Gazi Üniversitesi
Fen Bilimleri Dergisi
PART C: TASARIM VE TEKNOLOJİ

Gazi University
Journal of Science
PART C: DESIGN AND TECHNOLOGY

GU J Sci, Part C, 13(3): 932-954 (2025)

A Novel Approach to Objective Criterion Weighting: Extended Statistical Variance Procedure (ESVP)

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Article Info

Research article
Received: 04/05/2025
Revision: 12/07/2025
Accepted: 22/07/2025

Keywords

Variance
SVP
ESVP
Intrinsic Distinction
External Distinction

Makale Bilgisi

Araştırma makalesi
Başvuru: 04/05/2025
Düzeltme: 12/07/2025
Kabul: 22/07/2025

Anahtar Kelimeler

Varyans
SVP
ESVP
İçsel Dağılım
Dışsal Dağılım

Graphical/Tabular Abstract (Grafik Özet)

A novel criterion weighting method, the Extended Statistical Variance Procedure (ESVP), is proposed to enhance decision-making by integrating both internal variances and inter-criterion contrasts. ESVP outperforms classical SVP in robustness, sensitivity, and discrimination, offering a more balanced and comprehensive analytical framework. / Bu çalışmada, kriter ağırlıklandırma sürecine yeni bir bakış sunan Genişletilmiş İstatistiksel Varyans Yöntemi (ESVP) önerilmiştir. ESVP, içsel varyans ve kriterler arası karşıtlıkları bütüncül şekilde değerlendirerek, klasik SVP'ye kıyasla daha dengeli, duyarlı ve sağlam sonuçlar üretmektedir.

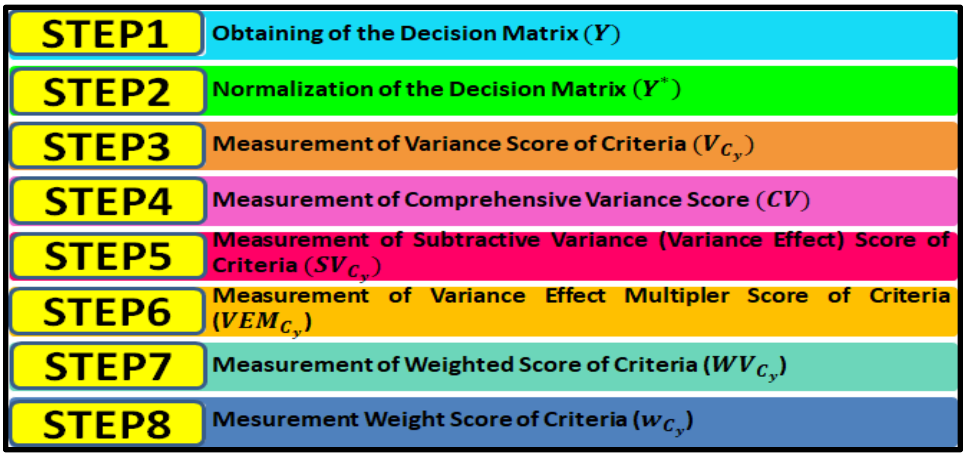

Figure A: *ESVP model /**Şekil A**:.ESVP modeli*

Highlights (Önemli noktalar)

- *The ESVP method offers a novel weighting approach by integrating internal variance with inter-criterion contrast. / ESVP yöntemi, içsel varyansla birlikte kriterler arası karşıtlığı entegre eden yeni bir ağırlıklandırma yaklaşımı sunmaktadır.*
- *The method's sensitivity, reliability, and structural consistency were validated through sensitivity, simulation and comparative analyses. / Duyarlılık, simülasyon ve karşılaştırmalı analizlerle yöntemin duyarlılık, güvenilirlik ve yapısal tutarlılığı doğrulanmıştır.*
- *It surpasses existing methods in sensitivity to zero/negative values, discriminative power, and variance homogeneity. / Yöntem, sıfır ve negatif değerlere duyarlılığı, yüksek ayırt ediciliği ve dağılım homojenliği açısından literatürdeki diğer yöntemlerden üstündür.*

Aim (Amaç): *The aim of this study is to propose an extended variance-based weighting method that simultaneously captures internal and external distributional structures of criteria./ Bu çalışmanın amacı, kriterlerin içsel ve dışsal dağılım yapısını eşzamanlı olarak dikkate alan genişletilmiş bir varyans temelli ağırlıklandırma yöntemi önermektir.*

Originality (Özgünlük): *Unlike SVP, ESVP considers both internal distributions and inter-criterion contrasts, offering a more holistic weighting approach./ SVP'den farklı olarak ESVP, içsel dağılımı ve kriterler arası karşıtlığı dikkate alarak daha bütüncül bir ağırlıklandırma sunar.*

Results (Bulgular): *ESVP showed high correlation with ENTROPY, SVP, SD, and MEREC, while maintaining stable rankings and homogeneous variance across simulations. ESVP, ENTROPY, SVP, SD ve MEREC ile yüksek korelasyon göstermiş, simülasyonlarda sıralama istikrarı ve homojen varyans sağlamıştır.*

Conclusion (Sonuç): *ESVP offers a robust and balanced alternative to SVP and other methods, particularly in complex MCDM problems requiring variance sensitivity and structural integrity./ ESVP, özellikle varyans duyarlılığı ve yapısal bütünlük gerektiren karmaşık MCDM problemlerinde, SVP ve diğer yöntemlere güçlü ve dengeli bir alternatiftir.*

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DOI: 10.29109/gujsc.1691115

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Abstract

This study proposes the Extended Statistical Variance Procedure (ESVP) method to introduce a new perspective to criterion weighting processes. To address the limitations of the traditional SVP method, which focuses solely on the internal variations of criteria, the proposed method comprehensively examines the contrasts among criteria and their contributions to decision-making processes. In this context, criterion weights are calculated through a mathematical model that integrates the internal distribution of each criterion with the effects of its contrasts with other criteria. The effectiveness of the method has been tested through analyses focusing on sensitivity, reliability, and robustness. When compared to other widely used weighting methods such as ENTROPY, CRITIC, SVP, SD, and MEREC, the ESVP method demonstrated high correlations with these methods and superior performance. The Simulation analyses further validated the stability of the method under varying scenarios, revealing that the variances of criterion weights remained homogeneous. Moreover, the method's sensitivity to zero and negative values, computational comprehensiveness, and its ability to evaluate contrasts among criteria to strengthen decision-making processes provide distinct advantages over other approaches in the literature. In conclusion, the ESVP method is considered an effective and reliable tool for decision-makers in multi-criteria decision-making problems that require criterion weighting.

Nesnel Kriter Ağırlıklandırmasına Yönelik Yeni Bir Yaklaşım: Genişletilmiş İstatistiksel Varyans Yöntemi (ESVP)

Makale Bilgisi

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Öz

Bu çalışma, kriter ağırlıklandırma süreçlerine yeni bir bakış açısı kazandırmak amacıyla Genişletilmiş İstatistiksel Varyans Yöntemi'ni (Extended Statistical Variance Procedure – ESVP) önermektedir. Geleneksel SVP yönteminin yalnızca kriterlerin içsel varyasyonlarına odaklanması nedeniyle ortaya çıkan sınırlılıkları gidermek üzere geliştirilen bu yöntem, kriterler arasındaki karşıtlıkları ve bu karşıtlıkların karar verme süreçlerine olan katkılarını bütüncül bir biçimde incelemektedir. Bu bağlamda, kriter ağırlıkları; her bir kriterin içsel dağılımını, diğer kriterlerle olan karşıtlık etkileriyle birlikte entegre eden matematiksel bir model aracılığıyla hesaplanmaktadır. Yöntemin etkinliği; duyarlılık, güvenilirlik ve sağlamlık odaklı analizlerle test edilmiştir. ENTROPY, CRITIC, SVP, SD ve MEREC gibi yaygın biçimde kullanılan ağırlıklandırma yöntemleriyle karşılaştırıldığında, ESVP yönteminin bu yöntemlerle yüksek korelasyon gösterdiği ve performans açısından üstünlük sergilediği ortaya konmuştur. Simülasyon analizleri, yöntemin farklı senaryolar altındaki istikrarını doğrulamış ve kriter ağırlıklarının varyanslarının homojen kaldığını ortaya koymuştur. Ayrıca, yöntemin sıfır ve negatif değerlere duyarlılığı, hesaplama kapsamlılığı ve kriterler arası karşıtlıkları değerlendirerek karar süreçlerini güçlendirme kapasitesi, literatürdeki diğer yaklaşımlara kıyasla özgün avantajlar sunmaktadır. Sonuç olarak, ESVP yöntemi, kriter ağırlıklandırması gerektiren çok kriterli karar verme problemlerinde karar vericiler için etkili ve güvenilir bir araç olarak değerlendirilmektedir.

1. INTRODUCTION (GİRİŞ)

Multi-Criteria Decision Making (MCDM) methodologies offer structured and systematic frameworks for evaluating alternatives based on multiple criteria [1]. One of the most critical components of these processes is determining the relative importance of each criterion, as this directly influences the accuracy and reliability of the resulting decisions [2]. Criterion weighting is

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generally categorized into two fundamental approaches: subjective and objective methods [3]. Subjective methods rely on the experience and judgment of decision-makers, whereas objective methods derive weights directly from data using mathematical models [4]. The primary aim of objective weighting techniques is to minimize the influence of decision-maker bias and to enable a more impartial, data-driven evaluation process [5]. In today's increasingly complex and multidimensional decision environments, MCDM problems present significant challenges for practitioners and analysts [2]. Within this context, accurately identifying the relative significance of decision criteria becomes essential for ensuring the validity, consistency, and credibility of the decision-making process. Objective weighting methods are widely recognized in the literature for their ability to facilitate analytical and data-oriented assessments that are independent of subjective judgments [1].

Among the most prominent objective weighting techniques in the literature are Standard Deviation (SD) [6], ENTROPY [7], Criteria Importance Through Inter-Criteria Correlation (CRITIC) [8], Statistical Variance Procedure (SVP) [9], Method Based on Removal Effects of Criteria (MEREC) [10], and Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW) [11]. The SVP method represents a statistical approach that determines weights by analyzing the variance levels of the criteria. Its fundamental assumption is that criteria with higher variance carry more informational value for the decision-making process [12]. However, the classical SVP approach focuses exclusively on the internal variation of individual criteria, without considering their external positions or the comparative relationships among them. This methodological limitation hinders the comprehensive assessment of contrast among criteria within the decision matrix, thereby offering a constrained perspective for distinguishing between alternatives. Furthermore, this restriction prevents the holistic evaluation of the overall variance structure embedded in the decision matrix and limits the model's ability to ensure adequate discrimination among criteria. In this context, the existing SVP methodology fails to adequately address a significant gap in the literature, particularly with respect to ensuring high discriminative capacity, structural consistency, and scenario-independent robustness.

In order to address the aforementioned limitations, this study proposes the Extended Statistical Variance Procedure (ESVP), an enhanced version of the classical SVP method. The ESVP method offers a more comprehensive weighting mechanism by holistically accounting for both the internal variation of each criterion and the interdependencies among criteria. Rather than merely evaluating the variance distribution of individual criteria in isolation, ESVP also considers the variance potentials of other criteria within the decision matrix during the weighting process. By doing so, the method analyzes the contribution of each criterion's variance to the overall variance structure of the full criterion set. This enables a more integrated assessment of both inter-criterion contrast and the overall structure of the dataset. In this regard, the ESVP method exhibits conceptual similarities with the weighting mechanism of the CRITIC method, where the internal dispersion of each criterion is measured by standard deviation and its external divergence from others is captured via correlation analysis [8]. Accordingly, ESVP goes beyond the classical SVP framework by simultaneously evaluating both internal distributions and external variance-based contrasts in a unified structure. This proposed approach does not only capture the influence of each criterion's variance on its own distribution but also considers its impact on the variance potential of other criteria. In this way, ESVP delivers a more balanced, discriminative, and consistent weighting structure. Such an integrative perspective allows ESVP to outperform traditional techniques, particularly in capturing the multidimensional variance structure embedded within the decision matrix.

The primary objective of this study is to comprehensively evaluate the effectiveness, sensitivity, and structural reliability of the proposed Extended Statistical Variance Procedure (ESVP) in comparison with the classical SVP approach and other widely adopted objective weighting techniques. To this end, sensitivity analyses were conducted, variance homogeneity tests were applied, and multi-scenario simulations were employed to assess the method's stability under varying conditions. The empirical results indicate that the ESVP method exhibits strong explanatory power and maintains its reliability across different decision environments. In this context, the present study aims to overcome the inherent limitations of the traditional SVP method and to fill a significant gap in the literature by offering a more robust, balanced, and consistent objective weighting approach. ESVP is introduced as a next-generation tool specifically designed for data-driven MCDM applications, providing both original and functional contributions to the field. The robustness of the ESVP method was verified through extensive sensitivity analyses, while its reliability and validity were tested through comparative evaluations. Furthermore, scenario-based simulation experiments were utilized to evaluate the methodological stability. The empirical findings consistently demonstrate that the proposed approach offers a high level of sensitivity, dependability, and robustness. Based on these results, ESVP is regarded as a valuable and practical tool for decision-makers.

In conclusion, this study seeks to address a critical deficiency in the literature by advancing beyond the constraints of the SVP method and proposing a stronger, more balanced, and structurally sound objective weighting mechanism. ESVP, tailored for contemporary data-intensive MCDM contexts, is expected to make a meaningful and impactful contribution to the decision sciences. Accordingly, the study first provides a comprehensive review of existing objective weighting techniques, followed by a detailed exposition of the mathematical formulation underlying the proposed method. Subsequently, the performance of the ESVP model is rigorously evaluated using a range of analytical tools and benchmarked against both the classical SVP and alternative objective approaches. The paper concludes with a discussion of the findings and offers directions for future research.

2. MATERIALS AND METHODS (MATERYAL VE METOD)

2.1. Various Objective Methods for Weighting Techniques and Their Characteristics (Ağırlıklandırma teknikleri için çeşitli nesnel yöntemler ve bu yöntemlerin özellikleri)

Selecting the most suitable option from a set of alternatives is a core component of decision-making. In such scenarios, alternatives often demonstrate varying performance levels across multiple criteria [13]. Accurate determination of the relative importance of these criteria is therefore crucial for effective alternative evaluation and optimal choice selection [14]. This holds particularly true in traditional MCDM problems, where criterion importance is typically represented by assigned weight values [15].

Subjective weighting approaches rely heavily on individual decision-maker judgment and experience, making them prone to personal biases. Consequently, assigned weights can differ significantly depending on the individual performing the evaluation [2]. Although expert opinions are often utilized to determine these weights, relying solely on subjective evaluations may lead to inconsistencies and biases in the decision-making process [3]. Conversely, objective weighting methods mitigate such biases by employing mathematical models and the data within the decision matrix to calculate weights, incorporating the inherent characteristics of the data into the evaluation [4].

The MCDM field offers a range of objective weighting techniques, including CRITIC [16], ENTROPY [17], SD [12], SVP [6], MEREC [18], and LOPCOW [19]. The CRITIC method operates by extracting pertinent information from the data. This method assigns higher importance to criteria exhibiting greater distinctiveness or variability [16]. Furthermore, CRITIC considers inter-criterion relationships by analyzing correlations to identify inconsistencies or conflicts. Weights are derived using calculated SD values, reflecting these interrelationships. This process involves constructing a decision matrix, normalizing it, and subsequently determining weight coefficients based on inter-criterion correlations [20].

The ENTROPY method provides a structured approach for determining the relative importance of criteria in decision-making. The method starts with the construction of a decision matrix and then continues by computing standardized values. ENTROPY is then employed to assess the degree of uncertainty or disorder associated with each criterion, capturing the information content inherent within each [21]. By applying the ENTROPY measure to these standardized values, weights are assigned to criteria based on their variability. Criteria exhibiting greater variability are assigned higher weights. This systematic approach ensures an objective, data-driven process, enabling decision-makers to conduct well-informed and balanced evaluations [22].

In the SD method, weights are determined by analyzing the extent to which each criterion's values deviate from their mean. Following normalization of the decision matrix, the SD for each criterion is computed, and these values are then used to derive the weights [23].

The SVP method, conversely, calculates weights by evaluating the variance of the data within the decision matrix [6]. Higher variance indicates greater significance in the decision-making process, implying that criteria demonstrating more variability are assigned larger weights. This ensures that criteria with higher variability exert a greater influence on the overall evaluation [12].

The MEREC method, like other weighting approaches, begins with constructing and normalizing the decision matrix. Next, the overall performance scores of the decision alternatives are computed using a natural logarithm-based framework [20]. These scores are then adjusted by incorporating the contribution of each alternative, with additional calculations utilizing the natural logarithm function. In the final step, the weight coefficients of the criteria are determined by evaluating the impact of removing each criterion, quantified as the sum of absolute deviations. Moreover, a criterion's weight coefficient increases in direct proportion to its influence on the decision alternatives [18].

The LOPCOW method utilizes a multidimensional approach to derive weights while minimizing the difference between the most and least influential criteria. It also accounts for interdependencies between criteria. The process commences by constructing and normalizing the decision matrix. Subsequently, the method calculates the average squared value as a percentage of each criterion's SD to mitigate the effects of differing data scales. This method ultimately generates weight coefficients for each criterion through a structured and systematic calculation [19].

2.2. Variance (Varyans)

Variance is calculated by dividing the sum of the squared deviations of values from their mean by the total number of values [24]. In other words, variance reflects the measurement of distributions within a dataset. Therefore, variance represents the variability within the dataset [25]. Variance stands out as a fundamental measure of dispersion in statistical data analysis, extending beyond central tendency measures to quantify the extent to which individual observations within a dataset deviate from one another and from the mean [26,27]. In its simplest definition, variance refers to the arithmetic mean of the squared deviations of observations from their mean [28,29]. In this regard, variance quantitatively reflects the degree of homogeneity or heterogeneity present in a given dataset [30,31].

As a core indicator of statistical variability, variance captures the spread and density of the distribution by measuring how far data points lie from the mean [32,33]. A high variance value indicates that observations are widely dispersed around the mean, suggesting a more scattered and heterogeneous data structure [34]. Conversely, low variance values imply that data points are tightly clustered around the mean, indicating a more homogeneous distribution [35]. A proper understanding and interpretation of variance is particularly important in relation to its mathematical and conceptual linkage with standard deviation (SD) [36]. While variance is expressed in squared units of the observed variable, standard deviation retains the original unit of measurement, making it more directly interpretable in practical contexts [37]. However, this difference does not diminish the analytical value of variance; on the contrary, as the square root of variance defines the standard deviation, variance remains a foundational construct in statistical theory and modeling [38]. Accordingly, clearly defining the relationship between variance and standard deviation is critical to ensuring methodological robustness in statistical analyses [39]. Standard deviation can be understood as the square root of variance, and this fundamental relationship is widely utilized across various analytical frameworks. In this context, the mathematical formulations for variance and standard deviation are presented in Equation 1 and Equation 2, respectively. Furthermore in the statistical literature, the unbiased estimator of the population variance is defined by Equation 3. Accordingly, the sample standard deviation is calculated based on the unbiased variance using Equation 4 [40].

σ: Standard deviation

n: Sample size

X: Each observation in the dataset

$\bar{X}$: Sample means

ϑ: Variance

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

$$\vartheta = \frac{\sum(X-\bar{X})^2}{n} \tag{2}$$

$$\vartheta = \frac{\sum(X-\bar{X})^2}{n-1} \tag{3}$$

$$\sigma = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} \tag{4}$$

2.3. The Use of Variance in Criteria Weighting: Statistical Variance Procedure (Kriter Ağırlıklandırmada varyansin kullanımı: İstatistiksel varyans yöntemi)

SVP is one of the objective weighting methods for decision alternatives. Therefore, in this method, the determination of the criteria weights is not influenced by the subjective assessments of experts [23]. In this approach, the weighting of criteria is based on measuring the variance values of the criteria [9]. After the variance values of the criteria are measured, the weights of the criteria are determined by calculating the ratio of the variance of a single criterion to the total variance of all criteria [41]. Accordingly, the literature related to the SVP method used for criterion weighting is presented in Table 1.

Table 1. SVP studies (SVP çalışmaları)

Author(s)	Method(s)	Theme
[42]	WED and SVP	Analysis of healthcare decision process
[43]	SVP	Analysis of normalization methods
[44]	SVP, SD and ENTROPY-CODAS	Comparative of criteria weight scores in CODAS
[45]	SVP-TOPSIS	Assessment of Athlete
[46]	SD and SVP-TOPSIS	Comparative analysis of methods
[47]	Entropy, CRITIC, LOPCOW, SVP, SD, and MEREC	Combined method analysis
[48]	SVP-TOPSIS	Determining of network for IoT

A review of the existing literature on the SVP method reveals that its integration with other MCDM techniques has been represented by a rather limited number of studies. Most of these investigations have been conducted by a small group of research teams, which restricts the scientific diversity, global awareness, and interdisciplinary diffusion of the method. In this context, the lack of broader research addressing SVP both in terms of methodological development and practical application has hindered the full recognition of its potential contributions. A key reason behind this limitation lies in the classical formulation of SVP, which adopts a unidimensional perspective focused solely on the internal variation of criteria. Such an approach falls short of satisfying the holistic assessment requirements demanded by complex multi-criteria decision-making environments. In particular, by disregarding the structural contrasts and inter-criterion divergences embedded within the decision matrix, the classical SVP model reduces methodological flexibility and complicates its integration with other MCDM frameworks. Nonetheless, SVP's core philosophy variance-based weighting offers significant advantages, as it enables an objective, data-driven evaluation. The method possesses strong explanatory power and, due to its sensitivity to the distributional structure of the decision matrix, it can play a critical role in data-intensive decision problems. To fully capitalize on these advantages, however, it is necessary to move beyond the conventional SVP formulation and develop extended, next-generation models that can better accommodate the complexity of real-world decision contexts. In this context, the steps of applying the IVP method are outlined below [6, 41].

C_r: $r-th$ evaluation criterion

d_{pr}: value of the $p-th$ alternative according to the $r-th$ evaluation criterion

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

e_{pr}: Normalized score of d_{pr}

Step 1: Construction of the Decision Matrix (X)

In the initial phase of the MCDM process, the decision matrix is constructed to systematically represent the quantitative performance of each alternative with respect to the relevant criteria. Denoted as X, this matrix comprises elements where d_{pr}indicates the performance value of the p alternative under the r criterion. The matrix is formulated in accordance with the structure defined in Equation 5 of the study, thereby establishing a robust analytical foundation that enables comprehensive evaluation across all criteria. The input data may derive from direct measurements or expert assessments. During the matrix construction, critical aspects such as the directionality of criteria, data scale compatibility, and inter-criteria comparability must be rigorously considered.

$$X = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ d_{11} & d_{12} & & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{5}$$

Step 2: Construction of normalized matrix (X^*)

At this stage, normalization is performed based on the orientation of each criterion. For benefit-oriented (maximization) criteria, normalization values are computed using Equation 6, whereas for cost-oriented (minimization) criteria, the calculations are carried out in accordance with Equation 7. In both cases, the primary objective is to transform the data into a dimensionless and comparable format across different measurement scales. Subsequently, the normalized decision matrix (X^*) is constructed by applying Equation 8 to the previously obtained normalized values. This matrix enables a balanced and scale-independent evaluation of all alternatives across the full set of criteria. In doing so, it establishes a robust and coherent data foundation for the subsequent phases of the decision-making process.

$$e_{pr} = \frac{d_{pr}}{max_{d_{pr}}} \tag{6}$$

$$e_{pr} = \frac{min_{d_{pr}}}{d_{pr}} \tag{7}$$

$$X^* = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ e_{11} & e_{12} & & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} \tag{8}$$

Step 3: Calculation of variance score of each criteria (ϑ_{Cr})

At this stage, the variance value for each criterion is calculated using the previously obtained normalized values, as defined in Equation 9. Variance serves as a quantitative indicator of how dispersed the alternatives are with respect to a given criterion, and simultaneously reflects the discriminative power of that criterion. In this context, criteria with higher variance indicate a greater potential to differentiate among alternatives, thereby assuming a more influential role in the decision-making process. Accordingly, this step is not merely a numerical computation, but a critical analytical phase aimed at quantifying the relative distinctiveness of each criterion. The resulting variance values are subsequently utilized as a foundational input in the weighting procedures of the next stage.

$$\vartheta_{Cr} = \frac{\sum(e_{pr} - \overline{C_r})^2}{m} \tag{6}$$

Step 4: Measurement of the weight of criteria (w_r)

At this stage, the weight of each criterion is calculated using Equation 10. The computation involves dividing the variance of each criterion by the total variance across all criteria. As a result, the obtained weights are normalized values within the [0, 1] range, and the sum of all criterion weights equals 1. This ensures that the relative contribution of each criterion to the decision-making process is quantitatively and proportionally represented. This variance-based weighting approach objectively reflects the discriminative capacity of each criterion within the decision model. In particular, criteria with higher variance indicating greater differentiation among alternatives are assigned proportionally higher weights. This step not only preserves the analytical integrity of the decision matrix but also establishes a balanced and coherent weighting structure among criteria.

$$w_r = \frac{\vartheta_{Cr}}{\sum_{r=1}^{n} \vartheta_{Cr}} \tag{9}$$

2.4. Proposed method (Expanded Statistical Variance Procedure-ESVP) (Önerien yöntem: Genişletilmiş istatistiksel varyans prosedürü)

When determining criterion weights, the degree of contrast, uniqueness, and discordance among criteria serves as an indicator of their inherent characteristics [4]. Consequently, criteria that exhibit greater divergence or opposition within a defined mathematical framework are assigned greater importance or weight [5]. In this respect, the proposed methodology shares conceptual similarities with the SVP method in its fundamental logic. The SVP method assigns importance to criteria based on the extent of variation present within their individual datasets, without considering the datasets of other criteria [6].

The proposed method extends the traditional SVP method by enhancing the representation of contrast and uniqueness among criteria, rendering these attributes more apparent and thorough. To accomplish this, the proposed approach evaluates the complete numerical sequence of each criterion to assess its degree of contrast holistically. Specifically, the method computes the change in the SVP of the remaining criteria after excluding the numerical sequence of a given criterion. This calculation quantifies the contribution of the removed criterion to the overall SD.The resulting influence is transformed into a factor that, when combined with the SVP values of the other criteria, defines the spatial arrangement of all criteria within a more comprehensive framework. The intrinsic SVP value of each criterion (representing its internal variability) is then multiplied by this factor (representing external variability). This adjustment amplifies the relative contrast of criteria by incorporating both their internal and external dispersion. Through this approach, the contrasts among criteria can be evaluated more comprehensively.

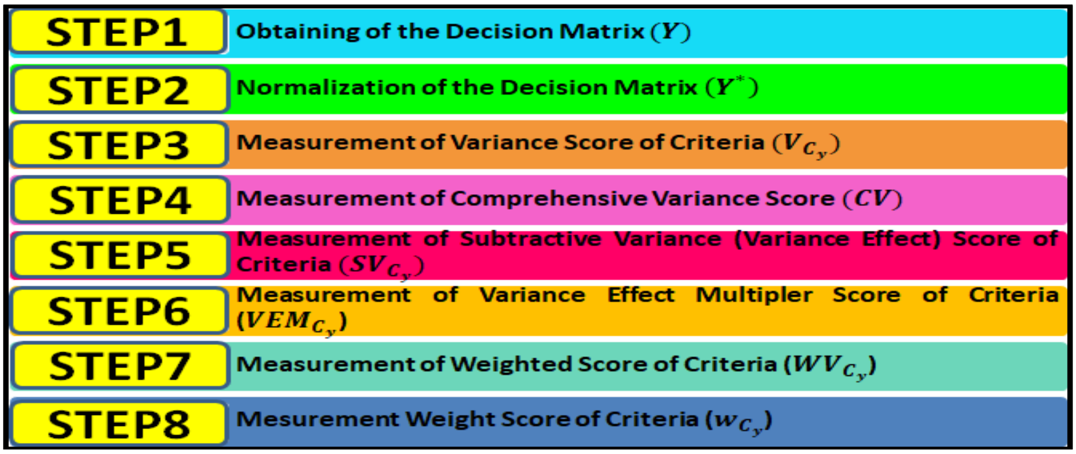

Figure 1. Basic logic of the proposed method (ESVP) (Önerien yöntemin temel mantığı)

As illustrated in Figure 1, Steps 1 through 3 correspond to the conventional Statistical Variance Procedure (SVP), which calculates the individual variance values for each criterion. In this traditional approach, the criterion with the highest variance is regarded as the most significant or influential in the decision-making process. However, this method focuses solely on the internal distribution of each criterion, based on its own values, and does not consider its interaction with other criteria. In contrast, the proposed method enhances the classical SVP starting from Step 4 by introducing the calculation of the Comprehensive Variance (CV), which represents the overall variance of the dataset, including all criteria. In Step 5, when a specific criterion is removed from the dataset, the change (increase or decrease) in the variance of the remaining criteria is observed. This change reflects the holistic influence of the removed criterion on the total variance and is denoted as Subtractive Variance (SV). In Step 6, the SV value obtained after the exclusion of a criterion is compared with the CV value of the full dataset. If SV>CV, it indicates that the removed criterion had a reducing effect on the overall variance. Conversely, if SV<CV, the criterion is interpreted as contributing positively to the increase in total variance. Based on this logic, the weight of the removed criterion in terms of its contribution to overall variance denoted as WEM is calculated by the ratio CV/SV. Here, SV is a derived variance measure that captures the shift in total variance resulting from the removal of a specific criterion, reflecting its external distribution relative to the others. In the subsequent step, the individual variance of each criterion (V) is multiplied by its corresponding WEM value to obtain the Weighted Variance (WV). Finally, in the last step of the method, the WV value of each criterion is divided by the sum of all WV values to determine the final normalized weights of the criteria. In this respect, the proposed method not only accounts for the intrinsic variance of each criterion but also integrates its extrinsic impact on the dataset as a whole. This dual consideration aligns the method closely with the CRITIC approach. In CRITIC, the weight of a criterion is calculated by multiplying its standard deviation (representing internal contrast, based on its own normalized values) with a measure of its conflict with other criteria (computed as the sum of one minus the Pearson correlation coefficients). To summarize, the proposed method simultaneously incorporates both the individual (intrinsic) variance and the systemic (extrinsic) contribution of each criterion. By doing so, it captures the contrast effect among criteria more comprehensively and refines the traditional SVP into a more balanced, robust, and informative weighting mechanism. The procedural steps of the method are detailed in the subsequent section.

V: Variance score

Y: Decision matrix

Y^*: Normalized decision matrix

C_y: $y-th$ evaluation criterion

e_{vy}: value of the $v-th$ alternative according to the $y-th$ evaluation criterion

σ_y: SD of the $y-th$ criterion $(y = 1, 2, \ldots, n)$

w_y: Weight of the $y-th$ evaluation criterion $(y = 1, 2, \ldots, n)$

f_{vy}: Normalized score of e_{vy}

Step 1: Obtaining of the Decision Matrix (Y)

The formulation presented in Equation 11 constitutes the foundational structure for constructing the decision matrix. This formulation enables the systematic and quantitative representation of alternatives with respect to the relevant criteria within the context of multi-criteria decision-making. As a result, a decision matrix is obtained that is both analytically processable and mutually comparable, thereby facilitating consistent evaluation by the decision-maker. Equation 13 provides the mathematical basis for generating this matrix, ensuring that the method can be implemented in a coherent and repeatable manner across different decision problems.

$$Y = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ e_{11} & e_{12} & & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} \qquad (11)$$

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

In the second stage, the normalization of the criterion values is performed to ensure comparability across different measurement scales. For benefit-oriented criteria, normalization is conducted using Equation 12, while Equation 13 is employed for cost-oriented criteria. This distinction allows the method to appropriately handle criteria with different directional objectives (maximization vs. minimization). Following the application of these normalization procedures, the normalized decision matrix is constructed using Equation 14. This matrix provides a standardized framework in which all criteria are dimensionless, facilitating a fair and consistent basis for further analysis in the multi-criteria decision-making process.

$$f_{pr} = \frac{e_{vy}}{max_{e_{vy}}} \qquad (12)$$

$$f_{pr} = \frac{min_{e_{vy}}}{e_{vy}} \qquad (13)$$

$$Y^* = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ f_{11} & f_{12} & & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix} \qquad (14)$$

Step 3: Measurement of Variance Score of Criteria (V_{C_y})

At this stage, the variance value of each criterion is calculated using Equation 15, independently of the normalized values of the other criteria. This computation is based solely on the normalized decision matrix and quantitatively reveals the degree of dispersion in the values associated with each individual criterion. In other words, the variance value can be interpreted as a statistical indicator that measures the discriminative power of a criterion, considering only the internal distribution of its own normalized values without reference to the behavior or distribution of the remaining criteria. This reflects the extent to which a given criterion contributes to the decision-making process on the basis of its intrinsic variability.

$$V_{C_y}(\sigma_y) = \sqrt{\frac{\Sigma(f_{vy} - \overline{C_y})^2}{m}} \qquad (15)$$

Step 4: Measurement of Comprehensive V Score (CV)

At this stage, the overall variance of the dataset is calculated by considering the distribution of all normalized criterion values across all alternatives. This computation is performed using Equation 16. The resulting Comprehensive Variance Score (CV) serves as a singular metric representing the overall variability of the decision matrix. In other words, the CV value statistically quantifies the degree of dispersion within the system when all normalized values of all criteria are evaluated collectively. This comprehensive measure functions as a higher-order variance indicator, taking into account the global distribution characteristics of the entire dataset. It provides a critical reference point for the subsequent steps, enabling a comparative assessment of each criterion's holistic influence on the system.

$$Y^* = [f_{11}, \quad f_{21,} \quad \cdots \quad f_{m1},$$

$$f_{12}, \quad f_{22}, \quad \cdots \quad f_{m2}, \quad f_{1n}, \quad f_{2n}, \quad \cdots \quad f_{mn}]$$

$$CV = \sqrt{\frac{\Sigma\left(f_{vy} - \overline{Y^*}\right)^2}{mxn}} \qquad (16)$$

Step 5: Measurement of Subtractive Variance (Variance Effect) Score of Criteria (SV_{C_y})

At this stage, the variance of the normalized dataset is recalculated by systematically removing each individual criterion, with the aim of evaluating how the exclusion of a specific criterion influences the overall variance of the system. In this context, the subtractive variance score, denoted as SV_{C_y}, is obtained by excluding the normalized values of the criterion in question and computing the resulting variance of the remaining dataset. This newly computed value is then compared with the

Comprehensive Variance (CV) of the complete dataset, which includes all criteria. The outcome of this comparison reveals both the direction and the magnitude of the excluded criterion's contribution to the system's overall variability. If the CV value is greater than the corresponding SV_{Cy}, it indicates that the excluded criterion had a positive effect on the overall variance, meaning its presence increased the variability of the dataset. Conversely, if the SV_{C_y} exceeds the CV, it implies that the criterion had a dampening effect, thereby reducing the system's overall variance. The entire procedure is conducted for each criterion individually, and the corresponding SV_{C_y} values are determined in accordance with Equations 17 through 21. This step enables the evaluation of each criterion's external influence on the global structure of the dataset, extending beyond the scope of its internal dispersion. In doing so, the method not only accounts for the intrinsic variability of a criterion but also captures the degree to which it structurally affects the variance of the decision space when removed, offering a more comprehensive and system-aware assessment of criterion importance.

$$1)\{\boldsymbol{C_1} \notin \boldsymbol{C}\};\ \{C_2, C_3, C_4, ., C_n \ \in C\};$$

$$\boldsymbol{SV_{C_1}}: [f_{12}f_{22} \cdot\cdot f_{m2}f_{13}f_{23} \cdot\cdot f_{m3}f_{14}f_{24} \cdot\cdot f_{m4}f_{1n}f_{2n} \cdot\cdot f_{mn}] = \sqrt{\frac{\sum(f_{vy} - \overline{SV_{C_1}})^2}{m*(n-1)}} \quad (17)$$

$$2)\{\boldsymbol{C_2} \notin \boldsymbol{C}\};\ \{C_2, C_3, C_4, ., C_n \ \in C\};$$

$$\boldsymbol{SV_{C_2}}: [f_{11}f_{21} \cdot\cdot f_{m1}f_{13}f_{23} \cdot\cdot f_{m3}f_{14}f_{24} \cdot\cdot f_{m4}f_{1n}f_{2n} \cdot\cdot f_{mn}] = \sqrt{\frac{\sum(f_{vy} - \overline{SV_{C_2}})^2}{m*(n-1)}} \quad (18)$$

$$3)\{\boldsymbol{C_3} \notin \boldsymbol{C}\};\ \{C_2, C_3, C_4, ., C_n \ \in C\};$$

$$\boldsymbol{SV_{C_3}}: [f_{11}f_{21} \cdot\cdot f_{m1}f_{12}f_{22} \cdot\cdot f_{m2}f_{14}f_{24} \cdot\cdot f_{m4}f_{1n}f_{2n} \cdot\cdot f_{mn}] = \sqrt{\frac{\sum(f_{vy} - \overline{SV_{C_3}})^2}{m*(n-1)}} \quad (19)$$

$$\boldsymbol{SV_{C_4}}: [f_{11}f_{21} \cdot\cdot f_{m1}f_{12}f_{22} \cdot\cdot f_{m2}f_{13}f_{23} \cdot\cdot f_{m3}f_{1n}f_{2n} \cdot\cdot f_{mn}] = \sqrt{\frac{\sum(f_{vy} - \overline{SV_{C_4}})^2}{m*(n-1)}} \quad (20)$$

$$\ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots$$

$$\ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots, \ldots$$

$$\boldsymbol{m})\ \{\boldsymbol{Cm} \notin \boldsymbol{C}\}; \{C_1, C_2, C_3, ., C_{(n-1)} \ \in C\} \in C;$$

$$\boldsymbol{SV_{C_m}}: [f_{11}f_{21} \cdot\cdot f_{m1}f_{12}f_{22} \cdot f_{m2}f_{13}f_{23} \cdot \cdot\cdot f_{2(n-1)} \cdot\cdot f_{m(n-1)}]] = \sqrt{\frac{\sum(f_{vy} - \overline{SV_{C_{(n-1)}}})^2}{m*(n-1)}} \quad (21)$$

Step 6: Measurement of Variance Effect Multipler Score of Criteria (VEM_{C_y})

In the subsequent step, the Variance Effect Multiplier Score (VEM_{C_y}) is calculated for each criterion. This calculation is performed by determining the ratio between the overall variance of the complete dataset (CV) and the variance of the remaining normalized dataset obtained after the exclusion of the respective criterion (SV). If CV is greater than SV, the resulting CV/SV ratio reflects the amplifying effect of the excluded criterion on the dataset's variability. Conversely, if SV exceeds CV, the same ratio indicates a dampening effect, implying that the exclusion of the criterion has reduced the overall variance. According to this approach, the (VEM_{C_y}) value for each criterion is systematically computed in accordance with Equations 22 and 23. In this way, the criterion's enhancing or diminishing influence on the system's total variance is quantitatively revealed. This step not only captures the distributional disparities among criteria, but also enables a more comprehensive evaluation of their structural contribution to the dynamic behavior of the overall decision system.

Contribution multiplier:

$$\boldsymbol{CV} > \boldsymbol{SV_{C_y}} \rightarrow VEM_{C_y} = (\boldsymbol{CV}) \backslash (\boldsymbol{SV_{C_y}}) \quad (22)$$

Reduction multiplier:

$$\boldsymbol{SV_{C_y}} > \boldsymbol{CV} \rightarrow VEM_{C_y} = (\boldsymbol{CV}) \backslash (\boldsymbol{SV_{C_y}}) \quad (23)$$

Step 7: Measurement of Weighted V_{Cr}Score of Criteria (WV_{C_y})

At this stage, consistent with the logic of the CRITIC method, the internal distribution state (V_{C_y}) of each criterion is multiplied by its external distribution state VEM_{C_y} in order to evaluate its overall spatial distribution within the system. In other words, the intrinsic variance of a given criterion calculated solely based on its own normalized values is adjusted by the variance effect multiplier, which reflects the criterion's relationship with all other criteria. Through this adjustment, the relative position and influence of each criterion within the global variance structure of the system are captured in a more holistic and integrated manner. As a result of this multiplication, the weighted standard deviation score (WV_{C_y}) is obtained for each criterion. This computation is carried out in accordance with Equation 24. The significance of this step lies in its ability to provide the decision-maker not only with a measure of individual variance, but also with a more refined and powerful weighting mechanism that incorporates the degree of interaction among criteria within the overall system.

$$WV_{C_y} = V_{C_y} * VEM_{C_y} \tag{24}$$

Step 8: Measurement of Weight of Criteria (w_{C_y})

In the final stage, the ultimate weight assigned to each criterion is calculated by evaluating the ratio between its weighted variance score (WV_{C_y}) and the total weighted variance scores ($\sum_{j=1}^{n} WV_{C_y}$) of all criteria. This ratio reflects the relative contribution of each criterion to the overall system variance and is expressed as a normalized value within the range of [0, 1]. As a result, the weights of all criteria are proportionally distributed such that their sum equals one. This computation process is formally defined in Equation 25 and constitutes the final step of the method's integrated weighting structure.

$$w_{C_y} = \frac{WV_{C_y}}{\sum_{j=1}^{n} WV_{C_y}} \tag{25}$$

The proposed methodology advances beyond the traditional SVP method by incorporating external influences, unlike the classical SVP which solely relies on intra-criterion observation distributions. This integration enhances the method's ability to accurately capture inter-criteria contrast. By considering impact multipliers, a more nuanced assessment of each criterion's influence is achieved, leading to more comprehensive and accurate decision-making outcomes. Furthermore, the proposed method provides an improved representation of criterion distribution within the dataset compared to the classical SVP approach. While latter primarily focuses on deviations from the mean, proposed method evaluates the distribution and criterion effect in significantly greater detail. This allows for a deeper understanding of each criterion's role in the final decision. Unlike the classical SVP method, which simply measures variance from the mean [43], proposed method assesses the individual contributions of each criterion to the overall decision, offering a clearer picture of its impact.

Furthermore, in contrast to the classical SVP method, which identifies outliers based solely on a criterion's own values, the proposed method detects outliers through a holistic evaluation, considering both the criterion's intrinsic and external status with other criteria. In short, proposed method provides a far more detailed, flexible, and realistic alternative to the classical SVP method, enhancing the reliability and validity of decision-making by incorporating weighting, external influences, and adaptability to diverse criteria. Moreover, the proposed method exhibits distinct advantages over other objective weighting techniques. A major benefit is its robustness to zero and negative values. For example, the ENTROPY and MEREC methods are sensitive to such values, which can result in undefined results within the decision matrix due to the logarithmic operations involved [17-18]. When the ENTROPY method is examined, the characteristics of the criteria are determined by entropy without considering the values of the other criteria. Therefore, in the ENTROPY method, the weights of the criteria are only evaluated based on their own intrinsic entropy distributions (internal distribution) [17]. In contrast, in the proposed method, the characteristics of the criteria are determined by considering both their own intrinsic values as well as the values of other criteria, thereby accounting for both internal and external distributions. In the MEREC method, the performance of each criterion associated with an alternative's cell is computed using a nonlinear logarithmic function. Following this, once the criterion is removed, the performance of the alternatives is recalculated. The influence of each criterion is assessed by analyzing the difference between the performance of the cell corresponding to that criterion and the recalculated performance of the alternatives after excluding the criterion [18]. Consequently, the MEREC method takes into account both the internal distribution of each criterion and its effect on the overall dataset (external distribution of each criterion), aligning with the framework of the proposed method. The key distinction between the two approaches lies in their respective methodologies: in the MEREC method, the focus is on the performance of the decision alternatives once the criteria are excluded, while in the proposed method, the performance of the criteria themselves is evaluated after their exclusion.

Compared to the CRITIC method, the proposed approach demonstrates technical similarities. Both methods determine criterion weights by considering the intrinsic distribution of each criterion (internal differentiation: standart deviation: (σ)) and its relationships with other criteria (external differentiation: Pearson cerrelation (p) ($\sum_{j=1}^{n}(1-p)$: Position of criteria according to other criteria) [4]. However, the proposed method refines the CRITIC approach by calculating the SV and VEM values, where internal differentiation is based on each criterion's variance, and external differentiation includes the influence of other criteria. Despite these similarities, the proposed method yields more accurate results. This is because the CRITIC method relies on Pearson's correlation coefficient, which assumes a normal distribution. In non-normally distributed datasets, Pearson's correlation coefficient can produce unreliable results [28].

The proposed method, by not relying on this assumption, offers a more adaptable and robust evaluation. Variance, being the square of the SD, means that, like the classical SD method, the SVP method identifies differences among criteria based solely on their intrinsic distributions or variance values [12]. However, the proposed method provides a more holistic weighting approach, making it more comprehensive than the SVP method. The LOPCOW method, while robust in addressing data scale issues, handles gaps in the dataset based only on the intrinsic values of the criteria, without considering the impact of other criteria [19]. Conversely, the proposed method incorporates the values of all other criteria in the weighting process. This integration allows for a more relational structure in evaluating differences among criteria, making their mutual influences more explicit.

In summary, the proposed method surpasses the classical SVP method by offering a more comprehensive, adaptable, and dependable weighting approach. Compared to other objective weighting methods, it presents several advantages, particularly in promoting more informed and effective decision-making. However, a limitation is that, unlike some other objective weighting methods, the weighting process in this approach is more complex and computationally intensive. This limitation becomes more prominent as the number of criteria and alternatives increases. In the application of the classical SVP, the skewness and kurtosis values of the criteria are not taken into account during the weighting process.

In contrast, the ESVP enhances the variance-based weighting mechanism by integrating both the intrinsic distributions of the criteria and their levels of contrast with one another. In this regard, ESVP represents a multidimensional and comprehensive approach that distinctly departs from the unidimensional structure of the traditional SVP method. Although the proposed method does not impose a strict assumption of normality, it is theoretically plausible that significant deviations in data distribution such as pronounced skewness or kurtosis may influence the calculation of variances, especially in the presence of outliers. Such deviations could, under certain conditions, lead to an artificial inflation of the variance for specific criteria, thereby resulting in disproportionally higher weight values.

2.5. Data Set (Veri seti)

The method proposed for the quantitative determination of criterion weights utilizes the most recent 2024 Global Innovation Index (GII) values for selected countries as its dataset. The reasoning behind choosing these data is that the criterion values do not exhibit extreme outliers, thereby facilitating a more accurate evaluation of the method's ability to differentiate between the criteria under these conditions. For ease of reference, the abbreviations for the GII criteria are presented in Table 2.

Table 2. Abbreviations of alternatives and criteria (Alternatif ve kriterlerin kısaltmaları)

GEHI Criteria	Abbreviations
Institutions	C1
Human Capital and Research	C2
Infrastructure	C3
Market Sophistication	C4
Business Sophistication	C5
Knowledge and Technology Outputs	C6

Creative Outputs	C7
Countries	**Abbreviations**
Austria	A1
Estonia	A2
Hong Kong	A3
Iceland	A4
Ireland	A5
Luxembourg	A6
Norway	A7

3. RESULTS (BULGULAR)

3.1. Computational examination (Hesaplamalı inceleme)

In the study, the decision matrix was first constructed using Equation 11. Subsequently, the normalization of the decision matrix values was performed through Equation 12 and 14. Accordingly, the decision matrix and the normalized decision matrix are presented in Table 3.

Table 3. Decision and normalized decision matrix (Karar ve normalize karar matrisi)

Decision Matrix							
Countries	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
A1	74.7	59.4	56.8	45.2	51	41.8	44.5
A2	78.7	44.5	61.3	66.5	48.1	39.9	49.7
A3	82.1	55.7	55.4	71.9	49.7	22.8	51.8
A4	78.6	47.5	64.9	52.4	52.4	30.3	45.6
A5	79.1	48.1	54.8	37.9	55.7	47.3	42.3
A6	83.9	46.9	45.7	45.8	58.3	30.5	53.6
A7	83.3	50.9	64.6	45.2	51.2	34.7	43.4
Maximum	83.9	59.4	64.9	71.9	58.3	47.3	53.6
Normalized Decision Matrix							
Countries	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
A1	0.890	1.000	0.875	0.629	0.875	0.884	0.830
A2	0.938	0.749	0.945	0.925	0.825	0.844	0.927
A3	0.979	0.938	0.854	1.000	0.852	0.482	0.966
A4	0.937	0.800	1.000	0.729	0.899	0.641	0.851
A5	0.943	0.810	0.844	0.527	0.955	1.000	0.789
A6	1.000	0.790	0.704	0.637	1.000	0.645	1.000
A7	0.993	0.857	0.995	0.629	0.878	0.734	0.810

In the third stage of the study, the variance value for each criterion was calculated using the normalized values through Equation 15. In the fourth stage, all criteria were considered in an integrated manner with the aid of Equation 16, and the comprehensive variance (CV) of the matrix, accounting for the normalized values of all criteria, was determined. In the fifth stage, based on the normalized values and CV values, the subtractive variance (SV) for each criterion was identified using Equations 17, 18, 19, 20, and 21. In the sixth stage, the variance effect multiplier (VEM) for each criterion was computed using Equations 22 or 23. In the seventh stage of the method, the weighted variance (WV) values were determined using Equation 24. Finally, in the last stage, the weights of the criteria (w) were obtained through Equation 25. The values obtained at each stage are presented in detail in Table 4.

Table 4. V, CV, SV, VEM, WV and w scores of criteria (Kriterlerin V, CV, SV, VEM, WV and w değerleri)

Criteria	**V**	**CV**	**SV**	**VEM**	**WV**	**w**	**Rank**
C1	0.0013	0.0172	0.0177	0.9717	0.0012	0.013	7
C2	0.0069		0.0189	0.9092	0.0063	0.068	4

C3	0.0092		0.0182	0.9432	0.0087	0.094	3
C4	0.0259		0.0128	1.3476	0.0349	0.378	1
C5	0.0031		0.0191	0.9015	0.0028	0.031	6
C6	0.0263		0.0136	1.2599	0.0331	0.359	2
C7	0.0058		0.0189	0.9106	0.0053	0.057	5
Sum					0.0923	---	

Upon examining Table 4, the ranking of the criterion weights is determined as C4, C6, C3, C2, C7, C5, and C4. As part of the study's findings, an illustrative solution for determining the weight of C1 is provided.

Normalized Value:

$A1 \rightarrow C_1 : Equ.12 \coloneqq 74{,}7/83{,}9 = 0{,}890$

$$\boldsymbol{Equ.16}: \boldsymbol{CV} = \begin{bmatrix} 0.890 \\ 0.938 \\ 0.979 \\ \cdots \\ \dots \\ \dots \\ 1 \\ 0.749 \\ \cdots \\ \dots \\ \dots \\ 1 \\ 0.810 \end{bmatrix} = 0.0172$$

$$\boldsymbol{Equ.17}: \boldsymbol{SV_{C_1}}\ (\boldsymbol{C_1} \notin \boldsymbol{Criteria}) = \begin{bmatrix} 1 \\ 0.749 \\ 0.938 \\ \cdots \\ \dots \\ \dots \\ 0.875 \\ 0.945 \\ \cdots \\ \dots \\ \dots \\ 1 \\ 0.820 \end{bmatrix}$$

$= 0.0177$

$$\boldsymbol{Equ.22}: \boldsymbol{VEM_{C_1}} = \frac{0.0172}{0.0177} = 0{,}9717$$

$$\boldsymbol{Equ.24}: \boldsymbol{WV_{C_1}} = 0.0013 * 0.9717 = 0.0012$$

$$\boldsymbol{Equ.25}: \boldsymbol{w_{C_1}} = \frac{0.0012}{0.0923} = 0.013$$

3.2. Sensitivity analysis (Duyarlılık analizi)

A robust method for assessing the sensitivity of weighting techniques involves introducing new alternatives into the original dataset or excluding less favorable ones. In such scenarios, the MCDM approach is expected to maintain stability by ensuring that the rankings of criteria remain largely consistent or experience minimal changes [49]. Given that the removal of any criteria modifies the criterion values, the scores assigned to the remaining alternatives are also likely to change (Rank reversal). To address this issue, a sensitivity analysis was conducted, beginning with the criteria identified as the least significant by the proposed method. The results of this analysis, including the revised criteria rankings, are detailed in Table 5, while a graphical representation is provided in Figure 2.

Table 5. Rank of criteria in scope of rank reversal method (Ters sıralama yöntemi kapsaında kriterlerin sıralaması)

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

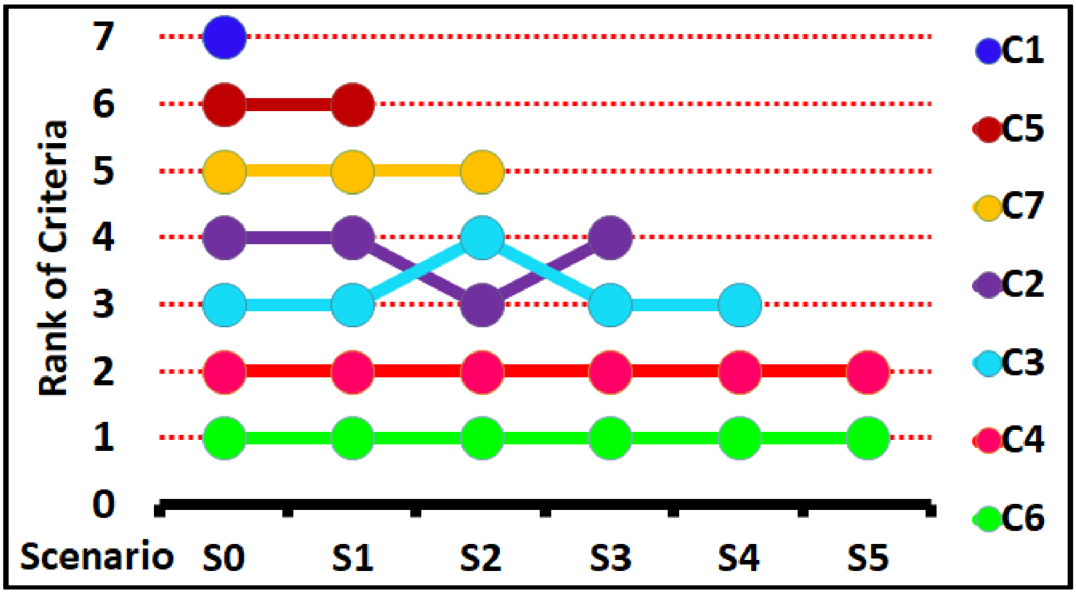

Figure 2. Rank reversal graph (Ters sıralama grafiği)

The rank reversal analysis conducted based on Table 5 and Figure 2 aims to evaluate the ranking stability and sensitivity level of the proposed ESVP method. Within this scope, the criteria were sequentially eliminated from the system in ascending order of their weight values, and changes in the rankings of the remaining criteria were examined at each scenario. The reference scenario, denoted as S0, includes all seven criteria and serves as the baseline for comparison across subsequent scenarios. In scenario S1, the criterion with the lowest weight, C1, was removed from the system. This elimination did not induce any changes in the ranking positions of the remaining criteria, indicating that the method maintains a high level of stability against the exclusion of low-impact elements. In scenario S2, where C5 the second least weighted criterion was additionally removed alongside C1, a minor shift was observed: criterion C2 moved from the fourth to the second position, while C3 dropped from third to fourth. Nevertheless, this change did not result in a structural disruption, and the overall ranking integrity was largely preserved. Scenario S3 involved the removal of C1, C5, and C7. Despite these exclusions, the rankings of the remaining four criteria remained unchanged, reflecting a consistent internal structure. Similarly, in scenario S4, where criterion C2 was further excluded, the rankings of the remaining three criteria were entirely unaffected. Finally, in scenario S5, following the elimination of C3 in addition to the aforementioned criteria, only C4 and C6 remained in the system, and their relative positions were maintained identically across all prior scenarios. These findings clearly demonstrate that the proposed method exhibits a high degree of robustness against the rank reversal phenomenon, with the ranking structure remaining substantially intact despite the sequential removal of criteria. The extraction of criteria induced only minimal and localized effects on the ranking outputs, suggesting that the method provides a stable and reliable analytical framework for decision-makers. Particularly noteworthy is the fact that even when criteria are removed from the least to the most significant in terms of weight, the method yields highly consistent results. This outcome affirms the ideal sensitivity characteristics of the ESVP method and its strong performance in stability-driven analyses.

3.3. Comparative analysis (Karşılaştırma analizi)

The comparative analysis evaluates the relationships and relative positions of the proposed approach against other methods used for determining weight values. The goal of the proposed method is to establish its reliability, consistency, and compatibility with widely accepted techniques, while also demonstrating a strong and statistically significant correlation with various weighting methods [18].

In the initial stage of the comparative analysis, criterion weights were calculated using ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC methods, which are commonly employed in MCDM studies. As a result, the weight values of the GEHI criteria and their respective rankings, as determined by these weighting methods, are presented in Table 6 and Figure 3.

Table 6. Weight scores of criteria (Kriterlerin ağırlık skorları)

Methods	CRITIC		SVP		LOPCOW		SD		ENTROPY		MEREC	
	S.	R.	S.	R.	S.	R.	S.	R.	S.	R.	S.	R.
C1	0.120	7	0.016	7	0.179	2	0.074	7	0.011	7	0.063	6
C2	0.156	2	0.088	4	0.112	7	0.121	4	0.072	4	0.100	5
C3	0.145	4	0.117	3	0.193	1	0.153	3	0.092	3	0.213	1
C4	0.129	6	0.330	2	0.115	5	0.284	1	0.367	2	0.194	2
C5	0.150	3	0.040	6	0.124	4	0.080	6	0.030	6	0.052	7
C6	0.162	1	0.335	1	0.163	3	0.188	2	0.371	1	0.186	4
C7	0.138	5	0.074	5	0.114	6	0.100	5	0.057	5	0.191	3

S.: Score. **R.:** Rank

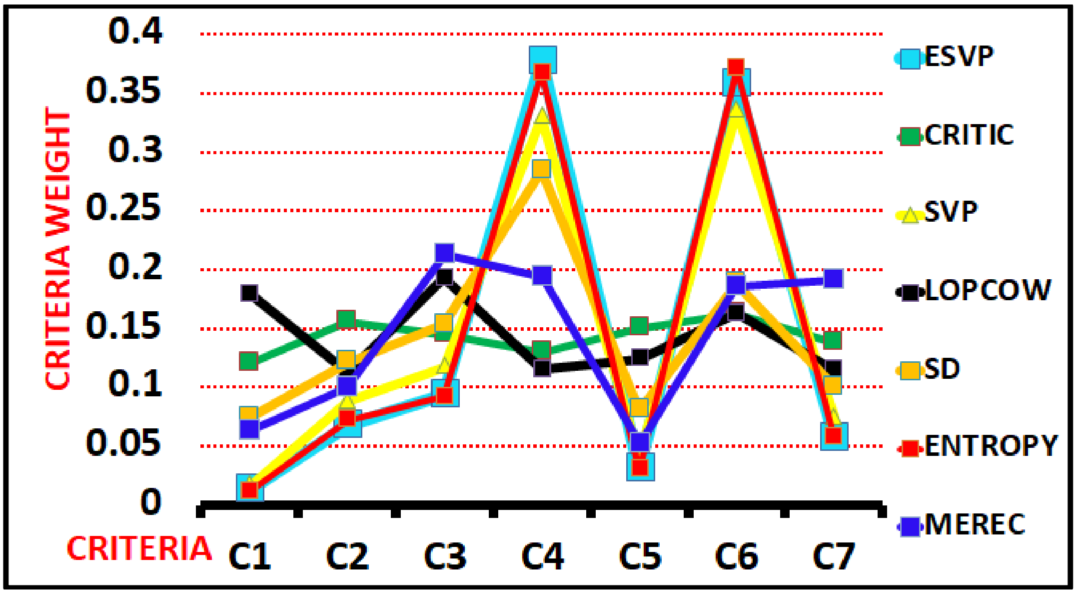

Figure 3. Positions of weighting methods (Ağılıklandırma yöntemlerinin pozisyonları)

When Table 4, Table 6, and Figure 3 are jointly examined, it becomes evident that the ranking of criterion weights produced by the proposed ESVP method closely aligns with those generated by the ENTROPY and SVP methods, and also demonstrates a high degree of similarity with the SD method. Particularly in terms of the upward and downward fluctuations observed across criteria, the trend patterns of the ESVP method exhibit a notable parallelism with those of the ENTROPY approach. Furthermore, the ESVP method shows significant structural proximity to information-theoretic models such as SVP and SD, and when evaluated from a broader perspective, it also displays meaningful overlaps with the MEREC method. From a graphical standpoint, both the ESVP and ENTROPY methods assign nearly identical maximum weights to criteria C4 and C6, suggesting a strong convergence in their discriminative capabilities. Similarly, for low-weighted criteria such as C1 and C5, both methods exhibit nearly identical value assignments. These findings clearly indicate that the ESVP method is highly correlated with ENTROPY, while also maintaining structural consistency with the SVP, SD, and, to a significant extent, the MEREC approaches. Based on these observations, it can be concluded that the ESVP method offers a robust and methodologically consistent alternative to established weighting models. The correlation coefficients (rho values) between the ESVP and other methods are comprehensively presented in Table 7. These results reveal that the ESVP method demonstrates strong and statistically meaningful associations with well-established information-based techniques in the literature, thereby affirming its validity, reliability, and suitability as a sound analytical tool for multi-criteria decision-making applications.

Table 7. rho correlation score (rho korelasyon skorları)

Methods	CRITIC	SVP	LOPCOW	SD	ENTROPY	MEREC
ESVP	0.286	0.964**	-0.071	0.998**	0.964**	0.714**

p**<.01

An analysis of the correlation coefficients presented in Table 7 reveals that the proposed ESVP method demonstrates a strong and statistically significant positive correlation with the SVP, SD, and ENTROPY methods, and to a slightly lesser but still meaningful extent with the MEREC method. In particular, the correlation coefficients with SVP, SD, and ENTROPY exceed 0.96 and are statistically significant at the $p < .01$ level, clearly indicating that the ESVP method exhibits a robust structural alignment with these information-theoretic models. Furthermore, the correlation with MEREC also suggests a substantial degree of concordance, underscoring that the ESVP approach is consistent not only with information-based techniques but also with broader objective weighting strategies. In contrast, the relatively low or even negative correlation coefficients observed with the CRITIC and LOPCOW methods suggest that these techniques are structurally divergent from the ESVP framework, likely due to fundamental differences in their underlying variance and distribution-based paradigms. When these findings are evaluated holistically, it becomes evident that the ESVP method offers both a high level of explanatory power and a statistically robust foundation that meets essential reliability and validity criteria. This demonstrates that ESVP represents a methodologically sound and credible alternative within the context of comparative model evaluation. Therefore, considering the quantitative results obtained through the comparative analysis, it can be confidently asserted that the proposed ESVP method is both credible and reliable, making it a viable and effective tool for multi-criteria decision-making applications.

3.4. Simulation analysis (Simülasyon analizi)

In the simulation examination, diverse scenarios were created by varying the values within the decision matrices. To evaluate the robustness of the proposed method's results, it is hypothesized that its outputs will increasingly deviate from those of other methods as the number of scenarios expands. Additionally, the method's capacity to distinguish criterion weights, based on variance, is expected to demonstrate robustness. Moreover, the consistency of these criterion weight variances across the scenarios will be examined using Analysis of Means for variances based on Levene’s test (ADM analysis). For the proposed method to be considered stable, homogeneity of variance across all scenarios is crucial [18]. In this study, an initial set of ten scenarios (decision matrices) was generated and subsequently partitioned into two separate groups. Following this, correlation coefficients between the proposed method and other weighting methods were computed for these generated scenarios. The resulting correlation values are displayed in Table 8 and Figure 4.

Table 8. Correlation scores in scope of scenarios (Senaryolar kapsamında korelasyon skorları)

Group	Scenarios	CRITIC	SVP	LOPCOW	SD	ENTROPY	MEREC
First	Sce.1	0.296	0.971**	-0.063	0.998**	0.971**	0.743**
	Sce.2	0.299	0.969**	-0.055	0.999**	0.968**	0.737**
	Sce.3	0.281	0.941**	-0.046	0.999**	0.961**	0.701**
Second	Sce.4	0.277	0.933**	-0.059	0.994**	0.955**	0.711**
	Sce5	0.287	0.948**	-0.065	0.995**	0.941**	0.692**
	Sce.6	0.255	0.923**	-0.079	0.973**	0.927**	0.677**
	Sce.7	0.230	0.891**	-0.088	0.951**	0.912**	0.651*
	Sce.8	0.222	0.882**	-0.093	0.934**	0.900**	0.628*
	Sce.9	0.206	0.867**	-0.106	0.911**	0.884**	0.604*
	Sce.10	0.189	0.855**	-0.115	0.892**	0.879**	0.589*

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

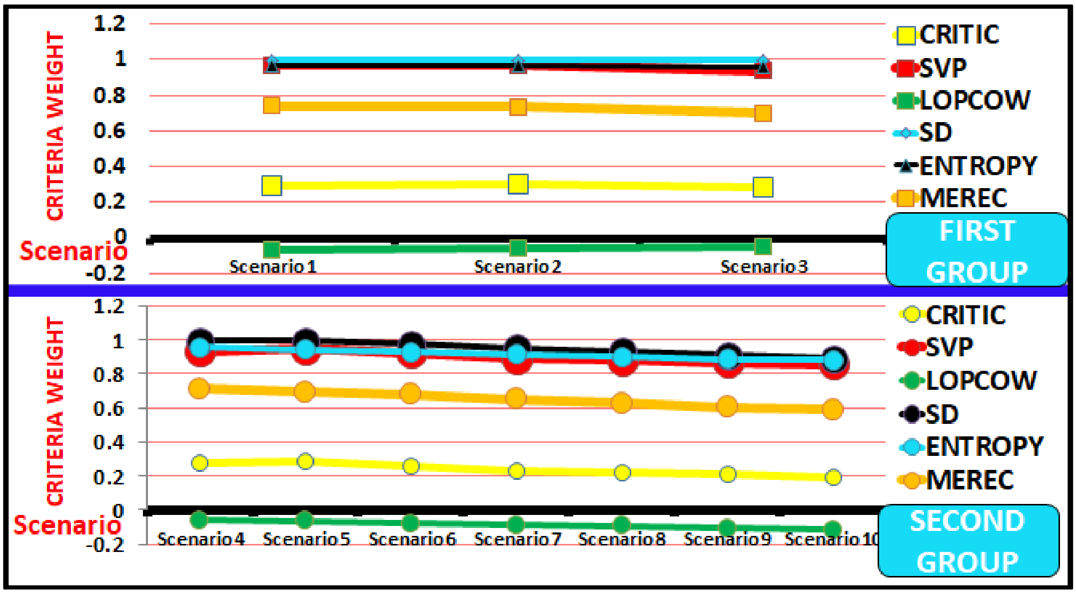

Figure 4. Correlation positions (Korelasyon posizyonları)

In the scope of the simulation analysis, both Table 8 and Figure 4 collectively provide compelling evidence regarding the dynamic behavior and methodological robustness of the proposed ESVP method under varying decision environments. As clearly depicted in Figure 4, the graphical trends across the ten simulated scenarios reveal a noticeable divergence between the ESVP method and several established MCDM weighting techniques. Particularly, in the second group of scenarios (Scenarios 4–10), the relative position of ESVP becomes more distinguishable, indicating an increasing deviation in performance patterns as the diversity and complexity of decision matrices expand. This observation is quantitatively supported by the correlation coefficients presented in Table 8. While the ESVP method maintains strong and statistically significant correlations with ENTROPY, SD and SVP) in the first group of scenarios, these correlations gradually diminish in the second group. For instance, the correlation between ESVP and SVP drops from 0.971 in Scenario 1 to 0.855 in Scenario 10, and the correlation with MEREC decreases from 0.743 to 0.589. This consistent downward trend signifies that the ESVP method exhibits an adaptive sensitivity to structural shifts within the decision matrices, thereby allowing its unique methodological characteristics such as contrast-based differentiation and variance-aware weighting to surface more explicitly as scenario complexity increases. Moreover, the variance-based analytical structure of ESVP appears to provide enhanced discriminative power, especially under diverse simulation conditions where traditional methods tend to converge or exhibit relatively static weighting behavior. The graphical separation observed in Figure 4 reinforces the assertion that the ESVP method maintains a stable internal variance distribution while simultaneously amplifying inter-methodological contrasts. This dual capacity is critical for achieving both robustness and flexibility in real-world multi-criteria decision-making applications. Taken together, these findings confirm that the ESVP method not only aligns with conventional techniques under standard conditions but also surpasses them in terms of interpretability and responsiveness in more challenging and variable contexts. The progressive divergence observed across scenarios further validates the methodological integrity of ESVP, establishing it as a robust and adaptive tool for criterion weighting in complex decision environments. As part of the comparative examination, the variance of the weight values for each method was calculated across the generated scenarios. Accordingly, the variance values of the methods developed for the scenarios, along with the average variance value, are presented in Table 9.

Table 9. Variance Scores in scope of sscenarios (Seneryolar kapsamında varyans skorları)

Methods	ESVP	CRITIC	SVP	LOPCOW	SD	ENTROPY	MEREC
Scenario1	0.147	0.018	0.129	0.037	0.071	0.149	0.066
Scenario2	0.144	0.045	0.134	0.049	0.079	0.151	0.078
Scenario3	0.148	0.063	0.141	0.066	0.088	0.144	0.099
Scenario4	0.139	0.039	0.115	0.041	0.059	0.145	0.045

Scenario5	0.139	0.028	0.128	0.089	0.045	0.155	0.049
Scenario6	0.145	0.071	0.144	0.077	0.099	0.172	0.055
Scenario7	0.141	0.073	0.119	0.069	0.088	0.129	0.066
Scenario8	0.147	0.081	0.125	0.101	0.129	0.131	0.099
Scenario9	0.159	0.028	0.133	0.093	0.131	0.148	0.101
Scenario10	0.161	0.041	0.149	0.111	0.133	0.156	0.093
Mean	0.147	0.049	0.132	0.073	0.092	0.148	0.075

The variance scores presented in Table 9 were evaluated to compare the performance of the proposed ESVP method with six other objective weighting approaches—namely, CRITIC, SVP, LOPCOW, SD, ENTROPY, and MEREC across a series of distinct scenarios. For each of the ten scenarios, variance values were computed to assess the extent to which each method distinguishes between criterion weights, thereby reflecting their discriminative power. In this context, the mean variance value of the ESVP method (0.147) was found to be significantly higher than those of CRITIC (0.049), SVP (0.132), LOPCOW (0.073), SD (0.092), and MEREC (0.075). This finding indicates that the ESVP method produces a more pronounced and differentiated distribution of criterion weights, allowing for sharper discrimination of relative importance levels among the criteria. Such a capability enhances decision-makers' ability to make more accurate choices, particularly in multi-criteria decision-making problems that demand high sensitivity and precision. Moreover, the average variance value of ESVP is found to be almost identical to that of the ENTROPY method (0.148), suggesting that both methods possess comparable levels of discriminative strength. However, ESVP demonstrates a more balanced distribution of variance across the evaluated scenarios, implying a greater degree of consistency and robustness under varying conditions.In conclusion, the ESVP method stands out not only for its high mean variance but also for its consistent performance across multiple scenarios, offering both discriminative accuracy and structural stability. These attributes position ESVP as a more reliable, interpretable, and methodologically sound alternative compared to other objective weighting techniques currently available, thereby reinforcing its practical value as a decision-support tool in complex multi-criteria environments. In the final phase of the simulation analysis, the homogeneity of variance for the criterion weights generated by the proposed method was evaluated using Analysis of Means for variances based on Levene's test (ADM analysis). This technique provides a graphical framework for assessing variance consistency. The graphical output comprises three primary elements: the overall mean ADM, depicted as the center line, along with the upper decision limit (UDL) and the lower decision limit (LDL). If the variance of a given group or cluster fall outside these decision boundaries, it indicates a statistically significant deviation from the overall mean ADM, signifying variance heterogeneity. Conversely, if the variance of all groups remain within the interval defined by the UDL and LDL, it confirms variance homogeneity [18]. Figure 5 illustrates the graphical results of the ADM analysis.

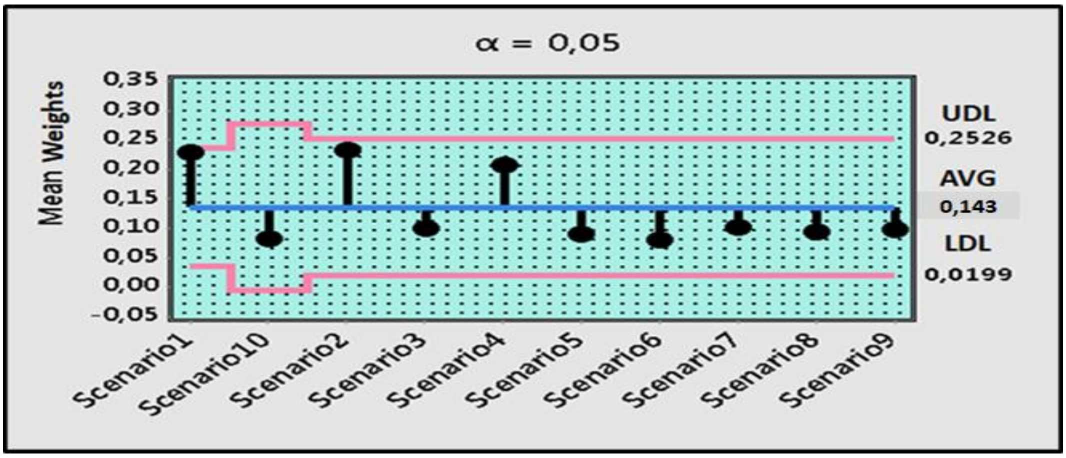

Figure 5. ADM Chart (ADM görseli)

The ADM chart presented in Figure 5 visually illustrates the mean variance scores of criterion weights across ten distinct scenarios. The chart includes three key reference lines: the average value line (AVG = 0.143), displayed as a horizontal blue line; the upper decision limit (UDL = 0.2526); and the lower decision limit (LDL = 0.0199), both indicated with pink lines. Each scenario's ADM value is represented by black dots accompanied by error bars. Upon examination of the graphical analysis, it becomes evident that all ADM values across the scenarios fall strictly within the defined decision interval (UDL–LDL). This finding indicates that the variance scores do not deviate significantly from the overall average and confirms that the weighting process remains structurally stable regardless of scenario-specific changes. These results strongly support the conclusion that the criterion weights exhibit consistency across different scenarios and that the outputs produced by the method adhere to the principle of homogeneity. This visual evidence clearly demonstrates the presence of variance homogeneity, indicating that the weighting mechanism functions reliably and remains unaffected by scenario-based fluctuations. Furthermore, this conclusion was statistically validated by Levene's test, with the detailed results comprehensively presented in Table 10.

Table 10. Levene score (Levene skoru)

Levene Statistic	df1	df2	Sig. (p)
0.130	2	10	0.149

p**<.05

Serving as the statistical complement to the visual assessment provided by the ADM chart, Table 10 presents the results of Levene's test, a widely recognized statistical procedure for evaluating the equality of variances. The test produced a Levene statistic of 0.130, with degrees of freedom (df1 = 2, df2 = 10), and a corresponding p-value of 0.149. As this p-value exceeds the conventional 0.05 threshold of statistical significance, the null hypothesis of equal variances cannot be rejected. This outcome indicates that there is no statistically significant difference in the variances of the criterion weights across the evaluated scenarios, suggesting a homogeneous distribution. This finding statistically substantiates the conclusions previously inferred from Figure 5, providing strong empirical support that the distribution of criterion weights does not exhibit meaningful variation across scenarios. When jointly evaluated with the ADM chart, the outcome of Levene's test confirms that the proposed method possesses a high level of structural robustness and consistency with respect to variance homogeneity. Taken together, these results clearly demonstrate that the proposed approach is capable of maintaining stability under varying conditions, thereby substantially enhancing its reliability and applicability in the context of MCDM problem.

4. DISCUSSION (TARTIŞMA)

It is clear that the proposed method offers a more comprehensive structure compared to the classical SVP method. While the classical SVP method performs weighting by considering the deviations of the criteria (Öztel and Alp, 2020), the proposed method evaluates the overall effects of each criterion. This approach ensures a more accurate identification of the contributions of the criteria to the contrast situations, which is central to the logic of weighting methods, and enables more accurate results in the decision-making process. When compared to other objective weighting methods, the proposed method demonstrates various strengths and weaknesses. One significant advantage over the ENTROPY method is the proposed method's insensitivity to zero and negative values. In the ENTROPY method, zero and negative values can create uncertainty due to logarithmic measurements (Ayçin, 2019). However, the ENTROPY method may be more effective in information-theory-based analyses (Öztel and Alp, 2020). The ENTROPY method determines criterion characteristics solely through entropy, disregarding other criteria's values. Consequently, criterion weights derive exclusively from their inherent entropy distributions (internal distribution) (Bircan, 2020). Conversely, the proposed method evaluates criteria by incorporating both their inherent values and those of other criteria, thus considering both internal and external distributions.

Compared to the CRITIC method, one of the key advantages of the proposed method is its ability to determine the contrasts of the criteria without relying on any distribution assumptions. The CRITIC method uses the Pearson correlation coefficient to evaluate the correlations between criteria (Diakoulaki et al., 1995), which is based on the assumption of a normal distribution. In datasets that do not follow a normal distribution, there could be limitations in this correlation coefficient

(Kalaycı, 2013). Therefore, the proposed method offers more reliable results regardless of the type of distribution. On the other hand, the CRITIC method may perform better in datasets with strong correlation structures (Ecer, 2020). However, from a technical perspective, the CRITIC method's determination of the internal distribution of the criteria by standard deviation (σ) and its external distribution based on the Pearson correlation coefficient between criteria (impact factor-(1-p)) is consistent with the logic of the proposed method within the framework of integrity ($(\sigma.\sum_{i=1}^{m}(1-p))$.

Compared to the SVP method, the proposed method provides a more comprehensive evaluation by considering both internal and external distributions. While the SVP method focuses solely on the variances of the criteria (Öztel and Alp, 2020), the proposed method offers a more detailed analysis of both the internal distribution and the contribution of contrasts within the criteria in a holistic context. However, the SVP method can be applied more quickly to large datasets due to its simpler calculations (Demir et al., 2021).

When compared to the MEREC method, one limitation of the MEREC method is its sensitivity to zero and negative values due to logarithmic calculations. However, such a restriction is not present in the proposed method. Specifically, in the MEREC method, the performance of each criterion corresponding to an alternative's cell is calculated using a nonlinear logarithmic function. Then, after removing the criterion, the performance of the alternatives is recalculated. The effect of each criterion is determined by examining the difference between the performance of the criterion's corresponding cell and the performance of the alternatives after the criterion is excluded (Keshavarz-Ghorabaee et al., 2021). Thus, in the MEREC method, the internal distribution of each criterion (internal distribution) and its effect on the overall dataset (external distribution) are considered, which is in line with the logic of the proposed method. The primary difference between these methods lies in the approach: in the MEREC method, the performance of the decision alternatives is considered after the criteria are removed, whereas in the proposed method, the performance of the criteria themselves is considered after they are excluded.

When compared to the LOPCOW method, the proposed method provides a more comprehensive evaluation by considering not only the internal values of the criteria but also the distributions of other criteria. The LOPCOW method can reduce gaps caused by the data dimensions and can offer advantages in certain decision problems (Ecer and Pamucar, 2021). However, the holistic approach of the proposed method ensures a more robust analysis of the contrasts between the criteria. Nevertheless, the proposed method has some disadvantages. It requires a more complex computation process compared to other objective weighting methods, which increases the computational burden when working with large datasets. Specifically, in decision problems with a high number of criteria and alternatives, the increased computation time may limit the practical applicability of the method. Moreover, excessive skewness and kurtosis in the data may lead to disproportionately large differences between the criterion weights. In this context, to establish a more comprehensive framework regarding the distributional characteristics of the dataset, future studies should consider calculating the skewness and kurtosis coefficients for each criterion and reporting them alongside descriptive statistics. Such a practice would significantly enhance the methodological transparency and overall credibility of the ESVP method. This extension is particularly valuable for evaluating the method's applicability in datasets that deviate from parametric assumptions or exhibit distributional irregularities.

In cases where extreme skewness or kurtosis is observed, it is advisable to apply appropriate preprocessing techniques to mitigate the influence of these distortions. Specifically, data transformations such as logarithmic transformation, Box–Cox transformation, or Winsorization may be employed to normalize the distributions of criterion values and limit the impact of outliers. Additionally, the integration of robust variance estimators or trimmed statistical measures into the ESVP framework could serve as an adaptive enhancement, enabling the method to produce stable and reliable results even in non-parametric environments. These methodological refinements would preserve the ESVP method's distinctive sensitivity to meaningful variance structures, while simultaneously preventing artificial inflation of criterion weights due to distributional anomalies thereby reinforcing the overall trustworthiness and analytical soundness of the method for decision-makers operating in diverse evaluation contexts. In general, The ESVP proposed in this study has been specifically designed to address the methodological shortcomings identified in the classical SVP approach. ESVP offers a more balanced, discriminative, and structurally robust weighting mechanism by considering not only the internal variance structure of each criterion, but also the degree of contrast and variance potential among all criteria. In doing so, the method enhances the theoretical soundness and practical applicability of the SVP model, effectively mitigating its limited recognition and susceptibility to criticism. In this regard, ESVP strengthens the scientific credibility of SVP and introduces a novel framework that facilitates its integration with other MCDM approaches, thereby expanding its methodological scope and interdisciplinary relevance.

Future research should focus on enhancing the ESVP method's applicability. This includes evaluating its performance with large-scale datasets, improving computational efficiency via AI and optimization integration, and assessing its robustness in uncertain environments through fuzzy logic, grey system theory, or fuzzy number incorporation. Comparative analyses with other MCDM methods are crucial to determine its suitability across diverse problem types. Potential application areas include sustainability, finance, supply chain, and healthcare, where its sectoral integration can be demonstrated. Finally, evaluating ESVP's adaptability to dynamic decision-making, particularly in contexts with evolving criteria, will establish its long-term effectiveness. These future studies aim to solidify ESVP's strengths and advance its contribution to MCDM.

5. CONCLUSIONS (SONUÇLAR)

This study introduces an extended SVP (ESVP) method for criterion weighting processes, offering a novel perspective to the existing literature. The primary contribution of this work is the development of a more comprehensive weighting approach that not only considers the internal distributions of individual criteria but also accounts for their contributions to the overall variance with other criteria.

Based on the research findings, the sensitivity level of the proposed method was tested using the rank reversal method. After eliminating certain criteria, only minor changes in the ranking were observed, indicating that the proposed method maintains an optimal level of sensitivity. Secondly, to assess the reliability and validity of the proposed method, a comparative analysis was conducted in line with the approach suggested by Keshavarz-Ghorabaee et al. (2021) [18]. In this analysis, criterion weights were calculated using commonly used objective weighting methods in the literature, such as ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW. The results revealed that the proposed method exhibited a high correlation with ENTROPY, SVP, SD, and MEREC, while showing deviations particularly from LOPCOW. The strong correlation between the proposed method and ENTROPY, SVP, SD, and MEREC can be attributed to the fact that these methods evaluate the internal variation of each criterion independently. Specifically, as the differences in variance values between criteria increase, the distinctness of the proposed method becomes more pronounced compared to ENTROPY, SD, and SVP. This is because, according to the findings, as scenarios progress, the correlation values of the proposed method with other methods decrease. On the other hand, while the proposed method accounts for external differentiation by considering the effects of all criteria in the entire dataset, other methods, except for CRITIC and MEREC, focus on the individual internal values of the criteria. In the simulation examination, to assess the stability and robustness of the proposed method, ten different decision matrices (scenarios) were created, and an ANOM analysis suggested by Keshavarz-Ghorabaee et al. (2021) [18] was conducted. The results indicated that the variance remained homogeneous across all ten scenarios, confirming the stability of the proposed method.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS’ CONTRIBUTIONS (YAZARLARIN KATKILARI)

***Furkan Fahri ALTINTAŞ*:** He conducted the calculations, analyzed the results and performed the writing process.

Hesaplamaları yapmış, sonuçlarını analiz etmiş ve maklenin yazım işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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