



A novel technique for criterion weighting in multi-criteria decision making: The Extended Standard Deviation (ESD) method

Çok kriterli karar verme kapsamında kriter ağırlıklandırılması için yeni bir teknik: Genişletilmiş Standart Sapma Yöntemi

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Abstract

Multi-Criteria Decision Making (MCDM) methods provide systematic approaches for evaluating alternatives under multiple criteria. Determining the relative importance of criteria is a critical step that directly affects the reliability of the obtained results. In this study, the Extended Standard Deviation (ESD) method is proposed to overcome the limitations of the classical Standard Deviation (SD) method. The proposed method offers a more comprehensive weighting process by considering not only the internal variations of individual criteria but also their effect with comprehensive value of all criteria. Unlike conventional SD, the ESD method calculates weights based on both the individual distributions of criteria and their effects on other criteria. This approach enables a more holistic evaluation of the degree of contrast among criteria and the overall structure of the dataset. The primary objective of this study is to conduct a comparative analysis of the proposed method against the classical SD method and other widely used objective weighting techniques, thereby identifying their respective advantages and limitations. To assess the applicability of the proposed method, sensitivity, comparative, and simulation analyses were performed, and the method was statistically evaluated by applying it to different decision matrices. The findings indicate that the proposed method provides a robust and reliable alternative in objective weighting processes.

Key words: Standard deviation (SD), Extended standard deviation (ESD), Intrinsic distinction, External distinction

1 Introduction

Multi-Criteria Decision Making (MCDM) methods are among the systematic approaches that enable the evaluation of alternatives under different criteria [1]. Determining the relative importance of criteria is a crucial phase that without any intermediary steps influences the reliability of obtained results in decision-making processes [2]. In the weighting process of criteria, two fundamental approaches are employed: subjective and objective methods [3]. Subjective approaches rely on the personal experience and expertise of decision-makers, whereas objective techniques calculate weights directly from the dataset using mathematical models [4]. In this context, objective weighting methods reduce dependence on the decision-maker, providing a more impartial and data-driven evaluation [5].

Among objective weighting methods, approaches such as Standard Deviation (SD) [6], ENTROPY [7], CRITIC (Criteria

Öz

Çok Kriterli Karar Verme (MCDM) yöntemleri, birden fazla kriter altında alternatifleri değerlendirmek için sistematik yaklaşımlar sunar. Kriterlerin göreceli önemini belirlemenin, elde edilen sonuçların güvenilirliğini doğrudan etkileyen kritik bir adımdır. Bu çalışmada, klasik Standart Sapma (SD) yönteminin sınırlamalarını aşmak amacıyla Genişletilmiş Standart Sapma (ESD) yöntemi önerilmektedir. Önerilen yöntem, yalnızca bireysel kriterlerin içsel varyasyonlarını değil, aynı zamanda diğer kriterlerle olan karşılıklı ilişkilerini de dikkate alarak daha kapsamlı bir ağırlıklandırma süreci sunmaktadır. Geleneksel SD'nin aksine, ESD yöntemi, kriterlerin bireysel dağılımlarını ve bunların bütünsel olarak diğer kriterler üzerindeki etkilerini dikkate alarak ağırlıkları hesaplamaktadır. Bu yaklaşım, kriterler arasındaki karşıtılı derecesinin ve veri kümesinin genel yapısının daha bütünsel bir değerlendirilmesini sağlar. Bu çalışmanın temel amacı, önerilen yöntemi klasik SD yöntemi ve diğer yaygın kullanılan objektif ağırlıklandırma teknikleri ile karşılaştırmalı bir analiz yaparak her birinin avantajlarını ve sınırlamalarını belirlemektir. Önerilen yöntemin uygulanabilirliğini değerlendirmek için duyarlılık, karşılaştırmalı ve simülasyon analizleri yapılmış ve yöntem, farklı karar matrislerine uygulanarak istatistiksel olarak değerlendirilmiştir. Elde edilen bulgular, önerilen yöntemin objektif ağırlıklandırma süreçlerinde güçlü ve güvenilir bir alternatif sunduğunu göstermektedir.

Anahtar kelimeler: Standard sapma (SD), genişletilmiş standart sapma, içsel dağılım, dışsal dağılım

Importance Through Inter-Criteria Correlation) [8], SVP (Statistical Variance Procedure) [9], MEREC (Method Based on Removal Effects of Criteria) [10], and LOPCOW (Logarithmic Percentage Change-driven Objective Weighting) [11] stand out. The SD is a statistical approach that determines weights based on the level of variation in criteria. The fundamental assumption of this method is that a criterion carries more information in the decision-making process if its data exhibit greater variability [11]. However, the classical SD method only considers the internal variations of the criteria and disregards the variances of other criteria. This limitation prevents the method from fully reflecting the holistic structure of the decision matrix and restricts the analysis of differences among alternatives to a limited perspective.

In this study, the Extended Standard Deviation (ESD) method is proposed to overcome the limitations of the classical SD method. The proposed method offers a more comprehensive weighting process by not only considering the internal

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variations of the criteria but also taking into account the values of other criteria in a holistic sense. Accordingly, the ESD method calculates weights based on both the individual distributions of criteria and the influence of other criteria. As a result, the degree of contrast among criteria and the overall structure of the dataset are evaluated from a more holistic perspective.

The primary motivation of this study is to conduct a comparative analysis of the proposed method with the classical SD and other widely used objective weighting methods, thereby identifying their strengths and constraints. Sensitivity, comparative, and simulation analyses were conducted to examine the proposed approach, demonstrating that it is sensitive, reliable, and robust. The findings suggest that the presented methodology offers considerable promise for practical use by those in decision-making roles. The paper commences with an extensive survey of diverse objective weighting methodologies documented in existing research. Subsequently, it provides a thorough exposition of the mathematical principles underpinning the proposed technique. The efficacy of this method is then evaluated through the implementation of several assessment strategies, with its performance benchmarked against both the traditional SD method and other frequently utilized objective weighting approaches. The study culminates in a discussion of the results obtained and proposes avenues for subsequent scholarly investigation.

2 Material and method

2.1 Different objective criteria weighting methods and their properties

Selecting from a range of options is a fundamental aim of decision process. In these circumstances, the performance of alternatives often varies across different criteria [13]. Consequently, accurately identifying the relative importance of these factors is crucial for a robust evaluation of alternatives and optimal decision-making [14]. This stems from the fact that, in conventional MCDM problems, the importance of each criterion is typically expressed through assigned weight coefficients [15].

Subjective approach usually stems from the individual assessments and experiences of specialists, rendering them intrinsically susceptible to personnel biases. As a result, these weights can vary considerably between individuals [3]. While expert opinions are frequently employed to establish these coefficients, a reliance solely on subjective evaluations can introduce inconsistencies and biases into the decision-making process [4]. In contrast, objective weighting methods mitigate such subjectivity and uncertainty by utilizing mathematical models and data from the decision matrix to measure criterion weights. Essentially, objective approaches integrate the inherent structural characteristics of the data into the weighting procedure, promoting a more consistent and dependable evaluation [5].

The MCDM literature includes a diverse array of objective weighting methods, such as CRITIC [16], ENTROPY [17], SVP [18], SD [19], MEREC [20], and LOPCOW [21]. The CRITIC method is primarily founded on the principle of extracting meaningful information from a given system [22]. It suggests that the more distinctive or variable a criterion is relative to others, the more influential it becomes [23]. In this context, the CRITIC method emphasizes the relationships between criteria. By examining the correlations between criteria, the method seeks to identify potential inconsistencies or contradictions.

These discrepancies are then addressed by weighting the criteria according to their standard deviations, enabling the systematic calculation of weight coefficients [8]. The procedure begins with constructing a decision matrix, which is then subjected to normalization. Following this step, the correlations among criteria are analyzed to compute their respective weight values [24].

The ENTROPY method is a valuable technique in decision-making, providing a structured framework for determining the relative significance of criteria. This approach begins with the construction of a decision matrix, followed by the computation of standardized values. Subsequently, the ENTROPY measure is applied to assess the level of uncertainty or disorder associated with each criterion, thereby capturing the amount of information it conveys [25]. By leveraging these standardized values along with the computed ENTROPY measure, the method assigns weights to criteria based on the extent of variability in the data. Criteria exhibiting greater variability are assigned higher weights [26]. This systematic process ensures a more objective and data-driven weight allocation, enabling decision-makers to make more informed and well-balanced evaluations [27]. The SD method determines criterion weights by assessing how much each criterion's values deviate from their arithmetic mean. The procedure starts by standardizing the data through the normalization process. Once normalization is complete, the SD for each criterion is computed, and these values are then used to assign weights accordingly [28]. The SVP method, on the other hand, calculates criterion weights based on the variances derived from the decision matrix data [12]. Since a higher variance indicates greater importance in the decision-making process, the weight assigned to a criterion increases as its variance grows. This approach ensures that criteria with higher variability exert a stronger influence on the overall evaluation [29]. The LOPCOW method adopts a multidimensional framework to identify the most suitable criterion weights, while simultaneously aiming to minimize the gap between the highest and lowest priority criteria [30]. Furthermore, the method takes into account the interdependencies among criteria. The process begins with the construction of the decision matrix, followed by the normalization of its values. Next, the method calculates average squared score as a proportion of each criterion's SD metric, thereby mitigating the effects of differences in data scale. This structured methodology ultimately results in the determination of weight coefficients for each criterion [11]. The MEREC method, consistent with other weighting methodologies, initiates with the development and subsequent normalization of the decision matrix. Subsequently, the overall performance scores for the decision alternatives are determined using a framework that integrates natural logarithms [31]. These performance scores are then refined by considering the contribution of each decision alternative, with further calculations employing the natural logarithm function. In the final stage, the weight coefficients for the criteria are established by assessing the removal impact of each criterion, expressed as the sum of absolute deviations. Furthermore, a criterion's weight coefficient increases proportionally with its influence on the decision alternatives [10].

2.2 SD method

SD is a statistical parameter that measures how observations in a dataset are distributed around the mean [32]. In other words, it is a measure of dispersion that indicates how far each data point deviates from the arithmetic mean [33]. Thus, SD uses the mean as a reference point and quantifies variability by

considering the distance between each value and the mean [34]. Consequently, researchers can determine whether values cluster closely around the mean or are widely dispersed using SD [35]. In other words, if all observations in a dataset are close to the arithmetic mean, the SD is low; if the observations are spread over a wide range, the SD is high [36].

SD is defined as the square root of variance [37]. Variance is calculated as the mean of the squared deviations of all observations in a dataset from the arithmetic mean [38–40]. Accordingly, SD can be computed in two ways: as the population SD and as the sample SD. The SD is calculated using Equation 1 when the sample size is greater than 30 ($n > 30$), whereas the sample SD is determined using Equation 2 when the sample size is less than 30 ($n < 30$) [41,42].

σ : Standard deviation

n : sample size

X : Each observation in the dataset

$\bar{X}$: Sample mean

$$\sigma = \sqrt{\frac{\sum(X - \bar{X})^2}{n}} \quad (1)$$

$$\sigma = \sqrt{\frac{\sum(X - \bar{X})^2}{n - 1}} \quad (2)$$

SD has several universally accepted properties. First, since SD is the square root of variance, it cannot assume negative values. The minimum value of SD can be zero, which indicates that all observations are identical and, therefore, no variability exists [43]. Second, SD is expressed in the same unit as the dataset from which it is measured [39]. Third, as it is calculated by considering all units in a dataset, SD is one of the most widely used and reliable measures of dispersion in practice [44]. Fourth, SD is evaluated in relation to the mean. A small SD indicates that the data points are clustered close to the mean, whereas a large SD suggests that the data are widely dispersed [45]. Fifth, SD is sensitive to outliers. Consequently, if a dataset contains extreme values (outliers), the SD may be significantly affected. Therefore, it is recommended to conduct an outlier analysis before calculating SD [46]. Sixth, in relation to normal distribution, SD represents the probabilistic distribution of values around the mean. In a normally distributed dataset, approximately 68% of the values fall within ± 1 SD of the mean, 95% within ± 2 SD, and 99.7% within ± 3 SD's [47–48]. Seventh, SD is sensitive to changes in scale. If all data points in a dataset are multiplied by the same factor, the SD will also be multiplied by the same factor [49].

2.3 SD method in criterion weighting

SD represents the square root of variance value, which explains the mean of the squared differences between data values and their arithmetic mean. However, within the SD method, the scale differences of the data are crucial when calculating the significance levels or weight coefficients of criteria. Therefore, it is necessary to normalize the scores of criteria [29]. In the SD method, the significance levels of the criteria are objectively determined based on their respective SD values [8]. The weight coefficients of the criteria are calculated by dividing each criterion's SD by the total SD of all criteria. Thus, the fundamental principle of this approach is grounded in the deviation of the criteria values from their arithmetic mean [50].

The calculation of weights scores in the SD method relies on fundamental mathematical phases and is not subject to any criterion constraints [51]. Moreover, the SD method mitigates the influence of decision-makers' subjectivity, thereby enabling more effective utilization of decision-related information [12]. In this regard, some studies in the literature that have applied the SD method for assigning weights to criteria is outlined in Table 1.

Table 1. SD studies

Author (s)	Technique(s)	Theme
[52]	SD (weighting)	Proposal for a novel methodology in MCDA analysis.
[53]	SD and Modified Integrated Weighting based COPRAS	Achieving sustainable development through a modified integrated weighting MCDM model for the ranking of agrarian datasets.
[54]	SD, ENTROPY, CRITIC, AHP based COCOSO, TOPSIS, VIKOR and MOORA	Assessment of robot
[55]	SD, IFI and RS based MARCOS	Evaluation of Hospital site
[56]	MW, PSI, SD, ENTROPY, CRITIC, MEREC	Prioritization of watersheds for evaluating flood risk
[57]	Entropy, CRITIC, SD	Comperative analysis of SD, ENTROPY and MEREC
[58]	SD and ENTROPY based Fuzzy TOPSIS	Establishing of industrial location
[59]	SD, ENTROPY, MEREC based SAW	Analysis of electric vehicle
[60]	ENTROPY, SD and rho based TOPSIS, VIKOR, COPRAS, and PROMETHEE II	Comparative analysis of MCDM methods
[61]	SD, CRITIC, ENTROPY, BWM, EW and rho based ORESTE, TOPSIS, VIKOR, WSM	Analysis of sustainable energy

The application steps of the SD method are based on simple mathematical operations. Accordingly, the implementation steps of the method are explained below [12,29].

Cr : r – th evaluation criterion

a_{pr} : value of the p – th alternative according to the r – th evaluation criterion

σ_r : standard deviation of the r – th criterion ($r = 1, 2, \dots, n$)

w_r : weight of the r – th evaluation criterion ($r = 1, 2, \dots, n$)

k_{pr} : Normalized score of a_{pr}

Step 1: Construction of the Decision Matrix (DM)

As the initial step, the decision matrix is formulated based on Equation 3.

$$DM = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \quad (3)$$

Step 2: Normalization phase (DM^*)

In the second phase, the DM values are computed using the vector normalization technique, as applied in Equation 4.

$$k_{pr} = \frac{a_{pr}}{\sqrt{\sum_{p=1}^m a_{pr}^2}} \quad (4)$$

Step 3: Calculation of the SD Values of the Criteria (σ_r)

At this stage, the SD of each criterion is calculated based on the normalized values using Equation 5.

$$\sigma_r = \sqrt{\frac{\sum_{p=1}^m (k_{pr} - \bar{k}_{pr})^2}{m}} \quad (5)$$

Step 4: Calculation of Weighting Score of the Criteria (w_r)

In the final step of the method, the weights of the criteria, determined in the third step, are calculated using Equation 6 by normalizing them with respect to the total weight of all criteria.

$$w_r = \frac{\sigma_r}{\sum_{p=1}^m \sigma_r} \quad (6)$$

2.4 Proposed method (Expanded Standard Deviation-ESD)

When determining the weights of criteria, contrasts, uniqueness, and contradictions among them reveal their inherent characteristics [5]. Therefore, if a criterion is more contrasting or opposite compared to others within the applied mathematical technique, its significance or weight becomes greater [3]. In this regard, the proposed method shares similarities with the SD method in terms of its application logic. In the SD method, the importance of criteria is directly proportional to the degree of contrast within their own dataset, without considering the datasets of other criteria [12].

The proposed method enhances the distinctiveness and comprehensiveness of the contrast and uniqueness levels of criteria in the classical SD method, highlighting their distinguishing features more explicitly and comprehensively. While determining the degree of contrast among criteria, the proposed method strengthens the contrast in a holistic manner by considering the entire numerical sequence of each criterion. In this approach, when the numerical sequence of a criterion is removed, the change in the SD of the remaining criteria is calculated. Consequently, by measuring the change in the SD of the remaining criteria after removing a particular criterion, the impact of the removed criterion on the overall SD is assessed.

This effect is then converted into a factor, which, when combined with the SD values of other criteria, determines the spatial distribution (position) of the criteria in a holistic sense. Subsequently, the intrinsic SD value of each criterion (internal dispersion) in the classical SD method is multiplied by this factor or weight (external dispersion), enriching the contrast position of the criteria relative to the classical SD method by considering both the internal distribution within each criterion and the distribution among other criteria. A visual representation illustrating the logic of the proposed model is presented in Appendix A. By doing so, the classical SD method is

modified to incorporate the influence of other criteria, making it a more comprehensive and robust weighting approach. In this regard, the steps of the suggested approach are outlined as follows.

DM : Decision matrix

DM^* : Normalized decision matrix

Cr : r – th evaluation criterion

a_{pr} : value of the p – th alternative according to the r – th evaluation criterion

σ_r : SD of the r – th criterion ($r = 1, 2, \dots, n$)

w_j : Weight of the r – th evaluation criterion ($r = 1, 2, \dots, n$)

b_{pr} : Normalized score of a_{pr}

Step 1: Construction of the Decision Matrix (DM)

The decision matrix is constructed using the formula presented in Equation 3.

Step 2: Normalization of the Decision Matrix (DM^*)

In the second step, the normalization of criterion values is performed based on Equation 7 if the criteria are benefit-oriented and on Equation 8 if they are cost-oriented.

For benefit oriented criteria:

$$b_{pr} = \frac{a_{pr}}{\sum_{p=1}^m a_{pr}} \quad (7)$$

For cost oriented criteria:

$$b_{pr} = \frac{\left(\frac{1}{a_{pr}}\right)}{\sum_{p=1}^m \left(\frac{1}{a_{pr}}\right)} \quad (8)$$

Normalized decision matrix:

$$DM^* = \begin{bmatrix} C_1 & C_2 & \dots & C_m \\ b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{mn} \end{bmatrix} \quad (9)$$

Step 3: Calculation of SD Score of Criteria (SD_{Cr})

At this stage, the SD value of each criterion in the dataset is measured using Equation 10.

$$SD_{Cr} = \sqrt{\frac{\sum (b - \bar{b})^2}{m}} \quad (10)$$

Step 4: Calculation of Comprehensive SD Score (CSD)

At this stage, the SD of all normalized values is measured using Equations 11, considering the distribution of all normalized criterion values across all alternatives.

$CSD =$

$$[b_{11} \ b_{21} \ \dots \ b_{m1} \ b_{12} \ b_{22} \ \dots \ b_{m2} \ b_{1n} \ b_{2n} \ \dots \ b_{mn}] = \sqrt{\frac{\sum (b - \bar{b})^2}{mxn}} \quad (11)$$

Step 5: Calculation of Subtractive SD (SD Effect) Score of Criteria (SSD_{Cr})

$$\begin{aligned}
& 3) C3 \notin C; C1, C2, C4, \dots, Cn \in C; \mathbf{SSD}_{C3} = \\
& [b_{11}b_{21} \dots b_{m1}b_{12}b_{22} \dots b_{m2}b_{14}b_{24} \dots b_{m4}b_{1n}b_{2n} \dots b_{mn}] \\
& = \sqrt{\frac{\Sigma(b - \bar{b})^2}{m(n-1)}} \quad (14) \\
& 4) C4 \notin C; C1, C2, C3, \dots, Cn \in C; \mathbf{SSD}_{C4} = \\
& [b_{11}b_{21} \dots b_{m1}b_{12}b_{22} \dots b_{m2}b_{13}b_{23} \dots b_{m3}b_{1n}b_{2n} \dots b_{mn}] \\
& = \sqrt{\frac{\Sigma(b - \bar{b})^2}{m(n-1)}} \quad (15)
\end{aligned}$$

Subsequently, the SD Effect Multiplier Score ($SDEM_{Cr}$) of each criterion is calculated by taking the ratio of the overall SD (CSD) to the SD of the remaining normalized dataset after removing the respective criterion (SSD). Accordingly, if $CSD > SSD$, the ratio CSD/SSD represents the amplification factor of the removed criterion, whereas if $SSD > CSD$, the same ratio denotes the reduction factor of the removed criterion. Based on

Step 7: Calculation of Weighted SD_{Cr} Score of Criteria (WSD_{Cr})

$$WSD_{Cr} = SDEM_{Cr} * SD_{Cr} \quad (19)$$
$$w_{Cr} = \frac{WSD_{Cr}}{\sum_{j=1}^n WSD_{Cr}} \quad (20)$$

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The proposed method also offers several advantages over other objective weighting methods. One key advantage is its insensitivity to zero and negative values. For instance, the ENTROPY and MEREC methods are sensitive to zero and negative values, which can lead to undefined values in the decision matrix due to logarithmic calculations [10,62]. When analyzing the ENTROPY method, the characteristics of the criteria are determined using entropy without taking into account the values of other criteria. As a result, in the ENTROPY method, the weights of the criteria are assigned solely based on their individual entropy distributions (internal distribution) [62]. In contrast, the proposed method determines the characteristics of the criteria by incorporating both their intrinsic values and the values of other criteria, thereby capturing both internal and external distributions.

In the MEREC method, the evaluation of each criterion corresponding to an alternative's cell is conducted using a nonlinear logarithmic function. Subsequently, once a criterion is removed, the performance of the alternatives is recalculated. The impact of each criterion is determined by examining the difference between the performance of its corresponding cell and the recalculated performance of the alternatives after its exclusion [10]. As a result, the MEREC method considers both the internal distribution of each criterion and its overall influence on the dataset (external distribution), which aligns with the conceptual foundation of the proposed method. The fundamental distinction between these approaches lies in their methodological focus: while the MEREC method assesses the performance of decision alternatives after criteria are removed, the proposed method evaluates the performance of the criteria themselves following their exclusion.

When compared to the CRITIC method, the proposed method exhibits technical similarities. In the CRITIC method, criterion weights are determined using both the intrinsic distribution of each criterion (internal differentiation—each criterion's individual SD value) and by considering the values of other criteria, it takes into account the contribution or impact of the holistic data (data from all criteria) within the entire dataset to the SD, while also considering external differentiation [8]. The proposed method follows a similar approach by computing SSD and SDEM values, where the intrinsic differentiation is based on each criterion's individual SD, while the external differentiation considers the values of other criteria. However, the proposed method provides more accurate results compared to the CRITIC method. The primary reason for this is that the CRITIC method relies on Pearson's correlation coefficient, which assumes normal distribution [5]. In datasets that do not follow a normal distribution, Pearson's correlation coefficient may produce unreliable results [44]. In contrast, the proposed method does not make such an assumption, allowing for a more flexible and robust evaluation.

Variance is calculated as the square of the SD. Therefore, similar to the classical SD method, the SVP method determines the contrasts among criteria solely based on their intrinsic distributions or variance values [12]. However, the proposed method adopts a more comprehensive weighting approach compared to the SVP method. The LOPCOW method, on the other hand, is a robust approach designed to eliminate gaps arising from the scale of data [11]. Nevertheless, in the LOPCOW method, this gap is addressed only based on the intrinsic values of the criteria, without considering the influence of other criteria. In contrast, the proposed method incorporates the values of other criteria in the weighting process. As a result, a

more relational structure is established in determining the contrasts among criteria, making their mutual effects more explicit. In conclusion, the proposed method surpasses the classical SD method by offering a more comprehensive, flexible, and reliable weighting approach. Compared to other objective weighting methods, it provides several advantages, particularly in facilitating more informed and effective decision-making processes. The only drawback of the method is that, compared to other objective weighting methods, the weighting process is more complex and time-consuming. This limitation becomes more pronounced as the number of criteria and alternatives increases.

2.5 Data set

The proposed weighting method utilizes the 2024 Global Environmental Health Index (GEHI) data for G7 nations, selected for their absence of extreme outliers, thereby enabling a clearer evaluation of the method's discriminative capacity. Abbreviations of the GEHI criteria are listed in Table 2.

Table 2. Data set

GEHI Criteria	Abbreviations
Air Quality	C1
Anthropogenic PM2.5 exposure	C2
Household solid fuels	C3
Ozone exposure	C4
SO2 exposure	C5
CO exposure	C6
VOC exposure	C7
Countries	Abbreviations
Canada	A1
France	A2
Germany	A3
Italy	A4
Japan	A5
UK	A6
USA	A7

3 Results

3.1 Computational analysis

In the study, the decision matrix was initially constructed using Equation 3. In the second step of the technique, normalization of values of DM were derived using Equations 7 and 9. The decision matrix and the normalized decision matrix are presented in Table 3.

Table 3. Decision and normalized decision matrix

Decision Matrix							
C.	C1	C2	C3	C4	C5	C6	C7
A1	72.4	67	96.7	51.9	41.7	61	57.3
A2	65.2	49	91.5	57.5	62	60.6	57.4
A3	66.9	50	96.7	43.5	62.1	61.3	60.4
A4	57.2	31.7	79.3	38.6	50.8	54.7	44.8
A5	59.9	42.2	86.7	62.9	33.9	58.9	43.9
A6	69.9	52.1	98.8	66.5	51.6	66.8	71.7
A7	65.8	61.5	91.6	33.8	35.7	60.3	35.5
Sum	457.3	353.5	641.3	354.7	337.8	423.6	371
Normalized Decision Matrix							
C.	C1	C2	C3	C4	C5	C6	C7
A1	0.418	0.49	0.398	0.377	0.319	0.38	0.4
A2	0.376	0.359	0.377	0.418	0.474	0.378	0.4
A3	0.386	0.366	0.398	0.316	0.475	0.382	0.421
A4	0.33	0.232	0.326	0.281	0.388	0.341	0.312
A5	0.346	0.309	0.357	0.457	0.259	0.367	0.306

A6	0.403	0.381	0.407	0.484	0.395	0.417	0.5
A7	0.38	0.45	0.377	0.246	0.273	0.376	0.248

In the third step of the study, the SD value for each criterion (SD_r) was measured using Equation 10 based on the normalized values. In the fourth step, the comprehensive SD (CSD_r) value of the matrix was determined by considering all the criterion values together using Equation 11. In the fifth step, the Subtractive SD (SSD_r) values for each criterion were calculated using Equations 12, 13, 14, 15, and 16, taking into account the normalized values and the CSD value. In the sixth step, the SD Effect Multiplier ($SDEM_r$) values for each criterion were determined using Equations 17 and 18. In the seventh step of the method, the Weighted SSD_r ($WSSD_r$) values were calculated using Equation 19. Then, in the final step, the weight coefficients of the criteria were determined based on Equation 20. The calculated values for each step are summarized and detailed in Table 4.

Table 4. SD, CSD, SSD, SDEM, WSD and w scores of criteria

Criteria	SD	CSD	SSD	SDEM
C1	0.028	0.025	0.0261	0.939
C2	0.079		0.0233	1.05
C3	0.026		0.0262	0.937
C4	0.084		0.023	1.07
C5	0.082		0.0231	1.062
C6	0.021		0.0263	0.933
C7	0.079		0.0234	1.049
Criteria	WSD	w	Rank	
C1	0.0266	0.064	5	
C2	0.0832	0.201	3	
C3	0.0243	0.059	6	
C4	0.0897	0.217	1	
C5	0.087	0.211	2	
C6	0.0193	0.047	7	
C7	0.0829	0.201	4	
Sum	0.4131	---	---	

Upon examining Table 4, the criteria weights are ranked as C4, C5, C2, C7, C1, C3, and C6. In the context of the findings, an example calculation for determining weight of C1 is presented below.

Normalized Value: Canada $\rightarrow$ C1 : Equation 2 := $\frac{72.4}{457.3} = 0.418$

$$CSD = \begin{bmatrix} 0.418 \\ 0.376 \\ 0.386 \\ \dots \\ \dots \\ 0.490 \\ 0.359 \\ \dots \\ \dots \\ 0.500 \\ 0.248 \end{bmatrix} = 0.025; SSD_{C1} (C1 \notin \text{Criteria}) = \begin{bmatrix} 0.490 \\ 0.359 \\ 0.366 \\ \dots \\ \dots \\ 0.398 \\ 0.377 \\ \dots \\ \dots \\ 0.500 \\ 0.248 \end{bmatrix}$$

$$= 0.026$$

$$SDEM_{C1} = \frac{0.025}{0.026} = 0.939; WSSD_{C1} = 0.939 * 0.028 = 0.0266$$

$$w_{C1} = \frac{0.0266}{0.4131} = 0.064$$

3.2 Sensitivity analysis

An effective approach to evaluating the sensitivity of MCDM methods involves adding new alternatives to the original

dataset or eliminating less favorable ones. In such cases, the MCDM method should demonstrate stability by ensuring that the ranking of alternatives remains consistent or does not undergo significant shifts [63]. Since the removal of each alternative alters the criterion values, the scores assigned to the remaining alternatives are also likely to be affected. To address this concern, a sensitivity analysis was performed, starting with the criteria identified as the weakest by the proposed method. The outcomes of this analysis, including the updated criteria rankings, are presented in Table 5, with a visual depiction provided in Figure 1.

Table 5. Rank reversal

Criteria	S0	S1	S2
C6	7		
C3	6	6	
C1	5	5	5
C7	4	4	4
C2	3	3	3
C5	2	2	2
C4	1	1	1
Criteria	S3	S4	S5
C6			
C3			
C1			
C7	3		
C2	4	3	
C5	2	2	2
C4	1	1	1

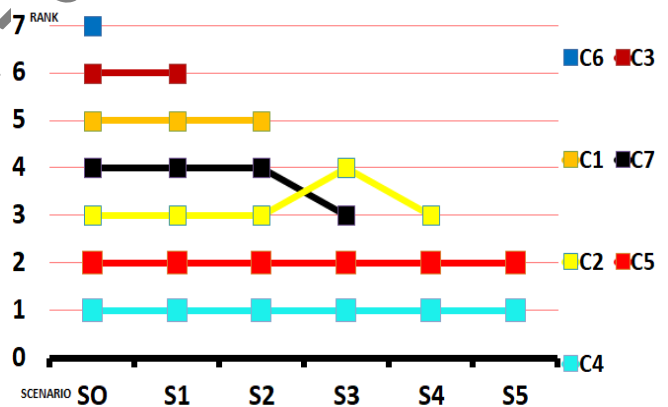


Figure 1. Rank reversal graph

An examination of Table 5 and Figure 1 reveals that the country rankings based on performance remain largely stable across the different scenarios evaluated through the rank reversal method applied for sensitivity analysis. According to Table 5 and Figure 1, the rankings of criteria C2 and C7 shifted by only one position in the third and fourth scenarios. Based on this result, since the weight distributions of the criteria did not exhibit significant changes following the exclusion process (from the lowest to the highest weight), the proposed method can be considered to have an optimal sensitivity level within the scope of rank reversal analysis.

3.3 Comparative analysis

This analysis examines the interconnections and relative standings of the suggested methodology in comparison to other method(s) utilized for deriving weighting outcomes. The proposed method aims to validate its reliability, consistency, and alignment with established techniques, while also

exhibiting a robust and statistically significant correlation with various weighting method(s) [10]. In the initial phase of the comparative analysis, the criterion weights were determined using ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC methods, which are widely applied in MCDM research. Consequently, the weight values of the GEHI criteria and their corresponding rankings, derived from these weighting methods, are displayed in Table 6 and Figure 2.

Table 6. Weight scores in scope of methods

Methods	CRITIC		SVP		LOPCOW	
	Score	Rank	Score	Rank	Score	Rank
C1	0.076	6	0.043	6	0.145	4
C2	0.081	5	0.206	3	0.153	3
C3	0.069	7	0.07	5	0.173	1
C4	0.203	2	0.234	1	0.126	6
C5	0.358	1	0.202	4	0.113	7
C6	0.083	4	0.019	7	0.155	2
C7	0.131	3	0.226	2	0.134	5

Methods	SD		ENTROPY		MEREC	
	Score	Rank	Score	Rank	Score	Rank
C1	0.071	5	0.027	5	0.105	5
C2	0.199	3	0.226	3	0.403	1
C3	0.065	6	0.023	6	0.116	4
C4	0.21	1	0.251	1	0.201	2
C5	0.205	2	0.238	2	0.135	3
C6	0.052	7	0.014	7	0.014	7
C7	0.198	4	0.22	4	0.026	6

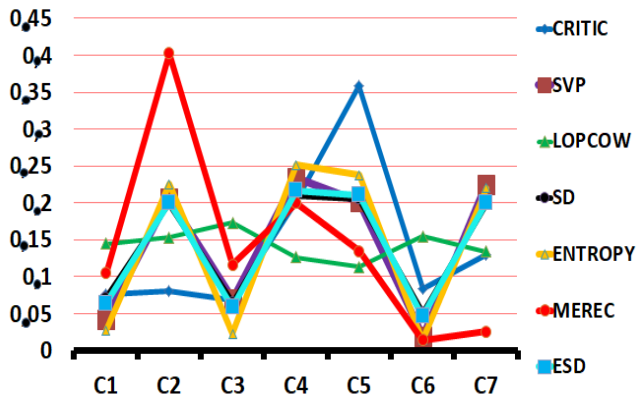


Figure 2. Position of methods

An analysis of Table 6 demonstrates that the rank positions of the criteria derived through the ESD method align perfectly with those obtained from both the SD and ENTROPY methods. Furthermore, when Table 6 and Figure 2 are analyzed together, it is observed that the ESD method exhibits a strong alignment with the SVP, SD, and ENTROPY methods, particularly in terms of the increasing and decreasing trends in criterion weights. Accordingly, the proposed method can be considered to establish a high correlation, especially with the ENTROPY, SD, and SVP methods. The correlation values between the proposed method and other objective weighting methods are presented in Table 7.

Table 7. Correlation scores

ESD	CRITIC	SVP	LOPCOW
Score	0.623**	0.986**	-0.723**
ESD	SD	ENTROPY	MEREC
Score	0.999**	0.999**	0.464*

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

An analysis of Table 7 indicates that the ESD method exhibits significant, positive, and very high correlation values, particularly with the SVP, SD, and ENTROPY methods. Therefore, considering the quantitative findings within the scope of the comparative analysis, the ESD method is evaluated as both credible and reliable.

3.4 Simulation examination

In the simulation examination, different scenarios are developed by assigning various values to the decision matrices. To verify the robustness of the results produced by the proposed method, it is expected that its outcomes will increasingly differ from those of other methods as the number of scenarios grows. Finally, consistency of variances in criterion weights across different scenarios should be evaluated using ADM analysis (ANOM for variances based on Levene). Therefore, for the method to be considered stable, the variances of the proposed method are expected to be homogeneous across the scenarios [10]. In this context, 10 scenarios (decision matrices) were initially generated and divided into two distinct groups. Following this, the correlation coefficients between the ESD method and other weighting methods were computed for these scenarios. The resulting correlation values are shown in Table 8.

Table 8. Correlation scores

Group	Scenarios	ENTROPY	CRITIC	IVP
First Group	Scenario1	0.998**	0.615**	0.988**
	Scenario2	0.999**	0.628**	0.991**
	Scenario3	0.995**	0.610**	0.983**
Second Group	Scenario4	0.997**	0.605**	0.988**
	Scenario5	0.991**	0.600**	0.976**
	Scenario6	0.888**	0.597**	0.872**
	Scenario7	0.876**	0.588**	0.864**
	Scenario8	0.855**	0.571*	0.854**
	Scenario9	0.842**	0.564*	0.839**
	Scenario10	0.813**	0.555*	0.827**
Group	Scenarios	SD	LOPCOW	MEREC
First Group	Scenario1	0.998**	-0.788**	0.478*
	Scenario2	0.999**	-0.781**	0.499*
	Scenario3	0.994**	-0.767**	0.455*
Second Group	Scenario4	0.996**	-0.751**	0.441*
	Scenario5	0.993**	-0.746**	0.430*
	Scenario6	0.895**	-0.721**	0.426*
	Scenario7	0.882**	-0.702**	0.412*
	Scenario8	0.866**	-0.686**	0.405
	Scenario9	0.854**	-0.664**	0.389
	Scenario10	0.843**	-0.651**	0.373

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

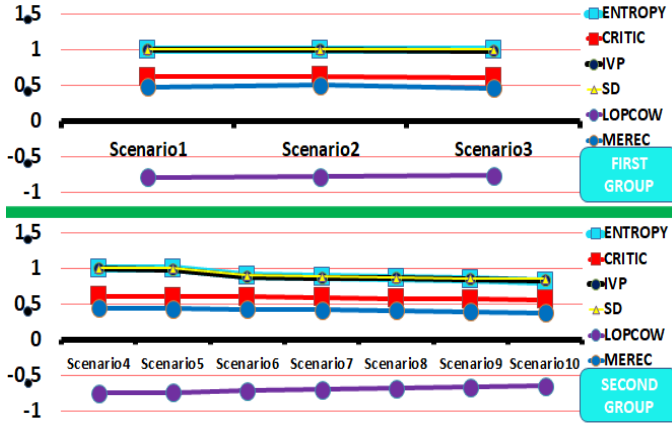


Figure 3. Correlation Positions of Methods with ESD

Analysis of Table 8 and Figure 3 reveals a tendency for correlation scores between the ESD method and other objective weighting methods to diminish with an increasing number of scenarios. Based on this finding, it can be inferred that the ESD method diverges more from other objective weighting methods with an increasing number of scenarios and may better reflect its distinctive characteristics.

The concluding stage of the simulation analysis involved evaluating the homogeneity of variance in the criterion weights generated by the ESD method across the various scenarios. This was accomplished using Analysis of Deviance for Means (ANOM) based on Levene's test for variances. This technique provides a visual means of assessing variance consistency. The graphical output comprises three primary elements. The average mean deviance (AVG) represented by the average line, the higher decision limit (UDL), and the lower decision limit (LDL). If the SDs of a particular category exceed these decision limits, it suggests a notable deviation from GMD, thus indicating heterogeneity of variance. Conversely, if the SDs of all groups remain within the UDL and LDL, it confirms homogeneity of variance [10]. The results of the ANOM analysis are illustrated graphically in Figure 4.

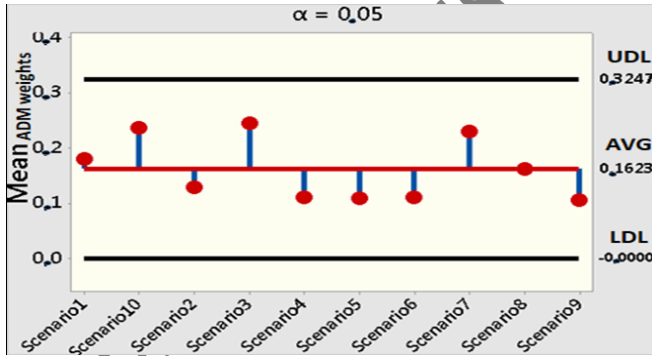


Figure 4. ADM chart

As shown in Figure 4, the ADM values calculated for each scenario remain within the range defined by the UDL and LDL. Thus, the variances of the determined weights across all scenarios explain Uniformity. This conclusion was validated using the Levene technique, with principal statistical outcomes presented in Table 9.

Table 9. Levene test score

Levene Statistic	df1	df2	Sig. (p value)
0.144	2	10	0.161

As shown in Table 9, the significant score ($p = 0.161$) exceeds level of 0.05, indicating consistent variances of criterion weight scores in scope of the scenarios. In conclusion, the simulation approach results underscore the stability and robustness of ESD approach.

4 Conclusions

This study introduces a novel approach to criterion weighting processes based on the SD method by proposing the Extended Standard Deviation (ESD) method, thereby contributing to the existing literature. The primary contribution of this study lies in the development of a more comprehensive weighting approach that not only considers the internal distribution of individual criteria but also accounts for their interactions with other criteria.

According to the findings, the rank reversal method was applied to test the proposed method's sensitivity level. Following the elimination of certain criteria, only minor changes were observed in the ranking of criterion weights, indicating that the proposed method maintains an optimal sensitivity level. A comparative evaluation, following the approach of Keshavarz-Ghorabae et al. (2021) [10], was conducted to validate the reliability of the proposed method, using widely recognized objective weighting techniques such as ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW. The results revealed that the proposed method exhibited a high correlation with ENTROPY, SVP, and SD, whereas it diverged from especially LOPCOW. The strong correlation between the proposed method and ENTROPY, SD, and SVP can be attributed to the intrinsic differentiation capability of these methods, which independently assess the internal variation of each criterion. Specifically, as the SD values of each criterion diverge in the proposed method, the distinctiveness of the method or its characteristics compared to ENTROPY, SD, and SVP methods becomes more pronounced. Conversely, the proposed method accounts for the external differentiation by considering the joint influence of all criteria, whereas LOPCOW focus solely on the individual intrinsic values of criteria. Additionally, due to the reliance on logarithmic operations in certain processes of the MEREC method, it exhibits technical differences from the proposed method. As a result, the proposed method exhibits partial divergence from MEREC and significant divergence from LOPCOW. Although the proposed method shares conceptual similarities with the CRITIC method, as both accounts for the intrinsic values of criteria as well as their interactions with others, there is a fundamental distinction between them. While CRITIC employs Pearson correlation to measure inter-criteria relationships, the proposed method relies on mutual influence values. Since "influence" and "relationship" represent distinct conceptual frameworks, the proposed method differentiates itself from CRITIC. Overall, the comparative analysis suggests that the proposed method establishes meaningful associations with ENTROPY, CRITIC, SD, SVP, and MEREC, thereby demonstrating its reliability and credibility. In the simulation analysis, 10 different decision matrices (scenarios) were generated to assess the stability and robustness of the proposed method. To achieve this, ANOM analysis, as recommended by Keshavarz-Ghorabae et al. (2021) [10], was conducted. The results indicated that variance remained homogeneous across all 10 scenarios, confirming that the proposed method is stable.

The key strength of the proposed method lies in its holistic assessment of all criteria, allowing each criterion's contribution to the standard deviation to be fully captured and thereby supporting more accurate and robust decision-making. This

characteristic makes the method particularly effective in analyzing criteria with significant distribution differences within the dataset. Sensitivity and simulation analyses further confirm the stability and reliability of the proposed method. Even when modifications are made to the decision matrix, the weighting values remain largely consistent, demonstrating the method's robustness and reliability in decision-making processes. In conclusion, this study introduces and thoroughly evaluates the ESD method, offering a novel perspective on the criterion weighting process in the literature. The proposed method is considered a strong alternative, particularly in MCDM problems, due to its capability to more accurately analyze criterion distributions within the dataset. Consequently, it is expected to contribute to more meaningful decision-making processes and serve as a viable tool for decision-makers in criterion weighting.

5 Discussion

This study presents a comprehensive analysis of the SD method, a key technique in criterion weighting, and introduces an expanded version known as the ESD method. The findings of the study demonstrate that the proposed method offers significant advantages not only compared to the classical SD method but also in relation to other objective weighting methods. Specifically, it is observed that the proposed method enhances the weighting process by considering not only the distributions of criteria within their own datasets but also analyzing the distributions of other criteria, thereby providing a more holistic approach.

Initially, it becomes evident that the proposed method offers a more comprehensive structure compared to the classical SD method. The traditional SD method utilizes the deviations of criteria from their mean values to calculate the weights [12]. In contrast, the proposed method internalizes between each criterion and others, evaluating their overall impact in the decision-making process. This approach enables a more precise determination of the degree of contrast among the criteria, leading to more accurate results in the course of decision-making.

The presented method exhibits various strengths and weaknesses when compared to other objective weighting techniques. In comparison to the ENTROPY method, one significant advantage of the proposed method is its insensitivity to zero and negative values. In the ENTROPY method, zero and negative values can create uncertainties due to logarithmic measurements [62]. However, the ENTROPY method can be more effective in information theory-based analyses [27]. In the ENTROPY method, criterion characteristics are determined solely based on their intrinsic entropy distributions, without considering other criteria. Thus, criterion weights are evaluated through internal distribution alone [5]. In contrast, the proposed method incorporates both intrinsic values and interactions with other criteria, accounting for both internal and external distributions.

When compared to the CRITIC method, one of the major advantages of the proposed method is its ability to determine the relationships between criteria without requiring any distribution assumptions. The CRITIC method uses the Pearson correlation coefficient to evaluate correlations between criteria, which relies on the assumption of a normal distribution. This relationship coefficient can have limitations when applied to datasets that do not follow a normal distribution [64]. Therefore, the proposed method provides more reliable results

regardless of the distribution type. On the other hand, the CRITIC method tends to perform better in datasets with strong correlation structures [8]. In contrast to the SVP method, the suggested approach provides a more thorough assessment by taking into account both internal and external distributions. While the SVP method focuses solely on the variances of the criteria, the proposed method provides a more detailed analysis by taking into account both the internal distribution and the contrasts between the criteria. However, since the SVP method involves simpler calculations, it can be applied more quickly to large datasets [29]. When compared to the MEREC method, the proposed method enhances the weighting process by considering both the general distribution and the contrasts of the criteria, making it more holistic. The MEREC method directly evaluates the impact of the criteria on alternative performance, while the proposed method offers a more independent weighting process based on the distribution of the criteria. The MEREC method evaluates criterion performance within an alternative's cell using a nonlinear logarithmic function. Subsequently, alternative performance is recalculated after criterion removal. Criterion influence is determined by comparing the original cell performance with the recalculated alternative performance [30]. Thus, MEREC considers both internal and external criterion distribution, similar to the proposed method. However, their methodologies differ: MEREC focuses on alternative performance post-criterion exclusion, while the proposed method evaluates the criteria's performance after their removal. Nonetheless, the MEREC method may yield more precise results in certain cases because it measures the direct effect of the criteria on the decision matrix [10]. Like the ENTROPY method, the MEREC method is highly sensitive to zero and negative values [64]. As a result, calculations based on normalization or logarithmic processes in these methods can become undefined. Finally, when compared to the LOPCOW method, the proposed method offers a more comprehensive evaluation by considering not only the intrinsic values of the criteria but also the distributions of other criteria. While the LOPCOW method may reduce gaps caused by data size and provide advantages in specific decision problems, the holistic approach of the proposed method allows for a more robust analysis of the relationships between criteria [11]. However, the proposed method does have some drawbacks. Since it requires a more complex computation process compared to other objective weighting methods, the computational load increases when working with large datasets. Particularly in decision problems where the number of criteria and alternatives is high, the increased computation time may limit the practical applicability of the method.

Future studies could focus on further developing the proposed method and exploring its applicability in various fields. Initially, the applicability of the method in large-scale datasets could be tested, with an emphasis on improving the efficiency of the computational processes. In this context, integrating artificial intelligence and optimization algorithms may lead to the creation of a faster and more automated model. Additionally, investigating how the method operates in uncertain decision-making environments is crucial. By integrating fuzzy logic, grey system theory, or fuzzy numbers, the sensitivity of the method to uncertainty could be tested. Furthermore, conducting a more comprehensive comparison between the ESD method and other MCDM methods and determining its suitability for different problem types could clarify the method's role in decision-making processes. Potential areas of application for the method include sustainability assessments, financial risk analysis,

supply chain management, and the healthcare sector. Testing the performance of the proposed method in studies within these fields would highlight how it can be integrated into various sectors. Finally, examining how the method can be adapted to dynamic decision-making processes is also essential. In environments where decision criteria may change over time, measuring the flexibility and stability of the ESD method could provide insights into its effectiveness in long-term decision-making. These future studies would reinforce the strengths of the method and make more substantial contributions to the literature on MCDM.

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7 Author Contributions

In the conducted study, Author 1 contributed to the formation of the idea, the design process, the literature review, the evaluation of the obtained results, the procurement of materials, the examination of the results, as well as the proofreading and content review of the article.

8 Ethics Approval and Conflict of Interest Declaration

"Ethical approval is not required for the preparation of this manuscript"

"There are no conflicts of interest with any individual or institution in the preparation of this manuscript."

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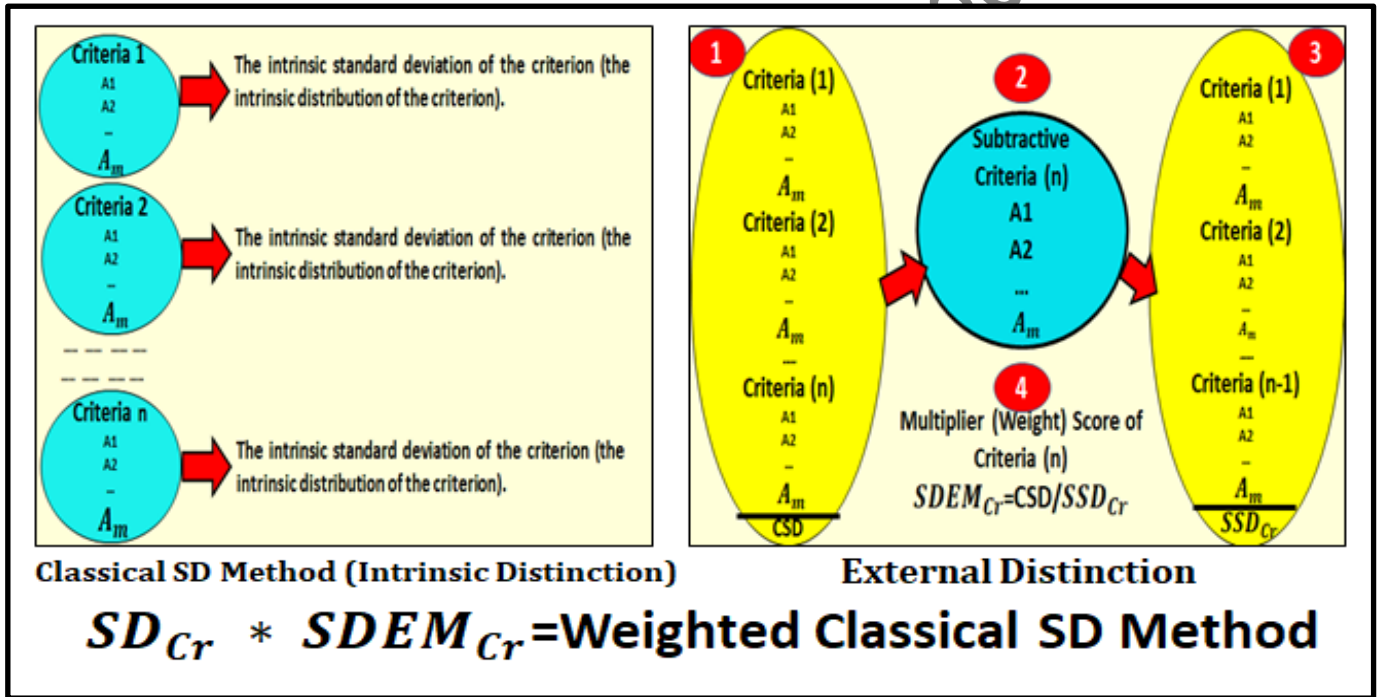
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Appendix A

In Figure 5, the visualization on the left illustrates the classical SD method, where each criterion's individual SD value is represented. Accordingly, the criteria with the greatest SD score can be interpreted as the most significant or the most heavily weighted criterion. In the proposed method, the standard SD approach is extended by considering the overall contribution of

each criterion to the dataset's SD (CSD). As shown in Figure 5, when the r-th criterion is removed from the dataset, any increase or decrease in the SD values of the remaining criteria indicates the overall impact of the removed r-th criterion on the total SD, denoted as $(SSD)_{Cr}$. If $(SSD)_{Cr}$ value of the r-th criterion is greater than the CSD value (i.e., the SD of the entire dataset), it implies that the criterion has a reducing effect on the overall dataset's SD. Conversely, if the $(SSD)_{Cr}$ value is smaller than the CSD value, it suggests that the criterion has an increasing effect on the overall SD of the dataset. Therefore, the weight of the r-th criterion in the overall SD is determined by the ratio of the CSD value to the $(SSD)_{Cr}$ value. Ultimately, the proposed approach integrates both the internal distribution (intrinsic dispersion or individual SD of the r-th criterion) and the external distribution (its contribution to the overall SD considering all other criteria). By doing so, the classical SD method is modified to incorporate the influence of other criteria, making it a more comprehensive and robust weighting approach.



Note: A: Alternative, m: alternative number, n: Criteria number, SD: Standard deviation, CSD: Comprehensive SD Score, $(SSD)_{Cr}$: Subtractive SD score of r-th criteria, $(SDEM)_{Cr}$: SD Effect Multiplier Score of r-th criteria.

Figure 5. Basic Logic of the Proposed Method