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RESEARCH ARTICLE

A Novel Method for Measuring the Performance of Decision Alternatives in Multi-Criteria Decision Making: Proportional Superiority Approach (PSA)

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HIGHLIGHTS

- *Effect and important of this article in literature*
- *Exchange between sources in related subjects of this article*
- *Contribution and strongest impact on the related sobject of this article*
- *Examined study and obtained results why is important*

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ABSTRACT

In the face of increasing complexity and uncertainty, new multi-criteria decision making (MCDM) methods facilitate making informed and rational decisions by enhancing problem-solving skills. Therefore, the discovery of new MCDM methods is of great importance. In this context, this study introduces a new MCDM model (Proportional Superiority Approach-PSA) based on the fundamental logic of measuring the performance of decision alternatives, which relies on the proportional increase of decision alternatives to each other, aiming to expand the modeling logic of MCDM and enrich MCDM literature. Initially, a comparative analysis of the proposed method was conducted. According to the findings, although the relationship of PSA with other MCDM methods included in the study was high. Therefore, based on the results of the comparative analysis, it was observed that the proposed method is credible and reliable. In the scope of the simulation analysis, 10 scenarios were obtained, and it was found that as the number of scenarios increased, the relationship levels of the PSA method with other methods differed. Furthermore, the PSA method was found to be capable of discriminating between the performances of decision alternatives through variance measurement. Finally, in the analysis, the level of variance of the PSA method was measured within the scenarios, and it was found that the variances of the PSA method were homogeneous within the scenarios. Therefore, according to the results of the simulation analysis, it was evaluated that the PSA method is robust and stable.

Keywords: *Rate of increase, proportional increase superiority, proportional superiority approach-PSA, MCDM*

I. INTRODUCTION

Multi-criteria decision-making (MCDM) methods are a critical tool for making informed decisions in complex situations. They enable decision-makers to consider multiple, often conflicting, criteria simultaneously, leading to more comprehensive and effective choices (Puška, 2013). MCDM methods are powerful tools that can significantly enhance the decision-making process. By providing a structured framework for considering multiple criteria, integrating diverse perspectives, and enhancing transparency, MCDM methods enable decision-makers to navigate the complexities of real-world decisions and make more informed, effective, and defensible choices (Triantaphyllou, 2010).

When examining the MCDM literature, it is possible to encounter many methods that measure the performances or optimality of decision alternatives. The most significant feature of these methods is that each has its own unique calculation method (Behl, 2020). Developing original and new MCDM methods is important to provide more specific and accurate solutions to problems, offer new perspectives and solution approaches, expand the application areas of MCDM, and benefit from scientific and technological advancements (Amor et al., 2021).

In this context, to contribute to, enrich, and provide a new perspective to the MCDM literature, the Proportional Superiority Approach (PSA) method, which is new and original in selection problems or measuring the performances of decision alternatives, is presented in the research. The motivation of the study is determined as the method's reliance on more realistic values for assessing the quantitative superiority of decision alternatives, compared to other MCDM methods that measure the performance of decision alternatives. This is because, except for the TODIM method, other MCDM methods are based on the idea that the decision-maker is always seeking a solution corresponding to the maximum value (Ecer, 2020). However, in the proposed method, as in the TODIM method, decision alternatives are compared with each other based on criteria, and those with quantitative superiority are ranked. Therefore, in this case, the true superiority value of the decision alternatives is determined by comparing the values corresponding to each criterion for each decision alternative. The basis of the proposed method lies in the increase rate of values of decision alternatives for each criterion. Accordingly, some commonly used MCDM methods in the literature and the proposed method are mentioned in the study. In the conclusion section, implications regarding the proposed method are provided based on the findings of the research.

II. MATERIAL AND METHOD

A. Some MCDM Methods in the Literature and Their Characteristics

When examining the MCDM literature, it is evident that numerous techniques are employed for the selection of decision alternatives or the measurement of their performances (Lopez et al., 2023; Van Thanh, 2020). Accordingly, when evaluating MCDM research, it is observed that many researchers utilize techniques such as SAW (Simple Additive Weighting), WPM (Weighted Product Method), WASPAS (Weighted Aggregated Sum Product Assessment), COPRAS (Complex Proportional Assessment), EDAS (Evaluation Based on Distance from Average Solution), ARAS (Additive Ratio Assessment), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), MAUT (Multiple Attribute Utility Theory), PSI (Preference Selection Index), and TODIM (Tornado de Decisao Interativa Multicriterio) for selection problems (Karende et al., 2016; Mousavi-Nasab and Sotoudeh-Anvari, 2017; Biswas et al., 2019; Chourabi et al., 2019; ; Yadav et al., 2019; Goswami et al., 2021; Karakış, 2021; Tiwari and Kumar, 2021; Dhanalakshmi et al., 2022). SAW is also described as a weighted linear combination or scoring method. For the method to be correctly applied, data must be numerical and comparable (Al Khoiry and Amelia, 2023; Taherdoost, 2023). In the method, the first step in calculating the performance of decision alternatives or solving selection problems is to create a decision matrix. Subsequently, the values in the decision matrix are normalized. In the third step, a weighted normalized decision matrix is obtained. In the final step, the normalized decision matrix values for each decision alternative are summed, and the summed values are sorted from highest to lowest (Sotoudeh-Anvari et al., 2018; Dinçer, 2019; Demirci, 2020).

WPM compares each decision alternative with others by multiplying several ratios for each criterion, one for each decision alternative. Due to the method's exponential nature, it is important for the sum of criterion weights to be equal to 1 (Chinnasamy et al., 2023). In this method, the first step involves creating a decision matrix. In the second step, the values in the decision matrix are normalized. In the third step, the exponential structure of the normalized values is assigned criterion weights. Finally, new values specific to decision alternatives are determined by multiplying criterion-wise values, and the resulting performance scores are ranked from highest to lowest (Demir et al., 2021; Onajite and Oke, 2021). WASPAS is a method provided by combining the SAW and WPM techniques. In this method, the combined optimality coefficient and total relative importance quantity are calculated. The total relative importance value explains the performance of decision alternatives or the preferred alternative in decision problems (Handayani et al., 2023). The first step of the WASPAS method involves preparing the decision matrix. In the second step, the normalization process of the decision matrix values is carried out. In the third step, the relative importance value of alternatives is determined according to the SAW and WPM methods. Finally, the combined optimal value of decision alternatives is calculated, and the calculated values are ranked from highest to lowest (Ayçin, 2019; Stanujkić and Karabašević, 2023).

COPRAS method places importance on whether criteria are benefit-oriented or cost-oriented. In this method, the comparison of decision alternatives can be achieved with percentage values (Varatharajulu et al., 2022). The first step of the method involves creating a decision matrix. In the second step, the values in the decision matrix are normalized. In the third step, the normalized decision matrix values are weighted. The fourth step takes into account benefit-oriented and cost-oriented criteria by separately summing them in the weighted normalized decision matrix. In the fifth step, the relative importance value of each decision alternative is calculated based on the benefit-oriented and cost-oriented weighted normalized values. In the final step of the method, the performance index value of each decision alternative is measured, and the measured values are ranked from highest to lowest (Paksoy, 2017; Hezer et al., 2021).

In the EDAS method, the best decision alternative is determined based on its distance from the average solution rather than positive (ideal) or negative (anti-ideal) solutions. In this context, calculating the positive and negative distances from the average solution is crucial. Accordingly, an increase in positive values and a decrease in negative distances from the average solution enhance the preference or performance of the decision alternative (Sudha, 2019). The first step of the method involves creating a decision matrix. In the second step, the average solution value is measured according to the criteria. In the third step, the positive (PDA) and negative distances (NDA) from the average solution are calculated for each criterion corresponding to each decision alternative. In the fourth step, PDA and NDA values are weighted, and the weighted values are summed for PDAs and NDAs separately on a decision alternative basis to calculate the weighted total of positive alternatives (SP) and negative alternatives (SN), respectively. In the fifth step, normalized SP values (NSP) are calculated by dividing SP values by the maximum SP value. Conversely, normalized SN values (NSN) are measured by subtracting SN values from 1 divided by the maximum SN values. Finally, the performance scores of decision alternatives are measured by averaging NSP and NSN values, and the ranked scores are sorted from highest to lowest (Özbek, 2019; Yıldırım et al., 2020; Trung, 2021).

In the ARAS method, the performance and selection of decision alternatives are determined based on the assessment of the benefit degrees of decision alternatives. For this purpose, the optimality value of each decision alternative needs to be compared with the optimality function value of the reference alternative (Vijayakumar, 2020). Accordingly, in the method, the first step involves obtaining a decision matrix. In the second step, the values in the decision matrix are standardized. In the third step, the standardized decision matrix values are weighted. In the fourth step, the optimality function value for each decision alternative is calculated based on the weighted standardized decision matrix values. In the final step of the method, the benefit degrees or performances of decision alternatives are measured by comparing the optimality function value of each decision alternative to the optimality function value of the best alternative, and the measured values are ranked from highest to lowest (Karabašević et al., 2015; Uludağ and Doğan, 2021).

In the TOPSIS method, the selection or performance of decision alternatives varies based on their proximity to the positive ideal and the distance from the negative ideal. In this context, the positive ideal solution comprises the best values obtained from the criteria, while the negative ideal solution consists of the worst values obtained from the criteria. Therefore, for a decision alternative to be selectable, it needs to be closest to the positive ideal or possess the maximum quantity derived from the criteria compared to other alternatives (Kabir and Hasin, 2012; Ciardiello and Genovese, 2023). In this method, the first step involves obtaining a decision matrix. In the second step, the values in the decision matrix are standardized. The third step of the method involves weighting the standardized decision matrix values. In the fourth step, the positive and negative ideal values for each decision alternative are determined. In the fifth step, the distance values from the positive and negative ideal solutions for each criterion are calculated. Finally, the relative closeness values for each decision alternative are measured, and the calculated values are ranked from highest to lowest (Aktaş et al., 2015; Çelikbilek, 2018; Kaya and Karaşan, 2018; Azad, 2019; Tepe, 2021).

The MAUT method is a technique based on a real-valued function or utility that needs to be maximized in any decision problem. In other words, this method is used to find the solution that maximizes utility in decision problems with multiple conflicting criteria. In the method, decision maker preferences are formulated as utility functions defined over the criteria (Maharani et al., 2021). Accordingly, the first step of the method involves providing a decision matrix. In the second step, normalization of the decision matrix values is carried out. In the third step of the method, for each decision alternative, the normalized value corresponding to the criterion is multiplied by the criterion weights, and then the new criterion values corresponding to the decision alternatives are summed to calculate the weighted total utility values for each decision alternative, and the calculated values are ranked from highest to lowest (Atan and Altan, 2020; Taufik et al., 2020; Öztel and Alp, 2020). Additionally, Ecer (2020) has described the standardization process of the decision matrix and the utility values differently in the MAUT method. According to this, for the standardization process of cost-oriented criteria in particular, it has been stated that 1 is added to the standard value of cost-oriented criteria in the classical MAUT method. Furthermore, the utility functions of decision alternatives are calculated by comparing the value derived from the score standardized as the power of the natural logarithm base 'e' minus 1 to the score standardized as the square of the value, minus 1, compared to the value of 1.71.

The PSI method relies on basic statistical knowledge, and its greatest advantage, unlike other MCDM methods, lies in not requiring assigning relative importance degrees among criteria or weighting criteria during the comparison of criteria. In this sense, the method is quite useful in situations where there is disagreement about assigning weights to the problem criteria (Tuş and Adalı, 2018). The method fundamentally relies on calculating preference variance, overall preference, and preference index. In this regard, the first step of the method involves providing a decision matrix. In the second step, normalization of the decision matrix values is achieved. In the third step, the average value of each criterion is calculated. Then, the sum of the squares of the differences between the normalized value and the normalized average value is calculated for each criterion. This way, the preference variance values for each criterion are determined. In the fourth step of the method, initially, the deviation scores of preference values are calculated by subtracting 1 from the preference values for each criterion. Then, the deviation scores of preference values for each criterion are divided by the sum of deviation scores of preference values for the criteria to obtain overall preference values for the criteria. In the final stage of the method, the normalized decision matrix values are multiplied by the overall preference values for each criterion corresponding to the decision alternatives, and the multiplied values are summed to calculate the preference index values for the decision alternatives (Petković et al., 2017; Ulutaş and Topal, 2020).

TODIM utilizes a global preference value measure that can be calculated using the expectation theory paradigm. The method's core principle is based on the dominance of decision alternatives over each other. In the TODIM method, the first step is to construct the decision matrix. The second step involves normalizing the values of the decision matrix. The third step of the method involves identifying the reference criterion, while the fourth step involves calculating the dominance values of the decision alternatives. Finally, the overall dominance level of the decision alternatives relative to each other is computed (Ecer, 2020).

B. Theoretical Background of Proposed Method: Proportional Superiority Approach (PSA)

In the MCDM literature, many methods have been developed with unique mathematical models or logic for measuring the performance of decision alternatives or solving selection problems (Ecer, 2020). Within the scope of MCDM, these mathematical models, obtained according to the respective method, demonstrate the quantitative superiority of decision alternatives and, consequently, their optimality or selectability. In this context, in the SAW method, the normalization of any decision alternative's criterion values and the corresponding criterion weight being higher indicate its quantitative superiority compared to other decision alternatives. This is because in the SAW method, the performances of decision alternatives are determined by the sum of the products of all normalized criterion values and their corresponding criterion weights (Churchman and Ackoft, 1954).

In the WPM method, the quantitative superiority of any decision alternative arises from the exponential structure of the WPM method, where criterion values and their weights in the decision matrix are higher compared to other decision alternatives (Bridgman, 1922). The WASPAS method, being a combination of the SAW and WPM methods, ensures the superiority of any decision alternative over others, as described in the SAW and WPM methods (Zawadskas et al., 2012). In the COPRAS method, the quantitative superiority of any decision alternative is achieved by the increase/decrease of the total weighted standardized indexes for each decision alternative in terms of benefit/cost direction (Zavadskas and Kaklauskas, 1996). In the EDAS method, the superiority of any decision alternative is ensured by the positive/negative direction of the values corresponding to benefit-oriented criteria for the respective decision alternative in the decision matrix being greater/less than the positive/negative direction average value. Conversely, for cost-oriented criteria, the superiority of any decision alternative is determined by the values corresponding to cost-oriented criteria for the respective decision alternative in the decision matrix being less/greater than the negative/positive direction average value (Ghorabaee et al., 2015).

In the ARAS method, the optimality of each decision alternative is measured by the total of the normalized weighted values for each criterion in the decision matrix, including the optimal values (the highest benefit-oriented value for each criterion and the lowest cost-oriented value). This is because for any decision alternative to be optimal, the ratio of the total of the normalized weighted values corresponding to the criteria for that decision alternative to the total of the optimal normalized weighted values is expected to be high (Zavadskas et al., 2010). In the TOPSIS method, the optimality of decision alternatives is determined by their distances to the ideal points. In this regard, if the negative distance value (negative ideal proximity) of any decision alternative in the normalized weighted matrix with respect to the criteria increases and the positive distance value (positive ideal proximity) decreases, the optimality level of that decision alternative increases. This is because a greater difference between the weighted normalized value of any decision alternative and the negative ideal solution value (the lowest value) implies a greater proximity of that decision alternative to the ideal solution. Conversely, a greater difference between the weighted normalized value of any decision alternative and the positive ideal solution value (the highest value) implies a lesser proximity of that decision alternative to the ideal solution (Hwang and Yoon, 1981). In the MAUT method, the higher the normalized values of any decision alternative, the higher its preference. This is because in this method, the optimality of decision alternatives is calculated by the sum of the products of criterion weights and normalized values for each decision alternative (Keeney and Raiffa, 1976).

In the PSI method, the optimal decision alternative can be determined by having low variance values for each criterion's preference variance (variability) after normalization. This is because in the PSI method, if the decision alternative values for each criterion in the normalized decision matrix are greater than the average criterion value, it will reduce the total variance (variability) of the criteria. Furthermore, to achieve the best optimal value for decision alternatives, it is necessary for the difference between the total variance (variability) value and 1 to be maximized (Maniya and Bhatt, 2010). The core idea of the TODIM method is to measure the dominance degree of each alternative over the others using the expected value function. Essentially, in this method, if an alternative has the highest overall dominance value over the other alternatives, then the quantitative superiority of that alternative is greater (Ecer, 2020).

In conclusion, SAW, WPM, WASPAS, and COPRAS methods focus solely on the mathematical model-based quantitative superiority of decision alternatives over each other without considering their relative dominance. On the other hand, EDAS, ARAS, and TOPSIS methods determine the performance of alternatives based on the mathematical model's consideration of the quantitative values that should be taken into account for each alternative. Unlike other MCDM methods, the TODIM method identifies the quantitative superiority of each alternative by comparing it to each other alternative based on the mathematical model. The fundamental logic of the proposed method's mathematical model relies on the increase ratio among criteria for each decision alternative. Therefore, in this method, the optimality of any decision alternative is sought based on the proportional increase of its criterion values compared to those of other decision alternatives. Therefore, it can be considered that the fundamental structure of the proposed method is based on the logic of the TODIM method. In this context, the implementation steps of the proposed method are outlined below:

Step 1: Obtaining the Decision Matrix
i: 1, 2, 3... n, where n represents the number of decision alternatives
j: 1, 2, 3,... m, where m represents the number of criteria
D: Decision matrix
C: Criterion
d_{ij}: The decision matrix is constructed according to Equation 1, where "i_j" represents the $i-th$ decision alternative on the j-th criterion.

$$D = [d_{ij}]_{mxn} = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ x_{11} & x_{12} & & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: Normalization of Decision Matrix (r_{ij}^*)
The normalization of the decision matrix is conducted through the utilization of the subsequent equation. Benefit criteria undergo normalization using Equation 2, whereas cost criteria are subjected to normalization employing Equation 3.

$$r_{ij}^* = \frac{x_{ij}}{x_j^{max}} \tag{2}$$

$$r_{ij}^* = \frac{x_j^{min}}{x_{ij}} \tag{3}$$

The generated normalized decision matrix is shown in Equation 4.

$$D = [r_{ij}^*]_{mxn} = \begin{bmatrix} x_{11}^* & x_{12}^* & \dots & x_{1n}^* \\ x_{21}^* & x_{22}^* & \cdots & x_{2n}^* \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^* & x_{m2}^* & \cdots & x_{mn}^* \end{bmatrix} \tag{4}$$

Step 3: Calculation of Proportional Increases in Criteria for Decision Alternatives (RI)
In this step, the proportional increases of each criterion for decision alternatives are calculated in two cases.
Case 1: When the normalized value of the criterion for the normalized decision alternative is numerically greater than that of the other decision alternative:
For the first criterion and the first alternative:

$$x_{11}^* > x_{21}^*$$

$$RI^+_{x_{11}^* \to x_{21}^*} = \frac{(x_{11}^* - x_{21}^*).100}{x_{21}^*} \tag{5}$$

$$x_{11}^* > x_{31}^*$$

$$RI^+_{x_{11}^* \to x_{31}^*} = \frac{(x_{11}^* - x_{31}^*).100}{x_{31}^*} \tag{6}$$

$$\begin{matrix} \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \end{matrix}$$

$$x_{11}^* > x_{m1}^*$$

$$RI^+_{x_{11}^* \to x_{m1}^*} = \frac{(x_{11}^* - x_{m1}^*).100}{x_{m1}^*} \tag{7}$$

For the first criterion and the second alternative:

$x_{21}^{*} > x_{11}^{*}$

$$RI_{x_{21}^{*}\rightarrow x_{11}^{*}}^{+} = \frac{(x_{21}^{*} - x_{11}^{*}).100}{x_{11}^{*}} \tag{8}$$

$x_{21}^{*} > x_{31}^{*}$

$$RI_{x_{21}^{*}\rightarrow x_{31}^{*}}^{+} = \frac{(x_{21}^{*} - x_{31}^{*}).100}{x_{31}^{*}} \tag{9}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$$RI_{x_{21}^{*}\rightarrow x_{m1}^{*}}^{+} = \frac{(x_{21}^{*} - x_{m1}^{*}).100}{x_{m1}^{*}} \tag{10}$$

For the first criterion, regarding the mth alternative:

$x_{m1}^{*} > x_{11}^{*}$

$$RI_{x_{m1}^{*}\rightarrow x_{11}^{*}}^{+} = \frac{(x_{m1}^{*} - x_{11}^{*}).100}{x_{11}^{*}} \tag{11}$$

$x_{m1}^{*} > x_{21}^{*}$

$$RI_{x_{m1}^{*}\rightarrow x_{21}^{*}}^{+} = \frac{(x_{m1}^{*} - x_{21}^{*}).100}{x_{21}^{*}} \tag{12}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

For the nth criterion, concerning the first alternative:

$x_{1n}^{*} > x_{2n}^{*}$

$$RI_{x_{1n}^{*}\rightarrow x_{2n}^{*}}^{+} = \frac{(x_{1n}^{*} - x_{2n}^{*}).100}{x_{2n}^{*}} \tag{13}$$

$x_{1n}^{*} > x_{3n}^{*}$

$$RI_{x_{1n}^{*}\rightarrow x_{3n}^{*}}^{+} = \frac{(x_{1n}^{*} - x_{3n}^{*}).100}{x_{3n}^{*}} \tag{14}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x_{1n}^{*} > x_{mn}^{*}$

$$RI_{x_{1n}^{*}\rightarrow x_{mn}^{*}}^{+} = \frac{(x_{1n}^{*} - x_{mn}^{*}).100}{x_{mn}^{*}} \tag{15}$$

For the nth criterion, concerning the second alternative:

$x_{2n}^{*} > x_{1n}^{*}$

$$RI_{x_{2n}^{*}\rightarrow x_{1n}^{*}}^{+} = \frac{(x_{2n}^{*} - x_{1n}^{*}).100}{x_{1n}^{*}} \tag{16}$$

$x_{2n}^{*} > x_{3n}^{*}$

$$RI_{x_{2n}^{*}\rightarrow x_{3n}^{*}}^{+} = \frac{(x_{2n}^{*} - x_{3n}^{*}).100}{x_{3n}^{*}} \tag{17}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x_{2n}^{*} > x_{mn}^{*}$

$$RI_{x_{2n}^{*}\rightarrow x_{mn}^{*}}^{+} = \frac{(x_{2n}^{*} - x_{mn}^{*}).100}{x_{mn}^{*}} \tag{18}$$

For the nth criterion, concerning mth alternative:

$x_{mn}^{*} > x_{1n}^{*}$

$$RI^{+}_{x^*_{mn}\rightarrow x^*_{1n}} = \frac{(x^*_{mn} - x^*_{1n}).100}{x^*_{1n}} \quad (19)$$

$x^*_{mn} > x^*_{2n}$

$$RI^{+}_{x^*_{mn}\rightarrow x^*_{2n}} = \frac{(x^*_{mn} - x^*_{2n}).100}{x^*_{2n}} \quad (20)$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x^*_{mn} > x^*_{(m-1)n}$

$$RI^{+}_{x^*_{mn}\rightarrow x^*_{(m-1)n}} = \frac{\left(x^*_{mn} - x^*_{(m-1)n}\right).100}{x^*_{(m-1)n}} \quad (21)$$

Case 2: When the normalized value of the criterion for decision alternative is numerically smaller than that of the other decision alternative:

For the first criterion and the first alternative:

$x^*_{11} < x^*_{21}$

$$RI^{-}_{x^*_{11}\rightarrow x^*_{21}} = \frac{(x^*_{21} - x^*_{11}).100}{x^*_{11}} \quad (22)$$

$x^*_{11} < x^*_{31}$

$$RI^{-}_{x^*_{11}\rightarrow x^*_{31}} = \frac{(x^*_{31} - x^*_{11}).100}{x^*_{11}} \quad (23)$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x^*_{11} < x^*_{m1}$

$$RI^{-}_{x^*_{11}\rightarrow x^*_{m1}} = \frac{(x^*_{m1} - x^*_{11}).100}{x^*_{11}} \quad (24)$$

For the first criterion and the second alternative:

$x^*_{21} < x^*_{11}$

$$RI^{-}_{x^*_{21}\rightarrow x^*_{11}} = \frac{(x^*_{11} - x^*_{21}).100}{x^*_{21}} \quad (25)$$

$x^*_{21} < x^*_{31}$

$$RI^{-}_{x^*_{21}\rightarrow x^*_{31}} = \frac{(x^*_{31} - x^*_{21}).100}{x^*_{21}} \quad (26)$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x^*_{21} < x^*_{m1}$

$$RI^{-}_{x^*_{21}\rightarrow x^*_{m1}} = \frac{(x^*_{m1} - x^*_{21}).100}{x^*_{21}} \quad (27)$$

For the first criterion, regarding the mth alternative:

$x^*_{m1} < x^*_{11}$

$$RI^{-}_{x^*_{m1}\rightarrow x^*_{11}} = \frac{(x^*_{11} - x^*_{m1}).100}{x^*_{m1}} \quad (28)$$

$x^*_{m1} < x^*_{21}$

$$RI^{-}_{x^*_{m1}\rightarrow x^*_{21}} = \frac{(x^*_{21} - x^*_{m1}).100}{x^*_{m1}} \quad (29)$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

For the nth criterion, concerning the first alternative:

$x^*_{1n} < x^*_{2n}$

$$RI^-_{x^*_{1n} \to x^*_{2n}} = \frac{(x^*_{2n} - x^*_{1n}).100}{x^*_{1n}} \tag{30}$$

$x^*_{1n} < x^*_{3n}$

$$RI^-_{x^*_{1n} \to x^*_{3n}} = \frac{(x^*_{3n} - x^*_{1n}).100}{x^*_{1n}} \tag{31}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x^*_{1n} < x^*_{mn}$

$$RI^-_{x^*_{1n} \to x^*_{mn}} = \frac{(x^*_{mn} - x^*_{1n}).100}{x^*_{1n}} \tag{32}$$

For the nth criterion, concerning the second alternative:

$x^*_{2n} < x^*_{1n}$

$$RI^-_{x^*_{2n} \to x^*_{1n}} = \frac{(x^*_{1n} - x^*_{2n}).100}{x^*_{2n}} \tag{33}$$

$x^*_{2n} < x^*_{3n}$

$$RI^-_{x^*_{2n} \to x^*_{3n}} = \frac{(x^*_{3n} - x^*_{2n}).100}{x^*_{2n}} \tag{34}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x^*_{2n} < x^*_{mn}$

$$RI^-_{x^*_{2n} \to x^*_{mn}} = \frac{(x^*_{mn} - x^*_{2n}).100}{x^*_{2n}} \tag{35}$$

For the nth criterion, concerning the mth alternative:

$x^*_{mn} < x^*_{1n}$

$$RI^-_{x^*_{mn} \to x^*_{1n}} = \frac{(x^*_{1n} - x^*_{mn}).100}{x^*_{mn}} \tag{36}$$

$x^*_{mn} < x^*_{2n}$

$$RI^-_{x^*_{mn} \to x^*_{2n}} = \frac{(x^*_{2n} - x^*_{mn}).100}{x^*_{mn}} \tag{37}$$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$x^*_{mn} < x^*_{(m-1)n}$

$$RI^-_{x^*_{mn} \to x^*_{2n}} = \frac{\left(x^*_{mn} - x^*_{(m-1)n}\right).100}{x^*_{(m-1)n}} \tag{38}$$

Step 4: Calculation of Proportional Increase Superiority (PIS) Values for Decision Alternatives

PIS values of the first decision alternative relative to each decision alternative (PIS_{DA_1})

For the second decision alternative: $PIS_{DA_1 \to DA_2} = \overbrace{\left[\sum_{j=1}^{n} RI^+_{1j}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI^-_{1j}\right]}^{Second\ Group}$ (39)

For the third decision alternative: $PIS_{DA_1 \to DA_3} = \overbrace{\left[\sum_{j=1}^{n} RI^+_{2j}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI^-_{2j}\right]}^{Second\ Group}$ (40)

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

For the mth decision alternative: $PIS_{DA_1 \to DA_m} = \overbrace{\left[\sum_{j=1}^{n} RI^+_{mj}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI^-_{mj}\right]}^{Second\ Group}$ (41)

PIS values of the second decision alternative relative to each decision alternative (PIS_{DA_2})

For the first decision alternative: $PIS_{DA_2 \to DA_1} = \overbrace{\left[\sum_{j=1}^{n} RI_{1j}^{+}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI_{1j}^{-}\right]}^{Second\ Group}$ (42)

For the third decision alternative: $PIS_{DA_2 \to DA_3} = \overbrace{\left[\sum_{j=1}^{n} RI_{2j}^{+}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI_{2j}^{-}\right]}^{Second\ Group}$ (43)

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

For the mth decision alternative: $PIS_{DA_2 \to DA_m} = \overbrace{\left[\sum_{j=1}^{n} RI_{mj}^{+}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI_{mj}^{-}\right]}^{Second\ Group}$ (44)

PIS values of the mth decision alternative relative to each decision alternative (PIS_{DA_m})

For the first decision alternative: $PIS_{DA_m \to DA_1} = \overbrace{\left[\sum_{j=1}^{n} RI_{1j}^{+}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI_{1j}^{-}\right]}^{Second\ Group}$ (45)

For the second decision alternative: $PIS_{DA_m \to DA_2} = \overbrace{\left[\sum_{j=1}^{n} RI_{2j}^{+}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI_{2j}^{-}\right]}^{Second\ Group}$ (46)

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots$

For the (m-1)th decision alternative: $PIS_{DA_m \to DA_{m-1}} = \overbrace{\left[\sum_{j=1}^{n} RI_{mj}^{+}\right]}^{First\ Group} - \overbrace{\left[\sum_{j=1}^{n} RI_{mj}^{-}\right]}^{Second\ Group}$ (47)

Step 5: Calculating the Total PIS Values of Decision Alternatives$(TPSI)$

$$TPIS_{DA_1} = PIS_{DA_1 \to DA_2} + PIS_{DA_1 \to DA_3} + \cdots + PIS_{DA_1 \to DA_m} = \sum_{i=1}^{m-1} PIS_{DA_1 \to DA_{i+1}} \tag{48}$$

$$TPIS_{DA_2} = PIS_{DA_2 \to DA_1} + PIS_{DA_2 \to DA_3} + \cdots + PIS_{DA_2 \to DA_m} = \sum_{i=0, i \neq 1}^{m-1} PIS_{DA_2 \to DA_{i+1}} \tag{49}$$

$\vdots \quad \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots$

$\vdots \quad \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots$

$$TPIS_{DA_m} = PIS_{DA_m \to DA_1} + PIS_{DA_m \to DA_3} + \cdots + PIS_{DA_m \to DA_{m-1}} = \sum_{j=1}^{m-1} PIS_{DA_m \to DA_j} \tag{50}$$

Step 6: Calculating the Proportional Superiority Performance PSP Values of Decision Alternatives

Case 1: The situation where all TPSI values of decision alternatives are positive

$$PSP = \frac{TPIS_j}{\sum_1^m TPIS_j} \tag{51}$$

Case 2: The situation where any of the TPSI values of decision alternatives is negative

In this case, firstly, Z-Score transformation is applied to the TPSI values. This ensures that the negative TPSI values become positive. The Z-Score formula is shown in Equation 52 (Zhang et al., 2014).

$$z_j = \frac{x_j - \overline{x_j}}{\sigma_j} \tag{52}$$

The values $\overline{x_j}$ and σ_j shown in Equation 52 represent the mean and standard deviation values of the jth criterion, respectively. By applying the transformations indicated in Equations 53 and 54, the data in the decision matrix are ensured to be positively oriented (Zhang et al., 2014).

$$z_j' = z_j + A \tag{53}$$

$$A > \left| min\, Z_j \right| \tag{54}$$

The value A is the value closest to the smallest z_{ij} value that is planned to be assigned. In this context, the equations related to $TPSI$ provided by Z-Score are shown below.

$$TPSI_{z_j} = \frac{TPSI_j - \overline{TPSI_j}}{\sigma_j} \tag{55}$$

$$TPSI_{z'_j} = TPSI_{z_j} + A \tag{56}$$

After calculating the $TPSI_{z'_j}$ values for decision alternatives, Equation 57 is used to measure the PSP values of decision alternatives.

$$PSP = \frac{TPSI_{z'_j}}{\sum_1^m TPSI_{z'_j}} \tag{57}$$

One of the most distinctive features of the PSA method is the absence of assigning criterion weights. This is because the method explicitly demonstrates, especially in its third step, the calculation of proportional increases in criteria for decision alternatives(RI), how much each alternative increases proportionally compared to others for each criterion, thereby indirectly calculating the strength of the criterion. Similarly, in the PSI method, the absence of criterion weights is due to the determination of the criterion's influence within the scope of the method's implementation steps, based on the deviation and overall (total) preference values of the criteria. Thus, in both methods, the true power of decision alternatives is determined not from their values on different criteria but rather from calculations made on different values of decision alternatives for each criterion. Moreover, when examining the MCDM literature, as explained in many MCDM methods, the evaluation of criterion weights is achieved through normalized decision matrix values. Even if weights are assigned to normalized decision matrix values in this method, there will be no change in the calculation of proportional increases of criteria(RI), as explained previously, since the true power of decision alternatives in the method is revealed through calculations made on different values of decision alternatives for each criterion. On the other hand, in some MCDM methods (MAUT, OWA operator), criterion weights are assigned during or after the specific calculation logic of the method. Because the main mathematical model in this method is the proportional increase calculated based on different values of decision alternatives for each criterion, applying weighting to these increase rates would result in the loss of logic of the method. In this context, as in the PSI method, no weight value is assigned to the proposed method.

The method has various advantages. Firstly, as previously mentioned, one of the advantages is the absence of assigning criterion weights in the method. Because the absence of criterion weight assignment can be quite useful in cases where there is disagreement regarding assigning weights to the criteria of the problem (Madic et al., 2017 cited in Tuş and Aytaç Adalı, 2018: 248). Secondly, the method clearly demonstrates which alternatives perform better than others based on the proportional increases of decision alternatives in each criterion. This is because in many MCDM methods, the superiority of decision alternatives to each other is generally calculated based on common values such as the optimal (maximum or minimum) values, mean value, standard deviation, etc., of decision alternatives' criteria. Therefore, by calculating the impact of each criterion on different decision alternatives in the method, it can make the decision-making process more objective. This, in turn, further increases the optimality of decision alternatives. Another advantage of the method is that, since the proportional superiority of decision alternatives is clearly calculated for each criterion, the method provides a good discrimination of performance scores of decision alternatives.

The method has both advantages and disadvantages. One of the disadvantages is that if the decision matrix takes on values of 0 or negative, it requires the calculation of Z-Score values to achieve a positive transformation of the decision matrix. Another disadvantage is that when the number of criteria and decision alternatives increases, it becomes more challenging to calculate the optimal values of decision alternatives in the method. However, complex calculations can be facilitated with various software programs such as Microsoft Excel.

C. Data Set and Analysis of the Study

The dataset of the research consists of values related to selected 10 criteria of the Economic Freedom Index (EFI) developed by the Heritage Foundation for the G7 countries for the year 2023. In this context, the performance of G7 countries has been measured using the PSA method based on selected EFI criteria values in the research. These 10 criteria were chosen to have different numerical ranges for each country. In the EFI literature, all criteria are utility-oriented. To better understand the characteristics of the proposed method, the EFI12 criterion has been transformed into a cost-oriented quantity. This transformation activity was calculated by subtracting the country's EFI12 value from 100. This is because, according to the EFI literature, considering that the maximum value of EFI criteria for countries is 100, the cost-oriented criterion value of any country can be calculated by subtracting the utility-oriented performance of the criterion from the 100 value of the criterion. Aside from these, the weight coefficients of all criteria are of equal quantity (Heritage Foundation, 2023). Additionally, in terms of methodology, the weight coefficients of the criteria used in comparative and simulation analyses with MCDM methods have been calculated as equal quantities ($^1/_{10} = 0{,}100$). In this context, abbreviations of EFI criteria are explained in Table 1 for convenience in the research.

Table 1. EFI Criteria and Abbreviations

Criteria	Abbreviations
Property Rights	EFI1
Government Integrity	EFI2
Judicial Effectiveness	EFI3
Tax Burden	EFI4
Business Freedom	EFI7
Labor Freedom	EFI8
Monetary Freedom	EFI9
Trade Freedom	EFI10
Investment Freedom	EFI11
Financial Freedom	EFI12

III. THE CASE STUDY

A. Computational Analysis

In the study, firstly, decision matrix was constructed with Equality 1. The decision matrix values pertaining to this are shown in Table 2.

Table 2. Decision Matrix

Countries	EFI1	EFI2	EFI3	EFI4	EFI7	EFI8	EFI9	EFI10	EFI11	EFI12
Criteria	**Max.**	**Max.**	**Max.**	**Max.**	**Max.**	**Max.**	**Max.**	**Max.**	**Max.**	**Min.**
Canada	88.5	95.1	83.1	75.0	87.9	69.0	74.8	83.4	80	20
France	93.0	83.9	75.5	52.9	78.2	59.2	76.9	78.6	75	30
Germany	94.8	93.1	89.4	60.2	79.7	52.8	75.3	78.6	80	30
Italy	81.2	77.9	61.1	57.3	73.8	70.6	82.6	78.6	80	50
Japan	94.1	94.7	80.7	68.1	78.3	66.8	87.1	75.2	60	40
UK	95.1	84.8	86.4	65.4	79.1	62.2	80.8	81.8	80	20
USA	94.7	76.1	73.4	75.4	83.8	76.3	78.0	75.4	85	20
Minimum	**81.2**	**76.1**	**61.1**	**52.9**	**73.8**	**52.8**	**74.8**	**75.2**	**60.0**	**20.0**
Maximum	**95.1**	**95.1**	**89.4**	**75.4**	**87.9**	**76.3**	**87.1**	**83.4**	**85.0**	**50.0**

Reference: Heritage Foundation. 2023

In the second step of the proposed method in the research, benefit-oriented normalization was conducted with Equality 2, while cost-oriented normalization was achieved with Equality 3. Subsequently, a normalized decision matrix was formed with Equality 4. The normalized values calculated based on the decision matrix values are explained in Table 3.

Table 3. Normalized Decision Matrix

Criteria	Canada	France	Germany	Italy	Japan	UK	USA
EFI1	0.930599	0.977918	0.996845	0.853838	0.989485	1	0.995794
EFI2	1	0.882229	0.97897	0.819138	0.995794	0.891693	0.80021
EFI3	0.92953	0.844519	1	0.683445	0.902685	0.966443	0.821029
EFI4	0.994695	0.701592	0.798408	0.759947	0.903183	0.867374	1
EFI7	1	0.889647	0.906712	0.83959	0.890785	0.899886	0.953356

EFI8	0.904325	0.775885	0.692005	0.925295	0.875491	0.815203	1
EFI9	0.858783	0.882893	0.864524	0.948335	1	0.927669	0.895522
EFI10	1	0.942446	0.942446	0.942446	0.901679	0.980815	0.904077
EFI11	0.941176	0.882353	0.941176	0.941176	0.705882	0.941176	1
EFI12	1	0.666667	0.666667	0.4	0.5	1	1

The calculation method for normalization is demonstrated below, taking into account the benefit-oriented EFI1 and cost-oriented EFI12 decision matrix values for Canada.
In the third step, the rates of increase (RI) of each decision alternative over other decision alternatives on a criterion basis were measured based on the normalized decision matrix values, considering their quantitative magnitudes and directions relative to each other. The relevant calculations were made using the pertinent equations from Equation 5 to Equation 38. The resulting values are presented in Table 4.

Table 4. Rates of Increase of Decision Alternatives (Countries) Over Each Other

CANADA						
Criteria	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**
EFI1	5.084746	7.11864407	8.990148	6.327684	7.457627	7.00565
EFI2	13.34923	2.14822771	22.07959	0.422386	12.14623	24.96715
EFI3	10.06623	7.58122744	36.00655	2.973978	3.971119	13.21526
EFI4	41.77694	24.5847176	30.89005	10.13216	14.6789	0.533333
EFI7	12.40409	10.2885822	19.10569	12.26054	11.12516	4.892601
EFI8	16.55405	30.6818182	2.318841	3.293413	10.93248	10.57971
EFI9	2.807487	0.6684492	10.42781	16.44385	8.02139	4.278075
EFI10	6.10687	6.10687023	6.10687	10.90426	1.95599	10.61008
EFI11	6.666667	0	0	33.33333	0	6.25
EFI12	50	50	150	100	0	0
FRANCE						
Criteria	**Canada**	**Germany**	**Italy**	**Japan**	**UK**	**USA**
EFI1	5.084746	1.935484	14.53202	1.182796	2.258064516	1.827957
EFI2	13.34923	10.96544	7.702182	12.87247	1.072705602	10.24967
EFI3	10.06623	18.4106	23.56792	6.887417	14.43708609	2.861035
EFI4	41.77694	13.79962	8.31758	28.73346	23.6294896	42.53308
EFI7	12.40409	1.918159	5.96206	0.127877	1.150895141	7.161125
EFI8	16.55405	12.12121	19.25676	12.83784	5.067567568	28.88514
EFI9	2.807487	2.124834	7.412224	13.26398	5.071521456	1.430429
EFI10	6.10687	0	0	4.521277	4.071246819	4.244032
EFI11	6.666667	6.666667	6.666667	25	6.666666667	13.33333
EFI12	50	0	66.66667	33.33333	50	50
GERMANY						
Criteria	**Canada**	**France**	**Italy**	**Japan**	**UK**	**USA**
EFI1	7.118644	1.935484	16.74877	0.743889	0.316456	0.105597
EFI2	2.148228	10.96544	19.5122	1.718582	9.787736	22.33903
EFI3	7.581227	18.4106	46.31751	10.78067	3.472222	21.79837
EFI4	24.58472	13.79962	5.061082	13.12292	8.637874	25.24917
EFI7	10.28858	1.918159	7.99458	1.787995	0.758534	5.144291
EFI8	30.68182	12.12121	33.71212	26.51515	17.80303	44.50758
EFI9	0.668449	2.124834	9.694555	15.67065	7.304117	3.585657
EFI10	6.10687	0	0	4.521277	4.071247	4.244032
EFI11	0	6.666667	0	33.33333	0	6.25
EFI12	50	0	66.66667	33.33333	50	50
ITALY						
Criteria	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**
EFI1	8.990148	14.53202	16.74877	15.8867	17.11823	16.62562
EFI2	22.07959	7.702182	19.5122	21.56611	8.85751	2.365309
EFI3	36.00655	23.56792	46.31751	32.07856	41.40753	20.13093

EFI4	30.89005	8.31758	5.061082	18.84817	14.13613	31.58813
EFI7	19.10569	5.96206	7.99458	6.097561	7.181572	13.55014
EFI8	2.318841	19.25676	33.71212	5.688623	13.50482	8.073654
EFI9	10.42781	7.412224	9.694555	5.447942	2.227723	5.897436
EFI10	6.10687	0	0	4.521277	4.071247	4.244032
EFI11	0	6.666667	0	33.33333	0	6.25
EFI12	150	66.66667	66.66667	25	150	150
JAPAN						
Criteria	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**
EFI1	6.327684	1.182796	0.743889	15.8867	1.062699	0.63762
EFI2	0.422386	12.87247	1.718582	21.56611	11.67453	24.44152
EFI3	2.973978	6.887417	10.78067	32.07856	7.063197	9.945504
EFI4	10.13216	28.73346	13.12292	18.84817	4.12844	10.71953
EFI7	12.26054	0.127877	1.787995	6.097561	1.021711	7.024266
EFI8	3.293413	12.83784	26.51515	5.688623	7.395498	14.22156
EFI9	16.44385	13.26398	15.67065	5.447942	7.79703	11.66667
EFI10	10.90426	4.521277	4.521277	4.521277	8.776596	0.265957
EFI11	33.33333	25	33.33333	33.33333	33.33333	41.66667
EFI12	100	33.33333	33.33333	25	100	100
UK						
Criteria	**Canada**	**France**	**Germany**	**Italy**	**Japan**	**USA**
EFI1	7.457627	2.258065	0.316456	17.11823	1.062699	0.422386
EFI2	12.14623	1.072706	9.787736	8.85751	11.67453	11.43233
EFI3	3.971119	14.43709	3.472222	41.40753	7.063197	17.71117
EFI4	14.6789	23.62949	8.637874	14.13613	4.12844	15.29052
EFI7	11.12516	1.150895	0.758534	7.181572	1.021711	5.941846
EFI8	10.93248	5.067568	17.80303	13.50482	7.395498	22.66881
EFI9	8.02139	5.071521	7.304117	2.227723	7.79703	3.589744
EFI10	1.95599	4.071247	4.071247	4.071247	8.776596	8.488064
EFI11	0	6.666667	0	0	33.33333	6.25
EFI12	0	50	50	150	100	0
USA						
Criteria	**Canada**	**France**	**Germany**	**Italy**	**Japan**	**UK**
EFI1	7.00565	1.827957	0.105597	16.62562	0.63762	0.422386
EFI2	24.96715	10.24967	22.33903	2.365309	24.44152	11.43233
EFI3	13.21526	2.861035	21.79837	20.13093	9.945504	17.71117
EFI4	0.533333	42.53308	25.24917	31.58813	10.71953	15.29052
EFI7	4.892601	7.161125	5.144291	13.55014	7.024266	5.941846
EFI8	10.57971	28.88514	44.50758	8.073654	14.22156	22.66881
EFI9	4.278075	1.430429	3.585657	5.897436	11.66667	3.589744
EFI10	10.61008	4.244032	4.244032	4.244032	0.265957	8.488064
EFI11	6.25	13.33333	6.25	6.25	41.66667	6.25
EFI12	0	50	50	150	100	0

To provide a better explanation of the proposed method and to illustrate an example calculation, in the fourth step, the rate of increase between Canada and France under the criterion EFI1 is computed using Equation 22 for Case 2 and Equation 8 for Case 1.

For Case 2, since $r^*_{EFI1:Canada\to France} = 0.930599 < 0.977918$, Equation 22 is considered.

$$RI^-{}_{EFI1:Canada\to France} = \frac{(0.977918 - 0.930599).100}{0.930599} = 5.084746$$

For Case 1, since $r^*_{EFI1:France\to Canada} = 0{,}977918 > 0{,}930599$, Equation 8 is considered.

$$RI^+{}_{EFI1:France\to Canada} = \frac{(0.977918 - 0.930599).100}{0.930599} = 5.084746$$

In the 5th step of the method, first, utilizing the relevant equations from Equation 39 to Equation 47, the Proportional Increase Superiority (PIS) values of each decision alternative over the other decision alternatives are calculated. In the 6th step of the method, the Total Proportional Increase Superiority (TPIS) values of the countries are determined using Equation 48, Equation 49, and Equation 50. The calculated values regarding this process are presented in Table 5.

Table 5. The PIS and TPIS Values of the Countries

Canada		France		Germany		Italy	
Countries	**PIS**	**Countries**	**PIS**	**Countries**	**PIS**	**Countries**	**PIS**
France	149.03184	**Canada**	-149.03184	**Canada**	-108.44190	**Canada**	-260.43225
Germany	108.44190	**Germany**	19.30215	**France**	39.44992	**France**	-76.77762
Italy	260.43225	**Italy**	61.37326	**Italy**	118.89413	**Germany**	-118.89413
Japan	150.54853	**Japan**	-12.79547	**Japan**	30.91035	**Japan**	-81.38181
UK	31.38861	**UK**	-113.42524	**UK**	-74.11423	**UK**	-227.03966
USA	25.03832	**USA**	-113.49407	**USA**	-86.24967	**USA**	-233.71169
TPIS	724.88144	**TPIS**	-308.07122	**TPIS**	-79.55140	**TPIS**	-998.23716

Japan		UK		USA	
Countries	**PIS**	**Countries**	**PIS**	**Countries**	**PIS**
Canada	-149.70375	**Canada**	-31.38861	**Canada**	-25.03832
France	-12.69371	**France**	113.42524	**France**	127.81632
Germany	-30.91035	**Germany**	74.11423	**Germany**	86.24967
Italy	38.24959	**Italy**	227.03966	**Italy**	193.44983
UK	-143.61110	**Japan**	120.26204	**Japan**	148.37291
USA	-163.31642	**USA**	-8.50748	**UK**	8.50748
TPIS	-461.98575	**TPIS**	494.945081	**TPIS**	539.357898

In the fifth step, as an example to illustrate the calculation of the relevant values of the method, Canada's PIS values are determined using Equation 39, Equation 40, and Equation 41, while the TPIS value of the countries is computed using Equation 48, Equation 49, and Equation 50, as shown below. For this purpose, it is necessary to first compare Canada's normalized values with those of other countries.

for PIS_{Canada}:

Since $r^*_{EFI1:Canada}(0.930599) < r^*_{EFI1:France}(0.977918)$, the value of $RI^-{}_{EFI1:Canada\rightarrow France}$ (5.084746) belongs to the second group.

Since $r^*_{EFI2:Canada}(1) > r^*_{EFI2:France}(0.882229)$, the value of $RI^+{}_{EFI2:Canada\rightarrow France}$ (13.34923) belongs to the first group.

Since $r^*_{EFI3:Canada}(1) > r^*_{EFI3:France}(8.44519)$, the value of $RI^+{}_{EFI3:Canada\rightarrow France}$ (10.06623) belongs to the first group.

Since $r^*_{EFI4:Canada}(0.994695) > r^*_{EFI4:France}(0.701592)$, the value of $RI^+{}_{EFI4:Canada\rightarrow France}$ (41.77694) belongs to the first group.

Since $r^*_{EFI7:Canada}(1) > r^*_{EFI7:France}(0.889647)$, the value of $RI^+{}_{EFI7:Canada\rightarrow France}$ (12.40409) belongs to the first group.

Since $r^*_{EFI8:Canada}(1) > r^*_{EFI8:France}(0{,}904325)$, the value of $RI^+{}_{EFI8:Canada\rightarrow France}$ (16.55405) belongs to the first group.

Since $r^*_{EFI9:Canada}(0.858783) < r^*_{EFI9:France}(0.882893)$, the value of $RI^-{}_{EFI9:Canada\rightarrow France}$ (2.80749) belongs to the second group.

Since $r^*_{EFI10:Canada}(1) > r^*_{EFI10:France}(0.942446)$, the value of $RI^+{}_{EFI10:Canada\rightarrow France}$ (6.10687) belongs to the first group.

Since $r^*_{EFI11:Canada}(0.941176) > r^*_{EFI11:France}(0.882353)$, the value of $RI^+{}_{EFI11:Canada\rightarrow France}$ (6.666667) belongs to the first group.

Since $r^*_{EFI12:Canada}(1) > r^*_{EFI12:France}(0.666667)$, the value of $RI^+{}_{EFI12:Canada\rightarrow France}$ (50) belongs to the first group.

$\boldsymbol{PIS_{Canada\rightarrow France}} = (13.34923 + 10.06623 + 41.77694 + 12.40409 + 16.55405 + 6.10687 + 6.666667 + 50) - (5.084746 + 2.80749) = 149.031839$

$$\boldsymbol{TPIS_{Canada}} = 149.03184 + 108.44190 + 260.43225 + 150.54853 + 31.38861 + 25.03832 = 724.88144$$

In the final step, to measure the proportional superiority performance (PSP) of decision alternatives based on their TPIS values, Equation 51 is utilized in Case 1 (where all countries' TPIS values are positive). However, in Case 2, where some countries' TPIS values are negative according to Table 5, Equations 51 to 57 are employed to assess the PSP values of decision alternatives. Within this framework, the PSP values for each country are presented in Table 6.

Table 6. Z-Scores, Std. Z-Scores, and PSP Values of Countries

Countries	TPIS	Z-Score	Z-Score Std. (Z')	PSP	Ranking
Canada	724.881444	1.17318763	2.773188	0.247606	1
France	-308.071219	-0.4698897	1.13011	0.100903	5
Germany	-79.5514023	-0.1063922	1.493608	0.133358	4
Italy	-998.237165	-1.5677097	0.03229	0.002883	7
Japan	-461.985746	-0.7147155	0.885284	0.079043	6
UK	494.945081	0.80743686	2.407437	0.21495	3
USA	539.357898	0.87808259	2.478083	0.221257	2
Mean	-12.6658728				
Std. Dev.	628.669532				
Minimum		-1.5677097			
Sum			11.2		

Upon examination of Table 6, countries' PSP or economic freedom performances are ranked as Canada, USA, UK, Germany, France, Japan, and Italy. To illustrate the calculation method, the calculation processes of Canada's Z-Score, Std. Z-Score, and PSP values are presented below.

$$Z - Score_{Canada} = \frac{(724.881444 - (-12.665873))}{628.669532} = 1.17318763$$

$$A_i = 1.6 > |-1.5677097|$$

$$Z - Score\ Std._{Canada} = (Z')_{Canada} = 1.17318763 + 1.6 = 2.773188$$

In the calculation of the Z-Score std. the value of A_i is determined to be 1,5. This is because Zwang et al. (2014) calculated the transformation of a Z value to its Z standard value by adding 0,1 to the decimal value of the smallest magnitude of Z values in the respective series (-1.5677097).

$$PSP_{Canada} = \frac{2.773188}{11.2} = 0.247606$$

B.Comparative Analysis

The proposed method's credibility and reliability are assessed by comparing its relationship and position with other objective weight coefficient calculation methods. In this comparison, we expect the new method to be consistent with existing methods, showing a close alignment and a positive, significant correlation with their weight coefficients (Keshavarz-Ghorabaee et al., 2021). In this context, the countries' economic freedom performances calculated using the ARAS, COPRAS, EDAS, TOPSIS, MUT, SAW, and PSI methods are described in Table 7.

Table 7. Economic Freedom Performances Calculated Using the ARAS, COPRAS, EDAS, TOPSIS, MUT, SAW, and PSI Methods for Countries

Countries	ARAS		COPRAS		WASPAS		EDAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Canada	0.995254	1	0.876253	1	0.955297	1	0.904122	1
France	0.685522	5	0.794085	6	0.841768	6	0.186509	6
Germany	0.689209	4	0.829318	5	0.874631	4	0.391865	5
Italy	0.444018	7	0.788778	7	0.800635	7	0.088996	7
Japan	0.539237	6	0.835338	4	0.858717	5	0.46174	4
UK	0.992253	3	0.847422	3	0.928109	3	0.73254	2

USA	0.993261	2	0.857283	2	0.935475	2	0.712476	3

Countries	**TOPSIS**		**MAUT**		**SAW**		**PSI**	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Canada	0.762192	1	0.777415	1	0.385482	1	0.954273	1
France	0.458788	6	0.420471	6	0.340626	6	0.852864	6
Germany	0.579839	4	0.553799	4	0.377422	3	0.88758	4
Italy	0.349307	7	0.289652	7	0.311637	7	0.82783	7
Japan	0.515877	5	0.552337	5	0.379115	2	0.880999	5
UK	0.681661	2	0.677601	2	0.372551	4	0.927058	3
USA	0.663196	3	0.639962	3	0.361703	5	0.934461	2

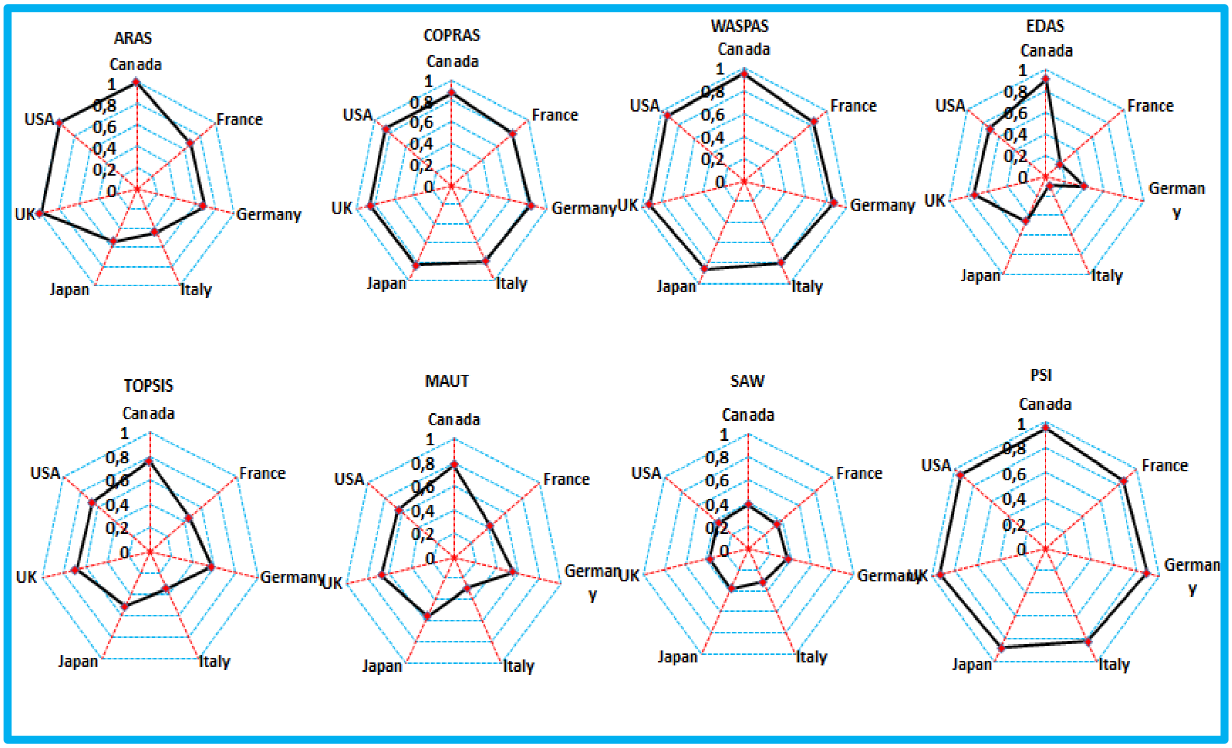

Figure 1. Positions of the ARAS, COPRAS, WASPAS, EDAS, TOPSIS, MAUT, SAW and PSI Methods
Note: The axises is graduated in increments of 0, 0.20, 0.4, 0.6, 0.8 and 1

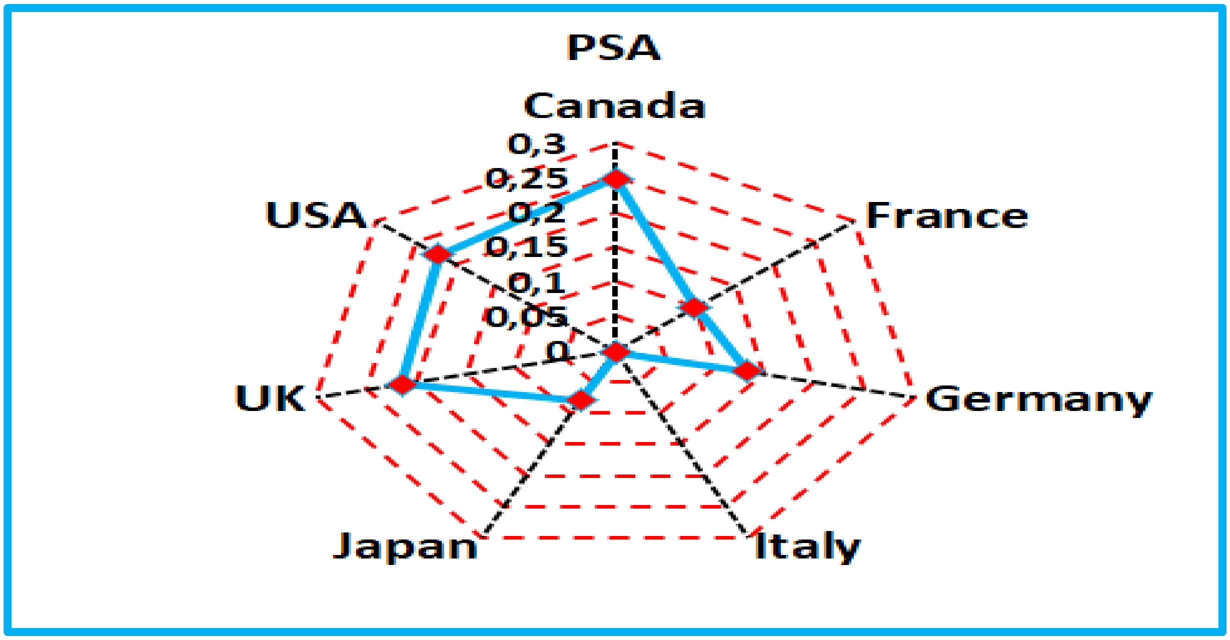

Figure 2. Position of PSA
Note: The axises is graduated in increments of 0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3

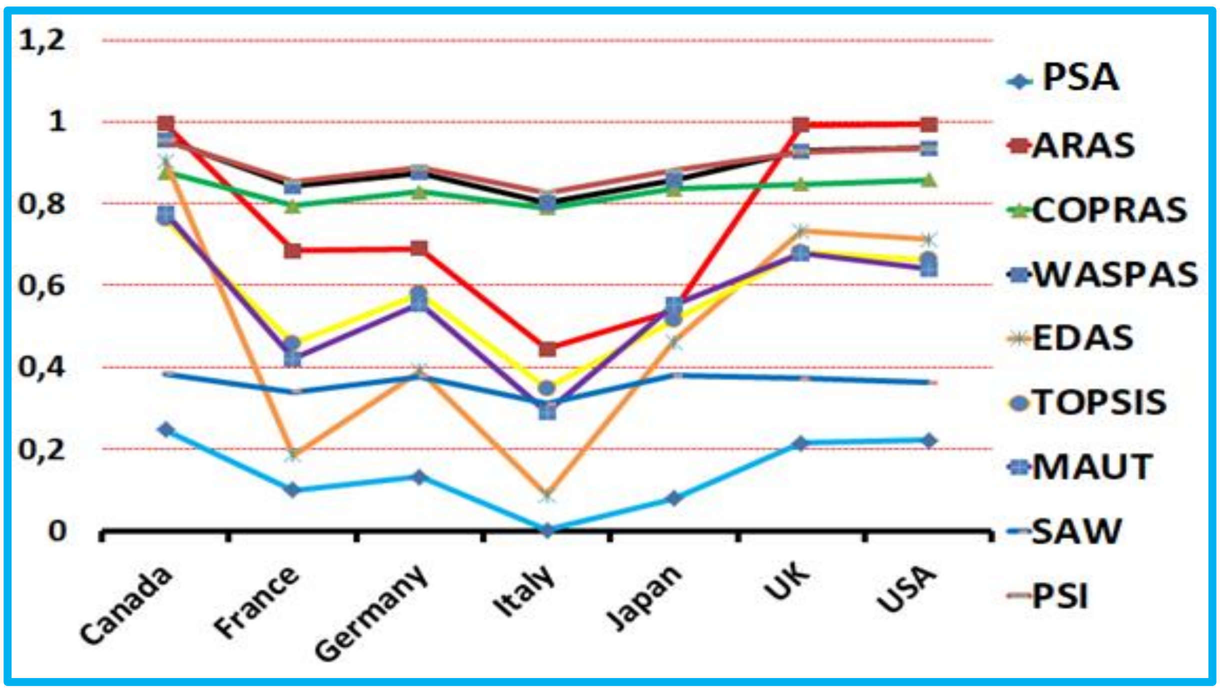

Figure 3. Positions of the PSA, ARAS, COPRAS, WASPAS, EDAS, TOPSIS, MAUT, SAW, and PSI Methods

When Table 7 and Figure 3 are examined together, it is observed that the fluctuations in the performance scores of countries according to the PSA method are generally consistent with the MCDM methods. Therefore, based on this visual structure, it is believed that there is a significant relationship between the performance values of countries calculated by the PSA method and those calculated by other MCDM methods. Accordingly, the correlation values of the PSA method with other MCDM methods are shown in Table 8.

Table 8. Pearson Correlation Values of the PSA Method with Other MCDM Methods

Methods	ARAS	COPRAS	WASPAS	EDAS	TOPSIS	MAUT	SAW	PSI
Score	0.980**	0.885**	0.986**	0.930**	0.974**	0.934**	0.700**	0.966**

p<.01. p*<.05**

Keshavarz-Ghorabaee (2021) citing the findings of Walters (2009), noted that when measuring the Pearson correlation among the MEREC method and other techniques (such as SD, ENTROPY, and CRITIC), a positive and significant correlation falling within the range of 0,400-0,600 indicates a moderate level of association between variables. Moreover, if the correlation exceeds 0,600, it signifies a substantial relationship. Accordingly, when Table 8 is examined, it is observed that the PSA method has a positive, significant, and very high-level correlation with all MCDM methods except for the SAW method, with which it has a significant and high-level correlation. Therefore, based on these results, it is evaluated that the PSA method's methodology shows more differences compared to the SAW method than other MCDM methods and that the PSA method is credible and reliable.

C.Simulation Analysis

To assess robustness and stability of the proposed method's results under various conditions, a simulation analysis is conducted using different scenarios represented by diverse decision matrices. Firstly, as the number of scenarios increases, the proposed method is expected to exhibit a greater degree of differentiation from other methods in terms of the resulting performance scores. This suggests that the proposed method is more sensitive to the specific context of each scenario. Secondly, on average, the variance of the performance scores obtained using the proposed method across different scenarios should be demonstrably greater than the variance observed with at least one or more alternative weight calculation methods. This indicates that the proposed method is more effective in differentiating the relative importance of different criteria. Thirdly, homogeneity of variances within scenarios: Within each individual scenario, the variances of the weights obtained using different methods should exhibit a degree of homogeneity. This implies that the proposed method, along with other methods, consistently captures the inherent variability of the weights within each specific scenario (Keshavarz-Ghorabaee, 2021). During the simulation analysis, the correlation coefficients of the PSA method with other methodologies were computed using the initial 10 scenarios, and these findings are outlined in Table 9.

Table 9. Correlation Values of the PSA Method with Other Methods under Different Scenarios

Scenarios	ARAS	COPRAS	WASPAS	EDAS	TOPSIS	MAUT	SAW	PSI
1. Sce.	0.985**	0.889**	0.989**	0.945**	0.981**	0.941**	0.725**	0.975**
2. Sce.	0.975**	0.883**	0.985**	0.935**	0.977**	0.935**	0.710**	0.966**
3. Sce.	0.970**	0.885**	0.990**	0.921**	0.965**	0.928**	0.685*	0.955**
4. Sce.	0.981**	0.887**	0.975**	0.923**	0.969**	0.915**	0.679*	0.949**
5. Sce.	0.967**	0.867**	0.973**	0.901**	0.958**	0.889**	0.677*	0.936**
6. Sce.	0.965**	0.869**	0.967**	0.885**	0.945**	0.885**	0.669*	0.941**
7. Sce.	0.967**	0.977**	0.965**	0.888**	0.949**	0.884**	0.683*	0.901**
8. Sce.	0.959**	0.961**	0.971**	0.887**	0.952**	0.988**	0.671*	0.885**
9. Sce.	0.963**	0.955**	0.975**	0.889**	0.963**	0.881**	0.668*	0.873**
10. Sce.	0.961**	0.951**	0.962**	0.883**	0.953**	0.879**	0.663*	0.865**

p<.01. p*<.05**

Upon examination of Table 9, it was observed that the PSA method exhibits positive and significant correlations with other MCDM methods in each scenario. Subsequently, scenarios 1, 2, and 3 were grouped as the first group, while the remaining 7 scenarios were grouped as the second group, and the correlation positions of these two groups were compared separately. Accordingly, a visual representation showing the encounter analysis between correlation groups under scenarios is presented in Figure 4.

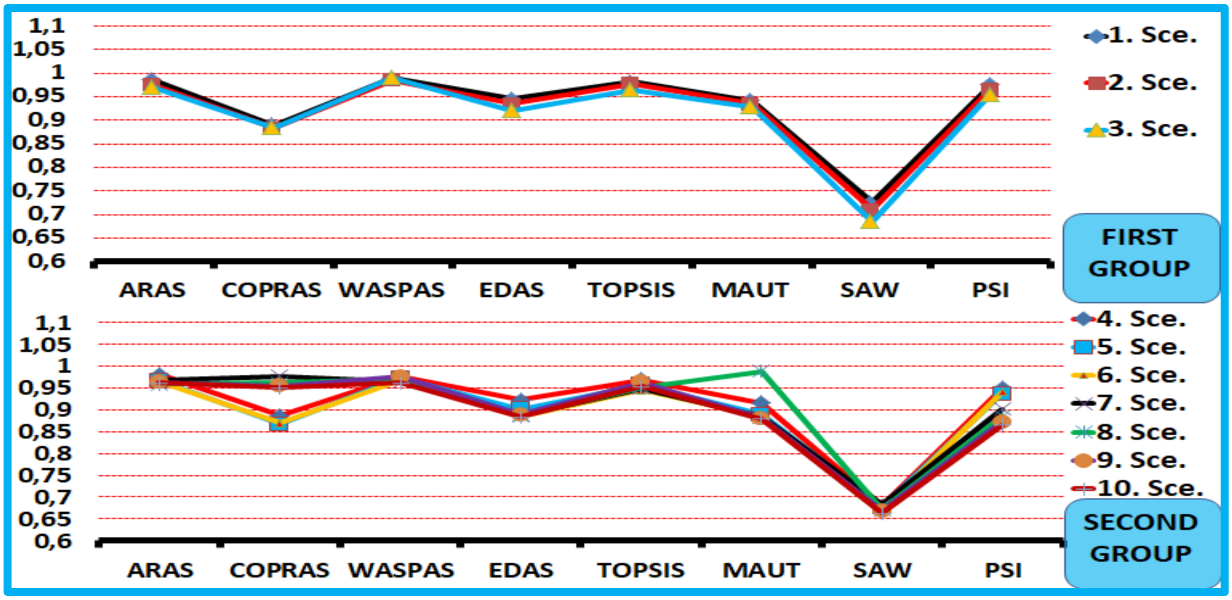

Figure 4. The Correlation Status of The PSA Method with Other Approaches within Various Scenarios

When Table 9 and Figure 4 are considered together, it is observed that as the scenarios increase, the correlation values of the PSA method with other MCDM methods diverge and decrease. As a consequence, it has been noted that the distinctive characteristics of the methodologies become increasingly conspicuous with the expansion of scenarios, leading to more pronounced disparities between them. Throughout the simulation analysis, the variance values of the methodologies were computed across various scenarios, and the resulting values are elaborated. The variance values of the performance scores determined for each scenario with respect to the mentioned scenarios, along with the mean variance values, are presented in Table 10.

Table 10. Variability in Methodologies Across Scenarios

Methods	ARAS	COPRAS	WASPAS	EDAS	
1.Sce	0.054313	0.001498	0.004313	0.092318	
2.Sce	0.053921	0.001201	0.004218	0.091921	
3.Sce	0.055433	0.001324	0.004519	0.093027	
4.Sce	0.054765	0.001465	0.004356	0.094156	
5.Sce	0.055187	0.001389	0.004478	0.093781	
6.Sce	0.054123	0.001527	0.004191	0.092519	
7.Sce	0.054929	0.001372	0.004587	0.094011	
8.Sce	0.055842	0.001438	0.004397	0.092878	
9.Sce	0.054621	0.001289	0.004245	0.095011	
10.Sce	0.055296	0.001503	0.004514	0.093687	
Mean	0.054842	0.001401	0.004382	0.093331	
Methods	**TOPSIS**	**MAUT**	**SAW**	**PSI**	**PSA**
1.Sce	0.023218	0.030218	0.000789	0.002523	0.008423
2.Sce	0.022991	0.028991	0.000852	0.002357	0.008212
3.Sce	0.021987	0.029987	0.000734	0.002568	0.008342
4.Sce	0.024156	0.028156	0.000916	0.002432	0.008476
5.Sce	0.022781	0.030781	0.000827	0.002497	0.008536
6.Sce	0.023519	0.029519	0.000895	0.002374	0.008489
7.Sce	0.024011	0.031011	0.000768	0.002586	0.008278
8.Sce	0.022878	0.029878	0.000912	0.002491	0.008355
9.Sce	0.025011	0.030011	0.000845	0.002425	0.008491
10.Sce	0.022687	0.028687	0.000781	0.002518	0.008578
Mean	0.023324	0.029724	0.000832	0.002477	0.008418

According to Table 10, within the scope of scenarios, the average variance value of the PSA method is higher compared to the PSI, SAW, WASPAS, and COPRAS methods, while it is lower compared to other MCDM methods. In this regard, it can be evaluated that the PSA method is more effective in distinguishing the performance of decision alternatives compared to the PSI, SAW, WASPAS, and COPRAS methods. It can be considered that the proposed method has capacity in distinguishing the performance of decision alternatives.
In the continuation of the simulation analysis, the consistency of variances in the criterion weights of the PSA method was assessed using ADM (Analysis of Means for variances with Levene) analysis across various scenarios. This analytical method offers a visual representation for evaluating the equality of variances. The visual representation consists of three elements: the overall mean ADM acts as the central line, accompanied by the upper decision limits (UDL) and lower decision limits (LDL). If the standard deviation of a group (cluster) surpasses the decision limits, it indicates a notable deviation from the general mean ADM, suggesting heterogeneity in variances. Conversely, if the standard deviations of all clusters lie within the LDL and UDL, it confirms the uniformity of variances. The graphical depiction of the ADM analysis is showcased in Figure 5.

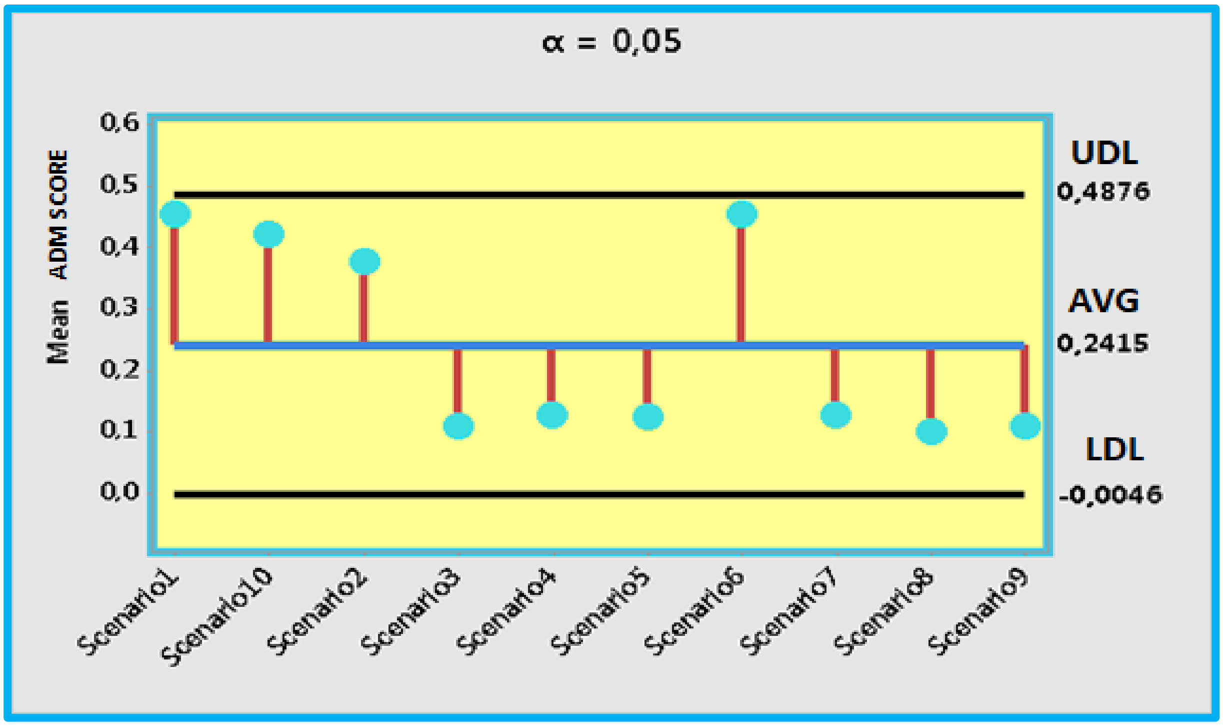

Figure 5. ADM Visual

Based on the information in Figure 5, the ADM analysis confirms that the variances in the identified performance for each scenario exhibit homogeneity. This means that the variations in the performance values across different scenarios are statistically similar. In simpler terms, the performance score are consistent across the scenarios. This finding is further corroborated by the results of the Levene Test, which are likely presented in Table 11.

Table 11. Levene Test

Levene Statistic	df1	df2	Sig.
0.268	2	10	0.124

p<.05**

The Levene Test is a statistical test specifically designed to assess the equality of variances between groups. Table 11 further corroborates the aforementioned conclusion. The p-value obtained from the Levene Test is 0,212, which is greater than the significance threshold of 0,05. This outcome statistically confirms the homogeneity of variances in the performance value of decision alternatives across different scenarios. Overall, the ADM analysis and Levene Test together provide strong evidence that the variances in the criterion weights are consistent across the different scenarios investigated in the simulation analysis. In conclusion, the findings of the simulation analysis provide compelling evidence regarding the robustness and stability of the PSA method. The consistent performance of the method across diverse scenarios demonstrates its the robustness, stability and potential for practical applications.

IV. CONCLUSION

The complex problems of today necessitate a systematic and consistent decision-making process that considers multiple criteria. This is because novel approaches can render the decision-making process more transparent and enable better coping with uncertainties. Therefore, developing new approaches and methods in multi-criteria decision-making is crucial for solving complex problems more effectively and making more informed decisions. In this context, this research proposes a new method (PSA) that can be used in measuring the performance of decision alternatives or in selection problems. The fundamental principle of the PSA method is based on the proportional increase in values assigned to each criterion across different decision alternatives. Therefore, any decision alternative whose increase in criterion values is higher compared to other decision alternatives enhances its performance. The most significant advantage of the method lies in enabling a clear and objective evaluation of decision alternatives' performances by comparing the increase rates in different criteria within the method. The method's most distinctive feature is the absence of weighting criteria. This is because by clearly indicating which alternatives perform better than others for each criterion, the strength of the criterion is implicitly calculated.

The research dataset consists of Economic Freedom Index criterion values for G7 countries. Initially, the results of the proposed method were compared with ARAS, COPRAS, WASPAS, EDAS, TOPSIS, MAUT, SAW, and PSI methods using the same dataset values. According to the findings, it was observed that the PSA method had a positive, significant, and very high correlation with the ARAS, COPRAS, WASPAS, EDAS, TOPSIS, MAUT, and PSI methods, and a high correlation with the SAW method. Based on all these results, the proposed method was evaluated as credible and reliable.

In the simulation analysis, initially, 10 different scenarios were created, and the relationship between the PSA method and other MCDM methods was evaluated according to these 10 scenarios. The results indicated that as the number of scenarios increased, the relationships between the PSA method and other MCDM methods decreased, making its characteristic feature more pronounced. Continuing with the simulation analysis, the average variance values of the methods were measured across the 10 scenarios. Upon examining the results, it was found that the PSA method had higher average variance values compared to the COPRAS, WASPAS, SAW, and PSI methods. Based on this result, it was evaluated that the PSA method has a capability to distinguish the performance of decision alternatives. Finally, an ADM analysis was conducted with 10 different scenarios for the PSA method. As a result, it was found that the homogeneity of variances was achieved. Considering all these results of the simulation analysis, it was concluded that the proposed method is robust and stable.

In future studies, decision-making problems concerning the superiority of decision alternatives based on criteria values can be addressed using different mathematical models to calculate or solve the selection problem of decision alternatives. The superiority, weaknesses, and contributions to the literature of models constructed by comparing different mathematical models explaining the performance of said decision alternatives can be discussed more comprehensively.

STATEMENT OF CONTRIBUTION RATE

Authors' contribution rates to the study are 100%

CONFLICTS OF INTEREST

They stated that no conflict of interest existed between the authors and their respective institutions.

RESEARCH AND PUBLICATION ETHICS

In the studies carried out within the scope of this article, the rules of research and publication ethics were followed.

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