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Addressing the Global Logistics Performance Index Rankings with Methodological Insights and an Innovative Decision Support Framework

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Abstract: This study examines the Logistics Performance Index (LPI) rankings developed by the World Bank from a methodological perspective and proposes an alternative decision support framework. LPI serves as an interactive tool that helps countries identify challenges, innovative solutions, and opportunities in their trade and logistics sectors. In this study, the efficiency of logistics operations in 118 countries was evaluated using an integrated multi-criteria decision-making (MCDM) model objectively weighted by the Entropy method. Countries were ranked using the MCRAT, SAW, TOPSIS, and FUCA methods. According to the findings, large datasets provide more robust insights for sensitivity analyses, and wider weighting coefficient combinations make the data more meaningful. In addition, it is suggested to use low-compensation methods instead of classical additive methods for LPI. Unlike other studies in literature, this research applied an innovative sensitivity analysis to test the robustness of the model and comprehensively examined the effects of weighting techniques based on over 2500 different MCDM results. The findings suggest that the FUCA method should be recommended to decision-makers for calculating LPI rankings due to its simplicity, practicality, low compensatory power, and low sensitivity. This study offers methodological improvements when evaluating logistics performance and provides significant contributions to decision-making processes. The findings are expected to provide a valuable resource for policymakers and businesses in understanding a country's position in global competition, as well as serving as a reference for researchers evaluating the logistics performance of countries.

Keywords: logistic performance index; multi-criteria decision making; entropy; MCRAT; sensitivity; compensatory

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1. Introduction

Logistics, a service network supporting the transportation of tangible products, plays a critical role in facilitating international trade through activities such as transport, delivery, terminal operations, brokerage, warehousing, and data handling. A country's capacity to participate effectively in international trade largely depends on traders with access to well-organized logistics frameworks [1]. Recent developments, including the growing competitiveness of less developed regions and the effects of globalization, have significantly influenced international trade. These factors have profoundly impacted logistics, an essential factor in lowering expenses during times of increased international trade by guaranteeing the security and efficiency of products and easing their transportation [2].

With globalization, logistics has become a fundamental component of international trade. Effective logistics services not only enhance the mobility, safety, and speed of

products but also contribute to reducing costs in cross-border trade [3]. This has created a need for systems to evaluate logistics performance [4]. Various metrics can be used to evaluate logistics performance, which plays a critical role in promoting trade expansion and is a significant determinant of national economic growth [5]. Evaluation can occur on a granular scale for individual companies or departments, while the overall performance of a nation or continent can be assessed on a macro scale. Over time, different approaches have been suggested for evaluating performance, encompassing raw financial data, input/output metrics, cost statistics, and performance benefits to assess the attainment of objectives across different areas [6].

Recognizing the importance of logistics for the national economy, a thorough evaluation was required. This led the World Bank research team to develop the Logistics Performance Index (LPI) in 2007 [4]. The LPI is a comprehensive indicator designed to help nations identify both the obstacles and opportunities present in their trade logistics performance [7]. Created by the World Bank to evaluate logistics performance across 160 countries, the LPI ranks countries based on their logistics quality. It serves as an interactive tool for countries to identify obstacles and prospects in their trade and logistics activities and to receive recommendations for performance improvement [8]. The LPI functions as a tool to pinpoint obstacles and potential advantages in the logistics of the analyzed region or country, offering pathways for enhancing logistical effectiveness. It represents the average score adjusted by weights derived from six essential criteria: "customs, infrastructure, international shipments, logistics competence and quality, timeliness, and tracking and tracing" [9]. The LPI is derived from a survey capturing the views and experiences of logistics experts, freight forwarders, and customs brokers across different countries concerning logistics operations [10]. It assigns scores on a scale from 1 to 5, where higher scores reflect superior logistics performance [11]. By employing principal component analysis, the World Bank assigns equal weight to indicators when determining LPI values, which can impede countries from crafting effective policies [12].

Research on multi-criteria decision making (MCDM) has gained significant traction within the field of operational research, especially over the past twenty years [13]. However, the use of MCDM techniques in the evaluation countries' LPI has been neglected. Currently, there are more than 200 types of MCDM methods [14]. Among these, the simple weighted aggregation method is the simplest and most primitive method used in LPI assessment. A classical approach is adopted to assign weights to the criteria in LPI. However, MCDM has several alternative weight coefficient assignment methods. Moreover, LPI is not interested in measuring the sensitivity of the rankings, nor does it benefit from MCDM insights in data normalization. However, using a method with high sensitivity implies robustness, reliability, and stability problems. This may cause doubts about the obtained ranking results and especially the best alternative.

In addition, the aggregation method based on equal weight coefficients used by the World Bank in the LPI measurement is problematic. Because the aggregation methods for the MCDM methodology are highly compensatory, a country that scores high in one or more criteria will compensate for possible low scores in other criteria. In other words, the criteria used are not independent. In this context, many alternative methods with low compensatory power in the MCDM family can be used. MCDM methods can be classified as compensatory, partially compensatory, and non-compensatory. It can be argued that MCDM methods based on the utility theory are more compensatory than methods based on the 'outranking' school [15]. Because the compensatory effect means that, for example, a low value in one criterion in a decision matrix can be compensated by a high value in another criterion, it is certain that this is unfair and, at minimum, evokes negativity [16]. The calculation used for classical LPI performance rankings is a simple weighted aggregation method and has compensability. For example, a country that is weak in 'Logistics Competence and Quality' and 'Infrastructure' will compensate for its weakness by focusing on criteria such as 'Timeliness' and 'Tracking and Tracing'. Therefore, a country that scores high in one or two criteria can get ahead of its competitors by obtaining a higher

score overall. In this sense, "superiority methods" or "distance-based methods" may have a softer compensatory effect compared to classical additive methods.

As is well known, sensitivity analyses in MCDM methods are generally used to examine the effect of weights on the results. However, in cases where a single dataset or a small number of weight coefficients are used, the results may differ and even lead to erroneous results. So far in the literature, such inconsistencies may not be noticed in analyses performed with small datasets and a small number of weight coefficients. Our findings show that consistency increases when more weighting coefficients and larger datasets are used. This raises the question: Could previous studies in the literature that used small datasets, and a small number of weighting coefficients have misjudged the performance of the methods? Using a small number of weight coefficients on small datasets may mean that decision models cannot fully explore the entire range of potential outcomes. When working with a small number of samples, it becomes difficult to filter the effect of noise in the data. This may make the results of methods, such as the sensitivity analysis, inconsistent. In other words, when small data are used, the results are more affected by random variations. If the results of sensitivity analyses vary too much with the size of the dataset, weight combinations, or method selection, this will undermine the reliability of the analyses. Therefore, when testing the robustness of MCDM methods, it is necessary to also test the robustness of sensitivity analyses.

Considering all these justified reasons, addressing LPI rankings with MCDM insights and methodology is an important research gap.

In this study, an integrated MCDM model has been presented to assess the logistics performance of countries. Criteria weights were determined using the Entropy method, which offers the advantage of reducing the influence of decision-makers' personal judgments and enhancing objectivity. Objective weighting techniques offer significant benefits in computational efficiency, and applying these methods is crucial for achieving more significant results and improving decision-making quality [17]. Conversely, in this study, the MCRAT method has been selected, as it is a relatively new and infrequently utilized technique for assessing alternatives. The relatively new MCRAT method has been investigated across multiple industries, including the mining sector [18], logistics [19], and banking [20], as well as in different topics including 3DP machine selection [21] and material selection [22,23]. In addition to its advantages such as clarity, rationalism, logic, adaptability, and dependability [19], the MCRAT technique has not previously been employed in LPI evaluation.

Among the methods employed for evaluating the alternatives, SAW, TOPSIS, and FUCA are also included. The SAW, also known as the scoring method, is one of the simplest MCDM methods [24]. In the literature, the SAW method is applied to solve various problems, such as institutional ranking [25], and cloud service selection [26]. The TOPSIS method, which is distance-based, is a popular MCDM method and has been applied to various topics such as financial performance measurement [27], credit rating prediction [28], and site selection [29]. The FUCA method, which is quite simple, ranks all solutions from best to worst [30,31]. Examples of its application in literature include the development of wood and pallet production processes [32].

This study contributes to the existing literature in several ways: (i) This MCDM model is being applied for the first time to evaluate the logistics performance of nations. (ii) This study demonstrates that robust results can be obtained using MCDM methods without normalization. (iii) To evaluate the model's robustness, a holistic sensitivity analysis incorporating an innovative approach was conducted, examining the impact of criterion weights on the results across 105 scenarios. (iv) The impact of variations in criterion weights on MCDM outcomes was tested not only for the MCRAT method but also for the SAW, TOPSIS, and FUCA methods as part of a comparative analysis. (v) A thorough analysis was conducted by examining all World Bank LPI reports, except for the 2007 edition. (vi) The research findings can assist countries in assessing their current logistics performance and formulating business strategies to enhance it.

2. Literature Review

Logistics refers to a component of the value chain that organizes, executes, and oversees the efficient movement of goods, services, and information from suppliers to consumers [33]. Globalization and rising competition have elevated logistics to a critical role in international trade. Effective logistics services ensure the swift and secure movement of products, lowering costs in cross-border transactions. Therefore, the significance of logistics lies in its capacity to efficiently manage transportation, storage, and packaging challenges, ultimately boosting the competitiveness of both businesses and the nation [3]. Logistics involves a wide range of functions and activities, making it a complex task to enhance competitiveness and ensure customer satisfaction. To succeed in these areas and meet performance objectives, it is essential to evaluate these functions and activities. A critical factor is considering the time and costs tied to logistics processes, such as customs clearance and transportation [8]. Historically, logistics performance at the micro level, focusing on individual firms or inter-firm operations, has been measured by cost efficiency and service quality [34]. In contrast, macro-level logistics performance, which focuses on national or international scales, primarily emphasizes calculating logistics costs related to transportation, warehousing, and inventory holding [35]. Research on logistics performance at the macro or national level remains relatively scarce [34]. However, the LPI remains the only comprehensive global measure for evaluating logistics service performance on a macroscale [11].

The LPI, introduced by the World Bank in 2007, was designed to evaluate countries' logistics performance and its related impacts. Initially, countries were assessed using seven criteria: customs, infrastructure, ease of shipment, logistics services, tracking ease, domestic logistics costs, and timeliness. In later editions released in 2010, 2012, 2014, 2016, 2018, and 2023, the LPI was refined to include six criteria [36]. The LPI enables the comparison of logistics performance across nations and provides insights into the quality of infrastructure needed for land and sea transport, customs processes, and logistics costs [3]. Countries can utilize the detailed LPI analysis, published biennially by the World Bank, to evaluate their logistics performance and competitiveness in the global logistics sector [37].

The LPI dataset is derived from an online survey involving around 1000 participants. Respondents assess performance across six key areas using a Likert scale, and these assessments are consolidated into an overall index through principal component analysis [38], and each LPI indicator is assessed with equal weights by the World Bank. However, refs. [12,39] argue that this equal weighting can hinder the development of effective policies by countries, which is a noted limitation of the World Bank's LPI calculation [37]. To mitigate this issue, some studies have applied objective methods to determine criterion weights [37,40]. Additionally, some research has utilized subjective weighting techniques [4,12,41,42], while others have combined both objective and subjective approaches [39].

The increasing importance of the LPI is highlighted in academic literature, where numerous researchers have used diverse MCDM methods and criteria to assess and rank countries' logistics performance [40]. The number of studies employing MCDM models to evaluate country-level logistics performance is steadily increasing in the existing literature. For example, ref. [39] identified that the top three performing countries were Germany, Sweden, and the Netherlands, while Finland, France, and Spain ranked at the bottom. In another study, ref. [8] applied the CRITIC-MARCOS model to assess the Western Balkan countries' logistics performance in 2018, also using World Bank data, and ranked Serbia as the best performer. Furthermore, ref. [43] assessed the 2014 performance of OECD nations through the application of CRITIC, SAW, and Peters' fuzzy regression models and found discrepancies between the results from Peters' FLR model and those obtained from other MCDM methods. In addition, ref. [44] evaluated the performance of Central and Eastern European (CEE) countries in 2018 by employing the Statistical Variance and MABAC methods, with the Czech Republic and Poland identified as the leading performers. In their study, ref. [12] analyzed OECD countries' performance over the period from 2010 to 2018 with the fuzzy AHP-ARAS-G model, identifying Germany as the top performer

and Latvia as the lowest. In another example, ref. [4] used the BWM method to evaluate the significance of six logistics performance criteria set by the World Bank, concluding that "Infrastructure" was the most important and "Tracking and Tracing" the least. Another study, [45], employed the grey SWARA-MOORA model to evaluate the logistics performance of transition economy countries, identifying "Infrastructure" as the top criterion and Serbia as the best-performing nation according to the grey MOORA results. Meanwhile, ref. [2] assessed the logistics efficiency of 141 nations over the period 2007 to 2014 using DEA, ranking Belgium first and Somalia last. Additionally, ref. [46] used the fuzzy AHP model to evaluate intermodal transport logistics performance in Thailand during 2005–2006, while [37] applied the MEREC-MARCOS model to assess the logistics performance of EU countries, with Germany ranking first. In their study, ref. [47] evaluated the logistics performance of EU countries and Turkey using the CRITIC-COPRAS model, identifying the Netherlands as the highest-ranked and Latvia as the lowest-ranked country. Furthermore, ref. [48] analyzed logistics performance in EU countries from 2007 to 2023 using LPI data announced by the World Bank, and [49] proposed an integrated approach using fuzzy c-means clustering (FCM) and MCDM to evaluate the logistics performance of 160 countries worldwide. Countries were clustered based on income groups considering per capita gross domestic product (GDP) and ranked using SAW, TOPSIS, MOORA, and ARAS methods with 2018 LPI data. The results were consistent with the LPI rankings published by the World Bank. In another study, ref. [40] determined the logistics performance of EU countries using 11 MCDM techniques across 33 indicators. Criteria weights were established using the Genetic Algorithm (GA), and different MCDM rankings were integrated using the Copeland method. It was found that the correlation between the actual LPI scores and the genetic algorithm results was higher compared to other weighting techniques (CRITIC, Entropy, and equal weight). Meanwhile, ref. [50] assessed the logistics performances of Turkey and EU countries using the Entropy-EDAS model, identifying Germany, Sweden, and Denmark as the top three performing countries. Similarly, ref. [51] evaluated the logistics performances of EU member states and 5 EU candidate countries using the COPRAS-G method, with Germany, the Netherlands, and Sweden ranking prominently. Finally, in their study evaluating the logistics performances of OECD countries, ref. [52] concluded that the countries with the highest logistics performance, according to the SWARA-EDAS model, were Germany, The Netherlands, and Sweden.

3. Methodology

This study integrates the MCDM methods into a hybrid model designed to evaluate the logistics performance of nations. The MCDM model is structured into three phases: establishing criterion weights using the Entropy method (i), identifying the most suitable alternative with the MCRAT, SAW, TOPSIS, and FUCA methods (ii), and validating the proposed methodologies through an innovative sensitivity analysis approach (iii).

3.1. Entropy Method

As is well known, the World Bank data have applied an equal weighting coefficient for LPI. However, since it is not realistic for all criteria to be equal, the entropy weighting coefficient has been suggested as an alternative in this study.

Entropy is an advanced technique that objectively determines criteria weights with precision. The methodology involves the following steps [53,54]:

Step 1: A decision matrix is constructed.

Assume there are m alternatives Ai (i = 1,2,. . ., m) and n selection criteria Cj (j = 1,2,. . ., n). The decision matrix can be formulated as follows:

$$X = \left[x_{ij}\right]_{n\times m} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & x_{ij} & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}$$

Step 2: The decision matrix is normalized:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (1)$$

where $|P_{ij}|$ represents the projection value. xij denotes the crisp value of alternative Ai with respect to Cj.

Step 3: The entropy value for each criterion is determined:

$$e_j = -k\sum_{i=1}^{n} P_{ij} \ln P_{ij_{\forall_j}} \quad (2)$$

$$k = \frac{1}{\ln(m)}$$

where m is the total number of evaluated alternatives, $\mathrm{In}(v_{ij})$ is logarithm based on e and ej is [0,1].

Step 4: The level of differentiation among the criteria is evaluated:

$$d_j = 1 - e_j, \forall_j \quad (3)$$

where d_j is the contrast density in the j structure.

Step 5: The weights of the criteria are calculated:

$$W_j = \frac{d_j}{\sum_{k=1}^{n} d_k} \quad (4)$$

$$\sum w_j = 1,\ 0 \le w_j \le 1$$

3.2. MCRAT Method

The MCDM approach presented by [18] employs the concept of perimeter similarity to determine the ranking of alternatives. The methodology consists of the following steps [18]:

Step 1: The decision matrix is normalized:

$$r_{ij} = \frac{x_{ij}}{max_i(x_{ij})}\ benefit \quad (5)$$

$$r'_{ij} = \frac{min_i(x_{ij})}{x_{ij}}\ cost \quad (6)$$

where r_{ij} and r'_{ij} represent the normalized values of benefit and cost-oriented criteria, respectively.

Step 2: The weighted normalized decision matrix is generated:

$$u_{ij} = w_j \times r_{ij} \quad (7)$$

Step 3: The best alternative is identified using the following set:

$$q_i = (\max(u_{ij}) | 1 \le j \le n), \forall_i \in [1, 2, \ldots, m] \quad (8)$$

$$Q = \{q_1, q_2, \ldots, q_j\}, j = 1, 2, \ldots, n$$

Step 4: The best alternative is divided into two subsets or components:

$$Q = Q^{max} \cup Q^{min}. \quad (9)$$

If k denotes the total number of criteria that need to be maximized, then h = n − k signifies the total number of criteria that should be minimized. Then, k and h = n − k represent the number of beneficial and cost criteria, respectively.

$$Q = \{q_1, q_2, \ldots, q_k\} \cup \{q_1, q_2, \ldots, q_h\};$$

$$k + h = j$$

Step 5: The alternatives are differentiated using Equation (10):

$$U_i = U_i^{max} \cup U_i^{min}, \ \forall_i \in [1, 2, \ldots, m] \tag{10}$$

$$U_i = \{u_{i1}, u_{i2}, \ldots, u_{ik}\} \cup \{u_{i1}, u_{i2}, \ldots, u_{ih}\}, \ \forall_i \in [1, 2, \ldots, m]$$

Step 6: The size of each element of the optimal alternative is determined using Equations (14) and (15):

$$Q_k = \sqrt{q_1^2 + q_2^2 + .. + q_k^2} \tag{11}$$

$$Q_h = \sqrt{q_1^2 + q_2^2 + .. + q_h^2} \tag{12}$$

Each alternative is addressed using the same method:

$$U_{ik} = \sqrt{u_{i1}^2 + u_{i2}^2 + .. + u_{ik}^2} \tag{13}$$

$$U_{ih} = \sqrt{u_{i1}^2 + u_{i2}^2 + .. + u_{ih}^2} \tag{14}$$

Alternatives are ranked based on the trace of a matrix and the similarity between the boundary of the optimal alternative and those of the other alternatives.

Step 6.1. T_i matrix is established.

$$T_i = FxG_i = \begin{bmatrix} t_{11;i} & 0 \\ 0 & t_{22;i} \end{bmatrix}, \forall_i, \in [1, 2, .., m] \tag{15}$$

Step 6.2. Alternatives are ranked

$$tr(T_i) = t_{11;i} + t_{22;i}, \ \forall_i, \in [1, 2, .., m] \tag{16}$$

The alternatives are ranked based on the descending order of (T_i).

3.3. SAW Method

The steps of the SAW method are as follows [26]:

Step 1. Establish the normalized decision matrix for a beneficial attribute:

$$r_{ij} = \frac{d_{ij}}{d_{ij}^{max}} \tag{17}$$

and for a non-beneficial attribute:

$$r'_{ij} = \frac{d_{ij}^{min}}{d_{ij}} \tag{18}$$

Step 2. Formulate the weighted normalized decision matrix:

$$V_{ij} = W_{ij} \ x \ r_{ij}, \ \sum_{i=1}^{n} W_i = 1 \tag{19}$$

Step 3. Determine the score for each alternative:

$$S_i = \sum_{j=1}^{m} V_{ij}\ i = 1, 2, 3, \ldots, n. \tag{20}$$

The alternatives are ranked in descending order based on their Si values. S_i is the matrix score.

3.4. TOPSIS Method

The steps of the TOPSIS method are as follows [55,56]:

Step 1. Normalize the decision matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}},\ i = 1, \ldots, m; j = 1, \ldots, n \tag{21}$$

where r_{ij} represents the normalized value of the jth criterion for the ith alternative A_i.

Step 2. Determine the weighted normalized decision matrix:

$$v_{ij} = w_j r_{ij}\ i = 1, \ldots, m; j = 1, \ldots, n \tag{22}$$

where w_j is the weight of the jth criterion.

Step 3. Identify the positive ideal and negative ideal solutions:

$$A^+ = \left\{v_1^+, \ldots, v_n^+\right\} \tag{23}$$

$$A^- = \left\{v_1^-, \ldots, v_n^-\right\} \tag{24}$$

where A+ and A− represent the positive and negative ideal solution. If the jth criterion is a beneficial one, then $v_1^+ = \max\{v_{ij}, i = 1,\ldots, m\}$ and $v_1^- = \min\{v_{ij}, i = 1,\ldots, m\}$. On the other hand, if the jth criterion is a cost criterion, then $v_1^+ = \min\{v_{ij}, i = 1,\ldots, m\}$ and $v_1^- = \max\{v_{ij}, i = 1,\ldots, m\}$.

Step 4. Compute the distances of each alternative from the positive ideal solution and the negative ideal solution:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{25}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{26}$$

where D_i^+ represents the distance between the ith alternative and the positive ideal solution and D_i^- represents the distance between the ith alternative and the negative ideal solution.

Step 5. Determine the relative closeness to the ideal solution;

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{27}$$

Step 6. Rank the alternatives in descending order according to their Ci values.

3.5. FUCA Method

The steps of the FUCA method are as follows [57]:

Step 1. For each objective, rank 1 is assigned to the highest value and rank m is assigned to the lowest value. If the optimization goal is to achieve a maximum value, then the highest value in the column is considered the best; conversely, if the goal is to achieve a minimum value, then the smallest value in the column is considered the best.

Step 2. A weighted sum is calculated for each optimal solution;

$$v_i = \sum_{j=1}^{n} r_{ij} \; x \; w_j \tag{28}$$

where r_{ij} represents the rank of solution i for objective j. The solution with the smallest v_i is considered the recommended optimal solution.

4. Application

In this section, the proposed MCDM model is applied to a dataset containing LPI information for countries. The flow diagram is presented in Figure 1, and the proposed methodology consists of three main components. In the first stage, the necessity of this study was identified, and the LPI reports published by the World Bank were examined. The number of countries for which the World Bank reports LPI scores varies significantly from year to year. Consequently, a consolidated dataset was developed, encompassing 118 countries for analysis. The data were gathered from the [36], which maintains LPI data from 2007 to 2023. The year 2007 was excluded from the analysis due to a lack of sufficient data. The dataset used for the evaluation process comprises six benefit-oriented criteria (C1: Customs, C2: Infrastructure, C3: International Shipments, C4: Logistics Competence and Quality, C5: Timeliness, C6: Tracking and Tracing) and 118 alternatives. The LPI indicators and their descriptions are presented in Table 1. In the second stage of the proposed methodology, the decision matrix was constructed, criteria weights were determined using the Entropy method, and the performance scores of the alternatives were assessed using four different MCDM methods. The MCDM results were compared with the World Bank LPI rankings. In the third stage, an innovative sensitivity analysis approach was applied to define criteria weights across 105 scenarios. The MCDM methods and World Bank LPI rankings were compared with the defined fixed factors, and the standard deviation value based on the obtained correlations was calculated. Subsequently, the ranking with the lowest sensitivity was determined based on these results.

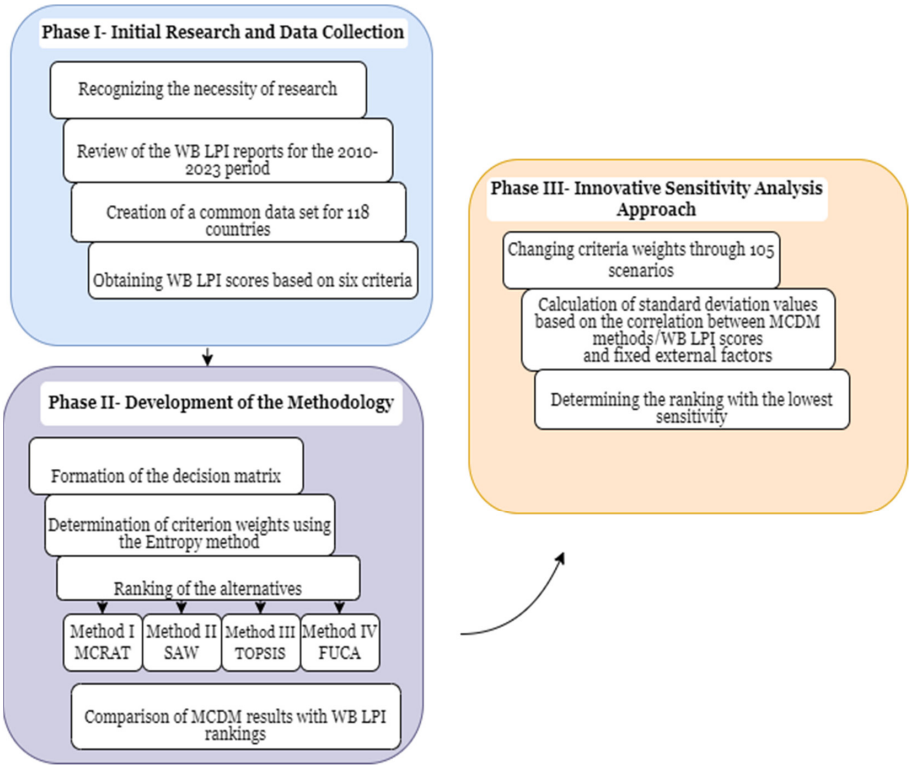


Figure 1. Flowchart of the proposed methodology.

Table 1. Explanations of the LPI indicators.

Indicators	Descriptions
Customs (C1)	The effectiveness of customs and border management processes.
Infrastructure (C2)	The standard of infrastructure related to trade and transportation
International Shipments (C3)	The convenience of organizing cost-effective international shipments
Logistics Competence and Quality (C4)	The skill and excellence of logistics services
Timeliness (C5)	The capability to monitor and trace shipments
Tracking and Tracing (C6)	The rate at which shipments arrive at their destinations within the promised or anticipated delivery timeframe

Source: [11].

4.1. Prioritization of Criteria Using the Entropy Method

The steps of the Entropy method (Equations (1)–(4)) were applied individually to six decision matrices to determine the criteria weights, and the results are displayed in Table 2.

Table 2. Criteria weights.

		C_1	C_2	C_3	C_4	C_5	C_6
2010	w_j	0.1993	0.2650	0.0914	0.1783	0.1712	0.0948
2012		0.1815	0.2376	0.1289	0.1747	0.1705	0.1067
2014		0.1942	0.2309	0.1167	0.1659	0.1595	0.1329
2016		0.1813	0.2242	0.1315	0.1712	0.1814	0.1105
2018		0.1807	0.2258	0.1268	0.1804	0.1743	0.1121
2023		0.1776	0.2271	0.1176	0.1687	0.1214	0.1876

According to the criterion weights determined by the Entropy method, as presented in Table 2 and Figure 2, for all the years covered in this study, the criterion with the highest importance is C2 ("Infrastructure").

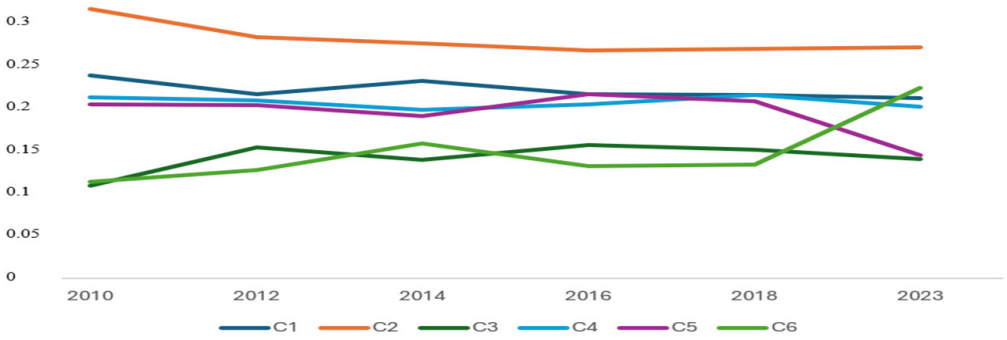


Figure 2. Importance of criteria weights between 2010 and 2023.

4.2. Ranking Alternatives Using the MCDM Methods

In the second stage of the proposed model, the MCRAT, SAW, TOPSIS, and FUCA methods were employed to evaluate the alternatives. In this section, since each criterion range in the decision matrix is the same or the value range is narrow (scores between 1 and 5), the analyses were performed without normalization. In this context, the MCDM results obtained using various normalization techniques were first compared with the non-normalized MCDM results, revealing a strong correlation between the two. In this section, to avoid any complexity due to the large number of outputs, only the MCRAT results will be presented.

As shown in Table 3, there is a very high correlation between the MCRAT results obtained using different normalization techniques and those without normalization. Moreover, a full correlation was observed between the results generated using the max normalization technique and the non-normalized MCRAT results. A similar situation applies to the other MCDM methods used in this study as well. These findings suggest that, for this study, normalization is not necessary when applying the MCDM methods. In this context, the MCRAT method steps (Equations (7)–(16)) were applied sequentially.

Table 3. The correlation coefficients between the normalized and non-normalized MCRAT results.

		Max-Based MCRAT	Sum-Based MCRAT	Vector-Based MCRAT	Peldschus-Based MCRAT
Non-Normalized MCRAT	2010	1	0.9999	0.9999	0.9947
	2012	1	0.9999	1	0.9950
	2014	1	0.9999	0.9999	0.9959
	2016	1	1	1	0.9943
	2018	1	1	1	0.9957
	2023	1	0.9999	1	0.9959

In 2010, Germany, the Netherlands, and Singapore were the leading countries in logistics performance, while Cuba, Rwanda, and Guinea-Bissau were at the bottom of the rankings. In 2012, Singapore, Hong Kong SAR, China, and Germany achieved the highest LPI scores, whereas Haiti, the Republic of Congo, and Djibouti recorded the lowest scores. For 2014, Germany, the Netherlands, and Singapore continued to lead, while Afghanistan, the Republic of Congo, and the Democratic Republic of Congo were at the bottom. In 2016, Germany, Sweden, and the Netherlands occupied the top positions, with Lao PDR, Haiti, and the Syrian Arab Republic at the lowest ranks. By 2018, Germany, Japan, and Sweden emerged as the top performers among 118 countries, while Haiti, Angola, and Afghanistan were ranked the lowest. In 2023, Singapore, Switzerland, and Finland exhibited the highest logistics performance, while Cameroon, Afghanistan, and Libya were at the bottom of the rankings. In the 2010 World Bank LPI report, Germany emerges as the top-performing country with an LPI score of 4.13. Singapore and Sweden follow Germany with LPI scores of 4.10 and 4.09, respectively. Rwanda, Cuba, and Guinea-Bissau occupy the bottom three ranks with LPI scores of 2.04, 2.68, and 2.10, respectively. For 2012, the top three were Singapore, Hong Kong, and Finland, whereas the lowest three were Djibouti, Haiti, and the Republic of Congo. Based on the 2014 results, Germany, the Netherlands, and Belgium emerged as the leading countries, while the Democratic Republic of Congo, the Republic of the Congo, and Afghanistan were among the poorest performers. In 2016, Germany, Luxembourg, and Sweden were the top three performers with LPI scores of 4.23, 4.22, and 4.2, whereas the Syrian Arab Republic, Haiti, and Tajikistan were at the opposite end of the spectrum with LPI scores of 1.6, 1.72, and 2.06. The 2018 results showed Germany, Sweden, and Belgium as high-performing countries, while Afghanistan, Angola, and Haiti were the lowest-performing. For 2023, Singapore and Finland occupied the top two positions, with Denmark, Germany, the Netherlands, and Switzerland sharing the third place. Cuba, Angola, Cameroon, Haiti, Afghanistan, and Libya were classified as the lowest-performing countries.

The rankings from MCRAT, SAW, TOPSIS, and FUCA generally differ from the LPI rankings; however, the position of the top-ranked alternative has remained unchanged. Specifically, for the years 2010, 2014, 2016, and 2018, Germany has been the top-ranked country across all methods. In 2012 and 2023, Singapore was the highest-performing alternative in all rankings. The six-year averages of the rankings from the four MCDM methods and the LPI are presented in Figure 3.

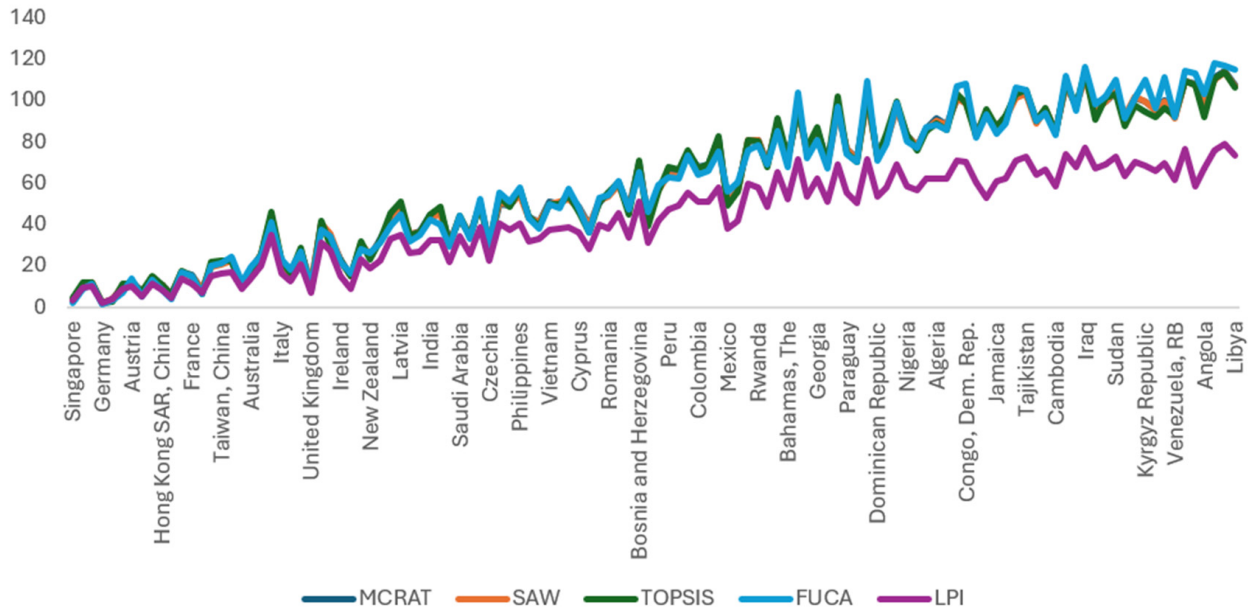


Figure 3. The six-year average of the rankings from the four MCDM methods and the LPI for different countries.

Figure 3 reveals that the rankings obtained using MCDM methods are very similar to each other. Although the MCDM and LPI rankings show a consistent trend, the country rankings differ between the two approaches. Despite some variations in the results averaged over six years, a notable common finding is that Germany consistently ranks first across all rankings, while Afghanistan is positioned at the bottom in each case.

5. An Innovative Robustness and Reliability Analysis

To validate the proposed integrated model, the impact of altering the criterion weights on the ranking results was examined. In this context, by adjusting the weight of each criterion, 105 scenarios were created to assess their effects on the preference levels of the alternatives. In previous studies, some researchers have modified the weight of the most important criterion [58], interchanged criterion weights [59,60], or made certain criteria more significant [60]. This study, however, considers the impact of all criteria on the results. The criterion weights presented in Table 4 were analyzed separately for six different sets and across four different MCDM methods to perform a comparative analysis, resulting in a total of over 2500 outcomes.

Table 4. Criterion weights for different scenarios.

	C_1	C_2	C_3	C_4	C_5	C_6
s1	0.34	0.21	0.21	0.08	0.08	0.08
s2	0.34	0.21	0.08	0.21	0.08	0.08
s3	0.34	0.21	0.08	0.08	0.21	0.08
s4	0.34	0.21	0.08	0.08	0.08	0.21
s5	0.37	0.23	0.1	0.1	0.1	0.1
s103	0.12	0.12	0.12	0.26	0.26	0.12
s104	0.12	0.12	0.12	0.26	0.12	0.26
s105	0.12	0.12	0.12	0.12	0.26	0.26

In this section, the degree, direction, and nature of sensitivity are examined using the innovative sensitivity analysis approach proposed by [13]. According to this approach, low sensitivity (as indicated by standard deviation) in MCDM rankings corresponds to a high correlation (rho) with a fixed external factor. However, it is important to acknowledge that sensitivity is influenced by various components, including the selected MCDM method, the characteristics of the problem, the type of data, and the weighting coefficients within the MCDM framework [31] However, while an external ranking was used in these studies, we determined an internal fixed factor. Thus, it eliminates the difficulty for decision-makers to search for an external factor in sensitivity analysis. We preferred Entropy-based MCDM as an external factor. We focused on the motion and sensitivity of the entire sequence because we considered that some approaches that consist of simply observing the best alternative in the literature may be shallow and inaccurate. Moreover, we preferred to focus on the motion and sensitivity of the entire sequence, as we thought that some approaches in the literature that consist solely of observing the best alternative may be superficial and inaccurate.

Accordingly, the impact of different weighting techniques on the results of the MCRAT method was assessed, using the Entropy-MCRAT results as the fixed external factor. In the first stage of the analysis, the MCRAT results obtained from 105 scenarios were compared with the Entropy-MCRAT results. For the SAW, TOPSIS, and FUCA results, the Entropy-SAW, Entropy-TOPSIS, and Entropy-FUCA rankings were considered as fixed factors. Additionally, the average correlations between the external fixed factor and the methods are presented in Table 5.

Table 5. Results obtained from the standard deviation of correlations between fixed factors and methods.

Years		MCRAT	SAW	TOPSIS	FUCA
2010	Mean	0.9794	0.9943	0.9828	0.9928
	StDv	0.0162	**0.0039**	0.0129	0.0048
2012	Mean	0.9899	0.9967	0.9902	0.9970
	StDv	0.0106	0.0074	0.0103	**0.0018**
2014	Mean	0.9886	0.9968	0.9892	0.9969
	StDv	0.0071	0.0019	0.0068	**0.0016**
2016	Mean	0.9926	0.9979	0.9929	0.9978
	StDv	0.0042	0.0011	0.0038	**0.0010**
2018	Mean	0.9900	0.9972	0.9896	0.9969
	StDv	0.0064	**0.0016**	0.0064	**0.0016**
2023	Mean	0.9875	0.9964	0.9886	0.9963
	StDv	0.0087	**0.0023**	0.0076	**0.0023**

Table 5 above is the first sign of interesting findings. The change in sensitivity results depending on the dataset shows that researchers who will conduct sensitivity analysis need to use very large datasets if they want to see the ultimate winner. When evaluating the results presented in Table 5 and Figure 4 on an annual basis, the methods with the highest and lowest average scores for 2010 are SAW and MCRAT, respectively. According to the standard deviation values, the ranking of methods is as follows: MCRAT> TOPSIS> FUCA> SAW. The SAW method, with the lowest standard deviation, exhibits the least sensitivity and the highest correlation with the constant factor (Entropy-SAW). Conversely, the MCRAT method, with the highest standard deviation, is the most sensitive and shows the lowest correlation with the constant factor. For 2012, the results indicate that FUCA and MCRAT have the highest and lowest averages, respectively. The FUCA method, which has the lowest standard deviation, demonstrates the least sensitivity and the highest correlation with the constant factor, whereas MCRAT has the highest standard deviation. In 2014, FUCA showed the highest averages, while MCRAT had the lowest. The FUCA method was identified as the method with the least sensitivity, whereas MCRAT was the most sensitive. For 2016, FUCA and MCRAT were again identified as having the highest and lowest averages, respectively. FUCA, with a standard deviation of 0.0010, is the method with the

least sensitivity, while MCRAT remains the most sensitive method. In 2018, TOPSIS had the lowest averages compared to other methods, while SAW had the highest. The SAW and FUCA methods also exhibit the lowest sensitivity (σ: 0.0016) and the highest correlation with the constant factor. Finally, for 2023, the SAW method maintained the highest average and MCRAT the lowest, consistent with previous years. The SAW and FUCA methods are identified as the methods with the least sensitivity, while MCRAT remains the most sensitive method.



Figure 4. Mean and standard deviation values between the fixed factors and methods.

Figure 4 shows how the sensitivity of each method changes among datasets from different years. Here, the FUCA and SAW methods are in a neck-and-neck competition. However, SAW's performance in 2012 does not look good. This shows how the diversity of the dataset affects the sensitivity. Obviously, methodologists may make mistakes in their interpretations when they use a single dataset and a small number of weighting coefficients.

We will try to obtain the big picture by combining data step-by-step and finding the truth in large datasets. Freeing sensitivity from data noise should be an important step for sensitivity methodologists. In the second stage of the analysis, the average of the standard deviation values obtained for six different years, based on each method, was calculated and is presented in Table 6.

Table 6. Mean standard deviations based on MCDM methods.

Years	MCRAT	SAW	TOPSIS	FUCA
2010	0.0162	0.0039	0.0129	0.0048
2012	0.0106	0.0074	0.0103	0.0018
2014	0.0071	0.0019	0.0068	0.0016
2016	0.0042	0.0011	0.0038	0.0010
2018	0.0064	0.0016	0.0064	0.0016
2023	0.0087	0.0023	0.0076	0.0023
Mean	0.0089	0.0030	0.0080	**0.0022**

According to the results presented in Table 6 and Figure 5, which display the averages of standard deviation values across six different years, the methods can be ranked as follows: MCRAT > TOPSIS > SAW > FUCA. MCRAT is identified as the method with the highest sensitivity, while FUCA exhibits the lowest sensitivity and, consequently, the highest correlation with the constant factor. Similarly, the SAW method is categorized among the low-sensitivity methods, whereas the TOPSIS method, like MCRAT, is determined to be highly sensitive.

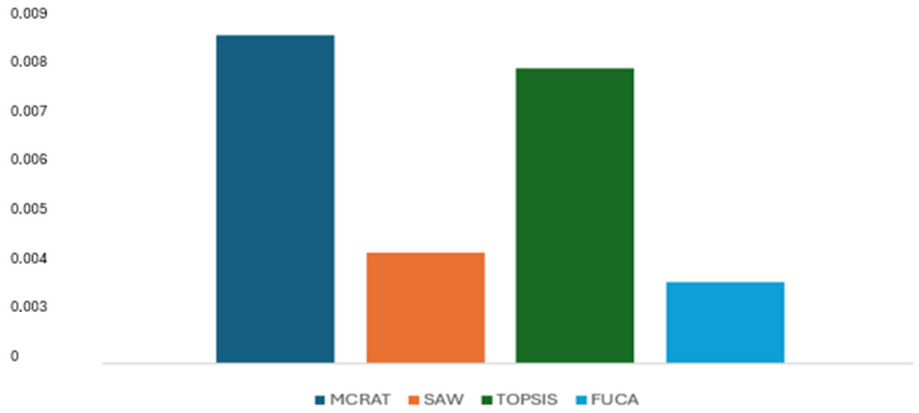


Figure 5. Mean standard deviations based on MCDM methods.

6. Discussion

In this paper, a combined dataset was created using LPI data published by the World Bank for the years 2010 to 2023, and the logistics performance of 118 countries was assessed utilizing a combined MCDM approach. The Entropy method was employed to determine the weights of the criteria. Infrastructure (C2) was recognized as the most crucial criterion for all years. This conclusion aligns with comparable findings in the literature, where [39] also identified "Infrastructure" as the key criterion. In addition, ref. [12] also determined "Infrastructure" to be the criterion with the highest significance. In Çalık et al.'s [41] study, which evaluated the logistics performance of 160 OECD countries, "Infrastructure" was again identified as the most important criterion. Similarly, ref. [50] determined "Infrastructure" to be the most important criterion, with criterion weights calculated using the Entropy method. Additionally, in the study conducted by [4], "Infrastructure" was also identified as the criterion with the highest importance. Furthermore, ref. [40] used 11 different MCDM techniques to assess the logistics performance of EU countries, and criterion weights were determined using genetic algorithms (GA). That study concluded that "Infrastructure" was the most important criterion.

The performance scores of the alternatives were determined using four MCDM methods: MCRAT, SAW, TOPSIS, and FUCA. Combining MCDM methods that are based on different theoretical principles can result in a more robust and complete decision-making process than using a single method [61]. Although there are minor variations in the results obtained from different MCDM methods, the position of the top-ranked alternative remained unchanged, and the correlation coefficients between the method results were high on a yearly basis. Specifically, Germany was in the top position for the years 2010, 2014, 2016, and 2018, while Singapore maintained the top position in 2012 and 2023. The countries ranked in the top five and bottom five positions, based on the six-year average of the MCDM and LPI rankings, are presented in Table 7.

Table 7. Countries with the highest and lowest logistics performance based on different rankings.

Rank	MCRAT	SAW	TOPSIS	FUCA	LPI
1.	Germany	Germany	Germany	Germany	Germany
2.	Singapore	Singapore	Netherlands–Singapore	Singapore	Singapore
3.	Netherlands	Netherlands	Sweden	Netherlands	Netherlands
4.	Sweden	Sweden	Belgium	Sweden	Sweden
5.	Belgium	Belgium	Japan	Belgium	Belgium
	.	.	.	.	.
	.	.	.	.	.
	.	.	.	.	.
114.	Angola	Angola	Angola–Libya–Gabon	Cuba	Gabon
115.	Cuba	Cuba	Cuba	Libya	Haiti
116.	Haiti	Haiti	Haiti	Iraq	Cuba
117.	Iraq	Iraq	Iraq	Afghanistan	Iraq

According to Table 7, the MCDM methods and LPI rankings are largely similar, though some minor differences exist. The most significant common result is that Germany ranks first across all rankings. This result is consistent with the findings of previous studies. For example, ref. [42] ranked Germany first in his analysis of the logistics performance of OECD countries in 2016, utilizing the improved TODIM method. In their study employing the MEREC-MARCOS model, ref. [37] identified that Germany possessed the highest LPI score. Using the PIV-SWARA-CRITIC model, ref. [39] also determined that Germany achieved the highest ranking. Furthermore, ref. [12] examined the logistics performance of OECD countries between 2010 and 2018 employing fuzzy AHP and ARAS-G methods, with Germany securing the top position. In addition, ref. [51] evaluated the logistics performance of EU and OECD countries for the period from 2010 to 2018, utilizing the COPRAS and COPRAS-G methods, and again ranked Germany as the leading country. Finally, ref. [52] measured the logistics performance of OECD countries using the SWARA-EDAS model, integrating results from the WB LPI from 2012 to 2018, and identified Germany as the highest-performing country.

In the third stage of this study, applying the innovative sensitivity analysis approach as described in Section 5, the impact of the criterion weights created in 105 scenarios on the results of the MCDM methods was tested, considering the fixed external factor. The Entropy-based MCRAT-SAW-TOPSIS-FUCA rankings were used as the fixed factors for the MCRAT, SAW, TOPSIS, and FUCA methods, respectively, and standard deviation values were calculated using the correlations among the rankings. In this section, World Bank LPI scores are included in these calculations. As previously mentioned, the World Bank determines the LPI values by assigning equal weights to the indicators and calculating their weighted totals. We designated the Entropy-LPI scores as a fixed factor and obtained standard deviation values by comparing them with the LPI results derived from 105 different sets of weights. Consequently, the Entropy-LPI and Entropy-SAW analyses involve similar analytical processes and can be assessed under the same category.

Figure 6 presents the six-year averages of the standard deviation values based on the rankings obtained from MCDM methods and the LPI. With an average standard deviation of 0.009, the MCRAT method was identified as the most sensitive method. It was followed by TOPSIS ($\sigma = 0.008$), SAW/LPI ($\sigma = 0.003$), and FUCA ($\sigma = 0.002$), respectively. Among all the rankings, the FUCA method was identified as the least sensitive method. In other words, it was determined that FUCA has the highest correlation with the fixed factor. As a result, we recommend the FUCA method to decision-makers for the calculation of LPI rankings because it is simple, practical, has low compensatory power, and has low sensitivity.

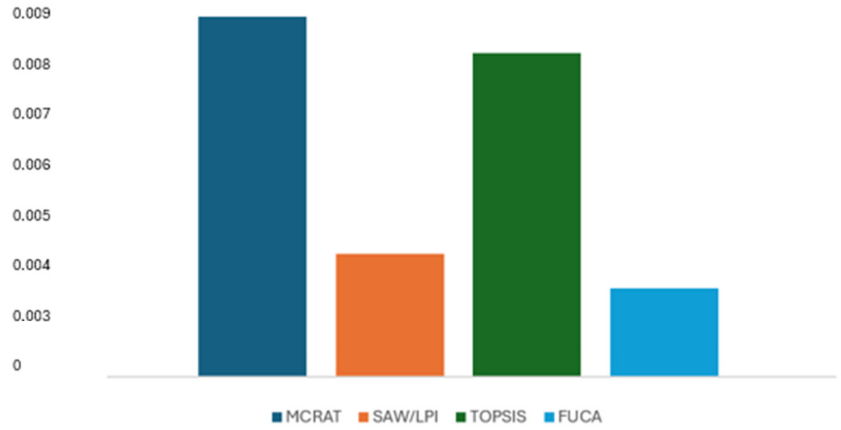


Figure 6. Mean standard deviations based on MCDM methods and LPI ranking.

7. Conclusions

This study aims to assess the logistics performance of 118 countries using a MCDM approach, specifically the Entropy-MCRAT model, based on six criteria defined by the World Bank for the years 2010–2023. According to the Entropy method criterion weight results, "Infrastructure" (C2) emerged as the most significant criterion across all years, while the least important criteria were "International Shipments" (C3) for the years 2010, 2014, and 2023, and C6 for the years 2012, 2016, and 2018.

The results of the Entropy-MCRAT model indicate that, in 2010, Germany, the Netherlands, and Singapore ranked in the top three positions, while Cuba, Rwanda, and Guinea-Bissau occupied the bottom three. For 2012, Singapore, Hong Kong SAR, China, and Germany had the highest LPI scores, while Haiti, the Republic of Congo, and Djibouti ranked lowest. In 2014, Germany, the Netherlands, and Singapore were again among the top three, whereas Afghanistan, the Republic of Congo, and the Democratic Republic of Congo had the lowest LPI scores. In 2016, Germany, Sweden, and the Netherlands ranked highest, while Lao PDR, Haiti, and the Syrian Arab Republic had the lowest performance. By 2018, Germany, Japan, and Sweden were the top performers among 118 countries, while Haiti, Angola, and Afghanistan had the lowest LPI scores. In 2023, Singapore, Switzerland, and Finland had the highest logistics performance, while Cameroon, Afghanistan, and Libya ranked at the bottom.

To validate the proposed methodology, a recently proposed innovative sensitivity analysis approach was applied. As part of this analysis, the impact of different weighting techniques on MCRAT results was assessed, with the Entropy-MCRAT scores treated as a fixed external factor. In this context, the influence of varying criterion weights on MCRAT results was tested across 105 scenarios. A similar analysis was conducted as part of the comparative analysis for the SAW, TOPSIS, and FUCA methods, yielding over 2.500 outputs. In this section, the Entropy-based SAW-LPI rankings, which share similar computational procedures, have been evaluated within the same category. The findings demonstrated that the method with the lowest standard deviation exhibited a high correlation with the fixed external factor. Based on this information, while the SAW/LPI ranking was identified as the least sensitive compared to other methods in 2010, FUCA outperformed all other rankings when considering all years. Conversely, MCRAT exhibited the worst performance across all years.

This study's contributions to the literature are as follows: (i) The Entropy-MCRAT model has been applied to logistics performance assessment for the first time. (ii) It has been demonstrated that non-normalized results from the MCRAT, SAW, TOPSIS, and FUCA methods are as accurate as normalized results. (iii) An extensive comparative assessment of the logistics performance of various countries was conducted based on six years of data published by the World Bank. (iv) The proposed methodology was validated using an innovative sensitivity analysis approach. (v) Through an extensive sensitivity analysis,

the impact of criterion weights on MCRAT results was examined across 105 scenarios. Additionally, the analyses were repeated for the SAW, TOPSIS, and FUCA methods in the comparative analysis. (vi) The findings are anticipated to assist policymakers and businesses, providing a useful resource for comprehending a country's standing in global competition. Moreover, this study is anticipated to provide a reference for researchers evaluating the logistics performance of countries.

This study presents a methodology that enables countries to assess various logistics infrastructure projects, thereby aiding decision-makers in identifying the project that would most effectively improve overall logistics performance. Moreover, the proposed model can be applied to optimize supply chain processes, facilitating the selection of the most appropriate suppliers and resulting in lower logistics costs and enhanced service quality. Additionally, governments can leverage this approach when formulating strategies to boost logistics performance. For example, during the prioritization of infrastructure investments or the evaluation of logistics regulations, impact analyses can be performed to determine the most effective strategies.

However, this study has some limitations. For example, the number of countries reported in the LPI reports published by the World Bank varies by year. In this study, a common data pool was established, and 118 countries were included in the analysis to enable comparability of alternatives. The findings are applicable only to these 118 countries and do not encompass other countries covered by the LPI. Additionally, the year 2007 was excluded from the analysis due to data constraints. Future research could include a larger number of countries based on different samples and assess the logistics performance of countries using a combination of subjective and objective MCDM methods.

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Nomenclature

LPI	Logistics Performance Index
MCDM	Multi-Criteria Decision-Making
MCRAT	Multiple Criteria Ranking By Alternative Trace
SAW	Simple Additive Weighting
TOPSIS	Techniques For Order Preference By Similarity To An Ideal Solution
FUCA	Faire Un Choix Adéqua
CRITIC	Criteria Importance Through Inter-Criteria Correlation
MARCOS	Measurement Of Alternatives And Ranking According To A Compromise Solution
OECD	The Organisation For Economic Co-Operation And Development
CEE	Central and Eastern European
MABAC	Multi-Attributive Border Approximation Area Comparison
AHP	Analytic Hierarchy Process
ARAS-G	Grey Additive Ratio Assessment
BWM	Best Worst Method
SWARA	The Stepwise Weight Analysis Ratio Assessment

MOORA	Multi-Objective Optimization On The Basis Of Ratio Analysis
DEA	Data Envelopment Analysis
MEREC	Method Based On The Removal Effects Of Criteria
EU	European Union
COPRAS	Complex Proportional Assessment
FCM	Fuzzy C-Means Clustering
GDP	Gross Domestic Product
ARAS	Additive Ratio Assessment
ROV	Range Of Value
GA	Genetic Algorithm
TODIM	Tomada De Decisão Iterativa Multicritério
WB	World Bank

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