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Operational Performance in Global Maritime Freight Transport: A Multi-Criteria Analysis of Selected Countries

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ABSTRACT

A general review of the literature reveals that performance in maritime freight transport is examined from various dimensions, such as port efficiency, transport costs, trade volume, operational times and infrastructure characteristics. Whilst econometric studies highlight the economic impacts of performance, multi-criteria analyses enable the integrated assessment of various indicators. However, it is evident that a significant proportion of studies focus on container ports or specific cargo types, whilst country-level comparisons predominantly utilise cargo volume and infrastructure indicators. Unlike the approaches discussed in the literature, this study evaluates the maritime freight transport performance of 22 countries using nine operational indicators relating to container, dry bulk and liquid bulk vessels. The combined analysis of vessels' median port dwell times, average carrying capacities and number of port calls enables a comparison of the operational characteristics of different modes of transport at the country level. In this respect, the study is expected to contribute to a multidimensional assessment of operational performance in maritime freight transport. In the study, the criterion weights were objectively determined using the LOPCOW and CRITIC methods and combined using the geometric mean, whilst the countries were ranked using the STENOZA method, which is based on triple normalisation. According to the findings, criteria relating to port dwell time accounted for approximately 45 per cent of the total weighting, with the dwell time of liquid bulk carriers being the most significant criterion. In the assessment based on 2023 data, China, Japan and Canada emerged as the countries with the highest performance, whilst the Philippines, Russia and Indonesia ranked at the bottom. Türkiye was ranked 18th because the port dwell times for both dry and liquid bulk carriers were above the sample mean. The consistency of the results was confirmed by a comparison using five different multi-criteria decision-making methods (Spearman ρ = 0.854–0.983), a weight sensitivity analysis involving 90 scenarios (average ρ = 0.995), a rank reversal test and a stability analysis covering the period 2018–2023 (Kendall's W = 0.969).

1. Introduction

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Examining the effects of recent crises in the global economy and, in particular, the disruptions experienced in maritime transport on national economies is of great importance in today's economic climate. As one of the fundamental elements of international trade, maritime transport holds a strategic position in the functioning of the global economic system. Given that approximately 90 per cent of world trade is conducted by sea, the importance of this mode of transport for the global economy becomes even more evident. From a national perspective, maritime transport should not be regarded merely as a logistical activity. This activity plays a decisive role in numerous areas, including international trade balances, industrial production, employment, the sustainability of supply chains and energy security. When viewed in a historical context, the efforts of coastal nations to transform their ports into key logistics hubs are particularly noteworthy. In particular, countries that have developed their ports in line with contemporary requirements, equipping them with the infrastructure to carry out fourth- and fifth-party logistics activities in an integrated manner, are able to gain a competitive advantage in global trade.

When making investment decisions, multinational companies take into account not only countries' economic and structural indicators but also indicators such as the Logistics Performance Index (LPI), which reflects the quality of logistics infrastructure and services. This highlights the importance of countries' logistics performance in terms of international investment decisions and global competitiveness. Maritime transport, one of the fundamental components of logistics activities, and ships, which are among the most important actors in this process, form the core focus of this study. Countries with coastlines can gain significant competitive advantages in international trade if they support their geographical advantages with effective port infrastructure, advanced logistics services and technological investment.

Maritime transport and the ports at the heart of these transport activities occupy an indispensable position in the functioning of the global economic system. However, countries may differ in terms of how they perceive and manage logistics processes. Viewing logistics as merely transport activities can lead to significant differences in countries' logistics performance and economic competitiveness. Today, the concept of logistics is evolving beyond traditional transport and warehousing activities to encompass fifth- and sixth-party logistics applications, moving towards technology- and data-driven smart logistics systems.

The Port of Shanghai serves as an example of this transformation. The management of data regarding which ships the containers handled at the port are to be loaded onto, which countries they are to be sent to, and the characteristics of the cargo they carry highlights the importance of advanced information and communication technologies and smart logistics systems. Smart logistics systems encompass the processes of collecting, storing, analysing and transforming large volumes of data into meaningful information. In this process, the effective use of technology is just as important as the development of new technologies and their integration into logistics operations.

Consequently, cargo handling and processing times at ports, the efficiency and speed of customs procedures, the quality of port infrastructure, vessels' waiting times at ports and their cargo-carrying capacities are among the key factors determining countries' maritime transport performance. This study aims to determine countries' performance in the fields of maritime transport and port logistics by addressing these factors through a holistic approach. To this end, multi-criteria decision-making (MCDM) methods are utilised to compare the current status of ships in terms of their waiting times at ports and cargo capacities, and to identify the countries that stand out in terms of performance.

1.1 Literature Review

The evaluation of operational performance in maritime freight transport is important for understanding countries' positions within the international transport system and the efficiency of their operations. Accordingly, the aim of the literature review is to examine studies on the measurement of operational performance in maritime transport, to evaluate the indicators and methods used, and to establish the position of the present study within the literature. Within this scope, studies relating to port efficiency, vessel dwell times, transport capacities, port calls and multi-criteria performance evaluations have been examined.

A significant portion of the studies on measuring port performance focuses on the efficiency of resource utilisation. Tongzon [1], by comparing selected ports in Australia and other countries using data envelopment analysis (DEA), determined that ports with similar resources can operate at different levels of efficiency. Bichou and Gray [2] emphasised that port performance should not be assessed solely on the basis of physical and financial indicators, and proposed a logistics and supply chain-focused approach. Cullinane et al. [3], on the other hand, examined the technical efficiency of container ports using DEA and stochastic frontier analysis methods and found a high degree of correlation between the results obtained from the different methods. These studies demonstrate the importance of the indicators and analytical methods used in measuring port performance on the results.

Research examining the economic impacts of port efficiency focuses particularly on transport costs. Sánchez et al. [4], in their econometric analyses based on Latin American ports, demonstrated that port efficiency is one of the key determinants of maritime transport costs. Clark et al. [5] established that improvements in port efficiency can reduce transport costs and, consequently, support international trade. Blonigen and Wilson [6] also demonstrated that there is a positive relationship between port efficiency and trade flows. Similarly, Wilmsmeier and Hoffmann [7], by examining the effects of regular liner services and port infrastructure on freight rates in the Caribbean region, highlighted the importance of maritime connections in terms of transport costs.

The relationship between port efficiency and international trade has been examined in subsequent studies using various econometric approaches. Chang et al. [8], by analysing 23 major container ports in China, found that improvements in port efficiency had a positive impact on international trade, using DEA and a gravity model. Munim and Schramm [9], in their structural equation modelling analysis using data from 91 countries, demonstrated that port infrastructure can contribute to economic growth via logistics performance and maritime trade. Ayesu et al. [10], by analysing data from 28 African countries for the period 2010–2018 using the system generalised method of moments (GMM), demonstrated that port efficiency and cargo volume are positively correlated with economic growth. Ayesu et al. [11], in their analysis covering 33 African countries, determined that an increase in port efficiency has a positive impact on foreign trade performance. These findings indicate that, in addition to the operational dimension of port performance, its economic outcomes must also be taken into account.

One of the key indicators of operational performance in maritime transport is the time vessels spend in port. Notteboom [12], in an examination of time management in liner shipping, noted that port congestion and operational delays affect the reliability of sailing schedules. Moon and Woo [13], in their system dynamics-based analysis, demonstrated that port operations are a determining factor in vessel operating costs and environmental impacts. Smith [14], by analysing vessel call data for container ports in the US, determined that port dwell time is more closely related to the scale of loading and unloading activities at the relevant port of call than to vessel capacity. Russo et al. [15], meanwhile, demonstrated in their regression analyses covering selected European ports that vessel capacity and port characteristics influence port dwell times.

The number of port calls and a port's position within transport networks are also important factors in assessing operational performance. Ducruet and Notteboom [16], by examining the spatial structure of the global container transport network, demonstrated that ports' connections and their positions within the network can change over time. Ducruet and Itoh [17] investigated the determinants of port dwell times using comprehensive vessel movement data for approximately 2,300 container ports. The study found that factors such as port connectivity, call counts and economic development are associated with operational dwell times. The findings reveal that port calls serve as an indicator reflecting not only the intensity of activity but also a port's position within the transport network.

Vessel size and carrying capacity are other factors that must be taken into account when assessing operational performance. Whilst large vessels can provide economies of scale, they may also impose higher demands in terms of port infrastructure and operational planning. Moon and Woo [13] and Russo et al. [15] have shown that the operational outcomes of vessel capacity must be assessed in conjunction with the service characteristics of ports. Ducruet and Itoh [17], on the other hand, have found that large vessels can, under certain conditions, increase their dwell times at port. Therefore, rather than evaluating average vessel capacity as a standalone indicator of efficiency, analysing it in conjunction with dwell times and the number of calls may yield more comprehensive results.

Time performance in port operations is not limited solely to the time vessels spend in port. Saini and Lerher [18] examined the factors influencing container waiting times within the port area, using approximately 2.8 million container records from 14 major ports. The study revealed that factors such as free waiting times, transhipment port characteristics and rail connections are decisive in container waiting times. However, the time containers spend within the terminal area and the time ships spend in port represent different operational processes. This distinction necessitates the clear definition of variables when selecting performance indicators.

It is observed in the literature that operational performance studies have largely focused on container transport, whilst other cargo types have been addressed to a more limited extent. Kutin et al. [19] compared 50 container ports and terminals in the ASEAN region using the DEA method and determined that the ports exhibited varying levels of efficiency. Efecan [20] examined the efficiency of 21 dry bulk and general cargo terminals in Türkiye over the 2018–2021 period using the interval DEA method and revealed performance differences between regions. Doymuş and Kaptan [21], focusing on liquid bulk cargo transport, analysed the port operations of crude oil tankers using Bayesian networks, demonstrating the significance of bottlenecks in ship–shore facility interactions on unproductive times. These studies demonstrate that operations involving different cargo types possess their own distinctive characteristics and that these differences must be taken into account in performance evaluations.

The evaluation of operational performance using multiple indicators has led to the widespread use of multi-criteria decision-making methods in port research. Kim [22] assessed the competitiveness of selected ports in China and South Korea using the Entropy and TOPSIS methods, identifying the ports of Shanghai, Shenzhen and Busan as the leading performers. Gök-Kısa et al. [23] compared the performance of five privatised ports in Türkiye using the Entropy, TOPSIS and ARAS methods and identified the Port of Mersin as the alternative with the highest performance. In another country-level study, Alişar Kayar and Avşar [24] examined the port performance of 24 European Union countries over the 2014–2023 period by integrating the grey system-based EDAS and ARAS methods with the fuzzy analytic hierarchy process. The study identified Italy, Spain, the Netherlands and Germany as high-performing countries. These studies demonstrate that multi-criteria methods can be used in comparisons at both port and country levels. However, it should be

borne in mind that the criteria used and the weighting approaches may influence the performance rankings.

The studies reviewed above reveal three gaps. First, operational performance research has concentrated largely on container ports, while dry bulk and liquid bulk operations have been examined separately and less often. Second, country-level comparisons rely mainly on cargo volume and infrastructure indicators rather than on vessel-level operational measures such as port dwell time. Third, multi-criteria studies of port performance frequently use Entropy-based weights, which can be dominated by scale-dependent and highly skewed indicators such as the number of port calls. Addressing these gaps is important because port dwell time directly affects transport costs, schedule reliability and the competitiveness of national supply chains. Accordingly, the objective of this study is to evaluate the operational maritime performance of 22 countries using nine indicators covering container, dry bulk and liquid bulk vessels, by combining LOPCOW and CRITIC objective weights and ranking the countries with the recently proposed STENOZA method. The robustness of the results is examined through a comparison with five other MCDM methods, a weight sensitivity analysis, a rank reversal test and a multi-period stability analysis.

2. Methodology

This section describes a three-stage decision model developed to evaluate port performance in maritime transport across 22 countries. In the first stage, criterion weights were calculated separately using two objective methods: LOPCOW and CRITIC. In the second stage, these two weight vectors were combined into a single vector using the geometric mean. In the third stage, countries were ranked using the STENOZA method, which is based on triple normalisation. At the end of the section, statistical measures used to test the validity and robustness of the results are provided. Throughout the methods, $i = 1,2, \dots, m$ refers to the alternatives (countries), whilst $j = 1,2, \dots, n$ refers to the criteria.

2.1 The LOPCOW Method (Logarithmic Percentage Change-Driven Objective Weighting)

LOPCOW is an objective weighting method proposed by Ecer and Pamucar [25]. The method divides the root mean square of the normalised values of each criterion by their standard deviation and takes the logarithmic percentage of this ratio as the information power of the criterion. The logarithmic transformation limits the dominance of criteria with skewed distributions in the weight vector. This feature is crucial for this study, which includes indicators such as the number of port calls, which can vary by several hundredfold depending on the scale of the country.

Step 1. The decision matrix is constructed. In Eq. (1), x_{ij} represents the performance value of the j criterion for the i alternative, m represents the number of alternatives, and n represents the number of criteria.

$$X = \left[x_{ij}\right]_{m \times n} \tag{1}$$

Step 2. The decision matrix is normalised using the min-max method. Eq. (2) is used for benefit-oriented criteria, and Eq. (3) is used for cost-oriented criteria.

$$r_{ij} = \frac{x_{ij} - min_i\, x_{ij}}{max_i\, x_{ij} - min_i\, x_{ij}}, \quad j \in B \tag{2}$$

$$r_{ij} = \frac{max_i\, x_{ij} - x_{ij}}{max_i\, x_{ij} - min_i\, x_{ij}}, \quad j \in C \tag{3}$$

Here, B represents the set of benefit-oriented criteria, and C represents the set of cost-oriented criteria.

Step 3. The percentage value PV_j for each criterion is calculated using Eq. (4). σ_j is the population standard deviation defined in Eq. (5); μ_j is the arithmetic mean of the normalised values for the criterion j.

$$PV_j = |\, ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} {r_{ij}}^2}{m}}}{\sigma_j}\right) \times 100| \tag{4}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} \left(r_{ij} - \mu_j\right)^2}{m}}, \quad \mu_j = \frac{1}{m}\sum_{i=1}^{m} r_{ij} \tag{5}$$

Step 4. The LOPCOW weight of each criterion is obtained by dividing its percentage value by the sum of the percentage values of all criteria.

$$w_j^L = \frac{PV_j}{\sum_{j=1}^{n} PV_j} \tag{6}$$

2.2 The CRITIC Method (CRiteria Importance Through Intercriteria Correlation)

CRITIC was developed by Diakoulaki et al. [26]. Whilst LOPCOW accounts for skewness, CRITIC accounts for information redundancy amongst criteria; thus, the two methods rely on complementary sources of information. The steps of the method are presented below Jahan et al. [27].

Step 1. The decision matrix is normalised using Eqs. (2) and (3), as in the LOPCOW method.

Step 2. The contrast intensity of each criterion is measured using the sample standard deviation s_j.

$$s_j = \sqrt{\frac{\sum_{i=1}^{m} \left(r_{ij} - \mu_j\right)^2}{m-1}} \tag{7}$$

Step 3. The Pearson correlation coefficients between pairs of criteria are calculated ρ_{jk}.

$$\rho_{jk} = \frac{\sum_{i=1}^{m} (r_{ij} - \mu_j)(r_{ik} - \mu_k)}{\sqrt{\sum_{i=1}^{m} \left(r_{ij} - \mu_j\right)^2 \sum_{i=1}^{m} (r_{ik} - \mu_k)^2}} \tag{8}$$

Step 4. The total information content for each criterion C_j is determined using Eq. (9), and the CRITIC weights are determined using Eq. (10).

$$C_j = s_j \times \sum_{k=1}^{n} \left(1 - \rho_{jk}\right) \tag{9}$$

$$w_j^C = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{10}$$

2.3 Integration of Weights

The weights obtained from the two methods were combined using the normalised geometric mean in Eq. (11). This formula is the two-component form of the multiplicative combination formula proposed by Jahan et al. [27] for integrating objective, subjective and correlation-based weights. Unlike the arithmetic mean, the geometric mean reduces the weight for criteria where the two methods do not agree. For a criterion to receive a high integrated weight, it must be distinctive according to both information sources. The result was also normalised so that the sum equals one.

$$w_j = \frac{\sqrt{w_j^L \times w_j^C}}{\sum_{j=1}^{n} \sqrt{w_j^L \times w_j^C}}, \quad \sum_{j=1}^{n} w_j = 1 \tag{11}$$

2.4 The STENOZA Method (STEvić NOvarlić ZAvadskas)

STENOZA is a ranking method developed by Stević et al. [28]. The structure of the method aims to reduce the ranking's dependence on a single scaling assumption. The three normalisation types are distinguished by superscripts (v: vector; nl: non-linear; l: linear).

Step 1. The decision matrix X in Eq. (1) is constructed.

Step 2. Three normalisations are applied to the decision matrix. Vector normalisation is performed using Eq. (12), non-linear normalisation using Eq. (13), and Type II linear normalisation using Eq. (14).

$$n_{ij}^{v} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}}, \; j \in B; \quad n_{ij}^{v} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}}, \; j \in C \tag{12}$$

$$n_{ij}^{nl} = \left(\frac{x_{ij}}{max_i\, x_{ij}}\right)^2, \; j \in B; \quad n_{ij}^{nl} = \left(\frac{min_i\, x_{ij}}{x_{ij}}\right)^3, \; j \in C \tag{13}$$

$$n_{ij}^{l} = \frac{x_{ij}}{max_i\, x_{ij}}, \; j \in B; \quad n_{ij}^{l} = \frac{min_i\, x_{ij}}{x_{ij}}, \; j \in C \tag{14}$$

In non-linear normalisation, a quadratic transformation is applied to the benefit criteria and a cubic transformation to the cost criteria. This asymmetry significantly increases the difference between alternatives close to the optimal value and the others in the cost criteria.

Step 3. Each normalised matrix is multiplied separately by the criterion weights.

$$v_{ij}^{h} = n_{ij}^{h} \times w_j, \;\; h \in \{v, nl, l\} \tag{15}$$

Step 4. For each weighted matrix, the ideal solution t_j^h and the non-ideal solution k_j^h are determined.

$$t_j^h = max_i\, v_{ij}^h, \quad k_j^h = min_i\, v_{ij}^h, \;\; j = 1,2, \dots, n \tag{16}$$

Step 5. The distance from the ideal solution dt_{ij}^h is calculated using Eq. (17), and the distance from the non-ideal solution dk_{ij}^h is calculated using Eq. (18). With this transformation, the best

alternative for each criterion takes the value 1 in the matrix dt_{ij}^h, whilst the worst alternative takes the value 0 in the matrix dk_{ij}^h.

$$dt_{ij}^h = v_{ij}^h + \left(1 - t_j^h\right) \tag{17}$$
$$dk_{ij}^h = v_{ij}^h + \left(0 - k_j^h\right) \tag{18}$$

Step 6. The distance matrices obtained from the three types of normalisation are combined using the arithmetic mean.

$$st_{ij} = \frac{dt_{ij}^v + dt_{ij}^{nl} + dt_{ij}^l}{3}, \quad sk_{ij} = \frac{dk_{ij}^v + dk_{ij}^{nl} + dk_{ij}^l}{3} \tag{19}$$

Step 7. The coefficients gt_i and gk_i are calculated. gt_i is defined as the average across the criteria, whilst gk_i is defined as the sum.

$$gt_i = \frac{\sum_{j=1}^n st_{ij}}{n}, \quad gk_i = \sum_{j=1}^n sk_{ij} \tag{20}$$

Step 8. The final values fc_i are calculated using Eq. (21), and the alternatives are ranked in descending order. The alternative with the highest fc_i value is the best alternative.

$$fc_i = \frac{gt_i + gk_i}{2} \tag{21}$$

2.5 Validity and Robustness Analyses

The consistency of rankings across methods was measured using the Spearman rank correlation coefficient (Eq. (22)) and the WS rank similarity coefficient proposed by Sałabun and Urbaniak [29] (Eq. (23)). In Eq. (22), d_i is the difference between the ranks of alternative i in the two rankings. Whilst the Spearman coefficient treats all rank differences as equally important, the WS coefficient assigns exponentially higher weights to differences in alternatives that rank higher in the reference ranking (R_{xi}).

$$r_s = 1 - \frac{6\sum_{i=1}^m {d_i}^2}{m(m^2-1)} \tag{22}$$
$$WS = 1 - \sum_{i=1}^m 2^{-R_{xi}} \times \frac{|R_{xi} - R_{yi}|}{max\{|R_{xi}-1|, |R_{xi}-m|\}} \tag{23}$$

To assess weight sensitivity, the weight of each criterion was adjusted by the ratios $\delta \in \{\pm 0.1, \pm 0.2, \pm 0.3, \pm 0.4, \pm 0.5\}$, and the weights of the other criteria were redistributed proportionally in accordance with Eq. (24) so that their total sum remained equal to one. Thus, 90 scenarios were obtained for 9 criteria and 10 adjustment ratios.

$$w_j' = w_j(1+\delta), \quad w_k' = w_k\left(1 - \frac{w_j\delta}{1-w_j}\right), \ \ k \neq j \tag{24}$$

In the dynamic rank reversal test, the alternative with the lowest rank was removed from the model at each step; LOPCOW, CRITIC and STENOZA calculations were performed anew using the

remaining alternatives, and the resulting ranking was compared with the relative order of the remaining alternatives in the base model. To assess inter-period consistency, the same model was applied separately to each year from 2018 to 2023, and the agreement between the annual rankings was measured using the Kendall's coefficient of concordance W. In Eq. (25), T represents the number of years, R_i represents the sum of the alternative's annual rankings, and $\overline{R}$ represents the average of these sums. The significance of the W coefficient was tested using the χ^2 -statistic with $m-1$ degrees of freedom (Eq. (26)).

$$W = \frac{12\sum_{i=1}^{m}\left(R_i-\overline{R}\right)^2}{T^2(m^3-m)} \tag{25}$$

$$\chi^2 = T(m-1)W \tag{26}$$

3. Results

3.1 Criteria, Alternatives and Data

The maritime port performance of countries was evaluated using nine criteria derived from the cross-tabulation of three ship types (container, dry bulk and liquid bulk) with three performance dimensions (dwell time, ship size and number of port calls). The criteria are defined below.

C1. Median time spent by container ships in port (days): the median of the time container ships spend during port calls. A short duration indicates high handling efficiency and port capacity.

C2. Median port dwell time for dry bulk carriers (days): the median duration that ships carrying bulk cargo such as coal, grain and ore spend in port.

C3. Median time spent in port by liquid bulk carriers (days): the median duration of stay in port for tankers carrying crude oil, petroleum products and chemicals.

C4. Average carrying capacity per container ship (TEU): the average capacity of container ships calling at the country's ports. As accommodating large ships requires deep-water access, sufficient quay length and crane capacity, this reflects the adequacy of the infrastructure.

C5. Average cargo-carrying capacity of dry bulk carriers (DWT): the average deadweight tonnage of dry bulk carriers calling at the ports.

C6. Average cargo capacity of liquid bulk carriers (DWT): the average deadweight tonnage of tankers calling at ports.

C7. Number of port calls by container ships: the total number of container ship calls at the country's ports during the year.

C8. Number of port calls by dry bulk carriers: the total number of port calls by dry bulk carriers during the year.

C9. Number of port calls by liquid bulk carriers: the total number of tanker port calls during the year.

Three criteria relating to port dwell time (C1–C3) are cost-oriented, whilst the other six criteria (C4–C9) are benefit-oriented. The alternatives comprise 22 countries: Australia, Canada, China, Croatia, Denmark, France, Germany, Greece, Indonesia, Italy, Japan, South Korea, the Netherlands, Norway, the Philippines, Russia, Singapore, Spain, Sweden, Türkiye, the United Kingdom and the United States. The data were obtained from the annual port call performance indicators published by the United Nations Conference on Trade and Development (UNCTAD) in the UNCTADstat Data Centre [30]. These statistics are derived from automatic identification system (AIS) data and cover ships of 1,000 gross tons and above.

The year 2023 was selected as the base year for the analysis. There are three reasons for this choice. First, as data for Singapore for 2018–2021 are missing, the only years for which all 22

countries are represented are 2022 and 2023. Second, the 2020–2022 period was characterised by pandemic-related port congestion; the dwell times of container ships in ports in Australia, Canada and Germany rose significantly during these years. Third, the Spearman correlation of country rankings between 2022 and 2023 is above 0.94 for all nine criteria; therefore, the 2023 data do not contain any year-specific outliers. The port call criteria are markedly right-skewed (skewness coefficient approximately 3.0; the ratio of the highest to the lowest value is 226). This situation may lead methods that are insensitive to skewness during the weighting phase to interpret scale effects as performance information. The decision matrix for 2023 is presented in Table 1.

Table 1
Decision matrix for 2023

Country	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
Direction	Min	Min	Min	Max	Max	Max	Max	Max	Max
Australia	1.4417	1.6736	1.3038	4,334	112,233	42,043	4,033	15,265	3,404
Canada	1.4569	0.3632	1.0708	5,469	48,148	38,649	2,009	13,602	4,584
China	0.6049	2.0118	1.1069	4,561	78,610	37,036	80,095	61,737	45,417
Croatia	0.6701	2.2444	1.0299	4,277	30,032	29,495	354	273	576
Denmark	0.5701	0.8069	0.6729	1,978	16,442	12,229	1,118	874	2,968
France	0.8535	3.2500	1.0486	5,579	42,694	24,091	4,440	1,647	8,965
Germany	1.0174	2.5160	0.4351	5,015	49,766	8,675	6,603	1,388	15,956
Greece	1.0340	0.6892	0.6125	4,376	12,011	8,069	3,454	2,877	12,516
Indonesia	0.9653	2.6931	1.3243	1,280	45,358	13,471	16,372	12,018	25,914
Italy	0.8997	3.4597	1.2635	3,963	43,325	31,686	8,496	2,240	9,466
Japan	0.3500	0.8958	0.3187	1,614	29,548	14,024	38,360	30,523	41,715
South Korea	0.6465	2.7062	0.7444	2,990	59,825	23,777	23,983	8,027	28,851
Netherlands	0.8007	1.0667	0.5434	3,151	66,062	17,792	10,104	3,990	47,111
Norway	0.2958	0.8556	0.6601	790	30,715	19,463	3,474	2,385	6,250
Philippines	0.8250	4.7142	0.8250	1,769	48,197	9,843	6,804	2,550	5,277
Russia	1.5562	2.8021	1.1677	1,295	48,524	28,134	3,324	6,098	19,165
Singapore	0.8521	0.7649	0.6382	5,345	24,465	17,210	16,854	767	34,655
Spain	0.6007	2.0441	0.8625	3,194	42,981	19,147	15,707	3,814	16,495
Sweden	0.6674	0.5826	0.6653	1,709	12,008	12,870	1,898	1,146	6,503
Türkiye	0.6528	3.6771	1.3236	2,815	42,005	31,913	12,555	5,269	9,029
United Kingdom	0.6812	2.5962	1.0875	3,467	40,853	21,680	7,274	1,753	10,941
United States	1.0840	2.2493	1.7062	5,691	52,746	64,920	19,418	14,487	22,585

3.2 Determination of Criterion Weights

The decision matrix was first normalised using Eqs. (2) and (3). As C1 is the cost criterion, the normalised value for Australia is calculated as follows:

$$r_{11} = \frac{1.5562 - 1.4417}{1.5562 - 0.2958} = 0.0908$$

The other values were calculated in the same way. The LOPCOW percentage value and weight for C1 were obtained from the normalised matrix using Eqs. (4)–(6) as follows:

$$PV_1 = \left| ln\left(\frac{0.6216}{0.2556}\right) \times 100 \right| = 88.8588$$

$$w_1^L = \frac{88.8588}{88.8588 + \cdots + 44.0296} = 0.1688$$

The interim results and weights of the LOPCOW method are presented in Table 2.

Table 2
Results of the LOPCOW method

Value	C1	C2	C3	C4	C5	C6	C7	C8	C9
$\sqrt{\frac{\sum_{i=1}^{m} {r_{ij}}^2}{m}}$	0.6216	0.6711	0.6120	0.6170	0.3900	0.3631	0.2673	0.2598	0.4668
σ_j	0.2556	0.2643	0.2446	0.3137	0.2184	0.2327	0.2148	0.2200	0.3006
PV_j	88.86	93.20	91.73	67.63	57.98	44.51	21.84	16.61	44.03
w_j^L	0.1688	0.1771	0.1743	0.1285	0.1101	0.0846	0.0415	0.0315	0.0836

The same normalised matrix was used in the CRITIC method. The Pearson correlation matrix between the criteria is presented in Table 3. The strongest positive relationship is between the number of container calls and the number of dry bulk calls ($\rho = 0.912$); the correlation between the number of container calls and the number of liquid bulk calls is also high ($\rho = 0.721$). These criteria largely convey the same information: the size of the country's port system. A significant portion of the high Pearson coefficient between C7 and C8 stems from China's outlier values in both criteria; the Spearman equivalent of this relationship in the raw data is only 0.52. Another notable relationship is between the port dwell time and the average size of liquid bulk carriers (C3 and C6, $\rho = -0.787$). As C3 is cost-oriented, it was inverted during normalisation, causing the relationship to appear negative. In the raw data, the port dwell time of tankers also increases in countries visited by large tankers; therefore, there is a genuine trade-off between these two criteria. The conflict component of the CRITIC method assigns a higher information value to such criteria.

Table 3
Pearson correlation matrix among normalised criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1.000	0.070	0.442	-0.367	-0.402	-0.374	0.311	0.080	0.187
C2	0.070	1.000	0.449	0.044	-0.265	-0.106	-0.010	0.100	0.167
C3	0.442	0.449	1.000	-0.252	-0.408	-0.787	-0.030	-0.144	0.232
C4	-0.367	0.044	-0.252	1.000	0.244	0.473	0.088	0.100	0.019
C5	-0.402	-0.265	-0.408	0.244	1.000	0.512	0.316	0.445	0.216
C6	-0.374	-0.106	-0.787	0.473	0.512	1.000	0.203	0.343	-0.020
C7	0.311	-0.010	-0.030	0.088	0.316	0.203	1.000	0.912	0.721
C8	0.080	0.100	-0.144	0.100	0.445	0.343	0.912	1.000	0.563
C9	0.187	0.167	0.232	0.019	0.216	-0.020	0.721	0.563	1.000

The information and weight for C1 using the CRITIC method were calculated as follows using Eqs. (7), (9) and (10):

$$C_1 = s_1 \times \sum_{k=1}^{n}(1-\rho_{1k}) = 0.2616 \times 8.0542 = 2.1072$$

$$w_1^C = \frac{2.1072}{2.1072 + \cdots + 1.8195} = 0.1276$$

Table 4
Results of the CRITIC method

Value	C1	C2	C3	C4	C5	C6	C7	C8	C9
s_j	0.2616	0.2705	0.2503	0.3211	0.2235	0.2382	0.2199	0.2252	0.3076
$\sum_{k=1}^{n}(1-\rho_{jk})$	8.0542	7.5514	8.4985	7.6501	7.3419	7.7565	5.4875	5.6009	5.9146
C_j	2.1072	2.0424	2.1274	2.4566	1.6411	1.8472	1.2066	1.2612	1.8195
w_j^C	0.1276	0.1237	0.1289	0.1488	0.0994	0.1119	0.0731	0.0764	0.1102

The two weight vectors are combined using Eq. (11). The calculation for C1 is shown below, and the results for all criteria are presented in Table 5.

$$w_1 = \frac{\sqrt{0.1688 \times 0.1276}}{0.9850} = \frac{0.1468}{0.9850} = 0.1490$$

Table 5
LOPCOW, CRITIC and integrated criterion weights

Value	C1	C2	C3	C4	C5	C6	C7	C8	C9
w_j^L	0.1688	0.1771	0.1743	0.1285	0.1101	0.0846	0.0415	0.0315	0.0836
w_j^C	0.1276	0.1237	0.1289	0.1488	0.0994	0.1119	0.0731	0.0764	0.1102
w_j	0.1490	0.1503	0.1521	0.1404	0.1062	0.0988	0.0559	0.0498	0.0975
Rank	3	2	1	4	5	6	8	9	7

Based on the integrated weights, the most important criterion is C3 (dwell time of liquid bulk carriers in port, 0.1521), whilst the least important criterion is C8 (number of calls by dry bulk carriers, 0.0498). At the dimension level, the port dwell time criteria account for 0.451 of the total weight, the vessel size criteria account for 0.345, and the number of calls criteria account for 0.203. The two methods are largely consistent in their rankings; the main difference lies in the number of calls criteria. Whilst LOPCOW assigns a total weight of 0.157 to these criteria, CRITIC assigns a weight of 0.260 due to the conflict between the criteria.

3.3 Ranking Countries Using the STENOZA Method

Three normalisations were applied to the decision matrix using Eqs. (12)–(14). The calculation for Australia's values in the C1 criterion is as follows:

$$n_{11}^{v} = 1 - \frac{1.4417}{4.2290} = 0.6591, \quad n_{11}^{nl} = \left(\frac{0.2958}{1.4417}\right)^{3} = 0.0086, \quad n_{11}^{l} = \frac{0.2958}{1.4417} = 0.2052$$

For the benefit-oriented C4 criterion, the following values were obtained for Australia: $n_{14}^{v} = \frac{4334}{17475.63} = 0.2480$, $n_{14}^{nl} = \left(\frac{4334}{5691}\right)^{2} = 0.5800$, and $n_{14}^{l} = \frac{4334}{5691} = 0.7616$. The three normalised matrices are presented in Tables 6–8.

Table 6
Matrix obtained through vector normalisation

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9
Australia	0.6591	0.8471	0.7186	0.2480	0.4835	0.3279	0.0399	0.2020	0.0327
Canada	0.6555	0.9668	0.7689	0.3130	0.2074	0.3015	0.0199	0.1800	0.0441
China	0.8570	0.8162	0.7611	0.2610	0.3386	0.2889	0.7934	0.8169	0.4368
Croatia	0.8415	0.7949	0.7777	0.2447	0.1294	0.2301	0.0035	0.0036	0.0055
Denmark	0.8652	0.9263	0.8548	0.1132	0.0708	0.0954	0.0111	0.0116	0.0285
France	0.7982	0.7030	0.7737	0.3192	0.1839	0.1879	0.0440	0.0218	0.0862
Germany	0.7594	0.7701	0.9061	0.2870	0.2144	0.0677	0.0654	0.0184	0.1535
Greece	0.7555	0.9370	0.8678	0.2504	0.0517	0.0629	0.0342	0.0381	0.1204
Indonesia	0.7717	0.7539	0.7142	0.0732	0.1954	0.1051	0.1622	0.1590	0.2492
Italy	0.7873	0.6838	0.7273	0.2268	0.1866	0.2472	0.0842	0.0296	0.0910
Japan	0.9172	0.9181	0.9312	0.0924	0.1273	0.1094	0.3800	0.4039	0.4012
South Korea	0.8471	0.7527	0.8393	0.1711	0.2577	0.1855	0.2376	0.1062	0.2775
Netherlands	0.8107	0.9025	0.8827	0.1803	0.2846	0.1388	0.1001	0.0528	0.4531
Norway	0.9301	0.9218	0.8575	0.0452	0.1323	0.1518	0.0344	0.0316	0.0601
Philippines	0.8049	0.5692	0.8220	0.1012	0.2076	0.0768	0.0674	0.0337	0.0508
Russia	0.6320	0.7439	0.7480	0.0741	0.2090	0.2194	0.0329	0.0807	0.1843
Singapore	0.7985	0.9301	0.8623	0.3059	0.1054	0.1342	0.1669	0.0101	0.3333
Spain	0.8580	0.8132	0.8139	0.1828	0.1852	0.1493	0.1556	0.0505	0.1586
Sweden	0.8422	0.9468	0.8564	0.0978	0.0517	0.1004	0.0188	0.0152	0.0625
Türkiye	0.8456	0.6640	0.7143	0.1611	0.1809	0.2489	0.1244	0.0697	0.0868
United Kingdom	0.8389	0.7628	0.7653	0.1984	0.1760	0.1691	0.0720	0.0232	0.1052
United States	0.7437	0.7945	0.6318	0.3257	0.2272	0.5064	0.1923	0.1917	0.2172

Table 7
Matrix obtained using non-linear normalisation

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9
Australia	0.0086	0.0102	0.0146	0.5800	1.0000	0.4194	0.0025	0.0611	0.0052
Canada	0.0084	1.0000	0.0264	0.9235	0.1840	0.3544	0.0006	0.0485	0.0095
China	0.1169	0.0059	0.0239	0.6423	0.4906	0.3255	1.0000	1.0000	0.9294
Croatia	0.0860	0.0042	0.0296	0.5648	0.0716	0.2064	0.0000	0.0000	0.0001
Denmark	0.1397	0.0912	0.1062	0.1208	0.0215	0.0355	0.0002	0.0002	0.0040
France	0.0416	0.0014	0.0281	0.9610	0.1447	0.1377	0.0031	0.0007	0.0362

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9
Germany	0.0246	0.0030	0.3930	0.7765	0.1966	0.0179	0.0068	0.0005	0.1147
Greece	0.0234	0.1464	0.1409	0.5913	0.0115	0.0154	0.0019	0.0022	0.0706
Indonesia	0.0288	0.0025	0.0139	0.0506	0.1633	0.0431	0.0418	0.0379	0.3026
Italy	0.0355	0.0012	0.0160	0.4849	0.1490	0.2382	0.0113	0.0013	0.0404
Japan	0.6037	0.0667	1.0000	0.0804	0.0693	0.0467	0.2294	0.2444	0.7840
South Korea	0.0958	0.0024	0.0785	0.2760	0.2841	0.1341	0.0897	0.0169	0.3750
Netherlands	0.0504	0.0395	0.2017	0.3066	0.3465	0.0751	0.0159	0.0042	1.0000
Norway	1.0000	0.0765	0.1125	0.0193	0.0749	0.0899	0.0019	0.0015	0.0176
Philippines	0.0461	0.0005	0.0576	0.0966	0.1844	0.0230	0.0072	0.0017	0.0125
Russia	0.0069	0.0022	0.0203	0.0518	0.1869	0.1878	0.0017	0.0098	0.1655
Singapore	0.0418	0.1071	0.1245	0.8821	0.0475	0.0703	0.0443	0.0002	0.5411
Spain	0.1194	0.0056	0.0505	0.3150	0.1467	0.0870	0.0385	0.0038	0.1226
Sweden	0.0871	0.2423	0.1099	0.0902	0.0114	0.0393	0.0006	0.0003	0.0191
Türkiye	0.0930	0.0010	0.0140	0.2447	0.1401	0.2416	0.0246	0.0073	0.0367
United Kingdom	0.0819	0.0027	0.0252	0.3711	0.1325	0.1115	0.0082	0.0008	0.0539
United States	0.0203	0.0042	0.0065	1.0000	0.2209	1.0000	0.0588	0.0551	0.2298

Table 8
Matrix obtained using Type II linear normalisation

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9
Australia	0.2052	0.2170	0.2444	0.7616	1.0000	0.6476	0.0504	0.2473	0.0723
Canada	0.2030	1.0000	0.2976	0.9610	0.4290	0.5953	0.0251	0.2203	0.0973
China	0.4890	0.1805	0.2879	0.8014	0.7004	0.5705	1.0000	1.0000	0.9640
Croatia	0.4414	0.1618	0.3094	0.7515	0.2676	0.4543	0.0044	0.0044	0.0122
Denmark	0.5189	0.4501	0.4736	0.3476	0.1465	0.1884	0.0140	0.0142	0.0630
France	0.3466	0.1118	0.3039	0.9803	0.3804	0.3711	0.0554	0.0267	0.1903
Germany	0.2907	0.1444	0.7325	0.8812	0.4434	0.1336	0.0824	0.0225	0.3387
Greece	0.2861	0.5270	0.5203	0.7689	0.1070	0.1243	0.0431	0.0466	0.2657
Indonesia	0.3064	0.1349	0.2407	0.2249	0.4041	0.2075	0.2044	0.1947	0.5501
Italy	0.3288	0.1050	0.2522	0.6964	0.3860	0.4881	0.1061	0.0363	0.2009
Japan	0.8451	0.4054	1.0000	0.2836	0.2633	0.2160	0.4789	0.4944	0.8855
South Korea	0.4575	0.1342	0.4281	0.5254	0.5330	0.3663	0.2994	0.1300	0.6124
Netherlands	0.3694	0.3405	0.5865	0.5537	0.5886	0.2741	0.1262	0.0646	1.0000
Norway	1.0000	0.4245	0.4828	0.1388	0.2737	0.2998	0.0434	0.0386	0.1327
Philippines	0.3585	0.0770	0.3863	0.3108	0.4294	0.1516	0.0849	0.0413	0.1120
Russia	0.1901	0.1296	0.2729	0.2276	0.4324	0.4334	0.0415	0.0988	0.4068
Singapore	0.3471	0.4748	0.4994	0.9392	0.2180	0.2651	0.2104	0.0124	0.7356
Spain	0.4924	0.1777	0.3695	0.5612	0.3830	0.2949	0.1961	0.0618	0.3501
Sweden	0.4432	0.6234	0.4790	0.3003	0.1070	0.1982	0.0237	0.0186	0.1380
Türkiye	0.4531	0.0988	0.2408	0.4946	0.3743	0.4916	0.1568	0.0853	0.1917
United Kingdom	0.4342	0.1399	0.2931	0.6092	0.3640	0.3339	0.0908	0.0284	0.2322
United States	0.2729	0.1615	0.1868	1.0000	0.4700	1.0000	0.2424	0.2347	0.4794

The normalised matrices were weighted using Eq. (15), and the ideal and non-ideal solutions were determined using Eq. (16). For C1, the ideal solutions were found to be $t_1^v = 0.1386,\ t_1^{nl} = 0.1490,\ t_1^l = 0.1490$; the non-ideal solutions were found to be $k_1^v = 0.0942,\ k_1^{nl} = 0.0010,\ k_1^l = 0.0283$. Since the best value for each criterion is 1 in both non-linear and linear normalisations, the ideal solution in these two matrices is directly equal to the criterion weight ($t_j^{nl} = t_j^l = w_j$). For Australia, the distances under the C1 criterion were calculated as follows using Eqs. (17)–(19):

$$st_{11} = \frac{0.0982 + (1 - 0.1386) + 0.0013 + (1 - 0.1490) + 0.0306 + (1 - 0.1490)}{3} = 0.8978$$

$$sk_{11} = \frac{0.0982 - 0.0942 + 0.0013 - 0.0010 + 0.0306 - 0.0283}{3} = 0.0022$$

After carrying out the same procedures for the other criteria, the coefficients for Australia were obtained using Eqs. (20) and (21) as follows:

$$gt_1 = \frac{0.8978 + \cdots + 0.9239}{9} = 0.9409,$$
$$gk_1 = 0.0022 + \cdots + 0.0030 = 0.2303,$$
$$fc_1 = \frac{0.9409 + 0.2303}{2} = 0.5856$$

The results of the STENOZA method are presented in Table 9.

Table 9
Results of the STENOZA method

Countries	gt_i	gk_i	fc_i	**Rank**
Australia	0.9409	0.2303	0.5856	7
Canada	0.9481	0.2949	0.6215	3
China	0.9582	0.3863	0.6723	1
Croatia	0.9324	0.1541	0.5433	14
Denmark	0.9302	0.1336	0.5319	19
France	0.9358	0.1841	0.5599	11
Germany	0.9393	0.2156	0.5775	8
Greece	0.9351	0.1784	0.5568	12
Indonesia	0.9281	0.1152	0.5217	20
Italy	0.9318	0.1479	0.5398	15
Japan	0.9546	0.3538	0.6542	2
South Korea	0.9383	0.2070	0.5727	9
Netherlands	0.9449	0.2658	0.6053	5
Norway	0.9382	0.2059	0.5720	10
Philippines	0.9252	0.0893	0.5073	22
Russia	0.9267	0.1020	0.5144	21
Singapore	0.9442	0.2603	0.6023	6
Spain	0.9341	0.1691	0.5516	13
Sweden	0.9311	0.1423	0.5367	17

Countries	gt_i	gk_i	fc_i	**Rank**
Türkiye	0.9304	0.1358	0.5331	18
United Kingdom	0.9314	0.1451	0.5383	16
United States of America	0.9458	0.2741	0.6099	4

According to the STENOZA results, the ranking of countries is as follows: China, Japan, Canada, the United States, the Netherlands, Singapore, Australia, Germany, South Korea, Norway, France, Greece, Spain, Croatia, Italy, the United Kingdom, Sweden, Türkiye, Denmark, Indonesia, Russia, the Philippines. China (0.6723) was identified as the top-performing country, whilst the Philippines (0.5073) was identified as the lowest-performing country. Türkiye (0.5331) ranks 18th based on its score. Türkiye's ranking is largely due to the port dwell times of dry bulk and liquid bulk carriers; the C2 (3.6771 days) and C3 (1.3236 days) values are amongst the highest in the sample.

When interpreting the results, two structural characteristics of the method must be taken into account. First, as gt_i is defined as the average based on the criteria, and gk_i is defined as the total (Eq. (20)), the scales of the two components are different. In this study, whilst the values of gt_i fall within a narrow range of 0.9252 to 0.9582, the values of gk_i vary between 0.0893 and 0.3863. Consequently, the final ranking is primarily determined by the distance from the non-ideal solution. Second, the cubic transformation in the cost criteria strongly favours alternatives that are close to the optimal value. The main reason Canada ranks third is the dwell time of 0.3632 days for dry bulk carriers in port; this figure is well below the sample average (2.03 days).

3.4 Comparative Analysis

To test the consistency of the STENOZA ranking, five different methods were applied using the same integrated weights: RAM [31], TOPSIS [32], MARCOS [33], EDAS [34] and CoCoSo [35] ($\lambda = 0.5$). These methods represent different decision-making logics. RAM is based on total normalisation and the root function; TOPSIS on Euclidean distance to ideal and anti-ideal solutions; MARCOS on utility levels relative to reference points; EDAS on deviations from the average solution; and CoCoSo on the compromise between additive and multiplicative aggregation. The rankings are presented in Table 10, and the similarity measures using STENOZA are presented in Table 11.

Table 10
Country rankings by method

Country	**STENOZA**	**RAM**	**TOPSIS**	**MARCOS**	**EDAS**	**CoCoSo**
China	1	1	1	1	1	1
Japan	2	2	2	2	2	2
Canada	3	8	6	3	8	7
United States	4	4	5	6	6	9
Netherlands	5	3	3	4	3	3
Singapore	6	5	4	5	4	4
Australia	7	7	8	8	9	10
Germany	8	10	12	9	10	8
South Korea	9	6	7	7	5	5
Norway	10	13	9	10	13	14
France	11	11	16	13	14	11

Country	STENOZA	RAM	TOPSIS	MARCOS	EDAS	CoCoSo
Greece	12	12	10	11	12	17
Spain	13	9	11	12	7	6
Croatia	14	18	15	15	15	20
Italy	15	16	19	16	17	15
United Kingdom	16	15	17	17	11	12
Sweden	17	19	13	14	19	18
Türkiye	18	17	20	18	18	16
Denmark	19	20	14	19	20	13
Indonesia	20	14	18	20	16	19
Russia	21	21	21	21	21	21
Philippines	22	22	22	22	22	22

Table 11
Similarity between the STENOZA ranking and the rankings of the comparison methods

Criterion	RAM	TOPSIS	MARCOS	EDAS	CoCoSo
Spearman's ρ	0.928	0.921	0.983	0.906	0.854
p-value	<0.001	<0.001	<0.001	<0.001	<0.001
WS coefficient	0.961	0.969	0.989	0.952	0.948

The Spearman correlations between the STENOZA ranking and the rankings of the other five methods range from 0.854 (CoCoSo) to 0.983 (MARCOS), and all are statistically significant at the $p < 0.001$ level. The average correlation is 0.918. The WS coefficient, which places greater weight on differences in the top rankings, ranges from 0.948 to 0.989. China and Japan ranked in the top two positions across all methods, whilst Russia and the Philippines ranked in the bottom two. The most pronounced discrepancy is observed in Canada: whilst Canada ranks third in STENOZA and MARCOS, it ranks eighth in RAM and EDAS. STENOZA and MARCOS use a ratio-based normalisation of the form $min_i\, x_{ij}\, / x_{ij}$ for cost criteria; this structure sharply distinguishes the alternative with the best value in a given criterion from the others. RAM and EDAS, on the other hand, are less sensitive to outliers as they employ scaling based on totals and averages. A similar situation is observed for Spain, but in the opposite direction. These differences stem from the normalisation logic of the methods and should be taken into account when interpreting STENOZA results. Whilst the comparative analysis supports the robustness of the ranking phase, it does not, on its own, prove the accuracy of the weights.

3.5 Sensitivity Analysis

The effect of changes in weights on the ranking was examined using 90 scenarios generated in accordance with Eq. (24). In each scenario, STENOZA was reapplied, and the resulting ranking was compared to the baseline ranking using the Spearman correlation coefficient. The results are presented in Table 12.

Table 12
Spearman correlations between the baseline ranking and the scenario rankings in weight change scenarios

δ	C1	C2	C3	C4	C5	C6	C7	C8	C9
−50%	0.993	0.989	0.995	0.949	0.985	0.988	0.998	0.999	0.993
−40%	0.997	0.994	0.995	0.970	0.988	0.988	0.998	0.999	0.997
−30%	0.997	0.997	0.995	0.982	0.991	0.990	0.999	1.000	0.997
−20%	1.000	0.998	1.000	0.989	0.995	0.995	0.999	1.000	0.998
−10%	1.000	1.000	1.000	0.998	0.999	0.999	1.000	1.000	0.999
+10%	0.997	0.994	0.999	0.999	1.000	1.000	1.000	1.000	1.000
+20%	0.993	0.993	0.995	0.998	1.000	1.000	1.000	1.000	0.999
+30%	0.991	0.990	0.990	0.997	1.000	0.999	1.000	1.000	0.999
+40%	0.990	0.975	0.988	0.992	0.998	0.999	1.000	1.000	0.995
+50%	0.982	0.974	0.979	0.992	0.997	0.997	1.000	1.000	0.994

The average Spearman correlation across the scenarios was found to be 0.995, with the lowest value being 0.949. The lowest correlation occurred in the scenario where the weight of C4 was reduced by 50 per cent. As this criterion carries the highest weight in the ship size dimension, reducing it shifts the rankings of countries in the middle of the list. Changes made to the criteria with low weightings (C7, C8) had virtually no effect on the ranking ($\rho \geq 0.998$). China remained the leading country in 87 out of 90 scenarios. Japan rose to first place only in the three scenarios where the weight of C3 was increased by 30 per cent, 40 per cent and 50 per cent. This result is explained by the small difference between the baseline fc_i values for China and Japan (0.6723 and 0.6542) and by the fact that Japan has the best value in the sample (0.3187 days) for the dwell time of liquid bulk cargo at the port. The findings indicate that the ranking remains stable in the face of reasonable changes to the weights; however, the relative positions of the top two countries depend on the C3 weight and therefore require careful interpretation.

3.6 Rank Reversal Analysis

In the dynamic rank reversal test, the country with the lowest rank was removed from the model at each step, and all calculations, including weights, were recalculated using the remaining countries. The results of the 19 steps are presented in Table 13.

Table 13
Results of the dynamic rank reversal test

Step	Country Removed	Number of Remaining Countries	Spearman's ρ	Number of countries with a changed rank
1	Philippines	21	1.000	0
2	Russia	20	1.000	0
3	Indonesia	19	0.998	2
4	Denmark	18	1.000	0
5	Türkiye	17	0.998	2
6	Sweden	16	1.000	0
7	United Kingdom	15	1.000	0
8	Italy	14	1.000	0

Step	Country Removed	Number of Remaining Countries	Spearman's ρ	Number of countries with a changed rank
9	Croatia	13	1.000	0
10	Spain	12	1.000	0
11	Greece	11	1.000	0
12	France	10	1.000	0
13	Norway	9	0.983	2
14	South Korea	8	1.000	0
15	Germany	7	1.000	0
16	Australia	6	0.943	2
17	Singapore	5	0.600	2
18	Netherlands	4	0.800	2
19	United States	3	1.000	0

In 13 of the 19 steps, the relative order of the remaining countries remained entirely unchanged. In each of the 6 steps where changes were observed, only two countries swapped places; these changes occurred between pairs of countries with very similar fc_i values (such as the Netherlands and Singapore, or Canada and the US). The Spearman correlation coefficient remained above 0.94 in all steps ranging from 20 to 6 countries. The values of 0.600 and 0.800 observed in the five- and four-country steps, respectively, are again due solely to a single country pair swapping places; since the impact of a single change on the coefficient increases as the number of alternatives decreases, these values should not be interpreted as an indicator of instability. When the same test was applied using the RAM method, the ranks of up to seven countries changed in a single step. This comparison demonstrates that STENOZA is more robust against changes in the set of alternatives.

3.7 Inter-Period Stability Analysis

To test the model's consistency from year to year, the LOPCOW–CRITIC and STENOZA frameworks were applied separately to each year from 2018 to 2023. As Singapore's data for 2018–2021 are missing, this analysis was carried out using 21 countries. The annual composite weights are highly stable; the weight of each criterion varied by no more than 0.012 points over the six-year period. The annual rankings are presented in Table 14.

Table 14
Annual STENOZA rankings for the 2018–2023 period

Country	2018	2019	2020	2021	2022	2023
China	2	1	1	2	1	1
Japan	1	2	2	1	2	2
Canada	3	5	3	3	3	3
United States	4	3	4	4	4	4
Netherlands	5	4	5	5	5	5
Australia	6	6	6	6	6	6
Germany	8	8	10	9	10	7
South Korea	10	9	9	8	7	8

Country	2018	2019	2020	2021	2022	2023
Norway	9	10	8	7	8	9
France	11	11	11	11	11	10
Greece	7	7	7	10	9	11
Spain	12	13	13	12	12	12
Croatia	14	18	18	15	14	13
Italy	15	16	17	17	17	14
United Kingdom	13	14	15	18	15	15
Sweden	18	12	12	13	16	16
Türkiye	16	15	16	14	13	17
Denmark	17	17	14	16	18	18
Indonesia	20	20	20	20	19	19
Russia	19	19	19	19	20	20
Philippines	21	21	21	21	21	21

Kendall's coefficient of concordance was calculated as $W = 0.969$ ($\chi^2 = 116.23$, $df = 20$, $p < 0.001$). Spearman's correlations between year pairs range from 0.936 to 0.983. China and Japan shared the top two spots in all years, whilst Canada, the US, the Netherlands and Australia ranked between third and sixth. The most notable change occurred in Greece: the country ranked seventh during the 2018–2020 period but dropped to eleventh place in 2023. Türkiye's ranking has fluctuated between 13th and 17th. These results demonstrate that the 2023 ranking is not specific to a single year and that the model produces highly consistent results across periods.

4. Conclusions

International trade and logistics activities are directly affected by crises occurring in the global economy. Recent disruptions in the Suez Canal and the preceding pandemic have caused disruptions in logistics operations. This has led to disruptions in global trade, which have deepened as economies caught off guard have entered a crisis. These developments have demonstrated that port operations do not merely affect the logistics process; they also influence a country's volume of foreign trade, its growth, productivity, and its competitiveness with other countries.

Ports play a crucial role in enhancing the efficiency of international trade. In particular, operational processes (such as the capacity to handle ships in port, loading and unloading times, port infrastructure and the use of technology, and the ability of large vessels to berth) have a positive or negative impact on maritime transport. This situation affects not only the transport sector but also industrial enterprises dependent on imported inputs, exporters and end consumers. Consequently, reducing the time spent at ports is a key requirement for improving countries' foreign trade performance and ensuring the sustainability of global supply chains.

The Review of Maritime Transport 2025 published by UNCTAD [36] indicates that waiting times at ports have begun to rise again on a global scale. According to the report, during the period December 2023–March 2024, the average waiting time for vessels prior to berthing at ports rose from 5.2 hours to 6.4 hours in developed countries, and from 10.2 hours to 10.9 hours in developing countries. Furthermore, the median dwell time for container ships at ports reached 0.8 days by the end of 2024. These figures highlight the importance of port operational efficiency and the timely management of vessel movements for international trade.

In this study, the maritime port performance of 22 countries for the year 2023 was evaluated using the LOPCOW–CRITIC integrated weighting method and the STENOZA ranking method, based on nine operational indicators relating to three types of vessel. The weighting results showed that differences in performance between countries were most significantly determined by the duration of vessel stays in port. Whilst these criteria accounted for approximately 45 per cent of the total weighting, the share of port calls remained at around 20 per cent; thus, the assessment focused on operational efficiency rather than market size. According to the STENOZA results, China and Japan ranked first and second, followed by Canada, the United States and the Netherlands. Türkiye, meanwhile, ranked 18th out of the 22 countries. Whilst Türkiye ranks among the top seven countries in terms of the port dwell time of container ships, the port dwell times for dry and liquid bulk carriers are among the highest in the sample. This indicates that the area for improvement in Türkiye is largely concentrated in bulk cargo operations. The resulting ranking was tested using a comparison based on five different multi-criteria decision-making (MCDM) methods, a weight sensitivity analysis involving 90 scenarios, a rank reversal test, and a stability analysis covering the 2018–2023 period, and was found to be highly consistent (Kendall's W = 0.969).

By evaluating countries' maritime transport and port performance with multi-criteria decision-making methods, this study identified the strengths and weaknesses of the countries examined. The results allow countries' international competitiveness to be compared on the basis of port dwell times, vessel sizes, and the number of port calls for different cargo types. These findings can inform decision-making on maritime transport policies, port investments and logistics strategies. Overall, the results suggest that countries with robust port infrastructure and high operational efficiency are better positioned in global trade.

Author Contributions

Conceptualization, A.U. and Ç.K.; methodology, A.U.; formal analysis, A.U.; writing – original draft preparation, A.U. and Ç.K.; writing – review and editing, A.U. and Ç.K. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data analyzed in this study are publicly available from the UNCTADstat Data Center [30].

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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