Multidecision criteria models for Logistics Performance Index in the EU countries

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Abstract. Key factors influencing multicriteria logistics performance in the European Union (EU) include the weighting of evaluation criteria, infrastructure efficiency, logistics quality, and environmental impact. The Logistics Performance Index (LPI), which evaluates logistics systems across six dimensions, highlights how the importance assigned to these criteria significantly impacts national rankings. This study aims to enhance the understanding of logistics performance dynamics within Europe, supporting informed decision-making and continuous improvement in the region's logistics sector. To determine country rankings, the study applies the CRiteria Importance Through Intercriteria Correlation (CRITIC) method for weighting criteria, alongside the Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Simple Additive Weighting (SAW) methods. The analysis utilizes LPI indicators from the 2023 World Bank dataset. The results indicate that Finland maintains its leading position in the LPI ranking. However, a significant number of countries experience shifts in their rankings depending on the weight assigned to each criterion, underscoring the sensitivity of logistics performance evaluation to methodological choices.

Keywords: CRITIC, Logistics Performance Index, MARCOS, SAW, TOPSIS

Received: February 20, 2025; accepted: June 27, 2025; available online: September 11, 2025

DOI: 10.17535/crorr.2026.0008

Original scientific paper.

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1. Introduction

Logistics performance in the European Union (EU) is influenced by several key factors, primarily assessed through the Logistics Performance Index (LPI). The LPI, developed by the World Bank, is a comprehensive benchmarking tool that provides a numerical score for each country based on factors such as infrastructure quality, customs efficiency, logistics competence, tracking and tracing capabilities, and the timeliness of shipments. These dimensions are essential for evaluating logistics systems and for guiding strategic decisions in transportation and trade.

This index evaluates logistics performance across multiple criteria, and the relative weighting of these criteria can significantly affect the ranking of EU countries. Understanding the dynamics and sensitivity of these rankings is crucial for enhancing logistics efficiency and competitiveness at both national and regional levels.

In recent years, a growing body of literature has examined the limitations of the LPIs equal weighting approach and emphasized the value of multi-criteria decision-making (MCDM) models for more nuanced assessments [4, 10, 21]. MCDM methods enable decision-makers to evaluate multiple, often conflicting, factors simultaneously, offering a more adaptable and context-sensitive framework for logistics analysis. Various techniques have been explored, including CRITIC, AHP, and Entropy for weighting, and methods such as TOPSIS, MARCOS, and SAW for ranking [3, 5, 6].

Moreover, new approaches such as the Green Logistics Performance Index (GLPI) have highlighted the increasing importance of environmental sustainability in logistics benchmarking, especially in light of the EU's ambitious CO_2 free urban logistics targets by 2030 [17]. These developments underscore the need for methodological transparency and multi-method validation in assessing national logistics systems [15, 19].

The contribution of this paper lies in its integrated application of several MCDM methods - CRITIC for objective criteria weighting, and MARCOS, TOPSIS, and SAW for alternative ranking - to evaluate the logistics performance of EU countries using the 2023 World Bank LPI dataset. While prior studies have applied individual methods, few have systematically compared multiple MCDM techniques on the same dataset. By doing so, this study not only strengthens the robustness of the results but also provides insights into how methodological choices influence country rankings.

This research supports informed decision-making in logistics strategy and policy by identifying performance disparities among EU countries, highlighting the methodological sensitivity of LPI rankings, and offering a replicable framework for similar evaluations in other regional contexts.

2. Literature review

The LPI provides information on various aspects of logistics performance, including customs efficiency, infrastructure quality, ease of arranging shipments, and timeliness. Countries are ranked based on their scores, which help identify strengths and weaknesses in their logistics systems. According to [1], LPI is essential for policy makers and stakeholders who want to improve logistics performance at the national and regional levels.

Infrastructure quality is a critical determinant of logistics performance. Research indicates that without adequate infrastructure, logistics services cannot achieve optimal efficiency. The integration of infrastructure efficiency with logistics quality and environmental impact is vital for sustainable logistics performance, as evidenced by benchmark studies in EU countries [8].

The environmental impact of logistics operations is increasingly recognized as a significant factor. Many EU countries struggle to balance operational efficiency with environmental sustainability, indicating the need for policies that address both aspects simultaneously [8]. In contrast, while the focus on logistics performance is essential, some argue that an overemphasis on ranking may overlook the unique challenges faced by individual countries, potentially leading to misaligned policy priorities.

The LPI is calculated using six equally weighted criteria, but the importance of these weights can vary significantly [4]. Studies have shown that adjusting these weights can alter the ranking of countries, highlighting the need for tailored evaluations based on specific national contexts [11]. The LPI reveals that the importance assigned to these criteria significantly affects national rankings, as demonstrated by various multi-criterion decision making (MCDM) methods employed in recent studies [5, 11, 22].

The integration of subjective and objective weighting methods improves the robustness of logistics performance evaluations, allowing countries to strategically focus on areas for improvement [21]. In general, these factors collectively shape the logistics landscape within the EU, influencing both regional and global competitiveness [4].

Methods such as CRITIC and FUCOM have been used to determine the optimal weighting of these criteria, demonstrating that sensitivity analysis is essential for accurate evaluations [4, 6, 21]. The CRITIC method is a robust objective weighting technique that balances variability and correlation to ensure criteria independence. However, alternative methods like Entropy (objective), AHP and BWM (subjective), or SWARA (semi-subjective) can be used based on data availability and decision-maker preferences. Selecting the appropriate method depends on whether the study emphasizes statistical objectivity (CRITIC, Entropy) or expert-driven evaluation (AHP, BWM, SWARA) [3].

Comparing the applied method to rank the different countries, MARCOS method provides precise and robust rankings but is complex and not yet widely validated. TOPSIS is easy to use and widely applied but suffers from sensitivity to normalization and rank reversal issues. SAW is computationally simple and stable but lacks the sophistication needed for handling more complex decision-making scenarios. The choice of method depends on the specific requirements of the decision problem, such as the complexity of alternatives, sensitivity to criteria weights, and the need for ideal solution considerations. [3]. These models enable organizations to make informed decisions that align with improving their LPI scores.

3. Methodology

The research starts by identifying pertinent studies from academic databases that align with the subject. It consolidates key insights from prior research on logistics performance indicators in EU nations, focusing on commonly utilized indicators, benchmarking standards, methodological best practices, and empirical findings regarding the determinants of logistics efficiency and effectiveness in the region.

Subsequently, logistics performance indicators (LPIs) were gathered, and potential quantitative methods were examined to address the distinct challenges and complexities associated with evaluating logistics efficiency and effectiveness in this context. Figure 1 illustrates the analytical approach adopted for assessing these indicators.

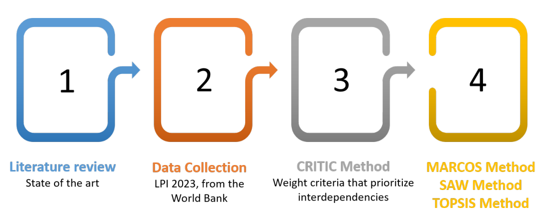


Figure 1: Evaluation framework of logistics performance

3.1. Data collection and spatial analysis

The World Bank gathers LPI data through a combination of surveys, interviews, and expert evaluations conducted with logistics professionals, policymakers, and business leaders in each country. These survey tools are designed to capture both qualitative and quantitative aspects of logistics performance, employing standardized questionnaires and scoring frameworks.

The collected LPI data are publicly available through multiple online platforms [24]. While the LPI covers countries worldwide, this study specifically focuses on European Union nations, with an emphasis on data from the 2023 report.

Geographic visualization of these criteria offers valuable insights into spatial disparities and regional logistics performance. By mapping these indicators, it becomes possible to better understand the contribution of each factor to overall logistics efficiency. Additionally, this approach supports evidence-based policymaking by identifying regional strengths and areas requiring improvement, ensuring that strategic decisions are informed by both quantitative rankings and their spatial distribution.

MARCOS, SAW, and TOPSIS were selected due to their complementary strengths in handling both additive and compromise-based decision logic, as well as their established use in logistics and performance benchmarking contexts.

3.2. Decision matrix and decision process

Let's consider a decision matrix in a usual multi-criteria decision making problem [14]. Each value of x_{ij} represents the achievement by the country i in the criterium j.

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \tag{1}$$

In a multi-decision criteria context, it is important to define if the criterium have the goal of maximizing (max) or minimizing (min) decision-making process [3]; in this case, all the six criteria are benefit, i.e., it should be maximized.

The goal is to evaluate and rank the alternatives (countries) according to the specified indicators. This assessment is performed by assigning weights w_j (where $w_j \geq 0$ and $\sum w_j = 1$) to different criteria. Then, the value for each country (V_i) should be calculated using weight additive function:

$$V_i = \sum_{j=1}^{n} w_j x_{ij} \tag{2}$$

3.3. CRITIC Method

The weights described in the previous subsection have different ways to be calculated. One of them is the CRITIC method. The CRITIC (Criteria Importance Through Inter-criteria Correlation) method offers a nuanced perspective by considering the inter-dependencies among decision criteria [10]. Logistics performance should consider interdependencies, as they affect the entire process of sending orders between countries. The CRITIC method comprises the four sequential steps:

Step 1. Define the decsion matrix according to the alternatives and the criteria.

Step 2. Normalize the initial decision matrix D according to the criteria type:

$$\text{benefit crit.:} \quad y_{ij} = \tfrac{x_{ij}-\min_i x_{ij}}{\max_i x_{ij}-\min_i x_{ij}}; \qquad \text{cost crit.:} \quad y_{ij} = \tfrac{x_{ij}-\max_i x_{ij}}{\min_i x_{ij}-\max_i x_{ij}} \tag{3}$$

Step 3. Calculate the symmetric linear correlation matrix $[r_{ij}]$, using statistical measures such as Pearson correlation coefficient. These correlations form the foundation for assigning relative weights to the criteria, where stronger correlations indicate greater importance.

Step 4. Calculate the objective weights as

$$w_j = \frac{K_j}{\sum_{j=1}^{n} K_j}, \tag{4}$$

where $K_j = \sigma_j \sum_{j=1}^{n}(1 - r_{ij})$, with σ_j corresponding to the standard deviation of the each column of $[y_{ij}]$.

After the weight process has been concluded, it is necessary to rank the countries to multi-criteria techniques. In this paper there are used three different techniques for this assessment: MARCOS, SAW and TOPSIS.

3.4. MARCOS Method

The MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution) method integrates correspondence analysis and similarity matrices to rank alternatives based on their performance across multiple criteria [18, 23]. This approach is goal-oriented and data-driven, ranking alternatives based on their similarity and removing the need for subjective weighting of criteria [16].

Step 1. After defining the decision matrix, it is necessary to extend it by adding two new rows for each criterion: the ideal alternative (AI) and the anti-ideal alternative (AAI), as follows:

$$\begin{array}{ll} \text{benefit crit.:} & AAI = min_i x_{ij} \text{ and } AI = max_i x_{ij} \\ \text{cost crit.:} & AAI = max_i x_{ij} \text{ and } AI = min_i x_{ij} \end{array} \tag{5}$$

Step 2. The normalization process for this method is:

$$\text{benefit criterion:} \quad n_{ij} = \tfrac{x_{AI}}{x_{ij}} \qquad \text{cost criterion:} \quad n_{ij} = \tfrac{x_{ij}}{x_{AI}} \tag{6}$$

Step 3. The determination of the weighted matrix ($[v_{ij}]$), with the weights (w_j) calculated in the previous subsection, is done as:

$$v_{ij} = n_{ij} \times w_j \tag{7}$$

Step 4. The determination of the utility degree of alternatives K_i can be calculated as:

$$K_i^- = \tfrac{S_i}{S_{AAI}} \qquad K_i^+ = \tfrac{S_i}{S_{AI}} \tag{8}$$

where S_i represents the sum of the elements of the weighted matrix $[v_{ij}]$, and S_{AI} and S_{AAI} corresponds to the sum of elements of alternative ideal and anti-ideal, respectively.

Step 5. The determination of the utility function of alternatives $f(K_i)$:

$$f(K_i) = \tfrac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}}, \quad \text{with} \quad f(K_i^-) = \tfrac{K_i^+}{K_i^+ + K_i^-};\ f(K_i^+) = \tfrac{K_i^-}{K_i^+ + K_i^-} \tag{9}$$

Step 6. The rank of the alternatives (countries) with the best values of the utility functions.

3.5. SAW Method

The Simple Additive Weighting (SAW) Method is a well-known approach within the family of multicriteria decision-making (MCDM) methods. It is widely applied in fields such as operations research, engineering, environmental science, and economics to address problems involving multiple criteria that must be balanced to make a decision. The SAW method is particularly popular due to its simplicity, intuitiveness, and effectiveness in aggregating diverse criteria into a single score for ranking alternatives [7, 20].

The SAW method is based on the principle of weighted linear combination, where each alternative's performance across criteria is aggregated into a single score. The alternative with the highest score is typically considered the most preferred [13].

Step 1. After defining the decision matrix, it is necessary to normalize the matrix, using the following criterion type:

$$\text{benefit criterion:} \quad n_{ij} = \frac{x_{ij}}{max(x_{ij})} \qquad \text{cost criterion:} \quad n_{ij} = \frac{min(x_{ij})}{x_{ij}} \tag{10}$$

Step 2. The determination of the weighted matrix ($[v_{ij}]$), with the weights (w_j) calculated in the previous subsection, is done as:

$$v_{ij} = n_{ij} \times w_j \tag{11}$$

Step 3. For each alternative i, calculate its total score S_i as:

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{12}$$

Step 4. The rank of the alternatives on their total scores S_i is the one with the highest score is the best option.

3.6. TOPSIS Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a widely used multi-criteria decision-making (MCDM) method that ranks alternatives based on their closeness to ideal and anti-ideal solutions. TOPSIS can handle both quantitative and qualitative criteria, making it applicable in various fields, including manufacturing process optimization [2, 9]. The method's popularity stems from its simplicity, rationality, and computational efficiency [12].

Step 1. After defining the decision matrix, it is necessary to normalize the matrix, using the following criterion type:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad \forall i, j \tag{13}$$

Step 2. The determination of the weighted matrix ($[v_{ij}]$), with the weights (w_j) calculated in the previous subsection, is done as:

$$v_{ij} = n_{ij} \times w_j \tag{14}$$

Step 3. Determine the Ideal and Anti-Ideal solutions, as follows:

- Ideal Solution (A^+) is the best performance for each criterion:

$$A^+ = \{v_1^+, v_2^+, \ldots, v_n^+\}, \quad v_j^+ = \begin{cases} \max(v_{ij}), & \text{if } j \text{ is a benefit criterion} \\ \min(v_{ij}), & \text{if } j \text{ is a cost criterion} \end{cases} \tag{15}$$

- Anti-Ideal Solution (A^-)is the worst performance for each criterion:

$$A^- = \{v_1^-, v_2^-, \ldots, v_n^-\}, \quad v_j^- = \begin{cases} \min(v_{ij}), & \text{if } j \text{ is a benefit criterion} \\ \max(v_{ij}), & \text{if } j \text{ is a cost criterion} \end{cases} \tag{16}$$

Step 4. Calculate the Separation Measures, using the distance of each alternative from the Ideal and Anti-Ideal solutions:

- Distance from Ideal Solution (S_i^+):

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad \forall i \tag{17}$$

- Distance from Negative-Ideal Solution (S_i^-):

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \quad \forall i \tag{18}$$

Step 5. Compute the Relative Closeness to the Ideal Solution, calculating the relative closeness C_i of each alternative to the ideal solution:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, \quad \forall i \tag{19}$$

The value C_i lies between 0 and 1, where a value closer to 1 indicates a better alternative.

Step 6. Rank the alternatives in descending order of C_i. The alternative with the highest C_i is considered the best choice.

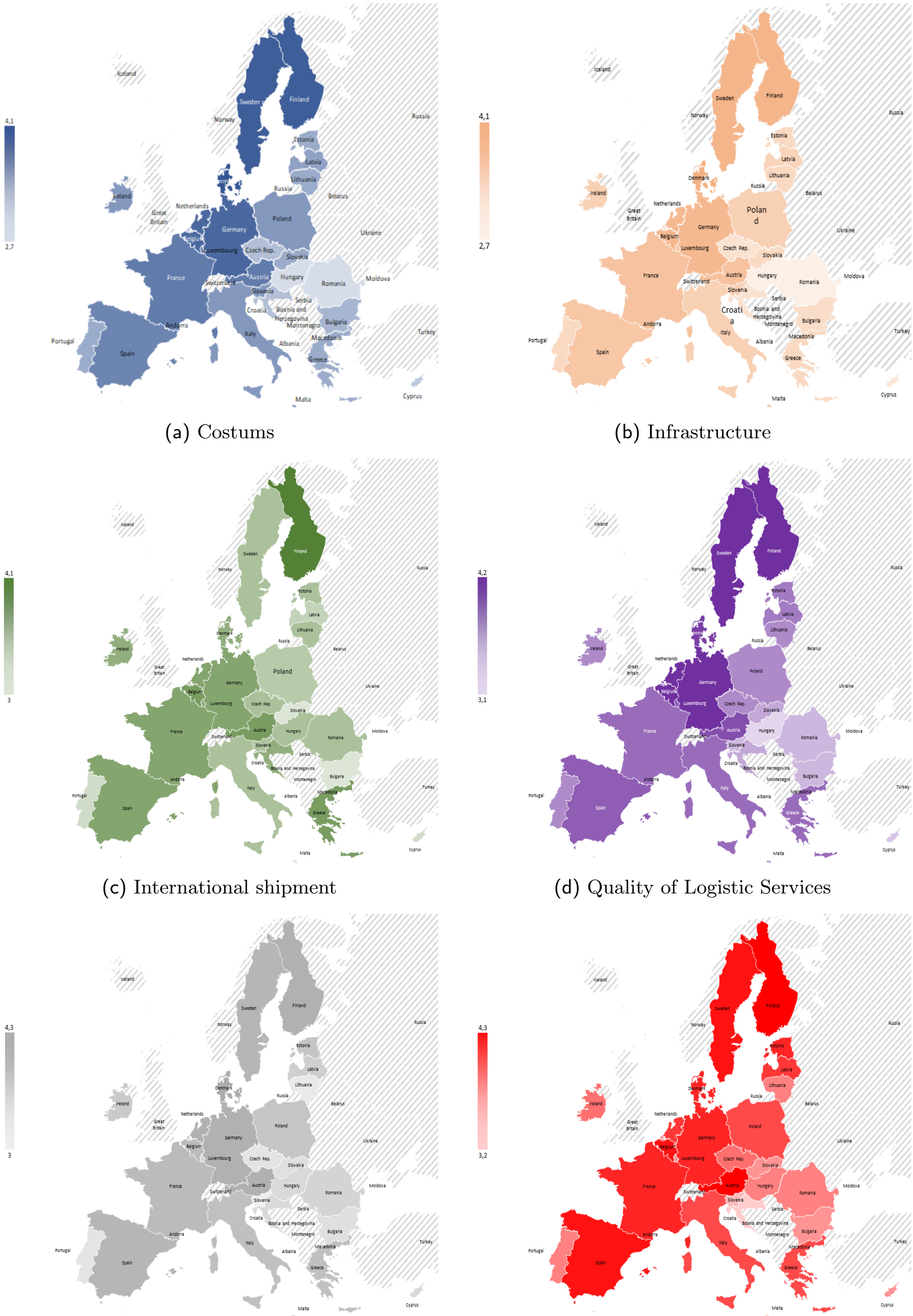
4. Analysis of the results

4.1. Spatial analysis of LPI

In this section various key performance indicators (KPIs) across different European Union countries in 2023 are analyzed. This analysis aims to highlight the disparities in performance and suggest potential strategies for enhancing efficiency and effectiveness in logistics operations.

Customs: When analyzing Fig. 2 (a), the first conclusion is that the countries with the best scores in 2023 for the Customs indicator are Sweden, Finland, and Denmark, with scores of 4 for Sweden and Finland, and 4.1 for Denmark. These high scores suggest that these countries have efficient customs processes, which likely contribute to smoother international trade and lower costs for businesses. On the other hand, the countries with the worst scores are Romania, Czech Republic, Cyprus, Croatia, and Hungary. These low scores indicate significant inefficiencies in customs procedures, which can lead to delays and increased costs.

Infrastructure: the countries with the lowest quality of infrastructure are Romania, Cyprus, Croatia, and the Czech Republic (Fig. 2 (b)). Poor infrastructure quality in these countries can hinder economic growth and reduce the efficiency of logistics operations . Conversely, the countries with the best infrastructure quality are Sweden, Finland, Belgium, Germany, the Netherlands, and Denmark (Fig. 2 (b)). High-quality infrastructure in these countries supports efficient logistics and supply chain operations, contributing to their economic competitiveness.



(a) Costums (b) Infrastructure

(c) International shipment (d) Quality of Logistic Services

(e) Tracking and Tracing (f) Timeless

Figure 2: Indicators of LPI (2023)

International Shipments: The countries where exporting at competitive prices is most difficult are Bulgaria, Slovakia, and Portugal. These scores suggest that businesses in these countries face challenges in maintaining competitive export prices, which can affect their global market presence. In contrast, the countries where competitive export prices are more achievable are Finland, Greece, Austria, and Belgium (see Fig. 2 (c)). These higher scores indicate a more favorable environment for exports, likely due to efficient logistics and supportive trade policies.

Quality of Logistics Services: Fig. 2 (d) shows the countries with the weakest scores in the Quality of Logistics Services indicator in 2023. The countries with the best scores are Denmark, Sweden, Germany, and the Netherlands. These high scores reflect the effectiveness and reliability of logistics services in these countries, which are crucial for maintaining supply chain efficiency and customer satisfaction. The countries with the weakest scores are Hungary and Cyprus. These low scores suggest that logistics services in these countries may be less reliable or efficient, potentially leading to higher costs and delays.

Tracking and Tracing: Fig. 2 (e) provides information on the countries with the highest and lowest scores for the Tracking and Tracing indicator. The countries with the highest scores are Austria, Germany, Finland, the Netherlands, Denmark, and Sweden. High scores in tracking and tracing indicate robust systems for monitoring shipments, which enhance transparency and reliability in the supply chain. The countries with the lowest scores are Slovenia, Lithuania, Czech Republic, and Portugal. These low scores suggest that these countries may face challenges in providing accurate and timely tracking information, affecting customer satisfaction and operational efficiency.

Timeliness: Analyzing Fig. 2 (f), the countries with the lowest scores for the Timeliness indicator in 2023 are Croatia, Malta, Slovenia, Bulgaria, Luxembourg, Cyprus, and Slovakia, Croatia, Malta, Slovenia, Bulgaria, Cyprus, Luxembourg, and Slovakia. These low scores indicate that shipments in these countries are often delayed, which can disrupt supply chains and increase costs. The countries with the highest scores are Belgium, Spain, Sweden, Austria, and Finland. High scores in timeliness reflect efficient logistics operations that ensure timely deliveries, which are critical for maintaining customer satisfaction and operational efficiency.

4.2. Weight criteria: CRITIC Mehod

In order to use the CRITIC method, it was necessary to clear the data, and selected the identifies the EU countries classified here as alternatives (rows of the decision matrix) $(A_i, i = 1, ...27)$. Then, the 6 indicators (columns of the decision matrix) that compose the LPI were defined as criteria: customs (C_1), Infrastructure (C_2), International Shipment (C_3), Quality Services (C_4), Tracking and Tracing (C_5) and Timeliness (C_6). Matrix normalization is performed according to Equation (3). The values of the initial matrix and normalized values are displayed in Table 1.

Additionally the corresponding correlation matrix between criteria is calculated (Table 2).

The final results for the weights as step 4 defined in the previous section are in Table 3. It is possible to observe that criterium related to the international shipment(C_3) was the one has more relevance, while the quality services (C_4) was the lowest scored.

4.3. Ranking countries: MARCOS, SAW and TOPSIS Methods

After calculating the weights using the CRITIC method, the next step is to determine the ranking of each country. This was achieved by applying the formulas outlined in the previous section for the three selected methods: MARCOS, SAW, and TOPSIS.

Table 4 shows the final ranking for the three methods. The ranking of countries across the four methods: original ranking, MARCOS, SAW, and TOPSIS, offers valuable insights into their relative performances and the impact of different decision-making approaches. The rankings provide a comprehensive view of how countries compare in terms of their attributes,

	Initial decision matrix						Normalized decion matrix					
	C_1	C_2	C_3	C_4	C_5	C_6	C_1	C_2	C_3	C_4	C_5	C_6
AUT	3.7	3.9	3.8	4	4.2	4.3	0.714	0.733	0.727	0.818	0.923	1.000
BEL	3.9	4.1	3.8	4.2	4	4.2	0.857	0.867	0.727	1.000	0.769	0.909
BGR	3.1	3.1	3	3.3	3.3	3.5	0.286	0.200	0.000	0.182	0.231	0.273
HRV	3	3	3.6	3.4	3.4	3.2	0.214	0.133	0.545	0.273	0.308	0.000
CYP	2.9	2.8	3.1	3.2	3.4	3.5	0.143	0.000	0.091	0.091	0.308	0.273
CZE	3	3	3.4	3.6	3.2	3.7	0.214	0.133	0.364	0.455	0.154	0.455
DNK	4.1	4.1	3.6	4.1	4.3	4.1	1.000	0.867	0.545	0.909	1.000	0.818
EST	3.2	3.5	3.4	3.7	3.8	4.1	0.357	0.467	0.364	0.545	0.615	0.818
FIN	4	4.2	4.1	4.2	4.2	4.3	0.929	0.933	1.000	1.000	0.923	1.000
FRA	3.7	3.8	3.7	3.8	4	4.1	0.714	0.667	0.636	0.636	0.769	0.818
DEU	3.9	4.3	3.7	4.2	4.2	4.1	0.857	1.000	0.636	1.000	0.923	0.818
GRC	3.2	3.7	3.8	3.8	3.9	3.9	0.357	0.600	0.727	0.636	0.692	0.636
HUN	2.7	3.1	3.4	3.1	3.4	3.6	0.000	0.200	0.364	0.000	0.308	0.364
IRL	3.4	3.5	3.6	3.6	3.7	3.7	0.500	0.467	0.545	0.455	0.538	0.455
ITA	3.4	3.8	3.4	3.8	3.9	3.9	0.500	0.667	0.364	0.636	0.692	0.636
LVA	3.3	3.3	3.2	3.7	3.6	4	0.429	0.333	0.182	0.545	0.462	0.727
LTU	3.2	3.5	3.4	3.6	3.1	3.6	0.357	0.467	0.364	0.455	0.077	0.364
LUX	3.6	3.6	3.6	3.9	3.5	3.5	0.643	0.533	0.545	0.727	0.385	0.273
MLT	3.4	3.7	3	3.4	3.4	3.2	0.500	0.600	0.000	0.273	0.308	0.000
NLD	3.9	4.2	3.7	4.2	4.2	4	0.857	0.933	0.636	1.000	0.923	0.727
POL	3.4	3.5	3.3	3.6	3.8	3.9	0.500	0.467	0.273	0.455	0.615	0.636
PRT	3.2	3.6	3.1	3.6	3.2	3.6	0.357	0.533	0.091	0.455	0.154	0.364
ROM	2.7	2.9	3.4	3.3	3.5	3.6	0.000	0.067	0.364	0.182	0.385	0.364
SVK	3.2	3.3	3	3.4	3.3	3.5	0.357	0.333	0.000	0.273	0.231	0.273
SVN	3.4	3.6	3.4	3.3	3	3.3	0.500	0.533	0.364	0.182	0.000	0.091
ESP	3.6	3.8	3.7	3.9	4.1	4.2	0.643	0.667	0.636	0.727	0.846	0.909
SWE	4	4.2	3.4	4.2	4.1	4.2	0.929	0.933	0.364	1.000	0.846	0.909

Table 1: Initial and normalized values for decion matrix for the CRITIC method, for the 27-EU countries in LPI context

	C_1	C_2	C_3	C_4	C_5	C_6
C_1	1.000	0.931	0.557	0.896	0.757	0.662
C_2	0.931	1.000	0.580	0.884	0.754	0.672
C_3	0.557	0.580	1.000	0.685	0.681	0.619
C_4	0.896	0.884	0.685	1.000	0.827	0.806
C_5	0.757	0.754	0.681	0.827	1.000	0.861
C_6	0.662	0.672	0.619	0.806	0.861	1.000

Table 2: Values for r_{ij}

as determined by the weights calculated using the CRITIC method. This analysis highlights both consistencies and discrepancies among the rankings produced by the various methods.

The rankings demonstrate significant consistency in identifying the strongest and weakest performers across all methods. For example, Finland (FIN) consistently holds the top rank (1st) in all methods, indicating its dominant performance irrespective of the evaluation technique. This robustness suggests that Finland's attributes are well-aligned with the criteria and weights applied in the decision-making process.

Similarly, Bulgaria (BGR) and Cyprus (CYP) consistently occupy the bottom ranks (24th to 27th) across all methods. This unanimity highlights their relatively weaker performance on the evaluated criteria, making them less sensitive to the methodological differences.

	C_1	C_2	C_3	C_4	C_5	C_6
σ_j	0.282	0.289	0.257	0.310	0.305	0.307
C_j	0.338	0.340	0.483	0.279	0.341	0.423
w_j	**0.153**	**0.154**	**0.219**	**0.127**	**0.155**	**0.192**

Table 3: Values for standard deviation (σ_j). C_j and weights (w_j)

	Score				Ranking			
Country	**Original**	**MARCOS**	**SAW**	**TOPSIS**	**Original**	**MARCOS**	**SAW**	**TOPSIS**
Austria	4.0	0.73	0.95	0.78	5	6	6	5
Belgium	4.0	0.74	0.95	0.82	5	4	4	2
Bulgaria	3.2	0.59	0.76	0.21	24	26	26	26
Croatia	3.3	0.60	0.78	0.30	19	22	22	21
Cyprus	3.2	0.58	0.75	0.17	24	27	27	27
Czech Republic	3.3	0.61	0.79	0.29	19	20	20	22
Denmark	4.1	0.74	0.95	0.78	2	3	3	6
Estonia	3.6	0.66	0.86	0.50	12	12	12	13
Finland	4.2	0.77	0.99	0.95	1	1	1	1
France	3.9	0.71	0.91	0.70	8	9	9	9
Germany	4.1	0.74	0.96	0.81	2	2	2	3
Greece	3.7	0.68	0.88	0.60	10	10	10	10
Hungary	3.2	0.60	0.77	0.26	24	25	25	24
Ireland	3.6	0.66	0.85	0.50	12	14	14	14
Italy	3.7	0.68	0.87	0.56	10	11	11	11
Latvia	3.5	0.64	0.83	0.42	16	16	16	16
Lithuania	3.4	0.63	0.81	0.36	17	17	17	17
Luxembourg	3.6	0.66	0.86	0.51	12	13	13	12
Malta	3.3	0.61	0.79	0.33	19	21	21	19
Netherlands	4.1	0.74	0.95	0.79	2	5	6	4
Poland	3.6	0.66	0.85	0.48	12	15	15	15
Portugal	3.4	0.62	0.80	0.33	17	18	18	20
Romania	3.2	0.60	0.77	0.26	24	24	24	23
Slovakia	3.3	0.60	0.78	0.25	19	23	23	25
Slovenia	3.3	0.61	0.79	0.35	19	19	19	18
Spain	3.9	0.71	0.92	0.71	8	8	8	8
Sweden	4.0	0.73	0.94	0.72	5	7	7	7

Table 4: Scores and Rankings for LPI Methods

While the top and bottom performers exhibit stability, countries in the middle tier show notable variability across methods. For instance, Denmark (DNK) ranks 2nd in the Original method but shifts to 3rd under MARCOS and SAW, and drops further to 6th in TOPSIS. This variability indicates that Denmark's performance is more influenced by the methodological nuances, particularly the treatment of ideal and negative-ideal solutions in TOPSIS.

Other middle-ranked countries, such as Ireland (IRL) and the Netherlands (NLD), also display moderate shifts in rankings. For example, the Netherlands moves from 2nd in the Original method to 5th in MARCOS, 6th in SAW, and 4th in TOPSIS. This reflects the sensitivity of their rankings to how criteria weights and normalization are applied in each method.

Figure 3 highlighting the comparison of rankings obtained using various methods. From the methodologycal point of view, MARCOS and SAW methods generally align closely with the original rankings, with only minor deviations. This alignment can be attributed to their additive or weighted-sum approaches, which emphasize cumulative performance without heavily penalizing deviations from an ideal solution. Conversely, TOPSIS introduces more pronounced shifts, particularly among middle-tier countries, due to its dual focus on proximity to the ideal solution and distance from the negative-ideal solution.

The consistency among methods for certain countries, alongside variability for others, underscores the importance of selecting an appropriate decision-making method based on the specific context and objectives. For example, TOPSIS may be more suitable for scenarios requiring a balanced evaluation of both positive and negative aspects, while MARCOS or SAW may be preferred for simpler additive aggregation.

The rankings provide critical insights for stakeholders and policymakers, particularly in understanding the relative positions of countries and the potential impact of different evaluation methods. For countries consistently ranked at the top or bottom, the results validate their performance as either strong or weak. However, for countries with variable rankings, further

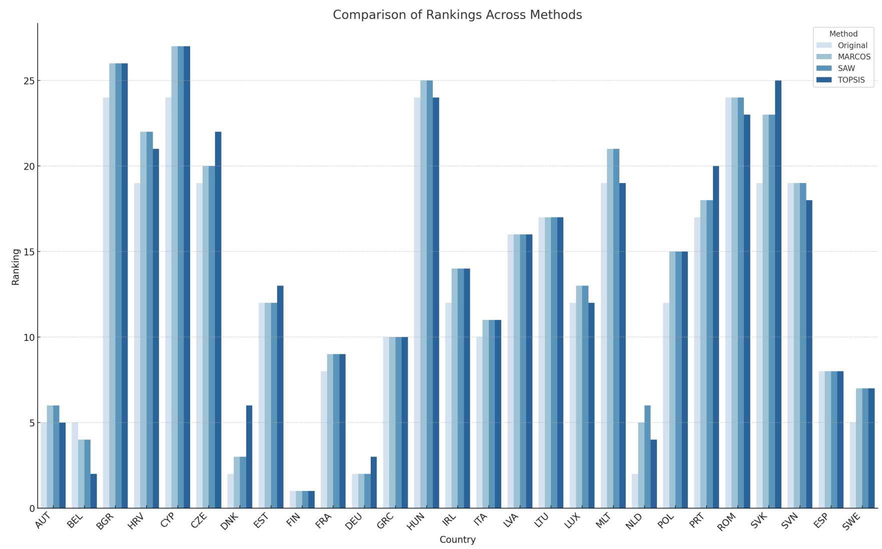


Figure 3: Comparison of Country Rankings Across Different Decision-Making Methods

analysis may be required to understand the underlying factors influencing their performance.

The LPI classified throught the two stage methodology CRITIC-MARCOS methods could be summarized in Figure 4. Finland and part of Western Europe are in the top of the ranking, while Central and Eastern Europe have the lower positions. Analyzing neighboring countries in relation to logistics indicators is crucial for several reasons. First, is important to think about trade efficiency, because when a company undestand the logistics infrastructure and capabilities of neighboring countries can help identify the most cost-effective routes for transporting goods, and could decrease significantly transit times. Second, understand what happens in different countries could increase the market access, specially, if regional trade agreements are prepared. Third issue is related to the resilience of supply chain, because by understanding the logistics capabilities of neighboring countries, businesses can diversify their supply routes, reducing dependency on a single route or country and enhancing resilience against disruptions. Finnaly, knowing what happen in different counties could lead to the increase of economic competitiveness, reducing the overall cost of goods sold, making products more competitive in the global market.

5. Conclusion

Analyzing the Logistics Performance Index within the European Union is vital for optimizing supply chains, enhancing market access, boosting economic competitiveness, improving supply chain resilience, informing policy and infrastructure development, supporting sustainable logistics, enhancing global trade competitiveness, and promoting economic growth, particularly for SMEs.

When the ranking for the three methods are provided, it is possible to see that Finland (FIN) consistently ranks first across all methods, demonstrating its robustness as the top performer. Similarly, Bulgaria (BGR) and Cyprus (CYP) are consistently ranked among the lowest, highlighting their weaker relative performance.

For middle-tier countries, such as Denmark (DNK) and the Netherlands (NLD), significant variability in rankings is observed, particularly in TOPSIS compared to the Original and additive methods (MARCOS and SAW). This suggests that the methodological differences, especially the treatment of proximity to ideal and negative-ideal solutions in TOPSIS, can notably influence rankings for countries with intermediate performance.

As future work, we intend to study the LPI, using other multi-criteria decision models and understand whether there are significant changes in the rankings presented.

Acknowledgements

This work was supported by the Centre for Research and Development in Mathematics and Applications (CIDMA) through the Portuguese Foundation for Science and Technology (FCT - Fundação para a Ciência e a Tecnologia), references UIDB/04106/2020 and UIDP/04106/2020 (Rodrigues); ADiT-Lab – Applied Digital Transformation Laboratory, an R&D unit of Polytechnic University of Viana do Castelo (Rodrigues and Silva); by Algoritmi through FCT – within the R&D Units Project Scope UIDB/00319/2020 (Silva). This research is part of Bruna Barros logistics master thesis.

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