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RESEARCH ARTICLE

A New Proposal for the Measurement of Criterion Weights in the Scope of Multi-Criteria Decision Making: Somer's D-DEMATEL based Hybrid Approach (SDBHA)

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ABSTRACT
The obtained results underscore the effectiveness of the SDBHA in objectively determining criteria weights across various countries. Sensitivity and comparative analyses with other well-established methods, such as ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC, were conducted to assess the sensitivity, credibility, and reliability of SDBHA. According to the findings, SDBHA is sensitive and close to a credible and reliable state. Remarkable observations include the effectiveness of SDBHA, as indicated by simulation analyses, in consistently distinguishing and determining criteria weights across various scenarios, demonstrating its stability and robustness. In conclusion, SDBHA emerges as a potent and objective criteria weighting technique, notably enhancing the DEMATEL method and providing significant contributions to the literature on MCDM.

Keywords: MCDM, Somer's D, DEMATEL, SDBHA, Criteria Weights

1. Introduction

Multi-criteria decision making (MCDM) is a methodology that is widely used in complex decision-making processes and mathematical modelling, often involving a variety of factors. MCDM seeks to evaluate and rank alternatives based on the preferences and priorities of decision makers. To achieve this, it is essential to determine the weights of the criteria, which represent the decision-makers' preferences (Saaty, 2008).

The field of MCDM offers a diverse array of techniques, such as ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW, for calculating criterion weights (Keleş, 2023). These techniques employ two fundamental characteristics of objective criterion weights: 1) the degree of performance contrast across decision alternatives for each criterion, reflecting the range between maximum and minimum values, and 2) the distinctiveness or conflict among criteria. By understanding and utilising these inherent data characteristics, decision makers can gain valuable insights to guide their decision-making process (Ecer, 2020). Therefore, in the MCDM criterion weighting literature, the criterion weighting logic can differ in methods that consider the relationships between criteria (CRITIC, DEMATEL, MEREC).

Subjective weight coefficients inherently rely on personal experiences and subjective evaluations of decision makers, making them susceptible to variations among individuals (Baş, 2021). Typically, these coefficients are derived from expert judgments, but relying solely on subjective assessments can introduce errors and biases into the decision-making process. In contrast, objective methodologies utilise mathematical models and information within the decision matrix to compute criteria weights, thus disregarding inconsistencies and uncertainties in decision-makers' judgments (Paksoy, 2017; Rahim, 2020; Demir, 2021). Therefore, this study aims to develop the DEMATEL method, a subjective weighting method, with Somer's D method to establish an objective structure. By doing so, the limitation of the DEMATEL method, which is commonly used by researchers, to have a subjective structure can be eliminated, thereby expanding its applicability.

In the study, the most important benefit situation of the Somer's D method, (the relationship status between two variables has an asymmetric structure and accordingly, the detection of the influencing and affected values of the criteria can be done objectively) and the most important benefit situation of the DEMATEL method (determination of the structure of the relationships between

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criteria and accordingly, the calculation of the criteria weights) were taken into consideration and the SDBHA (Somer's D-DEMATEL based Hybrid Approach) method was developed. In this context, with the proposed method, prioritising relationships among variables, the analysis and modelling of variables can be achieved more easily compared to the classical DEMATEL method, considering the constraint of subjectivity in the DEMATEL method. The proposed method constitutes a significant contribution to the existing body of literature on criterion weighting coefficient calculation methods, offering a fresh perspective to the field.

To achieve these objectives, the research delves into objective weighting methods, Somer's D and DEMATEL. Subsequently, the proposed method is employed to measure and rank the weights of criteria for the 19 G20 countries, utilising the Global Innovation Index data for these countries. The validity and reliability of the proposed method were assessed through sensitivity analyses. Comparative analyses were then conducted to evaluate the method's credibility and reliability levels. Finally, simulation analyses were performed to deconstruct the criteria weights and determine the stability of the method.

2. Literature

2.1. Methods for Calculating Criterion Weights in the Scope of the MCDM

Choosing the best option in decision making requires comparing alternatives across multiple criteria. Accurately weighting these criteria is essential for effective comparison and selection of the most suitable option (Saaty, 2008). Weight coefficients traditionally play this role in Multi-Criteria Decision Making (MCDM) problems (Ecer, 2020).

The field of MCDM offers a diverse array of objective weighting methods, such as CRITIC (Criteria Importance Through Inter Criteria Correlation), ENTROPY, CILOS (Criterion Impact Loss), IDOCRIW (Integrated Determination of Objective Criteria Weights), SVP (Statistical Variance Procedure), SD (Standard Deviation), MEREC (Method Based On Removal Effects of Criteria), LOPCOW (Logarithmic Percentage Change-driven Objective Weighting), and SECA (Simultaneous Evaluation of Criteria and Alternatives) (Ecer, 2020).

The CRITIC method assigns higher weights to criteria with greater variability (disorder) than others, reflecting their importance. It analyzes correlations within the decision matrix to identify inconsistencies between criteria. Standard deviation is used to quantify these contradictions, ultimately determining the criteria weights (Diakoulaki et al., 1995).

The ENTROPY method is a valuable tool for the decision-making process. Following the construction of the decision matrix, this method employs the standard values of the decision matrix and the ENTROPY measure of the criteria to determine the ENTROPY-based criterion weights (Ayçin, 2019; Ulutaş and Topal, 2020).

The CILOS method assigns higher weights to criteria with less impact deviation from ideal values (maximum or minimum). Criteria are evaluated on the basis of a decision matrix, and weights are calculated by solving a system of linear equations (Zavadskas & Podvezko, 2016; Sel, 2020).

The IDOCRIW method is a hybrid approach that combines both the ENTROPY and CILOS methods. This approach focuses on determining the relative impact of a missing index. Initially, the weight coefficients for the criteria are determined using the decision matrix values and the ENTROPY and CILOS methods. Subsequently, the ENTROPY and CILOS weights were integrated to yield the IDOCRIW weights (Pala, 2021).

The SVP method objectively determines criterion weights based on variance. Unlike subjective methods, it relies solely on data to calculate weights by dividing each criterion's variance by the total variance (Odu, 2019; Gülençer Türkoğlu, 2020; Nasser, 2023).

The SD method evaluates the deviation of criterion values from the arithmetic mean of these criteria to determine their weights. To apply this method, the decision matrix is first normalised using its contained values. Subsequently, the standard deviation values for each criterion were calculated and used to determine the criterion weights (Demir, 2021; Uludağ and Doğan, 2021).

Similar to other weighting methodologies, the MEREC method begins by obtaining the decision matrix and its normalised counterpart. Following this, the overall performance values of the decision alternatives are calculated using a natural logarithm-based framework. Subsequently, considering the value of each decision alternative, adjustments to the performance values of the other decision alternatives are recalculated on the basis of the natural logarithm. To conclude this method, the weight values for the criteria are determined by calculating the removal effect on each criterion, specifically the sum of absolute deviations. Additionally, in this method, as the influence of criteria on decision alternatives increases, the weight coefficients of the criteria also increase (Demir, 2021; Keshavarz-Ghorabaee et al., 2021).

The LOPCOW method integrates data to find balanced weights for the criteria. It considers both individual variability and the interrelationships between criteria. The method normalises the decision matrix and uses standard deviation to adjust for data magnitude, ultimately determining the weights (Ecer Pamucar, 2022).

The SECA method simultaneously evaluates decision alternatives and criterion weights. It analyzes the decision matrix using standard deviation to determine both disagreement between criteria and criteria weights through a multi-objective optimisation model (Keshavarz-Ghorabaee et al., 2018).

2.2. Somers'D Coefficient

Somer's D coefficient is a non-symmetric measure used to assess the relationship between two ordinal variables. It can also gauge the impact of an independent variable on a dependent variable. Ranging between -1 and +1, a value of 0 signifies no association (Somers, 1962; Karagöz, 2010a; Karagöz, 2010b). Moreover, Somer's D can be computed as long as the variables' effect and relationship status, along with their respective data, do not merge into a single cell (Demir, 2022).

Somer's D coefficient offers several quantitative measurement advantages. First, its simple structure allows integration into various mathematical models. Second, it is robust, resistant to outliers, and insensitive to linearity, yielding more reliable results, especially with real-world data showing non-uniform distribution. Third, it assists in identifying relationships between variables, distinguishing them as dependent or independent, and evaluating their impacts on each other. Finally, Somer's D coefficient accurately predicts positive or negative interactions and relational structures between variables (Newson, 2006).

Additionally, Somer's D method establishes a statistical framework by considering relationships and interactions among variables in decision matrices, focussing on the "Accuracy Ratio." This aspect underscores the method's reliability and stability in decision making. The correlation coefficients computed by this method demonstrate consistency in criterion weighting and its ability to yield results comparable to those of other methods, thereby enhancing its credibility (Orth, 2016). Fifth, Somers's D method aligns well with other measurement modelling methods, facilitating easier comparison of results and enabling more comprehensive analysis (Metsämuuronen, 2020). Sixth, Somers' D method has a nonparametric property (Oktay, 2017). Parametric tests generally require assumptions such as normal distribution of data and homogeneity of variances. However, nonparametric techniques do not require such strict assumptions and do not make any assumptions about the sample distribution (Kalaycı, 2019). Therefore, Somer's D can be used to measure relationships and effects between variables without any restrictions.

The Somer's D method offers distinct advantages over other interactive coefficients found in the literature. Among nominal-scale correlation coefficients such as Phi Coefficient, Contingency Coefficient, Cramer's V, Goodman-Kruskal Tau, and Uncertainty Coefficient, which are commonly used, Somer's D correlation coefficient stands out due to its ability to transition from an ordinal-scale structure to a nominal-scale structure. This inclusivity allows for the measurement of ordinal-scale correlation coefficients on a nominal scale, rendering Somer's D more versatile than others (Kalaycı, 2019). Conversely, Kendall's Tau b, Kendall's Tau c, Gamma, Spearman Coefficient (Rho), and Pearson correlation coefficients are symmetric, limiting their ability to calculate values indicating the influence of variables on each other and their mutual impact. Consequently, numerous studies in the literature use Somer's D relationship coefficient, especially in the context of objective criterion weighting methods. Table 1.

Table 1. *Somer's D coefficient in relation to current research*

Author(s)	Method(s)	Theme
Torres-Ruiz et al., 2021	AUC and Somer's D	Reassessing the Severity and Prognosis of COVID-19: Exploring the Influence of Clinical and Immunobiotype Factors
Yovi and Yamada, 2023	Somer's D	Analysis of the Relationship Among Fatigue Variables within the Scope of Occupational Health Status
Sánchez-Cabrero et al., 2023	Somer's D, chi-square, and Eta	Analysis of the Relationship Among Teaching Training Variables
Valencia-Arias et al., 2023	Somer's D	Analysis of the Relationship Among Variables of Student Satisfaction
Valencia-Arias and Restrepo, 2020	Somer's D	Analysis of Relationship Constructs Found in the Theory of Planned Behaviour

When the relationship between two variables is classified as dependent and independent variables, 11 application steps are required to determine the Somer's D correlation coefficient. The application steps of the Somer's D correlation coefficient are explained below (Oktay, 2017).

Step 1: Obtaining the Decision Matrix

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{1j} \\ x_{21} & x_{22} & x_{2j} \\ \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & x_{ij} \end{bmatrix} \tag{1}$$

Step 2: Calculating the P^*_{ij} Values

The P^*_{ij} values represent the sum of the cells to the south and east of the cell at (i,j) in the decision matrix, starting from the northwest corner. The calculation formula for P^*_{ij} is as follows:

$$P^*_{ij} = \sum_{i'>i}^{I} \sum_{j'>j}^{J} x_{i'j'} \tag{2}$$

The letter "I" represents the latest value of "i", and the letter "J" represents the latest value of "j".

Step 3: Calculating the C Value (Compatible Pairs)

$$P = \sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij} P^*_{ij} \tag{3}$$

Step 4: Calculating the R^*_{ij} Value

The R^*_{ij} value represents the sum of the cells to the southwest of the cell at (i,j) in the decision matrix, starting from the northeast corner. The calculation formula for R^*_{ij} is as follows.

$$R^*_{ij} = \sum_{i'<i}^{I} \sum_{j'>j}^{J} x_{i'j'} \tag{4}$$

Step 5: Calculating the R Value (Compatible Pairs)

$$R = \sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij} R^*_{ij} \tag{5}$$

Step 6: Calculating the Number of Values Dependent on Only the C_a Variable (T_{C_a})

In the context of different types of dependent values, if the observation in the *(i,j)* cell is dependent only on the values in the i-th row of the C_a variable, the number of observations dependent on C_a is calculated as shown in Equation 6.

$$2T_{C_a} = \sum_{i=1}^{I} x_{i+}^2 + \sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij}^2 \tag{6}$$

Step 7: Number of Observations Dependent on Only the C_b Variable (T_{C_b})

In the context of different types of dependent values, if the observation in the (i,j) cell is dependent only on the values in the i-th row of the C_b variable, the number of observations dependent on C_b is calculated as shown in Equation 7.

$$2T_{C_b} = \sum_{i=1}^{I} x_{+j}^2 + \sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij}^2 \tag{7}$$

Step 8: Number of Observations Dependent on Both the C_a and C_b Variables (C_{ab})

In the context of different types of dependent values, if the observation in the (*i,j*) cell is dependent on the values in the i-th row of both the C_a and C_b variables, the number of observations dependent on C_a and C_b is given in Equation 8.

$$2C_{ab} = \sum_{i=1}^{I}\sum_{j=1}^{J} x_{ij}^2 - x \tag{8}$$

Step 9: Determining the Effect of C_b on $C_a(\hat{d}_{C_b}C_a)$

The maximum likelihood estimator of the coefficient (θ) is given in Equation 9, depending on the multinomial sampling model.

$$\hat{d}_{C_b}C_a = \frac{P-R}{P+R+T_{C_b}} = \frac{2(P-R)}{x^2 - \sum_{i=1}^{I} x_{i+}^2} \tag{9}$$

Step 10: Determining the Effect of C_a on $C_b(\hat{d}_{ab})$

The effect of C_a on C_b can be estimated using the maximum likelihood estimator, which is given in Equation 10.

$$\hat{d}_{C_a}C_b = \frac{P-R}{P+R+T_{C_a}} = \frac{2(P-R)}{n^2 - \sum_{i=1}^{I} x_{i+j}^2} \tag{10}$$

Step 11: Determining Somer's D Correlation Coefficient ($\hat{d}$)

The Somer's D correlation coefficient can be estimated using the maximum likelihood estimator, which is given in Equation 11.

$$\hat{d} = \frac{2(P-R)}{x^2 - \frac{1}{2}(\Sigma_{i=1}^{I} x_{i+}^2 + \Sigma_{i=1}^{I} x_{+j}^2)} \tag{11}$$

2.3. DEMATEL Method

DEMATEL (Decision Making Trial and Evaluation Laboratory) is a subjective criterion weighting method devised by Gabel and Fontela in 1972. It facilitates the identification of interdependencies among variables with mutual relationships within a relational structure in multi-criteria decision-making (Dinçer, 2019; Tepe, 2021). In the DEMATEL method, variables exhibiting an "influencing" nature in the relationship structure are termed "causes," while those with an "affected" nature are referred to as "effects" (Dinçer, 2019; Atan and Altan, 2020).

The DEMATEL method has found successful applications in various technical and social problems. In addition to identifying the relationship structure between variables, it can also compute the importance values of these variables (Haste, 2020; Karadağ Albayrak, 2021). When preparing the decision matrix in the DEMATEL method, the influence values of variables can be determined through subjective opinions obtained from an expert or a group of experts (Paksoy, 2017; Kaya and Karaşan, 2020). Consequently, the DEMATEL method offers a means to visually represent the relationships between criteria (Çelikbilek, 2019; Özceylan and Özkan, 2020).

The DEMATEL method offers several advantages. First, it effectively analyses mutual influences, including both direct and indirect effects, among different factors, thereby unravelling complex cause-and-effect relationships in decision-making problems. Second, it visualises the interrelationships between factors, facilitating a clear understanding of which factors mutually influence one another. Third, DEMATEL can determine alternative rankings, identify critical evaluation criteria, and measure the weights of these criteria (Aghelie et al., 2016; Si et al., 2019). Fourth, the method can analyse an unlimited number of indicators and examine relationships even in the presence of data shortages (Ogradnik, 2018).

The DEMATEL method has been widely utilised by many researchers to determine inter-variable relationships, interactive structures, and criterion weights (Šmidovnik and Grošelj, 2021). In this context, current studies related to the DEMATEL method are presented in Table 2.

Table 2. *DEMATEL in relation to current research*

Author(s)	Method(s)	Theme
Kumar et al., 2023	Modified Pythagoreanfuzzy VIKOR and DEMATEL	Assessment of Sustainable Carbon Dioxide Storage in Geological Formations
Nezhad et al., 2023	Fuzzy DEMATEL and Fuzzy AHP	Evaluating Factors Affecting the Readiness for Implementing IoT in Industries
Özdemirci et al., 2023	T-Spherical fuzzy TOP-DEMATEL	Evaluation of Alternative Social Banking Systems
Mao et al., 2023	Cumulative prospect theory and fuzzy DEMATEL	Choosing Technology for the Treatment of Solid Plastic Waste
Pinto, 2023	Cognitive mapping and the DEMATEL	Examining the Roots of Urban Blight

The application steps of the method are as follows (Ayçin, 2019; Dinçer, 2019; Öksüz and Öngel, 2021).

Step 1: Creation of the direct relationship (impact values) matrix (D)

$$D = \begin{bmatrix} d_{11} & d_{1j} & d_{1n} \\ \vdots & \vdots & \vdots \\ d_{i1} & d_{ij} & d_{in} \\ \vdots & \vdots & \vdots \\ d_{m1} & d_{mj} & d_{mn} \end{bmatrix} \tag{12}$$

Given that *m=n*, the values of m and n represent the number of criteria. The values in the direct relationship matrix explain the direct relationship between the *i.th* variable and the *j.th* variable.

The direct relationship matrix is typically constructed by obtaining information from the decision maker or decision makers that are experts in the relevant subject. The decision-maker or decision-makers determine their decisions using an enhanced comparison scale, as shown in

Table 3. *DEMATEL comparative scale*

Numerical Value	Description
0	Ineffective
1	Low impact
2	Moderate impact
3	High impact
4	Very high impact

Step 2: Creation of the normalised decision matrix (x)

In order to normalise the direct relationship matrix, all values are normalized by dividing them by the maximum value of the row and column sums. The normalised decision matrix is used to create the total impact matrix. The normalisation process uses equations 13 and 14.

$$s = min\left[\frac{1}{max_i \sum_{j=1}^{m} |d_{ij}|}, \frac{1}{max_j \sum_{i=1}^{n} |d_{ij}|}\right] \tag{13}$$

$$x = s.d \tag{14}$$

Step 3: Creation of the total impact matrix *(T)*

Equation 15 is transformed into the matrix described in equation 16. The total impact matrix is created by subtracting the normalised direct relationship matrix from the identity matrix, taking the inverse, and then multiplying it by itself. Therefore, the total impact matrix reflects its relationship with the normalised decision matrix.

$$T = x + x^2 + \cdots + x^h = x(1-x)^{-1} \tag{15}$$

$$T = \begin{bmatrix} t_{11} & t_{1j} & t_{1n} \\ \vdots & \vdots & \vdots \\ t_{i1} & t_{ij} & t_{in} \\ \vdots & \vdots & \vdots \\ t_{m1} & t_{mj} & t_{mn} \end{bmatrix} \tag{16}$$

Step 4: Identification of the impact values (d_i)

The sum of each row value for the criteria in the total impact matrix is calculated.

$$d_i = \sum_{i=1}^{m} t_{ij} \rightarrow D = \begin{bmatrix} d_1 \\ \vdots \\ d_i \\ \vdots \\ d_m \end{bmatrix}_{mx1} \tag{17}$$

Step 5: Estimation of the impacted values (r_j)

The sum of each column value for the criteria in the total impact matrix is calculated.

$$r_j = \Sigma_{j=1}^{n} t_{ij} \rightarrow R[r_1, \ldots, r_j \ldots r_n]_{1xn} \tag{18}$$

Step 6: Estimation of the relationship intensity $(RC)_j$

$$(RC)_j = d_i + r_j \tag{19}$$

Step 7: Determining the Nature of Criteria as "Influencing" $d_i > r_j$: If the impact value of criterion (d_i) a is greater than the affected value of criterion (r_j) then criterion (d_i) is considered to be the cause of criterion (r_j).

Step 8: Determination of the Nature of Criteria as "Affected"

$d_i < r_j$: If the impact value of criterion (d_i) is less than the affected value of criterion (r_j), then criterion (d_i) is considered to be the effect of criterion (r_j).

Step 9: Determination of the Threshold Value

To create an appropriate influence diagram and make sound decisions, an appropriate threshold value is required. The threshold value can be determined by conducting interviews with stakeholders or researchers. However, it can be difficult to bring stakeholders together. In a more objective sense, the threshold value can be calculated as the arithmetic mean of the total relationship matrix (T) values.

Step 10: Calculation of the Criterion Weights (w_i)

First, the square of the sum of the values for the criteria's direct and indirect effects is added to the square of the difference between the values for the criteria's direct and indirect effects. The square root of the resulting value is then calculated. It was shown in Equation 20.

$$w_{ja} = \sqrt{\left[\sum_{i=1}^{m}(d_i) + \sum_{j=1}^{n}(r_j)\right]^2 + \left[\sum_{i=1}^{m}(d_i) - \sum_{j=1}^{n}(r_j)\right]^2} \tag{20}$$

Second, the weight coefficients of the criteria were calculated by dividing the value of each criterion by the total value of the criteria.

$$w_i = \frac{w_{i_a}}{\sum_{i=1}^{m} w_{i_a}} \tag{21}$$

3. Materials and Methods

3.1. Proposed Method (Somer's D-DEMATEL based Hybrid Approach)

In determining the weights of criteria, the distinctiveness and conflict among criteria highlight the nature of the criteria in terms of priority and importance (Ecer, 2020). Therefore, within the scope of MCDM, there can be various differences in the methods used to calculate weight coefficients.

In the DEMATEL method, the importance and weight of a variable is determined by the extent to which it positively or negatively affects other variables. Accordingly, if a criterion has the highest positive or negative influence on other criteria and the value of its impact on other criteria is maximal, then the weight assigned to that criterion will be the highest. Therefore, the variable that contributes the most to the relational structure in the DEMATEL method has the highest weight coefficient (Ecer, 2020; Valencia-Arias et al., 2023).

In the CRITIC method, the weight coefficient of a variable is maximised when the sum of its relationships with other variables is minimised (positive) or maximised (negative) and the standard deviation value is maximised (Diakoulaki et al., 1995). Therefore, in the CRITIC method, the weight value of a variable increases as it becomes more distinct from other variables. In the ENTROPY method, as the degree of uncertainty of criterion increases relative to other criteria, the weight coefficient of the criterion decreases. Thus, the criterion with the highest degree of uncertainty acquires a more distinctive quality than other criteria (Ayçin, 2019). In the MEREC method, the weight of a particular criterion increases as the absolute difference between the average of criteria with respect to decision alternatives, either by excluding or considering the criterion, and the average of criteria with respect to decision alternatives becomes smaller (Keshavarz-Ghorabaee et al., 2021). Consequently, the criterion with the highest weight has the greatest impact on decision alternatives. In the SD method, the weight of the criterion is maximised when its standard deviation is the highest (Demir, 2022). Similarly, in the SVP method, the weight of a criterion is maximised when its variance is the highest (Nasser, 2023). In the LOPCOW method, the mean square value of each criterion is calculated as a percentage of the standard deviations, effectively mitigating the discrepancy (gap) arising from the dimensionality of the data. Consequently, a decrease in the standard deviation of a criterion will reduce the gap attributed to the size of the data for that criterion, leading to an increase in the weight assigned to the criterion (Ecer and Paumucar, 2022).

The objective weighting methods described above (ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW) focus on determining the importance (weight coefficient) of a criterion by considering its differentiation from other criteria through their respective techniques. However, the DEMATEL method, unlike other methods, offers a more advantageous structure in determining criterion weights by considering both negative (divergence) and positive effects (similarity). In this context, the DEMATEL method provides a broader framework by incorporating contrasts that form the logic of criterion weighting, making it more advantageous than other methods.

The DEMATEL method, as explained earlier, is a subjective criterion weighting technique (Torres-Ruiz et al., 2021). Evaluations conducted within the scope of subjective weighting methods can lead to biases and errors (Rahim, 2020; Demir et al., 2021; Paksoy, 2021). In this context, the impact values between criteria can be determined using Somer's D coefficient, and these impact values can be integrated into the direct relation matrix created within the DEMATEL method. Subsequently, using Somer's D method, the total impact of each criterion on others and the total influence of each criterion by others are calculated. Then, these values are integrated into the DEMATEL method using Equation 20, and the criterion with the highest total impact and influence values is considered the most important. Thus, the subjective criterion weighting nature of the DEMATEL method can be transformed into objective weighting by turning towards Somer's D, resulting in the Somer's D-DEMATEL based Hybrid Approach (SBDHA). The DEMATEL method's first three steps are designed to identify the degree to which a criterion affects other criteria. In the proposed method, the values of the criteria affecting each other and being affected by each other are determined using Somer's D correlation coefficient from Equations 1 to 10. These values are then processed from Equations 22 to 32 to calculate the weights of the criteria.

Step 11: Construction of the impact matrix based on Somer's d

m=n: The number of criteria is denoted.
C_{ivi}: The text specifies the independent variable criteria in the column.
C_{dvj}: The text specifies the dependent variable criteria in the row
$\hat{d}_{C_j} \rightarrow$: The total influencing values of any criterion in the scope of Somer's D on other criteria are represented.
$\hat{d}_{C_j} \leftarrow$: The total affected values of any criterion in the scope of Somer's D on other criteria are represented.

$$SD = \begin{array}{c} C_{iv1} \\ C_{iv2} \\ \vdots \\ C_{ivm} \end{array} \begin{bmatrix} C_{dv1} & C_{dv2} & \dots & C_{dvm} \\ sd_{11} & sd_{12} & \dots & sd_{1m} \\ sd_{21} & sd_{22} & \dots & sd_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ sd_{n1} & sd_{n2} & \dots & sd_{nm} \end{bmatrix} \quad (22)$$

Step 12: Calculation of the total influence of criteria based on Somer's D Method ($\hat{d}_{C_j} \rightarrow$)

In this step, the total influence of each criterion on the other criteria is calculated using Somer's D correlation coefficient.

$$(1) for\ \hat{d}_{C_1\rightarrow} : |\hat{d}_{C_1\rightarrow C_2}| + |\hat{d}_{C_1\rightarrow C_3}| + |\hat{d}_{C_1\rightarrow C_4}| \dots \dots + |\hat{d}_{C_1\rightarrow C_n}| = \left(\sum_{j=1}^{n-1} \left|\hat{d}_{C_1} \rightarrow C_{j+1}\right|\right) \quad (23)$$

$$(2) for\ \hat{d}_{C_2\rightarrow} : |\hat{d}_{C_2\rightarrow C_1}| + |\hat{d}_{C_2\rightarrow C_3}| + |\hat{d}_{C_2\rightarrow C_4}| \dots \dots + |\hat{d}_{C_2\rightarrow C_n}| = \left(\sum_{j=0, j\neq 1}^{n-1} \left|\hat{d}_{C_2} \rightarrow C_{j+1}\right|\right) \quad (24)$$

$$(3) for\ \hat{d}_{C_3\rightarrow} : |\hat{d}_{C_3\rightarrow C_1}| + |\hat{d}_{C_3\rightarrow C_2}| + |\hat{d}_{C_3\rightarrow C_4}| \dots \dots + |\hat{d}_{C_3\rightarrow C_n}| = \left(\sum_{j=0, j\neq 2}^{n-1} \left|\hat{d}_{C_3} \rightarrow C_{j+1}\right|\right) \quad (25)$$

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

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

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

$$(m)\ for\ \hat{d}_{C_n\rightarrow} : |\hat{d}_{C_n\rightarrow C_1}| + |\hat{d}_{C_n\rightarrow C_2}| + |\hat{d}_{C_n\rightarrow C_3}| \dots \dots + |\hat{d}_{C_n\rightarrow C_{n-1}}| = \left(\sum_{j=1}^{n-1} \left|\hat{d}_{C_n} \rightarrow C_j\right|\right) \quad (26)$$

Step 13: Calculation of the Total Effectedness of Criteria Based on Somer's D Method ($\hat{d}_{C_{i\leftarrow}}$)

In this step, the total effect of each criterion on other criteria is calculated using Somer's D correlation coefficient.

$$(1)\ for\ \hat{d}_{C_1\leftarrow} : |\hat{d}_{C_1\leftarrow C_2}| + |\hat{d}_{C_1\leftarrow C_3}| + |\hat{d}_{C_1\leftarrow C_4}| \dots \dots + |\hat{d}_{C_1\leftarrow C_m}| = \left(\sum_{i=1}^{m-1} \left|\hat{d}_{C_1} \leftarrow C_{i+1}\right|\right) \quad (27)$$

$$(2)\ for\ \hat{d}_{C_2\leftarrow} : |\hat{d}_{C_2\leftarrow C_1}| + |\hat{d}_{C_2\leftarrow C_3}| + |\hat{d}_{C_2\leftarrow C_4}| \dots \dots + |\hat{d}_{C_2\leftarrow C_{cm}}| = \left(\sum_{i=0, i\neq 1}^{m-1} \left|\hat{d}_{C_2} \leftarrow C_{i+1}\right|\right) \quad (28)$$

$$(3)\ for\ \hat{d}_{C_3\leftarrow} : |\hat{d}_{C_3\leftarrow C_1}| + |\hat{d}_{C_3\leftarrow C_2}| + |\hat{d}_{C_3\leftarrow C_4}| \dots \dots + |\hat{d}_{C_3\leftarrow C_m}| = \left(\sum_{i=0, i\neq 2}^{m-1} \left|\hat{d}_{C_3} \leftarrow C_{i+1}\right|\right) \quad (29)$$

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

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

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

$$(m)\ for\ \hat{d}_{C_m\leftarrow} : |\hat{d}_{C_m\leftarrow C_1}| + |\hat{d}_{C_m\leftarrow C_2}| + |\hat{d}_{C_m\leftarrow C_3}| \ldots \cdots + |\hat{d}_{C_m\rightarrow C_{m-1}}| = \left(\sum_{i=1}^{m-1} \left|\hat{d}_{C_m} \leftarrow C_i\right|\right) \tag{30}$$

Step 14: Calculation of the Criteria Weights (w_i)

In this step, after the total influencing and affected values of the criteria are found, the logic of Equation 31 shown in the last step of the DEMATEL method is considered. Therefore, the square root of the sum of the squares of the total influencing and affected coefficients of a criterion and the sum of the squares of the differences between the total influencing and affected coefficients of the same criterion, is measured (w_{i_k}).

$$w_{i_k} = \sqrt{\left[(\hat{d}_{C_j} \rightarrow) + (\hat{d}_{C_i} \leftarrow)\right]^2 + \left[(\hat{d}_{C_j} \rightarrow) - (d_{C_i} \leftarrow)\right]^2} \tag{31}$$

After the criteria are evaluated, the weights (w_{i_k}) of the criteria are calculated by dividing the value of each criterion by the sum of the values of all criteria ($\Sigma_{i=1}^{m} w_{i_k}$).

$$w_i = \frac{w_{i_k}}{\Sigma_{i=1}^{m} w_{i_k}} \tag{32}$$

As a result, the SDBHA method is a hybrid method that combines Somer's D and DEMATEL methods. In this regard, the SDBHA method has several advantages. First, because the Somer's D impact coefficients are between 0 and 1 or -1 and 0, normalisation is not required before determining the criterion weights. This helps to reduce the number of processing steps. Second, the SDBHA method can be used to create a matrix of interactions between criteria, similar to the DEMATEL method. This characteristic, especially if there is a theoretical basis for the relationship between criteria, allows the analysis of which criteria should be affected by which criteria. This allows the development of strategies to improve and develop criteria. However, the ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW methods do not provide an interaction matrix between criteria. Third, the numerical interaction value diversity of the SDBHA method is greater than that of the classical DEMATEL method. In the classical DEMATEL method, the effects between the directly related matrices between criteria are 0, 1, 2, 3, and 4. However, in the SDBHA method, the aforementioned direct relationship matrix is provided with any effect values between 0 and 1 or -1 and 0, with the help of Somer's D correlation coefficient. This shows that the SDBHA method measures with real numerical values compared with the classical DEMATEL method, and therefore increases the reliability of the SDBHA method. The fourth advantage of the SDBHA method is that it is sensitive to 0 and negative values. In other words, even if there are zero or negative values in the decision matrix, the weight values of the criteria can be calculated using the SDBHA method. However, in the ENTROPY and MEREC methods, the weights of the criteria cannot be calculated because the subsequent steps are undefined when the values in the decision matrix are negative or 0 because the ENTROPY and MEREC methods have a logarithmic transformation feature. However, only negative values can be converted to positive values using the Z-score technique. Finally, the fifth advantage of the SDBHA method is that it considers both the separation and similarity of criteria in the measurement of criterion weights, similar to the DEMATEL method. However, in the ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW methods, the criterion weight measurement logic is based only on the separation of criteria from other criteria with mathematical models. In this context, the SDBHA method has a broader and more inclusive feature (separation and similarity) than other objective criterion weighting methods. Because, in the SDBHA method, similar to the DEMATEL method, when both positive and negative influence and affected values increase, the weight coefficient of criteria also increases.

While the SDBHA method offers advantages, it poses drawbacks, notably in determining criterion weight coefficients due to computational complexity. As the number of criterion increases, intricate interactions escalate, demanding complex calculations for Somer's D impact and affected coefficients. Although software like SPSS or Python can handle these computations, manual calculation of Somer's D coefficient without such tools is arduous and time-consuming. However, adapting formulas for Microsoft Excel can simplify the process to some extent, facilitating the extraction of interactive or reciprocal relationships between criteria.

3.2. Data Set and Analysis of the Study

The research dataset comprises the Global Innovation Index (GII) criteria for 2022, focussing on 19 countries within the G20 group. The rationale behind selecting this dataset is to assess the discriminatory efficacy of the proposed model criteria among countries, considering the substantial variations in values within this specific dataset. To facilitate understanding of the research, Table 4 elucidates the abbreviations associated with this dataset. Table 4

Table 4. *GII criterion abbreviations*

GII Criteria	Criteria Abbreviations
Institutions	GII1
Human Capital and Research	GII2
Infrastructure	GII3
Market sophistication	GII4
Business sophistication	GII5
Knowledge and technology outputs	GII6
Creative outputs	GII7

4. The Case Study

4.1. Computational Analyses

To facilitate the research, Somer's D method was used to calculate the values of the criteria affecting and being affected by each other for the 9th (Equation 9) and 110th (Equation 10) steps. Subsequently, Equation 22 is used to construct the Somer's d impact matrix. The results of these calculations are presented in Table 5.

Table 5. *Reciprocal influences of the GII criteria on each other and values of influence received from one another*

	Criteria	Dependent Variables							
		GII1	**GII2**	**GII3**	**GII4**	**GII5**	**GII6**	**GII7**	**Total Impact Values**
Independent Variables	**GII1**	0	0,585	0,444	0,766	0,591	0,497	0,38	3,263
	GII2	0,588	0	0,629	0,494	0,706	0,541	0,612	3,57
	GII3	0,447	0,629	0	0,447	0,624	0,482	0,624	3,253
	GII4	0,766	0,491	0,444	0	0,591	0,614	0,439	3,345
	GII5	0,591	0,702	0,62	0,591	0	0,673	0,614	3,791
	GII6	0,497	0,538	0,48	0,614	0,673	0	0,684	3,486
	GII7	0,389	0,623	0,635	0,449	0,629	0,701	0	3,426
	Total influence values	3,278	3,568	3,252	3,361	3,814	3,508	3,353	24,134

In the final step, the weights of the criteria were calculated using Equations 30 and 31. The results of these calculations are presented in Table 6.

Table 6. *Criteria weight*

Cri.	$\hat{d}_{C_{j\rightarrow}}$	$\hat{d}_{C_{i\leftarrow}}$	$\left(\hat{d}_{C_{j\rightarrow}}+\hat{d}_{C_{i\leftarrow}}\right)^2$	$\left(\hat{d}_{C_{j\rightarrow}}-\hat{d}_{C_{i\leftarrow}}\right)^2$	w_{i_k}	w_i	Ranking
GII1	3,263	3,278	42,7847	0,000225	6,541017	0,135513	**6**
GII2	3,57	3,568	50,9510	0,000004	7,138000	0,147881	**2**
GII3	3,253	3,252	42,3150	0,000001	6,505000	0,134767	**7**
GII4	3,345	3,361	44,9704	0,000256	6,706019	0,138932	**5**
GII5	3,791	3,814	57,8360	0,000529	7,605035	0,157557	**1**
GII6	3,486	3,508	48,9160	0,000484	6,994035	0,144899	**3**
GII7	3,426	3,353	45,9548	0,005329	6,779393	0,140452	**4**
			Total		48,26850		

4.2. Sensibility Analyses

This study evaluated the EXCEBM method's sensitivity in MCDM. Sensitivity analysis involves applying different weighting methods to a dataset and comparing the results. To assess EXCEBM's sensitivity, we expect the weight rankings it generates to differ from those obtained using established objective weighting techniques (Gigovič et al., 2016). Consistent with this approach, we utilised established objective weighting techniques to compute and arrange the weighting coefficients associated with the GII components. These techniques, which are widely employed in scholarly literature, include ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW. The corresponding numerical results are meticulously presented in Table 6.

Table 7. *Results from alternative approaches for calculating objective weighting coefficients*

Crireria	ENTROPY		CRITIC		SD	
	Value	Rank	Value	Rank	Value	Rank
GII1	0,164573	4	0,163467	5	0,142105	4
GII2	0,159298	5	0,175225	4	0,140713	5
GII3	0,070034	7	0,177098	3	0,095625	7
GII4	0,135129	6	0,212622	1	0,132316	6
GII5	0,197835	2	0,125705	7	0,157028	2
GII6	0,273132	1	0,145883	6	0,181573	1
GII7	0,181157	3	0,178453	2	0,150639	3
Crireria	**SVP**		**LOPCOW**		**MEREC**	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**
GII1	0,205301	1	0,145873	3	0,138346	5
GII2	0,130519	5	0,14274	4	0,121069	6
GII3	0,069559	7	0,150857	2	0,081209	7
GII4	0,143758	4	0,164339	1	0,179705	1
GII5	0,156056	3	0,130464	7	0,15391	3
GII6	0,17243	2	0,132647	6	0,153532	4
GII7	0,122378	6	0,13308	5	0,172229	2

An examination of Table 6 reveals that the rankings of the GII weight values according to the SDBHA method are significantly different from the rankings of the GII criterion weight values determined by other methods. This result indicates that the proposed method is sensitive to the underlying relationships among the criteria.

4.3. Comparative Analyses

The comparative analysis examines the similarities and differences between the proposed method and other objective weight coefficient calculation methods. The proposed method should be credible and reliable with other methods, while also demonstrating a positive and significant correlation with different weight coefficient methods (Keshavarz-Ghorabaee et al., 2021). In support of this, Figures 1 and 2 present a visual analysis of the weight coefficients determined according to the weight measurement methods shown in Table 7.

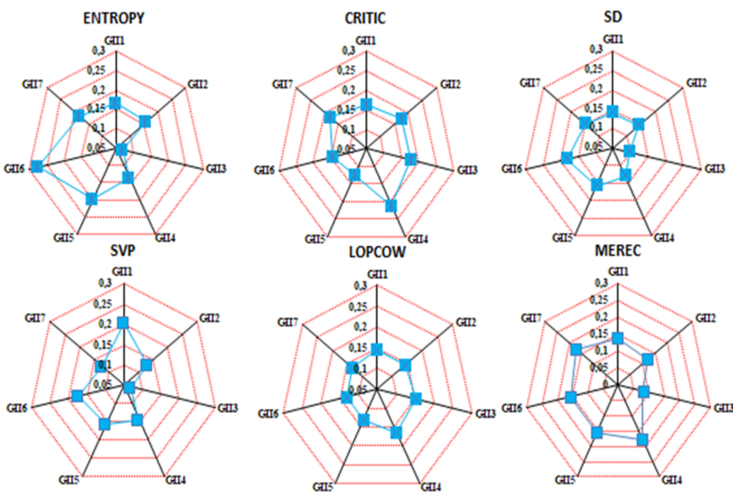

Figure 1. Positions of the ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC methods

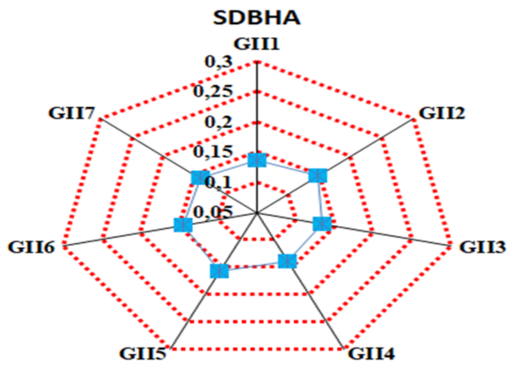

Figure 2. Positions of SDBHA-1

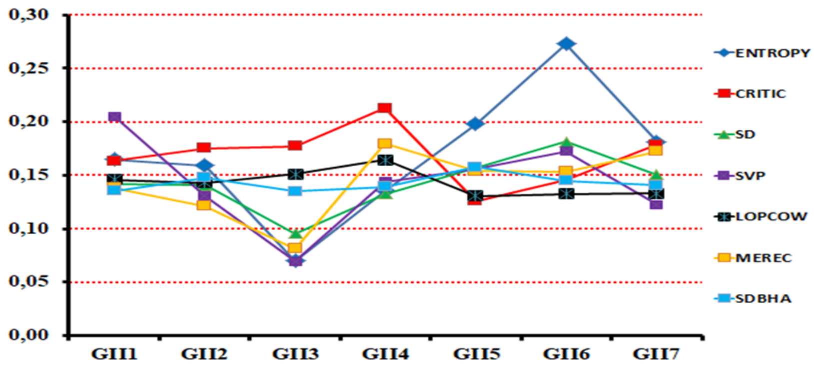

Figure 3. Positions of the methods

A visual analysis of Figures 1, 2, and 3 reveals that the decrease and increase stability rates of a certain criterion from a certain point to another point with the SDBHA method are more similar to those formed with the ENTROPY and SD methods than those formed with other methods. This indicates that the SDBHA method has a positive relationship with the SD and ENTROPY methods. The correlation values between the SDBHA method and other methods are presented in Table 7 to support this conclusion.

Table 8. *Correlation values of the SDBHA method with those of other methods*

Methods	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
SDBHA	0,513*	-0,659*	0,545*	0,182	-0,600*	0,242

p*<.05

4.4. Simulation Analyses

Simulations with varying decision matrices show the proposed method's robustness. It diverged from other methods as the scenarios increased, indicating stability. Furthermore, the proposed method's average weight variance across scenarios should surpass alternatives, demonstrating better discrimination between criterion weights. Finally, weight variance uniformity across methods should be confirmed (Keshavarz-Ghorabaee et al., 2021). To assess the consistency of the SDBHA method with other objective weighting methods, a simulation analysis was performed. This analysis involved generating 10 different scenarios, each with a unique set of decision matrix values. For each scenario, correlation coefficients between the SDBHA and other methods were calculated. The results of the simulation analysis are presented in Table 8 and Figure 4.

When Table 8 and Figure 4 are examined together, the 10 scenarios are divided into two groups. The first group consists of the first three scenarios, and the second group consists of the last seven scenarios. As shown in Figure 4, as the number of scenario increases, the correlation values of the SDBHA method with other methods diverge and decrease. Therefore, it is thought that the characteristic features of the SDBHA method become more pronounced as the number of scenario increases. In addition, it was determined that the correlation values of the SDBHA method with the ENTROPY, CRITIC, SD, and LOPCOW methods are significant in all scenarios. In addition, the distribution of the relationships of the SDBHA method with other methods in space within groups is specified in Figure 5.

Table 9. *Correlation values of the SDBHA method with other methods within the scope of scenarios*

Group	Scenarios	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
First group	**1. Scenario**	0,560*	-0,670*	0,585*	0,255	-0,642*	0,310*
	2. Scenario	0,535*	-0,650*	0,590*	0,245	-0,620*	0,320*
	3. Scenario	0,520*	-0,690*	0,610*	0,325	-0,590*	0,280*
Group	**Scenarios**	**ENTROPY**	**CRITIC**	**SD**	**SVP**	**LOPCOW**	**MEREC**
Second group	**4. Scenario**	0,569*	-0,650*	0,555*	0,21	-0,625**	0,235*
	5. Scenario	0,510*	-0,630*	0,550*	0,19	-0,560*	0,245*
	6. Scenario	0,500*	-0,680*	0,540*	0,13	-0,500*	0,220*
	7. Scenario	0,495*	-0,620*	0,450*	0,15	-0,534*	0,200*
	8. Scenario	0,480*	-0,600*	0,520*	0,145	-0,535*	0,195*
	9. Scenario	0,505*	-0,605*	0,540*	0,135	-0,525*	0,230*
	10. Scenario	0,480*	-0,590*	0,500*	0,125	-0,495*	0,210*
	Mean	0,515	-0,639	0,561	0,191	-0,563	0,245

p*<.05

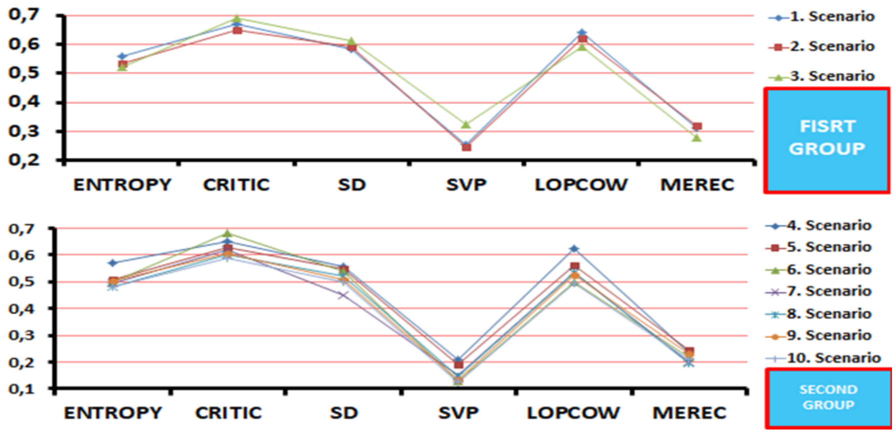

Figure 4. Correlation assessment of the SDBHA method with alternative approaches across diverse scenarios

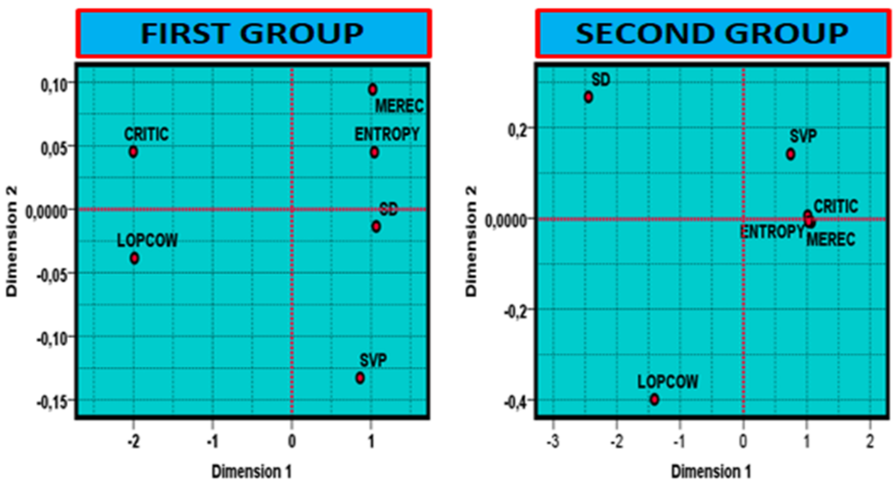

Figure 5. Discriminant analysis of the interrelation between the SDBHA method and alternative methodologies in diverse scenarios

Table 8 demonstrates a positive, moderate correlation between the SDBHA method and the ENTROPY and SD methods in various scenarios, consistent with the expected positive correlation between the SD and ENTROPY methods. Figure 5 further supports this observation, showing that the correlation values of the ENTROPY and SD methods closely group together in the first scenario group. However, in the second scenario group, correlations between the SDBHA method and SD/ENTROPY decreased, indicating reduced sensitivity of the SDBHA method to underlying criteria relationships as the number of scenarios increased. Similarly, in the first group of scenarios, the SDBHA method demonstrated a negative, moderate correlation with the

CRITIC and LOPCOW methods. However, in the second group of scenarios, correlation values between the SDBHA method and CRITIC/LOPCOW decreased, indicating reduced similarity between the CRITIC and LOPCOW methods as scenario numbers increased. Consequently, it is observed that distinct method characteristics become more pronounced with an expanding number of scenarios, leading to increasingly discernible differences between methods. Throughout the simulation analysis, the variance values for each method across scenarios were calculated, as outlined in Table 9.

Table 10. *Variation values of the methods across scenarios*

Scenario	SDBHA	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
1. Sce.	0,000286	0,000249	0,000213	0,000263	0,000253	0,000298	0,000307
2. Sce.	0,000272	0,000246	0,000226	0,000252	0,000265	0,000280	0,000289
3. Sce.	0,000279	0,000244	0,000209	0,000269	0,000249	0,000286	0,000294
4. Sce.	0,000293	0,000253	0,000235	0,000246	0,000272	0,000271	0,000289
5. Sce.	0,000266	0,000249	0,000239	0,000253	0,000258	0,000292	0,000302
6. Sce.	0,000285	0,000241	0,000204	0,000260	0,000263	0,000277	0,000282
7. Sce.	0,000288	0,000257	0,000230	0,000248	0,000259	0,000293	0,000299
8. Sce.	0,000269	0,000242	0,000217	0,000256	0,000269	0,000269	0,000277
9. Sce.	0,000276	0,000251	0,000240	0,000247	0,000256	0,000282	0,000290
10. Sce.	0,000289	0,000247	0,000199	0,000265	0,000260	0,000274	0,000289
Mean	0,000280	0,000248	0,000221	0,000256	0,000260	0,000282	0,000292

Table 9 clearly shows that the SDBHA method consistently demonstrates higher average variance values across scenarios compared with the variance values of the ENTROPY, CRITIC, SD, and SVP methods. Conversely, these values consistently remained lower than those observed for the LOPCOW and MEREC methods. Thus, the SDBHA method exhibits an enhanced ability to discern criteria weights, as evidenced by its higher average variance value relative to the ENTROPY, CRITIC, SD, and SVP methods.

To further assess the homogeneity of variances in the criterion weights of the SDBHA method, an ADM (ANOM for variances with Levene) analysis was conducted across various scenarios. This analytical approach offers a visual representation of variance uniformity, consisting of three elements: the general average ADM serving as the centreline, along with upper and lower decision limits (UDL and LDL). If the standard deviations of all clusters fall within the LDL and UDL, this confirms variance homogeneity (Keshavarz-Ghorabaee et al., 2021). Figure 6 presents a visual representation of the ADM analysis.

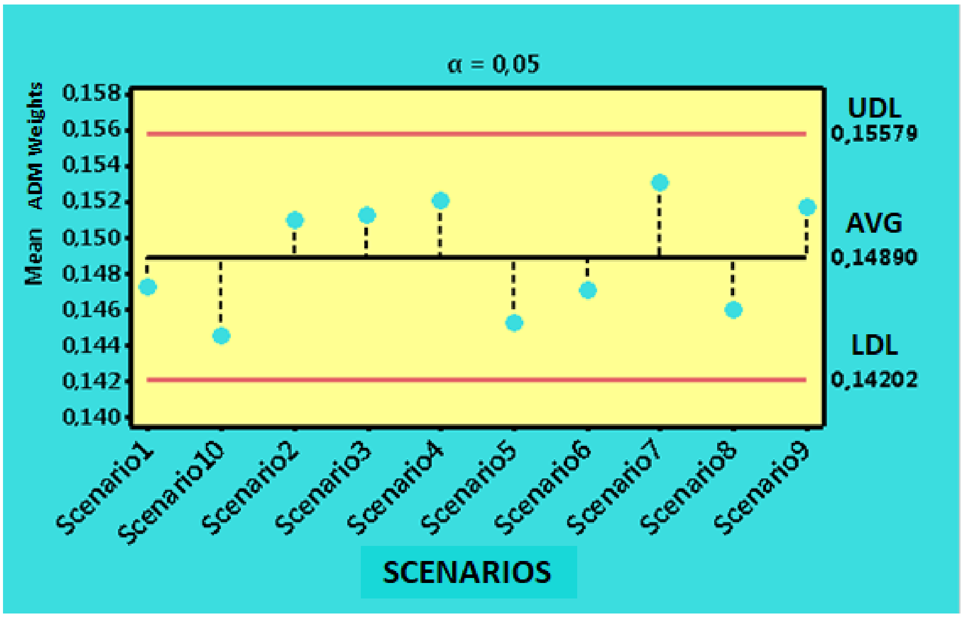

Figure 6. ADM Visual

As shown in Figure 6, the ADM values calculated for each scenario are located below the UDL values and above the LDL values. This indicates that the variances in the identified weights for each scenario are homogeneous. This determination was further confirmed by the Levene Test, the fundamental statistics of which are outlined in Table 10.

Table 11. *Levene test*

Levene Statistic	df1	df2	Sig.
0,510	2	10	0,240

p<.05**

The p-value of 0.240 from Table 10 exceeds the significance threshold of 0.05, indicating that the variances in criterion weights across scenarios are homogeneous. Overall, the results of the simulation analysis indicates the robustness and stability of the SDBHA method.

Conclusion

Complex decision-making scenarios often necessitate the consideration of multiple criteria, a process effectively addressed by MCDM methodologies. Assigning appropriate weights to these criteria is essential to reflect their varying degrees of importance and ensure an unbiased decision-making process. Researchers have developed diverse weight determination methods, enriching the field of MCDM. This study introduces Somer's D-DEMATEL based Hybrid Approach (SDBHA) as a novel approach for determining criterion weights.

The research dataset consisted of values related to the Global Innovation Index (GII) criteria for 19 countries in the G20 group. This study first calculated and ranked the weights of the GII criteria for countries according to the proposed method (SDBHA). Second, the weights of the criteria were calculated and ranked using the ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC objective weighting methods based on the GII values of the countries in question. These findings indicates that the SDBHA method is sensitive because the GII rankings of the SDBHA method are very different from those of the other methods.

The SDBHA method was compared with other methods to assess their relationships. Results revealed a positive, significant, and moderate correlation between the SDBHA method and the ENTROPY and SD methods, indicating its reliability and credibility. In the simulation analysis, 10 scenarios emerged by varying quantities assigned to countries. Positive, significant, and moderate correlations were consistently observed between the SDBHA method and the ENTROPY and SD methods across all scenarios. The scenarios were then categorised into two groups, revealing differing and decreasing relationships between the SDBHA method and other methods as scenario numbers increased. In general, the different characteristics of the methods became more pronounced as the number of scenarios increased. The differences and characteristics between the methods were also increasingly noticed. The variance values of the SDBHA and other criterion objective weighting methods were also calculated and compared within the scenarios. The SDBHA method was found to have a higher variance value than the ENTROPY, CRITIC, SD, and SVP methods. This indicates that the SDBHA method performs better in discriminating between criteria than the other methods. In the final stage of the simulation analysis, the homogeneity of the variances in the criterion weights of the SDBHA method was examined. The ADM (ANOM for variances with Levene) and Levene test analyses showed that the ADM values calculated for each scenario were below the UDL values and above the LDL values. This indicates that the SDBHA method is robust and stable.

Discussion

This study aims to transform the subjective nature of the DEMATEL method into an objective one. This will allow the weights of the criteria for decision alternatives to be calculated without the need for subjective judgement, expert opinion, or personal evaluation. In addition to the original DEMATEL method being subjective and the proposed DEMATEL method being objective, this study also increases the comprehensiveness of the DEMATEL method (with the proposed method) compared with other weighting methods. In future studies, the proposed method can be further developed to create a relationship map and impact diagram that are objective in nature. This will allow the mutual interactions and relationships between variables within the DEMATEL framework to be revealed objectively. Furthermore, further development of the proposed method can contribute to the field of statistics by providing a framework for modelling the relationships and interactions between variables, such as structural equation modelling, curve estimation analysis, relationship coefficient analysis, canonical correlations, and probit and logit functions. In addition, future research could develop new objective weighting methods based on the properties of methods that determine the relationships and effects between criteria. In addition, curve estimation could be used to objectively calculate the weights of criteria by taking into account the relationships between criteria using regression analysis with various functions (quadratic, cubic, logarithmic, S-curve, exponential, etc.

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