EKOIST Journal of Econometrics and Statistics,
EKOIST 2025, 42: 154–174

https://doi.org/10.26650/ekoist.2025.42.1614814

Submitted 07.01.2025
Revision Requested 02.05.2025
Last Revision Received 05.05.2025
Accepted 21.05.2025

EKOIST Journal of Econometrics and Statistics

Research Article

Open Access

Investıgatıng the Productıve Capacıty Performance of E7 Countrıes Using the WENSLO-ARTASI Model

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Abstract

The E7 countries, which are among the major economies in the world with high growth rates, are expected to have a significant share of the world's total GDP shortly. This study intends to analyse the productive capacity performance assessment of the E7 countries from 2003 to 2022 using a WENSLO-ARTASI integrated model. For this purpose, all variables considered in calculating the productive capacity index published by UNCTAD (United Nations Conference on Trade and Development) are used in the study. The WENSLO (Weights by ENvelope and SLOpe) method is employed to reveal the importance levels of the evaluation criteria, while the ARTASI (Alternative Ranking Technique based on Adaptive Standardised Intervals) method is used to determine the productive capacity performance ranking of the E7 countries. Additionally, the reliability of the proposed model was tested through various sensitivity analyses. Because of the study, it was concluded that the information and communication technologies index holds the highest importance among the evaluation criteria. In the productive capacity evaluation, when the ranking results for all years are averaged, the rankings are China, Turkey, Russia, Mexico, Brazil, Indonesia, and India. Furthermore, when the years are analysed separately, it is observed that the productive capacity index ranking published by UNCTAD aligns with the productive capacity index ranking.

Keywords productive capacity · performance analysis · WENSLO · ARTASI · E7

Citation: Kahreman, Y. (2025). Investıgatıng the productıve capacıty performance of E7 countrıes using the WENSLO-ARTASI model. *EKOIST Journal of Econometrics and Statistics*, 42, 154-174. https://doi.org/10.26650/ekoist.2025.42.1614814

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Investıgatıng the Productıve Capacıty Performance of E7 Countrıes Using the WENSLO-ARTASI Model

Every country takes care to adopt a long-term and stable approach when setting economic growth targets. A review of the literature reveals that many theories explain economic growth. However, since the 1990s, it has been emphasised that traditional indicators are insufficient in explaining growth. In this context, the importance of productive capacity has become increasingly prominent in economic growth analyses in recent years (Gnangnon, 2021).

Productive capacity refers to a country's ability to produce goods and services that support its economic growth (Hall and Jones, 1996). Although there is no clear definition of productive capacity in the literature, this concept is viewed as a dynamic tool that can ensure the economic development of countries. The productive capacity index indicator consists of sub-dimensions such as human capital, natural capital, energy, transport, information and communication technology, institutions, the private sector, and structural transformation (Gnangnon, 2021).

UNCTAD (United Nations Conference on Trade and Development) published the Productive Capacity Index (PCI) for the first time in 2021. The PCI data published for the first time by UNCTAD covers the years 2000-2018 and covers 199 countries. When the reports published in the following period are analysed, the PCI data covers the period 2000-2022 for 199 countries. UNCTAD uses the eight dimensions mentioned above while calculating PCI. These eight dimensions used for the PCI calculation differ for each country. There are indicators that each country is good or bad in these 8 dimensions. These differences make the calculation of the productive capacity index a decision-making problem. In this context, an integrated Multi-Criteria Decision Making (MCDM) model is proposed in this study. In the proposed model, the weights of the performance evaluation criteria are determined by the WENSLO method. The productive capacity performance rankings of the countries considered were carried out with the ARTASI method. The main motivation for the choice of the WENSLO and ARTASI methods is explained in the methodology section of the methods. In addition, the advantages of the methods used in the proposed model and their unique features that differ from those of other MCDM methods are explained.

The proposed integrated model is tested with the productive capacity performance of the E7 (Emerging Seven) countries. The main motivation for considering these countries is that the E7 countries have high growth rates and their role in the global economic order is increasing. In addition, when the reports of PricewaterhouseCoopers are analysed, it is estimated that the E7 countries will cover a significant portion of the world's total GDP (Gross Domestic Product) in the near future. The report predicts that the world economy will soon shift to the Pacific Ocean. It is argued that China, especially among the E7 countries, will lead this process. It is estimated that the Chinese economy will surpass the US (United States of America) economy soon. Furthermore, it is argued that the E7 countries will soon reach a level where they can economically compete with the G7 (Group of Seven) countries (Samadder et al., 2012; Koşaroğlu, 2021; Cheng et al., 2024).

The main objective of this study is to determine the productive capacity performance of the E7 countries for the period 2003-2022. Although UNCTAD has published the relevant variables for the period 2000-2022, the study covers 2003-2022 due to the absence of data for Indonesia during 2000-2002. In this research, the eight dimensions considered in calculating the productive capacity index published by UNCTAD serve as the foundation.

This study aims to make the following contributions:

(i) The fact that a study addressing all eight dimensions used in the calculation of the productive capacity index has not been conducted before distinguishes this study from other studies in the literature.

(ii) A new approach has been developed to determine the productive capacity performance of countries.

(iii) By using the WENSLO (Weights by ENvelope and SLOpe) and ARTASI (Alternative Ranking Technique based on Adaptive Standardised Intervals) methods together, the advantages of these two methods are combined, and a contribution is made to the literature by enabling the use of these methods in different fields.

(iv) This study is the first application in which the WENSLO and ARTASI methods are used together.

(v) The productive capacity performance of the E7 countries has been evaluated for the first time in this study.

(vi) By making a comparison with the productive capacity index published by the UNCTAD, an alternative method for calculating the productive capacity index is presented. The structure of the paper is as follows: The subsequent section provides a review of the literature on the relationship between the PCI and economic performance. The third section introduces the proposed integrated model, detailing the MCDM methods employed and the dataset used in the study. The next section presents the application of the model and discusses the results. The final section concludes the paper by offering policy implications and addressing the study's limitations.

Literature review

In the detailed literature review, only one study measuring the performance of the PCI (Productive Capacity Index) was found. Studies on PCI show that the relationship between PCI and macroindicators is generally analysed. In this context, only one study that analysed the performance of the PCI could be cited as an example. In addition, some studies using the PCI and its dimensions are summarised below. In a 2022 study, Altıntaş evaluated the productive capacity of G20 countries from 2000 to 2018. The research employed the Entropy and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) methods, considering all the indicators used in the calculation of the PCI. The Entropy method was used to establish the importance levels of the criteria, while the TOPSIS method was used to rank the countries according to their productive capacity performance. The findings revealed that Germany, the USA, and South Korea demonstrated the highest levels of productive capacity, while Indonesia, Mexico, and Brazil showed the lowest performance. Turkey ranked 12th in terms of productive capacity performance.

Hicks analysed the relationship between economic development and the human capital index in his 1980 study. While Jones examined the relationship between economic growth and the natural capital index in his 1996 study, Hall and Jones analysed income inequality through human and natural capital indices in their 1996 study. In 2001, Bassani and Scarpetta examined whether human and natural capital indices have an impact on the economic development of OECD (Organisation for Economic Co-operation and Development) countries. In his study in 2001, Deliktaş analysed the relationship between economic development and the human capital index in 75 countries. Middendorf (2005) analysed the relationship between economic development and human capital in OECD countries.

There are various studies dealing with other dimensions of productive capacity other than the human capital index and the natural capital index. In his study conducted in 2008, Salim analysed the productive capacity of food firms in Bangladesh. In his study conducted in 2010, Ayrdin analysed the relationship between economic growth and the energy index. Molua et al. 2010 analysed the impact of climate change indicators on productive capacity. Türedi analysed the relationship between economic development and information and communication technologies in 2013. Cornia and Scognamillo 2016 analysed the relationship between GDP per capita and PCI in 48 selected countries. In his study conducted in 2017, Balac analysed the relationship between foreign direct investment and productive capacity index indicators for 73 countries. Hayaloğlu (2018) analysed the relationship between the institutions index and economic growth, while Özkan and Çelik (2018) focused on the relationship between the information and communication technology index and economic growth in Turkey.

Gonzales-Blanco et al. (2019) investigated the PCI of manufacturing firms in Brazil, while Mian et al. (2019) examined the relationship between financial and macroeconomic indicators and the PCI. In a similar vein, Doğanay and Değer (2020) explored the connection between economic growth and the institutional development index across countries at various stages of development. Kartal (2021) studied the relationship between Turkey's energy index and economic growth. Gnangnon (2021) analysed the link between the PCI and economic growth in 126 countries. Olarte et al. (2021) investigated the relationship between macroeconomic variables and PCI in South Africa. Demiral and Demiral (2021) examined the association between socioeconomic indicators and the PCI in 125 countries, while Wilson (2021) analysed the correlation between inflation data and the PCI in 35 countries.

Since there is no study directly related to the study, similar studies are included above. Also, some studies in which the method of the study was used are given in Table 1.

Table 1

Literature Review of the WENSLO-ARTASI Methods

Some Case Studies Using the WENSLO Method	
Author	**Problem**
Pamucar et al. (2023)	The process of assigning weights to various criteria is used to evaluate the green growth performance of countries.
Kara et al. (2024a)	The process of assigning weights to different variables to assess the sustainable brand value.
Kara et al. (2025)	The process of determining the relative importance of indicators to choose the best logo from those created by Artificial Intelligence.
Some Case Studies Using the ARTASI Method	
Kara et al. (2024b)	Selection of the most suitable web design for human resources
Yalçın et al. (2024)	Selection of the commercial insurance

Research questions

The main research questions that this study seeks to answer are as follows:

i. Q1. Which structural and sectoral indicators should be prioritised to improve production capacity performance in the E7 countries?

ii. Q2. Which of the E7 countries perform better when production capacity indicators are considered, and how can these differences be interpreted?

iii. Q3. Can an efficient and responsive analytical framework integrated with the MCDM methods be developed to measure and evaluate the productive capacity performance?

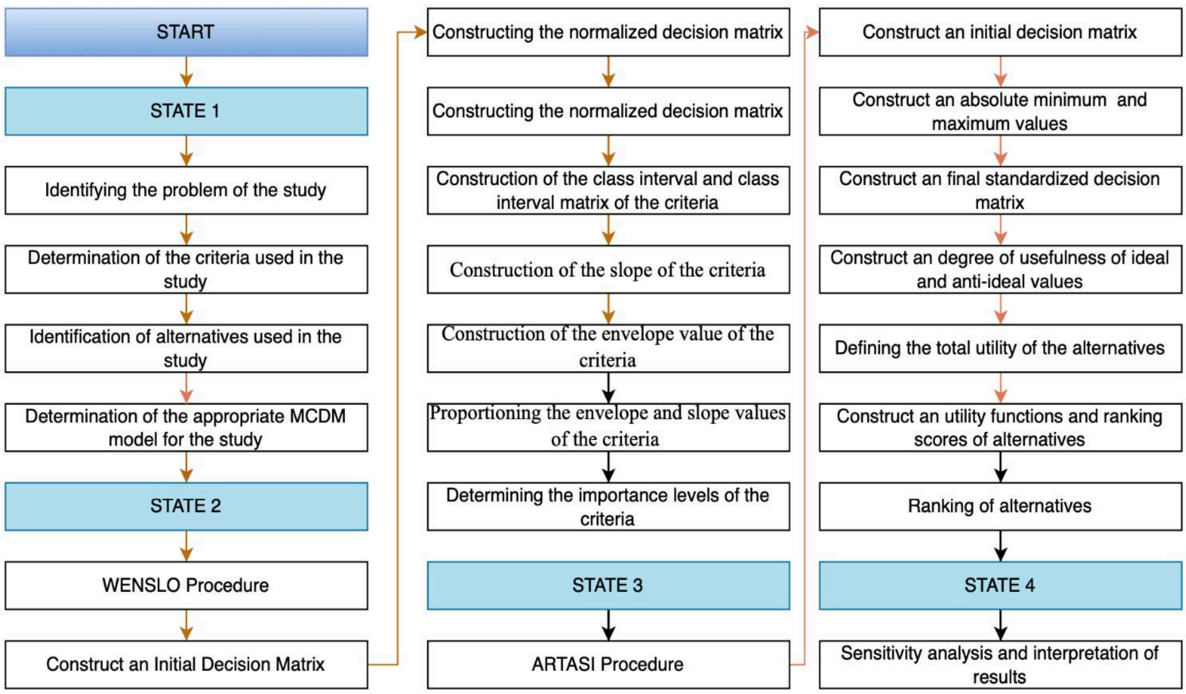
These research questions are based on the main gaps observed in the existing literature. The number of studies on production capacity indicators is quite limited, and most of the existing studies directly use only the production capacity index values published by UNCTAD. However, these approaches do not sufficiently include the weighting of the criteria behind the index values or alternative evaluation methods. In this context, the integrated MCDM model proposed in this study offers a new methodological contribution that will enable decision makers to conduct more holistic, sensitive, and comparable analyses. Thanks to this model, the production capacity performance can be analysed in more depth, and country-specific policy recommendations can be developed.

Methodology

This section presents the proposed WENSLO-ARTASI integrated MCDM model for assessing the productive capacity performance of the E7 countries. A review of the MCDM literature reveals that there are many objective weighting methods. In this study, the WENSLO method, which is a new approach in the MCDM literature and is not affected by the benefit or cost orientation of the criteria, is preferred as a weighting method. This method, which is not affected by the benefit or cost orientation of the criteria, further reduces the influence of the decision-maker and increases the objectivity of the method. The WENSLO method considers the envelope and slope values of the criteria. In this way, the method can evaluate the impact of the criteria more accurately. In addition, the application algorithm of the WENSLO method is quite simple (Pamucar et al., 2023; Kara et al., 2024a). The ARTASI method, which is used for ranking E7 countries, has also been recently introduced to the MCDM literature. The ARTASI method uses a unique standardisation algorithm for the criteria. It differs from other MCDM methods with its unique standardisation algorithm. The ARTASI method also uses an inverse ranking algorithm. In this way, the minimum criteria are reversed and the benefit or cost difference between the criteria is eliminated. With the elimination of the difference between the criteria, the information complexity about the criteria is eliminated and a more flexible structure is put forward when ranking (Pamucar et al., 2024). The fact that both the WENSLO and ARTASI methods are not affected by whether the criteria are benefit or cost orientated increases the compatibility of these two methods and supports the advantages of these methods. The evaluation stages of the productive capacity performance are shown in Figure 1.

Figure 1

Flow Chart of the Study



WENSLO method calculation procedure

The WENSLO method, introduced to the MCDM literature by Pamucar et al. in 2023, is an objective weighting method consisting of 7 steps. The basic steps of this method are summarised as follows (Pamucar et al., 2023):

Step 1: Creating the decision-making matrix

$$\begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{\mathrm{m}1} & y_{\mathrm{m}2} & \cdots & y_{\mathrm{mn}} \end{bmatrix} \quad (1)$$

Step 2: Constructing the normalised decision matrix

The values in the initial decision matrix are normalised by Equation 2.The values are normalised by dividing each value in the initial decision matrix by the total value of that column. All normalised values are between 0 and 1 and the normalised decision matrix presented in Equation 3 is obtained.

$$s_{\mathrm{ij}} = \frac{y_{\mathrm{ij}}}{\sum_{i=1}^{\mathrm{m}} y_{\mathrm{ij}}}; i = 1, 2, 3, ..., m; j = 1, 2, 3, ..., n \quad (2)$$

$$[s_{\mathrm{ij}}]_{m\times n} \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1j} \\ s_{21} & s_{22} & \cdots & s_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ s_{\mathrm{i}1} & s_{\mathrm{i}2} & \cdots & s_{\mathrm{ij}} \end{bmatrix}; (0 < s_{\mathrm{ij}} < 1) \quad (3)$$

Step 3: Calculating the class interval and class interval matrix of the criteria

The normalised decision matrix was used to determine the effect of the criteria on the ranking. In this step, subjective judgements are eliminated when weighting the criteria. The value Δs_ij in Equation 4 represents the class range size of the criteria.

$$\begin{gathered} \Delta s_{\mathrm{ij}} = \frac{\mathrm{maxs}_{\mathrm{ij}} - \mathrm{mins}_{\mathrm{ij}}}{1 + 3.322 \times \log(i)} \text{ i;Number of alternatives} \\ \text{maxs\_ij;the maximum value in each column} \\ \text{mins\_ij;the minimum value in each column} \end{gathered} \quad (4)$$

Step 4: Calculating the slope of the criteria

The slope of the criteria was calculated using Equation 5.

$$\mathrm{tanf}_{\mathrm{j}} = \frac{\sum_{\mathrm{i}=1}^{m} s_{\mathrm{ij}}}{(i-1) \times \Delta s_{\mathrm{ij}}} i; \text{ Number of alternatives} \quad (5)$$

Step 5: Calculation of the envelope value of the criteria

The envelope values calculated by Equation 6 represent the sum of the Euclidean distances. The distance between the initial and final normalised values for each criterion is called the Euclidean distance.

$$K_j = \sum_{i=1}^{m-1} \sqrt{\left(s_{((i+1))_j} - s_{\mathrm{ij}}\right)^2 + \Delta s_{\mathrm{j}}^2} \quad (6)$$

Step 6: Proportion the envelope and slope values of the criteria

$$h_{\mathrm{j}} = \frac{K_{\mathrm{j}}}{\mathrm{tanf}_j} \quad (7)$$

Step 7: Determine the importance levels of the criteria

$$w_j = \frac{h_j}{\sum_{i=1}^{n} h_{\mathrm{j}}} \tag{8}$$

ARTASI method calculation procedure

The ARTASI method, which was introduced to the MCDM literature by Pamucar et al. in 2024 and has its own standardisation algorithm, is used for ranking alternatives. The stages of this method are as follows (Pamucar et al., 2024):

Step 1: Creating the decision-making matrix

The first decision matrix consists of the evaluation criteria for m sets of alternatives. ϑ_{ij} is the j. Criterion value of alternative i. $(i = 1, 2, 3, \ldots, m; j = 1, 2, 3, \ldots, n)$.

$$\left[\vartheta_{\mathrm{ij}}\right]_{m \times n} \begin{bmatrix} \vartheta_{11} & \vartheta_{12} & \ldots & \vartheta_{1n} \\ \vartheta_{21} & \vartheta_{22} & \ldots & n \\ \vdots & \vdots & \ddots & \vdots \\ \vartheta_{\mathrm{m1}} & \vartheta_{\mathrm{m2}} & \ldots & \vartheta_{\mathrm{mn}} \end{bmatrix} \tag{9}$$

Step 2: Calculating the absolute minimum $\left(\vartheta_j^{\min}\right)$ and maximum $\left(\vartheta_j^{\max}\right)$ values

Equation 10 represents the absolute minimum value in the initial decision matrix and Equation 11 represents the absolute maximum value in the initial decision matrix. The value m in the equations represents the number of alternatives considered.

$$\vartheta_j^{\min} = \min\left(\vartheta_{\mathrm{ij}}\right) - \left(\min\left(\vartheta_{\mathrm{ij}}\right)\right)^{\frac{1}{m}} \tag{10}$$

$$\vartheta_j^{\max} = \max\left(\vartheta_{\mathrm{ij}}\right) + \left(\max\left(\vartheta_{\mathrm{ij}}\right)\right)^{\frac{1}{m}} \tag{11}$$

Step 3: Creating the standardised decision matrix

Depending on the criteria considered, the initial decision matrix may include both cost-side and benefit-side criteria. In order to eliminate this difference, the matrix should be standardised. In other MCDM methods, the normalised decision matrix takes values between 0 and 1. This may cause the criteria to converge or diverge. The ARTASI method, which aims to eliminate this situation, standardises the decision matrix according to the original values. The ARTASI method determines lower $\left(\varphi^{(l)}\right)$ and upper $\left(\varphi^{(r)}\right)$ boundaries according to the size of the problem. This boundary expands or contracts according to the size of the problem. When the problem is larger, the boundaries expand, and when the problem is smaller, the boundaries shrink. In this method, a threshold range of (1-100) is considered sufficient for solving many problems. Furthermore, the standardisation process in the ARTASI method occurs in two stages. In the first stage, all the elements of the initial decision matrix are standardised using Equation 12. In the second stage, if a cost criterion exists among the criteria, all criteria are adjusted for uniformity by applying Equation 13 to the elements of that criterion. The benefit-oriented criteria remain unchanged in the matrix $\left(\phi_{\mathrm{ij}} = \mu_{\mathrm{ij}}\right)$.

$$\mu_{\mathrm{ij}} = \frac{\varphi^{(r)} - \varphi^{(l)}}{\vartheta_j^{\max} - \vartheta_j^{\min}} \times \vartheta_{\mathrm{ij}} + \frac{\vartheta_j^{\max} \times \varphi^{(l)} - \vartheta_j^{\min} \times \varphi^{(r)}}{\vartheta_j^{\max} - \vartheta_j^{\min}} \tag{12}$$

$$\phi_{\mathrm{ij}} = -\mu_{\mathrm{ij}} + \max\left(\mu_{\mathrm{ij}}\right) + \min\left(\mu_{\mathrm{ij}}\right) \tag{13}$$

Step 4: Calculating the degree of usefulness of ideal $\left(\theta_{\mathrm{ij}}^{+}\right)$ and anti-ideal $\left(\theta_{\mathrm{ij}}^{-}\right)$ values

The degree of usefulness for the ideal value is calculated using Equation 14. The process for determining the degree of usefulness of the anti-ideal value occurs in two stages. In the first stage, the degree of usefulness for the anti-ideal value is transformed on the basis of Equation 15. In the second stage, the degree of usefulness for the anti-ideal value is obtained by applying Equation 16. The variable w_j in both Equations 14 and 15 indicates the importance level of the criteria.

$$\theta_{\mathrm{ij}}^{+}=\frac{\phi_{\mathrm{ij}}}{\max\left(\phi_{\mathrm{ij}}\right)}\times w_j\times\varphi^{(r)} \tag{14}$$

$$\theta_{\mathrm{ij}}=\frac{\min\left(\phi_{\mathrm{ij}}\right)}{\phi_{\mathrm{ij}}}\times w_j\times\varphi^{(r)} \tag{15}$$

$$\theta_{\mathrm{ij}}^{-}=-\theta_{\mathrm{ij}}+\max\left(\theta_{\mathrm{ij}}\right)+\min\left(\theta_{\mathrm{ij}}\right) \tag{16}$$

Step 5: Defining the total utility of the alternatives

The optimal value obtained by Equation 14 is derived by summing the degree of usefulness and the anti-ideal degree of usefulness obtained by Equation 16 separately. The process applications are shown in Equations 17 and 18, respectively. For ideal values, the total degree of utility is represented as (ξ_i^{+}), while for anti-ideal values, the total degree of utility is represented as (ξ_i^{-}).

$$\xi_i^{+}=\sum_{j=1}^{n}\theta_{\mathrm{ij}}^{+} \tag{17}$$

$$\xi_i^{-}=\sum_{j=1}^{n}\theta_{\mathrm{ij}}^{-} \tag{18}$$

Step 6: Calculation of the utility functions and ranking scores of the alternatives

Equation 19 and 20 use the total utility degrees obtained with the ideal and anti-ideal values to derive the utility functions. The utility function for ideal values is represented as f(ξ_i^{+}), while the utility function for anti-ideal values is represented as f(ξ_i^{-}). The ranking score of the alternatives is represented as (¥) and calculated using Equation 21. The parameter α in Equation 21 represents the effect of the total utility levels on the final decision, while the parameter β represents the balancing parameter of the cluster. In the study by Pamucar et al., α was set to 0.5 to eliminate the effect of utility functions in the ARTASI method, while β was set to 1 to reveal the cluster equilibrium.

$$f(\xi_i^{+})=\frac{\xi_i^{+}}{\xi_i^{+}+\xi_i^{-}} \tag{19}$$

$$f(\xi_i^{-})=\frac{\xi_i^{-}}{\xi_i^{+}+\xi_i^{-}} \tag{20}$$

$$¥_i=(\xi_i^{+}+\xi_i^{-})\times\{\alpha.(f(\xi_i^{+}))^{\beta}+\left(1-\alpha<(f(\xi_i^{-}))^{\beta}\right\}^{1/\beta}\alpha\in[0,1];\beta\in[0,+\infty) \tag{21}$$

The final ranking values are obtained by ranking the ranking scores $(¥_i)$ of the obtained alternatives in descending order.

Case Study

This study introduces an integrated decision model that combines the WENSLO and ARTASI methods to assess the productive capacity performance of the E7 countries. This section will first provide explanatory information regarding the dataset used in the analysis, followed by the presentation of the results obtained from the analyses conducted with the proposed integrated models.

Data

The indicators used in the study and the codes to be used in the tables are given in Table 2. The indicators were obtained from the UNCTAD data bank. Since all of the evaluation criteria considered are indices, they are benefit-oriented. The study focuses on the E7 countries: Brazil (BRA), China (CHN), India (IND), Indonesia (IDN), Mexico (MEX), Russia (RUS), and Turkey (TUR). In this study, the dataset was constructed by considering all 8 indicators used by UNCTAD in calculating the productive capacity index. These indicators are the indicators accepted by the UNCTAD to accurately and comprehensively assess productive capacity. Therefore, no indicator was excluded from the dataset, and the analysis was conducted using all of them. This approach ensures an assessment that fully reflects the productive capacity.

Table 2

Performance Evaluation Criteria

Code	Performance Criteria	Definition
HC	Human Capital Index	It covers the level of education, skills, health facilities, and research and development capability. In addition, the gender dimension and fertility status are considered.
NC	Natural Capital Index	Includes the net income from natural resources. This index also includes agricultural activities and measures the capacity of countries to reduce their dependence on raw materials.
EN	Energy Index	Includes indicators of the availability, sustainability, efficiency, and accessibility of energy resources. It also provides assessments on green energy.
TRS	Transportation Index	It shows the level of logistics development and includes data on the transport of goods and people.
ICT	Information and Communication Technology Index	It reflects the level of access to communication systems and adaptation to technology. Indicators such as fixed line, mobile phone, and internet usage are used in the index calculation.
INS	Institutions Index	This index incorporates governance-related indicators such as political stability, freedom of expression, regulatory quality, and measures to combat corruption.
PS	Private Sector Index	It comprises data related to domestic credit availability, costs associated with exports and imports, facilitation of cross-border trade, and initiatives supporting the private sector.
SC	Structural Change Index	This index highlights the enhancement of factor productivity. Key indicators include export diversification, fixed capital intensity, and the contributions of the industrial and service sectors to GDP.

Results obtained from the proposed ıntegrated model algorithm

In the initial stage of the proposed model, the relative importance of the criteria was determined using the WENSLO method. The application of the procedures outlined in Equations 1-8 is presented in the tables below. Table 3 illustrates the initial decision matrix for 2022.

Table 3

2022 Initial Decision Matrix

	HC	NC	EN	TRS	ICT	INS	PS	SC
BRA	57	39.8	52.2	37.1	47.7	50.3	43.9	66.8
CHN	63.9	39.8	69.7	38.2	66.2	50.8	81.2	99
IND	37.8	44.7	48.3	45925	37.5	53.6	54.6	76.1
IDN	40.2	37.6	60.1	45804	48.8	54.7	49.4	68.7
MEX	47.3	37.8	62	38.1	53	44	51.7	69.8
RUS	57.7	36.4	71.8	46.1	63	40.1	44.5	61.3
TUR	58.3	35.9	68.2	44.5	53.5	46.4	56	81.7

By applying Equation 2 to the variables in the initial decision matrix, the values were normalised, resulting in the matrix presented in Equation 3. The details of the matrix and the corresponding values are provided in Table 4.

Table 4

Normalised Initial Decision Matrix for Year 2022

	HC	NC	EN	TRS	ICT	INS	PS	SC
BRA	0.1574	0.1463	0.1207	0.1441	0.1290	0.1480	0.1151	0.1276
CHN	0.1764	0.1463	0.1612	0.1484	0.1791	0.1495	0.2130	0.1891
IND	0.1044	0.1643	0.1117	0.1006	0.1014	0.1577	0.1432	0.1454
IDN	0.1110	0.1382	0.1390	0.1068	0.1320	0.1609	0.1296	0.1313
MEX	0.1306	0.1390	0.1434	0.1480	0.1434	0.1294	0.1356	0.1334
RUS	0.1593	0.1338	0.1661	0.1791	0.1704	0.1180	0.1167	0.1171
TUR	0.1610	0.1320	0.1578	0.1729	0.1447	0.1365	0.1469	0.1561
Maximum Value	0.1764	0.1643	0.1661	0.1791	0.1791	0.1609	0.2130	0.1891
Minimum Value	0.1044	0.1320	0.1117	0.1006	0.1014	0.1180	0.1151	0.1171
Total	1	1	1	1	1	1	1	1

This study determined the class intervals using Equation 4 and the normalised values. Then, it constructed the matrix based on these intervals. The findings are shown in Table 5.

Table 5

Class Intervals and Class Range Matrix of the Criteria for 2022

	HC	NC	EN	TRS	ICT	INS	PS	SC
BRA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CHN	0.0150	0.0067	0.0113	0.0163	0.0161	0.0089	0.0203	0.0150
IND	0.0300	0.0135	0.0226	0.0326	0.0323	0.0179	0.0407	0.0300
IDN	0.0450	0.0202	0.0339	0.0490	0.0484	0.0268	0.0610	0.0449
MEX	0.0600	0.0269	0.0452	0.0653	0.0646	0.0357	0.0814	0.0599
RUS	0.0749	0.0336	0.0565	0.0816	0.0807	0.0447	0.1017	0.0749
TUR	0.0899	0.0404	0.0678	0.0979	0.0969	0.0536	0.1221	0.0899
Class Range Values	0.0150	0.0067	0.0113	0.0163	0.0161	0.0089	0.0203	0.0150

The slope values of the criteria were calculated using Equation 5, and the envelope values of the criteria were calculated using Equation 6. Finally, the importance levels of the criteria were calculated using Equation 8. The findings obtained from these calculations are presented in Table 6.

Table 6

Slope, Envelope, and Weight Values of the Criteria for 2022

	HC	NC	EN	TRS	ICT	INS	PS	SC
Slope Values	111191	247656	147394	102099	103212	186535	81907	111238
Envelope Values	0.1864	0.0751	0.1739	0.1817	0.2480	0.0986	0.2824	0.2091

	HC	NC	EN	TRS	ICT	INS	PS	SC
Weight Values	0.1270	0.0230	0.0894	0.1348	0.1821	0.0400	0.2613	0.1424

For the year 2022, which is taken as an example, all the steps made above have been applied separately for each year in the period 2003-2022, and the importance levels of the criteria obtained are presented in Table 7.

Table 7

2003-2022 Period Weight Values of the Criteria

	HC	NC	EN	TRS	ICT	INS	PS	SC
2022	0.1270	0.0230	0.0894	0.1348	0.1821	0.0400	0.2613	0.1424
2021	0.1350	0.0211	0.0928	0.1429	0.1683	0.0426	0.2535	0.1437
2020	0.1206	0.0330	0.1055	0.1399	0.1754	0.0333	0.2562	0.1362
2019	0.1238	0.0298	0.1027	0.1028	0.2246	0.0256	0.2326	0.1580
2018	0.1096	0.0271	0.0997	0.0923	0.2366	0.0295	0.2512	0.1540
2017	0.0949	0.0389	0.1078	0.1011	0.2386	0.0328	0.2566	0.1293
2016	0.0844	0.0383	0.1124	0.1054	0.2443	0.0395	0.2678	0.1079
2015	0.0819	0.0339	0.1018	0.1069	0.2667	0.0489	0.2394	0.1205
2014	0.0873	0.0360	0.1236	0.1006	0.2806	0.0531	0.1884	0.1304
2013	0.0903	0.0420	0.1352	0.0975	0.2904	0.0744	0.1403	0.1300
2012	0.0933	0.0442	0.1464	0.0893	0.2832	0.0926	0.1251	0.1257
2011	0.0948	0.0455	0.1725	0.0778	0.2690	0.1015	0.1075	0.1314
2010	0.0948	0.0457	0.1517	0.0714	0.3118	0.1040	0.1167	0.1038
2009	0.1034	0.0475	0.1512	0.0674	0.3402	0.0861	0.1190	0.0852
2008	0.1066	0.0569	0.1703	0.0786	0.3343	0.0785	0.1037	0.0711
2007	0.1080	0.0554	0.1822	0.0661	0.3400	0.0833	0.0981	0.0670
2006	0.1102	0.0556	0.1818	0.0656	0.3084	0.0860	0.1188	0.0736
2005	0.1085	0.0626	0.1849	0.0667	0.2945	0.0886	0.1193	0.0748
2004	0.1272	0.0604	0.1840	0.0649	0.2806	0.0928	0.1192	0.0708
2003	0.1218	0.0579	0.1783	0.0638	0.2674	0.1178	0.1252	0.0680

After obtaining the results using the WENSLO method, the second phase of the proposed model, the ARTASI method, was implemented. This phase began with the construction of the initial decision matrix, marking the first step of the ARTASI method. In the subsequent step, the absolute maximum and minimum values were computed. Both the initial decision matrix and the corresponding absolute values are presented in Table 8.

Table 8

2022 Initial Decision Matrix and Absolute Values

	HC	NC	EN	TRS	ICT	INS	PS	SC
BRA	57	39.8	52.2	37.1	47.7	50.3	43.9	66.8
CHN	63.9	39.8	69.7	38.2	66.2	50.8	81.2	99
IND	37.8	44.7	48.3	45925	37.5	53.6	54.6	76.1
IDN	40.2	37.6	60.1	45804	48.8	54.7	49.4	68.7
MEX	47.3	37.8	62	38.1	53	44	51.7	69.8

	HC	NC	EN	TRS	ICT	INS	PS	SC
RUS	57.7	36.4	71.8	46.1	63	40.1	44.5	61.3
TUR	58.3	35.9	68.2	44.5	53.5	46.4	56	81.7
Absolute Maximum Value	65581	46308	73506	47714	67889	56349	82933	100776
Absolute Minimum Value	39375	37465	49924	27402	39073	41686	45504	62973
Absolute Difference	26207	8843	23582	20312	28816	14663	37428	37803

In the third stage of the ARTASI method, the initial decision matrix is subjected to standardisation. This process is conducted in two stages, with the final result being a standardised decision matrix. The findings are presented in Table 9.

Table 9

2022 Final Standardised Decision Matrix

	HC	NC	EN	TRS	ICT	INS	PS	SC
BRA	−0.930	−1398	−4924	−1766	−2617	−0.657	26126	−4369
CHN	−0.671	−1398	−0.619	−1589	−0.851	−0.622	−0.888	−0.505
IND	12699	−0.463	8937	13484	18207	−0.477	−3382	−1361
IDN	−15261	−15085	−1189	−57672	−2330	−0.437	−7497	−3010
MEX	−2031	−7982	−1005	−1604	−1642	−2339	−4874	−2551
RUS	−0.895	3477	−0.560	−0.925	−0.964	4003	51154	14245
TUR	−0.867	2299	−0.669	−1011	−1586	−1184	−2946	−0.962

After final standardisation, ideal and anti-ideal matrices were obtained from these data. The resulting matrices are shown in Table 10.

Table 10

Ideal and Anti-Ideal Matrices for 2022

				Ideal Matrix				
	HC	NC	EN	TRS	ICT	INS	PS	SC
BRA	9165	0.761	1016	7064	5922	2665	−0.888	1647
CHN	12699	0.761	8088	7849	18207	2817	26126	14245
IND	−0.671	2299	−0.560	−0.925	−0.851	3668	6861	5285
IDN	0.558	0.071	4209	0.216	6653	4003	3095	2390
MEX	4196	0.133	4976	7777	9442	0.749	4761	2821
RUS	9523	−0.306	8937	13484	16082	−0.437	−0.454	−0.505
TUR	9831	−0.463	7482	12343	9774	1479	7875	7476
				Anti-Ideal Matrix				
	IS	DS	EN	NK	BI	KR	OS	YD
BRA	−1632	−10209	8937	−42422	18207	2321	17531	14245
CHN	−1891	−10209	4632	−42599	16441	2286	44546	10381
IND	−15261	−11145	−4924	−57672	−2617	2142	47039	11237
IDN	12699	3477	5202	13484	17920	2102	51154	12886

MEX	−0.531	−3625	5018	−42584	17232	4003	48531	12427
RUS	−1667	−15085	4573	−43263	16554	−2339	−7497	−4369
TUR	−1695	−13906	4682	−43177	17176	2848	46604	10838

The final step of the ARTASI method is to calculate the final values and rank the alternatives considered. The results are shown in Table 10. In the first application of this method, it was stated that the α value used as a parameter could take a value between 0 and 1 and was considered in practice to be 0.5. For this reason, the α value was considered to be 0.5 in the study, but this value was tested with different values between 0 and 1 in the sensitivity analysis.

Table 11

Utility Functions and Ranking of Alternatives for 2022

	Function(Ideal)	Function(Anti-Ideal)	Evaluation Score for the ARTASI	Rank
BRA	0.797	0.203	13777	5
CHN	0.794	0.206	45499	1
IND	−0.939	1939	8522	7
IDN	0.151	0.849	11022	6
MEX	0.463	0.537	17696	4
RUS	−6845	7845	27085	3
TUR	0.705	0.295	28046	2

All transactions for 2022 have been carried out one by one for the years 2003-2022 and are presented in Table 12.

Table 12

Assessing the Productive Performance of the E7 Countries 2003-2022

	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013
BRA	5	5	5	5	5	5	5	5	4	3
CHN	1	1	1	1	1	1	1	1	1	1
IND	7	7	7	7	7	7	7	7	7	7
IDN	6	6	6	6	6	6	6	6	6	6
MEX	4	4	4	4	4	4	4	3	5	5
RUS	3	3	3	3	3	3	3	4	3	4
TUR	2	2	2	2	2	2	2	2	2	2
	2012	**2011**	**2010**	**2009**	**2008**	**2007**	**2006**	**2005**	**2004**	**2003**
BRA	3	3	4	4	4	5	5	5	5	5
CHN	1	2	2	1	2	2	2	2	1	3
IND	7	7	7	7	7	7	6	6	6	6
IDN	6	6	6	6	6	6	7	7	7	7
MEX	5	5	5	5	5	4	3	3	3	2
RUS	4	4	3	3	3	3	4	4	4	4
TUR	2	1	1	2	1	1	1	1	2	1

Examining Table 12, It is evident that the countries with the best performance in terms of productive capacity among the E7 countries are China and Turkey. Russia, on the other hand, ranks 4th in 8 years and 3rd in other years. The countries with the worst performance in terms of productive capacity among the E7 countries are India and Indonesia. To provide a clearer interpretation of the results and to make recommendations based on these findings, it is crucial to test the robustness, reliability, and consistency of the proposed model. Therefore, several sensitivity analyses were conducted.

Sensitivity analysis

One of the sensitivity analyses conducted is based on the method developed by Božanić et al. (2021) and Pamucar et al. (2021), which involves reducing the weight of the most important criterion by 2% in each scenario. As a result of the literature review, the approach of reducing the weight of the criterion with the highest importance level among the performance criteria by 2% in each scenario and redistributing this reduced weight to other criteria stands out as a frequently preferred method. In this context, it is seen that the same ratio is used in the studies conducted by Božanić et al. (2021), Pamucar et al. (2021), and Işık (2022). Therefore, in the sensitivity analysis carried out in this study, this rate was considered as 2%. This ensures that the sum of the criteria weights in each scenario remains equal to 1. The results obtained after re-weighting are presented in Figure 2.

Figure 2

Sensitivity Analysis According to the Criterion Importance Level (80 Scenarios)

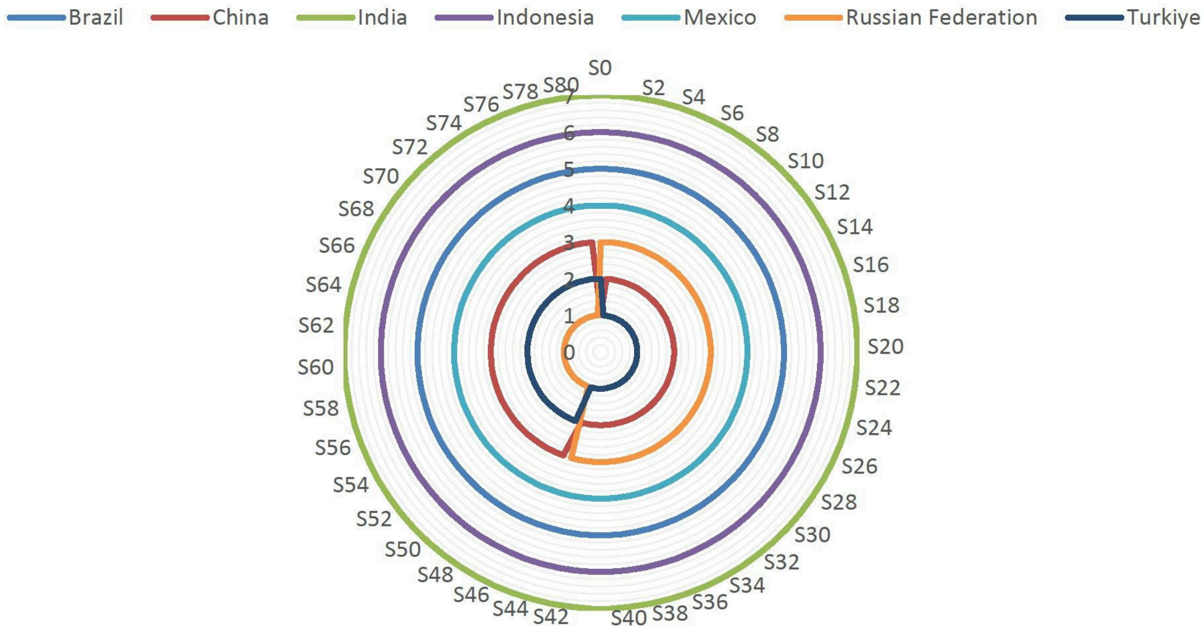
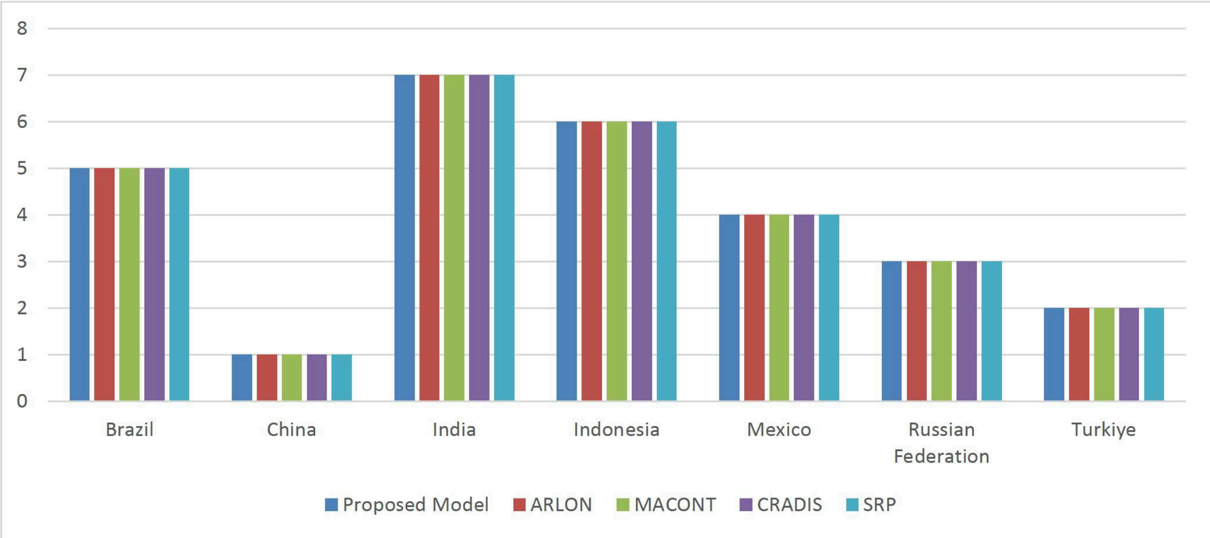


Figure 2 shows that there is no change in the rankings of India, Indonesia, Brazil, and Mexico in all scenarios. This shows that these countries have maintained their positions in the rankings even though the criteria weights have changed. It can also be concluded that there is a significant difference between these countries in terms of their productive capacity rankings. On the other hand, for China, Russia, and Turkey, there is a slight change in the rankings because of the change in the criteria weights. The findings indicate that the productive capacity performances of the countries are close to each other. Changing the criterion weights. As a result of changing the Krtier weights, Turkey and Russia have shown a positive change in their productive capacity performance rankings. The findings indicate that Turkey and Russia should focus on these criteria. It is argued that China should direct its investments to the evaluation criteria with a high importance level in order to maintain its stability.

In order to test the reliability of the proposed integrated model, the findings obtained with different MCDM methods were compared. ARLON (Approximate Ranking with Logical Operators and Normalisation), MACONT (Multi-Attribute Assessment Based on the Consistency Technique), CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution) and SRP (Simple Ranking Process) methods were compared with the ARTASI method in the proposed model. The main reason for choosing the methods compared is that they are up-to-date methods such as the proposed model. The MACONT method by Wen et al. (2020), CRADIS method by Puška et al. (2022), SRP method by Zakeri et al. (2023) and ARLON method by Kara et al. The obtained analysis results are presented in Figure 3.

Figure 3

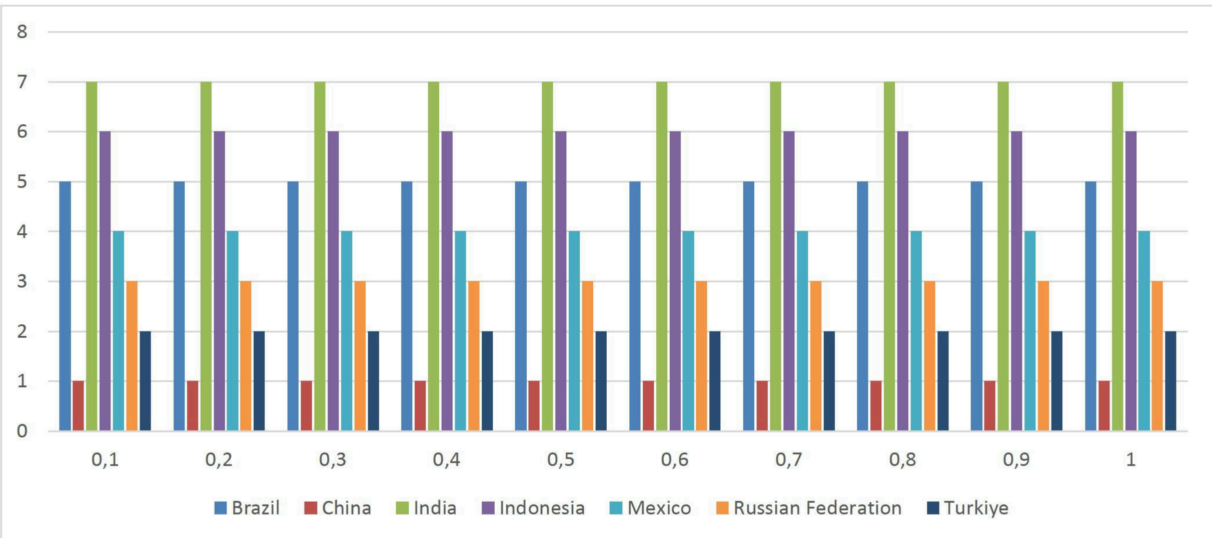
Comparison of the Model Proposal with Different MCDM Methods



The results obtained using the proposed model are the same as those obtained with other MCDM methods. This reveals that the proposed model is a suitable tool for measuring the productive capacity performance. It also demonstrates the reliability and robustness of the proposed model. Pamucar et al. (2024) indicated that the parameters utilized in the ARTASI method may range from 0 to 1 and adopted a value of 0.5 for these parameters in their study.As a matter of fact, the parameters were taken as 0.5 in this study. However, in order to test the consistency of the model, this parameter was changed and analysed and the results obtained are presented in Figure 4.

Figure 4

Evaluation of the ARTASI Method Using the α Parameter



The results of the sensitivity analysis performed by changing the parameter show that the results do not change at all values. This shows that the proposed model is consistent. In addition, there is a threshold limit range in the ARTASI method. This threshold limit range is determined according to the size of the decision-making problem. Although Pamucar et al. left the determination of the threshold range to the decision maker, they argued that taking the threshold range between 1 and 100 is sufficient for many decision-making problems. In the study they conducted in this context, they determined the threshold boundary range as 1-100. In this study, the threshold limit value was set as 1-100 and no sensitivity analysis over the threshold limit range was required. The main reason for this is the size of the problem. In addition, it was thought that the threshold limit range of 1-10 would not reflect the results of the study correctly. In the application steps of the study, while the threshold limit range was taken as 1-100, it was tried as 1-1000 and it was seen that the results did not change. For this reason, it was considered sufficient to set the threshold limit range as 1-100 and it shows that expanding the equal limit range will not affect the decision-making process.

Finally, the findings obtained with the proposed model are compared with the PCI values published by UNCTAD for the E7 countries. In this comparison, a high degree of agreement was observed. This comparison is presented in the appendix. UNCTAD takes the geometric mean when calculating the PCI. This situation causes countries to have the same PCI value in some years. The proposed model is designed to eliminate this problem, and the proposed model reveals even negligible differences for each country.

Conclusion and Policy Proposals

Upon analysis of the findings, it was determined that the private sector, information and communication technologies, and energy indicators hold the greatest significance in the assessment of productive capacity. The results of the proposed model indicate that China exhibits the highest level of productive capacity. While China was ranked third and second in the initial years, it has since risen to the top position in 2012. Turkey occupied the second position among the E7 countries after 2012 but had been in the first position before this year. Russia has remained in third place since 2016. Mexico, on the other hand, had been ranked second in 2003 but had subsequently dropped to fifth place. In Table 11, Brazil is usually ranked fifth, Indonesia sixth and India mostly last.

As there is only one study in the existing literature that uses the productive capacity indicators by employing the MCDM method, it is not feasible to directly compare the findings obtained with those of other studies. However, when compared with this study on G20 countries, it is evident that Brazil, Indonesia, and Mexico are positioned at the lowest levels of the ranking, while Turkey and Russia have achieved relatively high rankings. Conversely, it is observed that China occupies the top position among the G20 countries. A comparison of the results obtained with the existing literature reveals a similar outcome. Furthermore, a novel methodology for calculating the published PCI has been proposed. In this way, a more detailed examination has been proposed for countries with the same PCI indices published by UNCTAD. UNCTAD may alternatively utilise the integrated MCDM model employed in the study instead of the geometric mean employed in the calculation of the PCI.

China, which initially occupied the third position in the production capacity evaluation in 2003, subsequently ascended to the top ranking in 2012. A review of the GDP data for China reveals a significant increase in production capacity, with an 11-fold growth in GDP from 2003 to 2022. Turkey, which was in second place in the ranking of production capacity evaluation, held this position until 2012, after which another country overtook it. An analysis of the GDP values of Turkey reveals that the country's GDP increased approximately threefold from 2003 to 2022. This situation provides evidence that the PCI has a significant impact on GDP. While China has improved its productive capacity performance by two places and increased its GDP by 11 times, Turkey has declined by one place in its productive capacity performance and increased its GDP by only

3 times. There are likely many factors affecting GDP. However, productivity is considered to be an important factor for GDP, given the concept of obtaining higher output with the same amount of input.

In this context, an increase in a country's productive capacity will increase its economic development. The findings, when considered alongside GDP values, demonstrate that countries must enhance their productive capacity to elevate their GDP. It is thus proposed that the criteria be improved to enhance the precision of production capacity assessments. Furthermore, in the proposed model, the importance levels of the criteria were determined, and it was observed that the information and communication technologies indicator was of the greatest importance. This situation demonstrates that for the E7 countries to enhance their production capacity, it is imperative to prioritise the improvement of the ICT indicator. Furthermore, it is proposed that the E7 countries adopt the economic policies currently in place in China to increase their GDP. Consequently, the E7 countries will be able to enhance their GDP by optimising their productive capacity performance. It follows that the prediction made by PricewaterhouseCoopers for E7 countries, namely that these countries will catch up with G7 countries in the future, will only be realised if these countries increase their productive capacity performance. While numerous predictions have been posited in the study, several limitations remain.

The limitations of this study are that the dataset used is limited to E7 countries only. Therefore, the generalizability of the findings is limited. In future studies, the generalizability of the results can be improved using a larger group of countries and comprehensive data sets. Moreover, analysing long-term trends with time series data can expand the scope of the study. Panel data models, Granger causality tests, and regression approaches can be used in econometric analysis. Such models will more clearly reveal the dynamic factors affecting the productive capacity. Moreover, a more in-depth examination of the variables considered in the study in econometric analyses may improve the accuracy of the model.

Peer Review Externally peer-reviewed.
Conflict of Interest The author has no conflict of interest to declare.
Grant Support The author declared that this study has received no financial support.

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Appendix

Figure 1

UNCTAD's PCI Ranking of E7 Countries

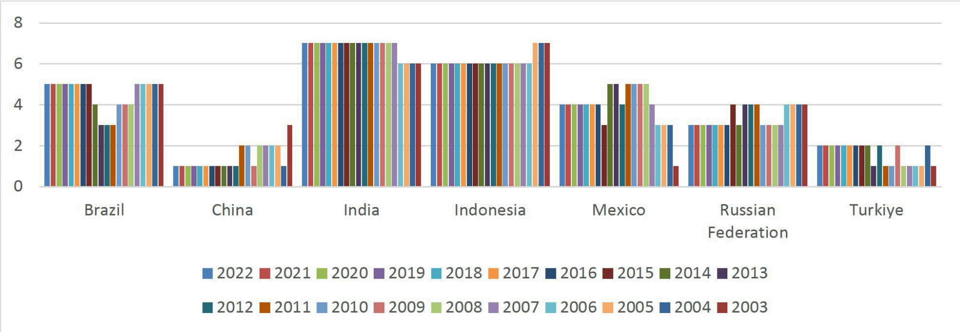

Figure 2

The Proposed Model's Ranking of the Productive Capacities of the E7 Countries

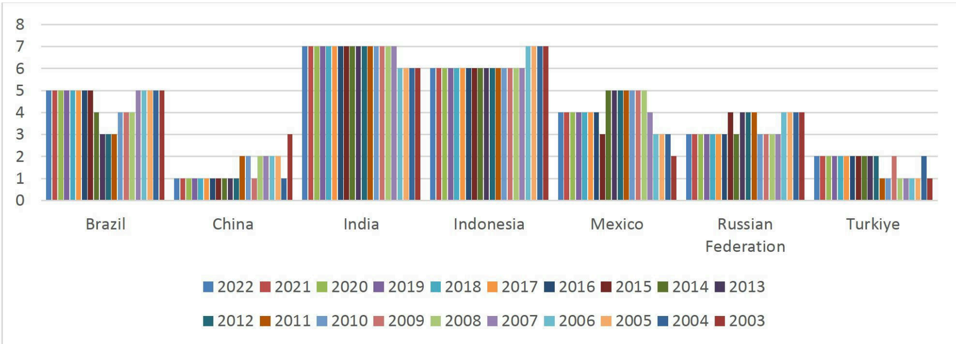

Table 1

GDP Values of the E7 Countries for the Period from 2003 to 2022 ($ Millions)

	Brazil	China	Indonesia	India	Mexico	Russian Federation	Turkey
2022	558,234	1,660,281	234,772	607,699	765,55	430,347	314,596
2021	669,289	1,955,347	256,837	709,149	819,459	591,017	408,865
2020	891,634	2,285,961	285,869	820,382	917,572	764,016	506,315
2019	1,107,627	2,752,119	364,571	940,26	1,020,265	989,932	557,076
2018	1,397,114	3,550,328	432,217	1,216,736	1,102,356	1,299,703	681,321
2017	1,695,855	4,594,337	510,229	1,198,895	1,161,553	1,660,848	770,449
2016	1,666,996	5,101,691	539,58	1,341,888	943,437	1,222,646	649,289
2015	2,208,838	6,087,192	755,094	1,675,616	1,105,424	1,524,917	776,967
2014	2,616,156	7,551,546	892,969	1,823,052	1,229,014	2,045,923	838,785
2013	2,465,228	8,532,185	917,87	1,827,638	1,255,110	2,208,294	880,556
2012	2,472,820	9,570,471	912,524	1,856,722	1,327,436	2,292,470	957,799
2011	2,456,044	10,475,625	890,815	2,039,126	1,364,508	2,059,242	938,935
2010	1,802,212	11,061,573	860,854	2,103,588	1,213,294	1,363,482	864,314
2009	1,795,693	11,233,314	931,877	2,294,797	1,112,233	1,276,786	869,683
2008	2,063,515	12,310,491	1,015,619	2,651,474	1,190,721	1,574,199	858,988
2007	1,916,934	13,894,908	1,042,272	2,702,930	1,256,300	1,657,329	778,972
2006	1,873,288	14,279,969	1,119,100	2,835,606	1,305,212	1,693,115	761,006

	Brazil	China	Indonesia	India	Mexico	Russian Federation	Turkey
2005	1,476,107	14,687,744	1,059,055	2,671,595	1,120,741	1,493,076	720,338
2004	1,649,623	17,820,460	1,186,505	3,150,307	1,312,558	1,836,892	819,865
2003	1,920,096	17,963,171	1,319,100	3,416,646	1,465,854	2,240,422	907,118

Source: World Bank DataBank