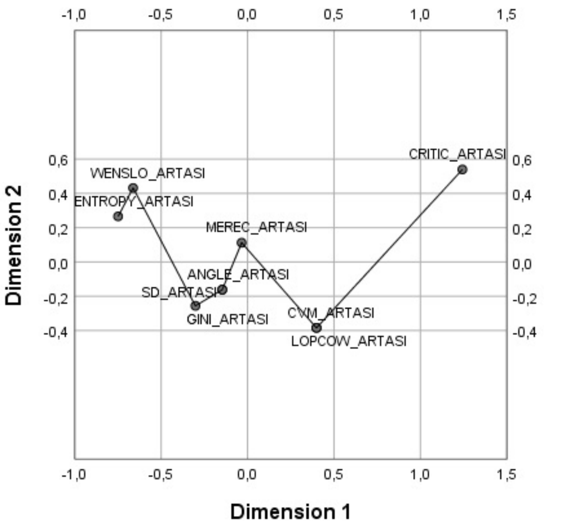

Fig. 7d: For EUc-EUm in the ARTASI method

In all three figures, the WENSLO method is quite close to the ENTROPY and GINI findings, but far from the CRITIC findings. Therefore, the findings are compatible with the study in which the WENSLO method was introduced to the literature (Pamucar et al., 2023). In the discriminant analysis of WENSLO-ARTASI findings, ENTROPY-ARTASI and GINI-ARTASI findings were observed as the closest, and CRITIC-ARTASI was found to be the most distant, similarly. Discriminant analysis findings support previous findings in terms of weights, rankings, and weight-based rankings.

5.CONCLUSION

This study addresses a relevant and timely topic in the field of logistics performance. In this regard, the use of innovative methods (WENSLO and ARTASI) sets the paper apart from other studies. One key advantage of the WENSLO method is explained as the weights of the criteria being independent of individual judgments or expert groups; this is a common feature of objective criterion weight determination methods. Another positive side of the WENSLO method is that the calculation process is not influenced by whether the criteria are classified as benefits or costs. However, this situation can be easily eliminated in another way, that is, by using the normalization technique. From a different perspective, the criterion weights calculated by the WENSLO method can be used in combination with or in place of the ENTROPY, ANGLE, and GINI methods (if further calculation steps are taken into account), which are also similar criterion weighting techniques with high correlations. On the other hand, the same statements can be used for the ARTASI method. If the longer, more complex, and error-prone calculation steps are taken into consideration, it can be used instead of MABAC, MARCOS, WASPAS, CRADIS, PIV, and CoCoSo methods, except for TOPSIS. Moreover, the most important advantage of the ARTASI method is to rank the alternatives between certain desired limit values (0-2; 0-10; 0-100).

The comparison of the study findings with the literature is considered to add value to the existing study. First, the criteria weights obtained at three different levels can be compared with the literature. The LPI criterion weights obtained using the WENSLO method for EUc are highly correlated (Pearson) with the subjective criterion weighting methods used in the literature (Mercangoz et al. (2020)-FAHP r=0.757, Ulutaş and Karaköy, (2019)-SWARA r=0.703, Rezaei et al. (2018)-BWM r=0.649, Çalık et al. (2023)-FAHP=0.613, AHP=0.598, PFAHP=0.459); by the way, WENSLO-CRITIC weights were found to be negatively correlated in this study, as were in the literature (Mešić et al. (2022)-CRITIC r=-0.603, Çakır, (2017)-CRITIC r=-0.474, Ulutaş and Karaköy, (2019)-CRITIC r=-0.035). Similar findings apply to assessments at the EUm, EUm and EUc country levels, but with lower levels of correlation. Based on the compared weight-based methods, findings are highly consistent with the literature.

On the other hand, high correlations (Spearman's Rho) are found when the rankings are compared with the literature for EUm (Arvis et al. (2023) r=0.975, Ulutaş and Karaköy, (2019)-PIV r=0.788, Miškić et al. (2023)-MARCOS r=0.780). The same can be said for the comparison of EUm and EUc with literature (Arvis et al. (2023) r=0.987, Mercangoz et al. (2020)-COPRAS-G r=0.867). Since there is no study in the literature that ranks only EUc, there was no possibility of comparison. This can be presented as an originality of the study. As a result of all the comparisons, it can be said that the results are consistent with the literature, so it is considered that the WENSLO-weighted ARTASI method can be successfully applied to real-life and decision-making problems.

When the countries were assessed in terms of their logistics performance, Türkiye stood out compared to the others in the first stage calculations made only for the candidate countries. This result is consistent with the findings of Mercangoz et al. (2020) and Arman & Organ (2023). Türkiye stands out among the EUc in terms of LPI in all criteria. In the second stage calculations for EUm and the third stage calculations for EUm and EUc, logistics performances are compared: Finland, Germany, and Denmark have taken the top three rankings. The high rankings of Finland, Germany, and Denmark in logistics performance are directly related to the investments these countries have made in transportation and logistics infrastructure, the importance they give to technology and innovation, the adoption of effective management strategies, the advantages provided by their strategic geographical locations, and their strong economic structures. The common features of Finland, Germany, Denmark, and the next rank of the Netherlands are that they have high per capita income, the best or near the best values of the many criteria, and maritime connections. Finland's top ranking can be explained by the fact that it does better than the others for competitively priced international shipments and scores more favorably, if not best, for the other criteria. At the same time, Germany and the Netherlands have some of the most important ports in the world. While these features described reflect the situations of the best in the first three ranks, they are also recommendations for policymakers for other countries that will take measures from now on. Especially investing in digital technologies can lead to simultaneous improvement in multiple components of LPI. Moreover, investing in the areas where EUc countries have a geographic advantage in terms of logistics is also crucial. At that point, it is noteworthy to mention Türkiye seems to have a comparative advantage among EUc countries in this regard if this type of policy is applied by creating a connected ecosystem. In terms of managerial insights, study findings offer a different way of looking at the LPI ranking. Managers can take into account the results of the study while preparing their long-term plan for export marketing, investing in logistic warehouses, distribution centers or logistics routing options. Accordingly, this study will guide academics who will conduct research from now on with its variety of methods, 3-stage examples, and analysis findings. Even though this study explains a new LPI-2023 with current decision-making methods, it has some limitations, such as not comparing it with the LPI data of previous years. Another limitation of the study is that these new methods introduced to the literature cannot be compared with more methods in order to avoid confusion. In future studies, the WENSLO weighted ARTASI method can be compared and extended with the LPI data of previous years or by using different methods in different applications such as social sciences and engineering.

REFERENCES

Aggarwal, S., Aggarwal, G. & Bansal, M. (2024). Effect of Different MCDM Techniques and Weighting Mechanisms on Women Vulnerability Index. *International Journal of Intelligent Systems and Applications in Engineering. 12*(21s), 3291-3299.

Alnıpak, S. (2024). AHS-COCOSO Yöntemi ile APEC Ülkelerinin Lojistik Performanslarının Değerlendirilmesi. *Tarsus Üniversitesi Uygulamalı Bilimler Fakültesi Dergisi. 4*(1), 13-26.

Altıntaş, F. F. (2023). A Novel Approach to Measuring Criterion Weights In Multiple Criteria Decision Making: Cubic Effect-Based Measurement (CEBM). *Nicel Bilimler Dergisi*, *5*(2), 151-195. https://doi.org/10.51541/nicel.1349382

Akbulut Acar, E., Ulutaş, A., Yürüyen, A.A., & Balalan, S. (2024). Hibrit bir ÇKKV Modeli ile G20 Ülkelerinin Lojistik Performansının Ölçülmesi, *BMIJ 12*(1): 1-21 https://doi.org/10.15295/bmij.v12i1.2300

Arman, K & Organ, A., (2023). AB'ye Üye ve Aday Ülkelerin Lojistik Performanslarının MEREC ve CoCoSo Yöntemleri ile Değerlendirilmesi. *Uluslararası Ticaret ve Ekonomi Araştırmaları Dergisi, (7)*2, 36-46. https://doi.org/10.30711/utead.1360959

Arvis, J.F., Ojala, L., Shepherd, B., Ulybina, D. & Wiederer, C. (2023). *Connecting to Compete 2023: Trade Logistics in an Uncertain Global Economy-The Logistics Performance Index and Its Indicators*. The World Bank.

Çakır, S. (2017). Measuring logistics performance of OECD countries via fuzzy linear regression. *Journal of Multi-Criteria Decision Analysis, 24*, 177-186. https://doi.org/10.1002/mcda.1601

Çalık, A., Erdebilli, B., Özdemir, Y.S., (2023). Novel Integrated Hybrid Multi-Criteria Decision-Making Approach for Logistics Performance Index. *Transportation Research Record, 2677*(2), 1392-1400. https://doi.org/10.1177/03611981221113314

Çıray, D., Özdemir, Ü. & Mete, S. (2024). An Evaluation of the logistics Performance Index Using the ENTROPY-based ORESTE Method. Journal of Transportation and Logistics. 9(1), 68-82. https://doi.org/10.26650/JTL.2024.1437070

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.

Ersoy, N. (2021). Application of the PIV method in the presence of negative data: an empirical example from a real-world case. *Hitit Journal of Social Sciences, 14*(2), 318-337. http://doi.org/10.17218/hititsbd.974522

Gürler, H.E., Özçalıcı, M. & Pamucar, D. (2024). Determining criteria weights with genetic algorithms for multi-criteria decision-making methods: The case of logistics performance index rankings of European Union countries. *Socio-Economic Planning Sciences, 91*. 1-32. https://doi.org/10.1016/j.seps.2023.101758

Ha, L. D. (2023). Selection of suitable data normalization method to combine with the CRADIS method for making multi-criteria decision. *Applied Engineering Letters, 8*(1), 24-35. https://doi.org/10.18485/aeletters.2023.8.1.4

İnce, Ö., Çetiner, B., & Ecer, F. (2023). Benchmarking of logistics performances in G20 countries before and during COVID-19 periods: A MEREC and CODAS ıntegrated approach. *Journal of Transportation and Logistics, 8*(2), 112-147. https://doi.org/10.26650/JTL.2023.1317958

Isik, Ö., Aydin, Y. & Koşarolu, S. (2020). The assessment of the logistics performance index of CEE countries with the new combination of SV and MABAC methods. *LogForum. 16*(4), 549-559. http://doi.org/10.17270/J.LOG.2020.504

Janno, J., Mochalina, E.P., Ivankova, G.V., Labanova, O., Latonina, M., Safulina, E. & Uukkivi, A. (2021). The impact of initial data on the logistics performance index estimation: Estonian and Russian study. *LogForum, 17*(1), 147-156. https://doi.org/10.17270/J.LOG.2021.554

Kara K., Bentyn Z. & Yalçın G.C. (2022). Determining the logistics market performance of developing countries by entropy and MABAC methods. *LogForum, 18*(4), 421-434. https://doi.org/10.17270/J.LOG.2022.752

Kale, M. V. & Tilki, İ. (2024). Dünya Ülkelerinin Lojistik Performanslarının Çok Kriterli Karar Verme Yöntemi İle Değerlendirilmesi: 2023 Yılı Dünya Bankası Raporu İle Karşılaştırmalı Analizi. *Dumlupınar Üniversitesi Sosyal Bilimler Dergisi.* 80, 13-30. https://doi.org/10.51290/dpusbe.1387317

Keleş, N. (2023). Measuring performances through multiplicative functions by modifying the MEREC method: MEREC-G and MEREC-H. *International Journal of Industrial Engineering and Operations Management. 5*(3), 181-199. https://doi.org/10.1108/IJIEOM-12-2022-0068

Keleş, N. & Pekkaya, M. (2023) Evaluation of logistics centers in terms of sustainability via MCDM methods. *Journal of Advances in Management Research, 20*(2), 291-309. https://doi.org/10.1108/JAMR-04-2022-0087

Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2021). Determination of objective weights using a new method based on the removal effects of criteria (MEREC). *Symmetry, 13*(4), 525.

Kizielewicz, B., Bączkiewicz, A., Shekhovtsov, A., Wątróbski, J. & Sałabun, W. (2021). *Towards the RES development: Multi-criteria assessment of energy storage devices.* In 2021 International Conference on Decision Aid Sciences and Application (DASA) (pp. 766-771). IEEE. https://doi.org/10.1109/DASA53625.2021.9682220

Kizielewicz, B., Shekhovtsov, A. & Sałabun, W. (2023). Pymcdm-The universal library for solving multi-criteria decision-making problems. *SoftwareX, 22*, 101368. https://doi.org/10.1016/j.softx.2023.101368

Manavgat, G., Demirci, A., Korkmaz, O., Koluman, A. (2023) Global scale integrated logistics performance analysis and its spillover effect. *LogForum, 19*(2), 245-262. https://doi.org/10.17270/J.LOG.2023.826

Marti, L., Martín, J.C. & Puertas, R. (2017). A Dea-Logistics Performance Index. *Journal of Applied Economics, (20*)1, 169-192. https://doi.org/10.1016/S1514-0326(17)30008-9

Mercan, Y. & Aydın, H. (2024). Logistics Performance Index of Africa: An Indicator for Türkiye And Africa Trade Relations? Süleyman Demirel University Visionary Journal. 15(42) 553-569. https://doi.org/10.21076/vizyoner.1409760

Mercangoz, B.A., Yildirim, B. & Yildirim, S.K. (2020). Time Period Based COPRAS-G Method: Application on the Logistics Performance Index. *LogForum 16*(2), 239-250. https://doi.org/10.17270/J.LOG.2020.432

Mešić, A., Miškić, S., Stević, Ž. & Mastilo Z. (2022). Hybrid MCDM solutions for evaluation of the logistics performance index of the Western Balkan countries. *Economics, 10*(1), 13-34. DOI: https://doi.org/10.2478/eoik-2022-0004

Miškić, S., Stević, Ž., Tadić, S., Alkhayyat, 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. https://doi.org/10.1504/WRITR.2023.132501

Nguyen, P. H., Tsai, J. F., Nguyen, V. T., Vu, D. D., & Dao, T. K. (2020). A decision support model for financial performance evaluation of listed companies in the Vietnamese retailing industry. *The Journal of Asian Finance, Economics, and Business, 7*(12), 1005-1015.

Özekenci, E. K. (2023). Assessing the logistics market performance of developing countries by SWARA-CRITIC based CoCoSo methods. *LogForum, 19*(3), 375-394. http://doi.org/10.17270/J.LOG.2023.857

Pala, O. (2023). MEREC-Corr ve Saw temelli lojistik performans değerlendirme*. Dicle Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 13*(25), 117-135.

Pamucar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation Area Comparison (MABAC). *Expert Systems with Applications, 42*(6), 3016–3028. https://doi.org/10.1016/j.eswa.2014.11.057

Pamucar, D., Ecer, F., Gligorić, Z., Gligorić, M. & Deveci, M. (2023). A Novel WENSLO and ALWAS Multicriteria Methodology and Its Application to Green Growth Performance Evaluation. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2023.3321697

Pamucar, D., Simic, V., Görçün, Ö.F. & Küçükönder, H. (2024). Selection of the best Big Data platform using COBRAC-ARTASI methodology with adaptive standardized intervals. *Expert Systems with Applications, 239,* 122312. https://doi.org/10.1016/j.eswa.2023.122312

Rezaei, J., van, Roekel, W.S. & Tavasszy L. (2018). Measuring the relative importance of the logistics performance index indicators using Best Worst Method. *Transport Policy, 68,* 158-169. https://doi.org/10.1016/j.tranpol.2018.05.007

Sałabun, W. & Urbaniak, K. (2020). *A new coefficient of rankings similarity in decision-making problems.* In Computational Science–ICCS 2020: 20th International Conference, Amsterdam, The Netherlands, June 3–5, 2020, Proceedings, Part II 20 (pp. 632-645). Springer International Publishing. https://doi.org/10.1007/978-3-030-50417-5_47.

Senir, G. (2021). Comparison of domestic logistics performances of Turkey nd European Union countrıes in 2018 with an integrated model. *LogForum 17*(2), 193-204, http://doi.org/10.17270/J.LOG.2021.576

Shemshadi, A., Shirazi, H., Toreihi, M., & Tarokh, M. J. (2011). A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. *Expert systems with applications, 38*(10), 12160-12167.

Shuai, D., Zongzhun, Z., Yongji, W., & Lei, L. (2012, May). A new angular method to determine the objective weights. In *2012 24th Chinese Control and Decision Conference (CCDC)* (pp. 3889-3892). IEEE.

Stevic, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to Compromise solution (MARCOS). *Computers & Industrial Engineering,* 140, 106231. https://doi.org/10.1016/j.cie.2019.106231

Türkoğlu, M. & Duran, G., (2023), Çok Kriterli Karar Verme Yöntemleri ile Bölgesel Kapsamlı Ekonomik Ortaklık (RCEP) Ülkelerinin Lojistik Performanslarının Değerlendirilmesi, *Ekonomi Bilimleri Dergisi, 15*(1): 45-69., https://doi.org/10.55827/ebd.1247297

Ulutaş, A. & Karaköy Ç. (2019). An analysis of the logistics performance index of EU countries with an integrated MCDM model. *Economics and Business Review, 5*(4), 49-69. DOI:https://doi.org/10.18559/ebr.2019.4.3

Wang, T. C., ve Lee, H. D. (2009). Developing a fuzzy TOPSIS approach based on subjective weights and objective weights*.* *Expert systems with applications, 36*(5), 8980-8985.

WTO, (n.d.). *Merchandise Trade Values*. Retrieved October 19, 2024 from https://stats.wto.org/

Yazdani, M., Zarate, P., Zavadskas, E. K., & Turskis, Z. (2018). A Combined Compromise Solution (COCOSO) method for multi-criteria decision-making problems. *Management Decision, 57*(9), 2501–2519. https://doi.org/10.1108/MD-05-2017-0458

Yildirim, B.F. & Mercangoz, B.A. (2020). Evaluating the logistics performance of OECD countries by using fuzzy AHP and ARAS-G. *Eurasian Economic Review, 10*(1), 27-45. https://doi.org/10.1007/s40822-019-00131-3

Yu, M.M. & Rakshit I. (2023). An alternative assessment approach to global logistics performance evaluation: Common weight H-DEA approach. *International Transactions in Operational Research*. 1-24. https://doi.org/10.1111/itor.13360

Zavadskas, E. K., Turskis, Z., Antucheviciene, J., & Zakarevicius, A. (2012). Optimization of weighted aggregated sum product assessment. *Elektronika ir Elektrotechnika, 122*(6), 3–6. https://doi.org/10.5755/j01.eee.122.6.1810

Appendix 1. LPI criterion weights and correlations of EUm

	WENSLO	ANGLE	CRITIC	CVM	ENTROPY	GINI	LOPCOW	MEREC	SD
C1	0.239	0.191	0.153	0.169	0.215	0.202	0.170	0.199	0.189
C2	0.242	0.199	0.154	0.173	0.233	0.217	0.174	0.205	0.213
C3	0.125	0.135	0.219	0.155	0.106	0.118	0.154	0.129	0.117
C4	0.125	0.152	0.127	0.168	0.135	0.154	0.168	0.157	0.159
C5	0.106	0.146	0.192	0.170	0.126	0.137	0.170	0.155	0.146
C6	0.164	0.177	0.155	0.165	0.184	0.172	0.165	0.155	0.176
WENSLO	1								
ANGLE	0.939	1							
CRITIC	-0.396	-0.567	1						
CVM	0.506	0.668	-0.645	1					
ENTROPY	0.950	0.999	-0.536	0.660	1				
GINI	0.939	0.986	-0.627	0.732	0.986	1			
LOPCOW	0.503	0.667	-0.649	1.000	0.659	0.731	1		
MEREC	0.902	0.911	-0.544	0.816	0.917	0.954	0.813	1	
SD	0.864	0.968	-0.676	0.804	0.965	0.982	0.803	0.926	1

Appendix 2. LPI criterion weights and correlations of EUm and Candidates

	WENSLO	ANGLE	CRITIC	CVM	ENTROPY	GINI	LOPCOW	MEREC	SD
C1	0.240	0.200	0.154	0.170	0.227	0.202	0.170	0.199	0.189
C2	0.251	0.215	0.158	0.172	0.256	0.217	0.172	0.205	0.213
C3	0.091	0.122	0.235	0.125	0.090	0.118	0.126	0.129	0.117
C4	0.144	0.154	0.123	0.169	0.162	0.154	0.170	0.157	0.159
C5	0.116	0.139	0.177	0.192	0.107	0.137	0.189	0.155	0.146
C6	0.1059	0.171	0.151	0.172	0.158	0.172	0.172	0.155	0.176
WENSLO	1								
ANGLE	0.990	1							
CRITIC	-0.500	-0.540	1						
CVM	0.340	0.377	-0.693	1					
ENTROPY	0.986	0.984	-0.571	0.322	1				
GINI	0.990	1.000	-0.553	0.388	0.984	1			
LOPCOW	0.369	0.407	-0.720	0.999	0.354	0.418	1		
MEREC	0.976	0.954	-0.501	0.457	0.954	0.954	0.480	1	
SD	0.951	0.981	-0.634	0.507	0.957	0.982	0.536	0.926	1

Appendix 3. LPI Ranks and Scores of EUm

	ARTASI	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo	ARTASI	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo
Germany	2	2	2	2	2	2	2	2	95.48	0.40	0.75	0.97	0.88	0.94	0.01	3.83
Austria	7	7	7	7	7	7	7	7	91.51	0.31	0.73	0.94	0.75	0.88	0.01	3.56
Belgium	5	6	6	6	5	6	6	5	93.92	0.36	0.74	0.95	0.84	0.91	0.01	3.72
Bulgaria	24	24	24	24	22	24	24	24	60.93	-0.28	0.59	0.76	0.23	0.59	0.05	1.46
Czechia	22	22	22	22	24	22	22	20	63.48	-0.23	0.60	0.77	0.22	0.61	0.05	1.80
Denmark	3	3	3	3	3	3	3	3	95.09	0.39	0.75	0.97	0.87	0.93	0.01	3.81
Estonia	14	13	15	15	16	15	15	13	77.37	0.01	0.66	0.84	0.46	0.72	0.04	2.62
Finland	1	1	1	1	1	1	1	1	98.12	0.46	0.77	0.98	0.94	0.97	0.00	4.03
France	9	9	9	9	8	9	9	9	87.50	0.21	0.71	0.91	0.70	0.83	0.02	3.27
Cyprus	27	27	27	27	27	27	27	27	55.41	-0.35	0.57	0.73	0.14	0.56	0.06	1.24
Croatia	23	23	23	23	23	23	23	23	62.12	-0.25	0.59	0.76	0.23	0.60	0.05	1.55
Netherlands	4	4	4	4	4	4	4	4	94.41	0.37	0.75	0.96	0.86	0.92	0.01	3.76
Ireland	13	14	13	13	14	13	13	14	77.51	0.00	0.66	0.84	0.49	0.72	0.04	2.60
Spain	8	8	8	8	9	8	8	8	88.11	0.23	0.71	0.91	0.69	0.83	0.02	3.32
Sweden	6	5	5	5	6	5	5	6	93.76	0.36	0.75	0.96	0.84	0.92	0.01	3.72
Italy	10	10	10	10	10	10	10	10	82.00	0.10	0.68	0.87	0.59	0.77	0.03	2.90
Latvia	16	16	16	16	18	16	16	16	73.54	-0.06	0.64	0.82	0.40	0.69	0.04	2.38
Lithuania	17	17	19	19	20	19	19	17	69.43	-0.14	0.62	0.80	0.38	0.66	0.04	2.11
Luxembourg	12	12	12	12	11	12	12	12	79.29	0.04	0.67	0.86	0.55	0.74	0.03	2.72
Hungary	25	26	25	25	25	25	25	26	58.34	-0.31	0.58	0.74	0.19	0.58	0.06	1.26
Malta	19	18	17	17	15	17	17	21	69.10	-0.14	0.63	0.81	0.46	0.67	0.04	1.76
Poland	15	15	14	14	13	14	14	15	77.28	0.00	0.66	0.84	0.49	0.72	0.04	2.59
Portugal	18	19	18	18	19	18	18	18	69.20	-0.14	0.62	0.80	0.40	0.66	0.04	2.09
Romania	26	25	26	26	26	26	26	25	58.08	-0.30	0.58	0.74	0.17	0.58	0.06	1.42
Slovakia	21	21	21	21	21	21	21	22	64.77	-0.22	0.61	0.78	0.31	0.62	0.05	1.67
Slovenia	20	20	20	20	17	20	20	19	67.54	-0.16	0.62	0.80	0.42	0.65	0.05	1.87
Greece	11	11	11	11	12	11	11	11	81.45	0.09	0.68	0.87	0.53	0.76	0.03	2.88

Appendix 4. LPI Ranks and Scores of EUm and Candidates

	ARTASI	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo	ARTASI	MABAC	MARCOS	WASPAS	TOPSIS	CRADIS	PIV	CoCoSo
Germany	2	2	2	2	2	2	2	2	96.98	0.35	0.83	0.97	0.93	0.95	0.01	4.71
Austria	7	7	7	7	7	7	7	7	94.19	0.29	0.80	0.94	0.85	0.89	0.01	4.50
Belgium	6	6	6	6	6	6	6	6	95.87	0.33	0.81	0.96	0.91	0.92	0.01	4.63
Bulgaria	25	25	25	25	23	25	25	25	74.92	-0.09	0.65	0.76	0.51	0.64	0.05	3.09
Czechia	23	23	23	23	24	23	23	23	76.59	-0.05	0.65	0.77	0.50	0.65	0.05	3.23
Denmark	3	3	3	3	3	3	3	3	96.472	0.34	0.82	0.97	0.92	0.94	0.01	4.69
Estonia	13	13	13	14	15	13	14	13	84.95	0.10	0.72	0.84	0.66	0.75	0.03	3.81
Finland	1	1	1	1	1	1	1	1	98.68	0.39	0.84	0.98	0.96	0.97	0.00	4.86
France	9	9	9	9	8	9	9	9	91.39	0.23	0.77	0.91	0.81	0.85	0.02	4.28
Cyprus	29	29	29	29	29	29	29	28	72.09	-0.13	0.62	0.73	0.44	0.60	0.06	2.92
Croatia	24	24	24	24	25	24	24	24	75.59	-0.07	0.65	0.76	0.49	0.64	0.05	3.16
Netherlands	4	4	5	5	4	5	5	4	96.21	0.33	0.82	0.96	0.92	0.93	0.01	4.65
Ireland	15	15	15	15	14	15	15	14	84.77	0.09	0.72	0.84	0.68	0.75	0.03	3.78
Spain	8	8	8	8	9	8	8	8	91.87	0.24	0.78	0.91	0.80	0.85	0.02	4.32
Sweden	5	5	4	4	5	4	4	5	95.98	0.33	0.82	0.96	0.91	0.93	0.01	4.63
Italy	10	10	10	10	10	10	10	10	87.85	0.16	0.75	0.88	0.74	0.80	0.03	4.01
Latvia	16	16	16	16	17	16	16	16	82.60	0.06	0.70	0.82	0.62	0.72	0.04	3.63
Lithuania	17	17	19	19	20	19	19	17	79.97	0.00	0.68	0.80	0.60	0.69	0.04	3.45
Luxembourg	12	12	12	12	11	12	12	12	86.01	0.12	0.73	0.86	0.72	0.77	0.03	3.88
Hungary	27	27	26	26	27	26	26	27	73.68	-0.10	0.63	0.74	0.46	0.62	0.05	3.04
Malta	19	19	17	17	16	17	17	19	79.83	0.00	0.69	0.81	0.65	0.70	0.04	3.42
Poland	14	14	14	13	13	14	13	15	84.79	0.09	0.72	0.84	0.68	0.75	0.03	3.78
Portugal	18	18	18	18	19	18	18	18	79.89	0.00	0.68	0.80	0.62	0.70	0.04	3.43
Romania	26	26	27	27	28	27	27	26	73.70	-0.10	0.63	0.74	0.44	0.62	0.05	3.05
Slovakia	22	22	22	22	22	22	22	22	77.14	-0.05	0.66	0.78	0.57	0.66	0.05	3.24
Slovenia	21	21	20	21	18	20	20	21	78.89	-0.01	0.68	0.80	0.62	0.69	0.04	3.37

Greece	11	11	11	11	12	11	11	11	87.42	0.15	0.74	0.87	0.70	0.79	0.03	4.00
Albania	34	34	34	34	32	34	34	34	48.94	-0.44	0.50	0.59	0.24	0.44	0.08	1.08
Ukraine	33	33	33	33	34	33	33	33	54.62	-0.38	0.52	0.61	0.21	0.46	0.08	1.89
Moldova	35	35	35	35	35	35	35	35	44.64	-0.47	0.48	0.56	0.12	0.41	0.09	1.04
Bosnia and Herzegovina	30	30	30	30	30	30	30	30	65.74	-0.23	0.58	0.68	0.34	0.55	0.07	2.53
North Macedonia	28	28	28	28	26	28	28	29	72.41	-0.13	0.63	0.74	0.48	0.62	0.05	2.92
Montenegro	31	31	31	31	31	31	31	31	62.23	-0.28	0.56	0.66	0.30	0.52	0.07	2.31
Serbia	32	32	32	32	33	32	32	32	56.90	-0.35	0.53	0.62	0.22	0.48	0.08	2.05
Türkiye	20	20	21	20	21	21	21	20	79.64	0.00	0.68	0.80	0.58	0.69	0.04	3.42

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1. The authors of this article confirm that their work complies with the principles of research and publication ethics (Bu çalışmanın yazarları, araştırma ve yayın etiği ilkelerine uyduklarını kabul etmektedirler).

2. No potential conflict of interest was reported by the authors (Yazarlar tarafından herhangi bir çıkar çatışması beyan edilmemiştir).

3. This article was screened for potential plagiarism using a plagiarism screening program (Bu çalışma, intihal tarama programı kullanılarak intihal taramasından geçirilmiştir).