Research Article GU J Sci, Part A, 12(2): 445-478 (2025) 10.54287/gujsa.1673755

Gazi University
Journal of Science
PART A: ENGINEERING AND INNOVATION
http://dergipark.org.tr/gujsa

A Novel Technique for Criteria Weighting in Multi-Criteria Decision-Making: Tanimoto Contrast Approach (TCA)

Furkan Fahri ALTINTAŞ[1*]

[1] *Aydın Provincial Gendarmerie Command, Aydın, Türkiye*

Keywords

Tanimoto Similarity
Tanimoto Contrast
MCDM
Criteria Weight

Abstract

This study introduces the Tanimoto Contrast Approach (TCA), a novel objective method for determining criterion weights in Multi-Criteria Decision-Making (MCDM) problems. Built on the internal–external dispersion logic of the CRITIC method, TCA replaces Pearson correlation with Tanimoto similarity to capture both linear and non-linear relationships, enabling a more comprehensive evaluation of inter-criterion contrasts and similarities. The method was tested using the 2024 Global Innovation Index data from selected seven countries. Sensitivity analysis revealed that TCA maintains ranking stability under varying conditions, while comparative analysis showed strong correlation with ENTROPY, SVP, and MEREC methods, confirming its reliability and credibility. In addition, simulation analysis based on ten different decision matrix scenarios demonstrated that TCA produces high average variance and consistent, homogeneous weight distributions evidence of its robustness and stability. TCA's advantages include distribution free applicability, insensitivity to zero or negative values, scale independence, and effectiveness with large datasets. Moreover, its comparative performance against widely used objective weighting methods such as ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW has been thoroughly discussed. In conclusion, TCA offers contrast-based, decision-maker-independent weighting framework that generates meaningful, balanced, and sensitive results. Its integration into MCDM applications provides a valuable contribution to the advancement of objective weighting techniques.

Cite

Altıntaş, F.F., (2025). A Novel Technique for Criteria Weighting in Multi-Criteria Decision-Making: Tanimoto Contrast Approach (TCA). *GU J Sci, Part A*, *12*(2), 445-478. doi:10.54287/gujsa.1673755

Author ID (ORCID Number)		Article Process	
0000-0002-0161-5862	Furkan Fahri ALTINTAŞ	**Submission Date**	10.04.2025
		Revision Date	13.05.2025
		Accepted Date	21.05.2025
		Published Date	30.06.2025

1. INTRODUCTION

Criterion weighting is a critical component in Multi-Criteria Decision Making (MCDM), as it defines the relative importance of each criterion, effectively structuring decision-making processes (Ecer, 2020; Thakkar, 2021). Objective weighting methods, rooted in data-driven analysis, mitigate subjectivity and enhance consistency, contrasting with subjective approaches prone to bias (Baş, 2021; Zardari et al., 2014). Thus, advancing innovative objective weighting techniques is vital to accurately model criterion interdependencies and improve decision-making precision (Bircan, 2020; Demir et al., 2021).

In this context, this study introduces a novel analytical framework, the Tanimoto Contrast Approach (TCA), which determines criterion weights by scrutinizing spatial contrasts among criteria and leveraging Tanimoto similarity. The assessment of contrast in TCA adopts a methodology analogous to that of the CRITIC method,

*Corresponding Author, e-mail: furkanfahrialtintas@yahoo.com

albeit with notable divergences. CRITIC is utilized as the foundational framework owing to its established reliability in quantifying criterion contrasts (Ecer, 2020). Furthermore, Tanimoto similarity is integrated into the approach due to its efficacy in accurately and consistently capturing the relationships between variables (Sharma & Lal, 2011; Chung et al., 2019). By incorporating Tanimoto similarity, the proposed methodology facilitates the development of diverse algorithms and models grounded in both distances (contrasts) and similarities (Surendran et al., 2025).

The primary motivation behind the proposed method is to assess sensitivity through sensitivity analysis at an ideal level, to evaluate credible and reliable results through comparative analysis, and to measure robustness and stability through simulation analysis. Another aim of the study is to highlight the advantages of the proposed method. Furthermore, there has been no study in the existing MCDM literature that uses Tanimoto similarity in determining criterion weights. In this context, the proposed method integrates Tanimoto similarity based on the CRITIC technique and is the first study to apply this approach in criterion weighting. This study makes a significant contribution to the MCDM literature, particularly in the areas of criterion weighting and Tanimoto similarity. In the materials and methods section of the study, various objective criterion weighting methods are first explained, followed by a detailed description of how Tanimoto similarity is applied and the advantages of the proposed method. Finally, the findings are discussed, and the results of the study are summarized and concluded.

2. MATERIAL AND METHOD

2.1. Some Objective Criteria Weighting Methods and Their Characteristics

Subjective weight coefficients are frequently determined by the decision-makers' personal experiences and judgments, thus reflecting inherent individual biases. Consequently, these coefficients can vary substantially among different decision-makers (Baş, 2021). Typically, these weights are assigned based on expert opinions. However, relying exclusively on expert evaluations may introduce biases and inaccuracies into the decision-making process (Bircan, 2020). Conversely, objective methods disregard the subjective inconsistencies and uncertainties present in decision-makers' inputs. These methods employ mathematical models and utilize data derived from the decision matrix to ascertain the criterion weights. Essentially, objective weighting techniques prioritize the inherent structural properties of the data during the evaluation process (Demir et al., 2021).

In the realm of MCDM, a variety of objective weighting methodologies are employed, including CRITIC (Criteria Importance Through Inter-criteria Correlation) (Dhara et al., 2022; Momena et al., 2024), ENTROPY (Eligüzel & Eligüzel, 2024; Wang et al., 2023), SVP (Statistical Variance Procedure) (Tayalı & Timor, 2017; Nasser et al., 2019), SD (Standard Deviation) (Baydaş, et al., 2024; Mukhametzyanov, 2021), MEREC (Method Based on Removal Effects of Criteria) (Yazdi et al., 2025; Sehgal et al., 2025), and LOPCOW (Logarithmic Percentage Change-driven Objective Weighting) (Durdu, 2025; Yasin et al., 2025). The CRITIC method, notably, operates on the principle of leveraging the inherent information within a system. A fundamental tenet of CRITIC is that a criterion's significance is directly proportional to its variability or distinctiveness in relation to other criteria (Diakoulaki et al., 1995). Consequently, CRITIC places a strong emphasis on the interrelationships among criteria. The methodology involves analyzing correlations between criteria to identify any inconsistencies or contradictions (Ulutaş & Topal, 2020). These are subsequently addressed by applying weights derived from the standard deviation, thereby facilitating the computation of appropriate weights for each criterion (Ecer, 2020). The process commences with the construction of a decision matrix, followed by the normalization of its constituent values (Aydemir, 2025). Upon completion of the normalization, the correlations between the criteria are evaluated to determine their respective weights (Sleem et al., 2023).

The ENTROPY methodology offers a structured and impartial framework for ascertaining the relative significance of criteria within decision-making processes. This technique commences with the development of a decision matrix, succeeded by the calculation of normalized values (Ayçin, 2019). Subsequently, the ENTROPY metric is employed to evaluate the degree of indeterminacy or irregularity associated with each criterion, thereby quantifying the informational content it contributes (Dinçer, 2019). This approach utilizes the standardized values and the derived ENTROPY metric. The said metric is determined by the ratio of the negative sum of the product of each criterion's standardized value and the natural logarithm of that standardized value to the natural logarithm of the number of alternatives (Ulutaş & Topal, 2020). This approach augments objectivity in weight assignment, empowering decision-makers to conduct more equitable and evidence-based assessments (Baş, 2021).

The SD technique determines criterion weights by quantifying the dispersion of each criterion's values relative to its arithmetic mean (Öztel & Alp, 2020). Initially, the decision matrix undergoes normalization to achieve data standardization. Subsequently, the standard deviation for each criterion is calculated, and these values are then utilized to derive the corresponding weights (Uludağ & Doğan, 2021).

Conversely, the SVP methodology establishes criterion weights by computing the variance of each criterion based on the data within the decision matrix (Dinçer, 2019). Given the criteria exhibiting higher variance are assigned greater weights, reflecting their amplified influence on the overall decision-making framework (Öztel & Alp, 2020).

The LOPCOW employs a multifaceted approach to ascertain optimal weights, while simultaneously striving to mitigate disparities between the most and least influential criteria (Keleş, 2023). This methodology also accounts for the interrelationships among criteria. Initially, a decision matrix is constructed, and its values are subsequently normalized. Following this, the mean squared value, expressed as a percentage of the standard deviation for each criterion, is computed to minimize the impact of variations in data scale. This process culminates in the calculation of weight coefficients for each criterion (Ecer & Pamucar, 2022).

The MEREC initiates its process, analogous to other weighting methodologies, with the creation and normalization of a decision matrix. Subsequently, the aggregate performance indices of decision alternatives are calculated utilizing a framework grounded in natural logarithmic functions. Following this, these performance indices are refined by factoring in the contribution of each decision alternative, with iterative recalculations performed employing the natural logarithm (Keshavarz-Ghorabaee, et al., 2021). In the concluding stage of the methodology, criterion weight coefficients are derived by quantifying the removal effect of each criterion, specifically through the summation of absolute deviations. Furthermore, as the influence of a criterion on decision alternatives escalates, its corresponding weight coefficient also increases, thereby ensuring a more representative and reflective weighting paradigm (Popović et al., 2022).

2.2. Tanimoto Similarity

Tanimoto similarity is a statistical measure that numerically expresses the similarity between two sets. It is commonly used to assess the overlap and differences between sets, especially in binary data, where the presence or absence of a feature is represented by 1 or 0, respectively (Lipkus, 1999). This measure plays a critical role in various fields such as information retrieval (Zainudin & Nurjana, 2018; Thiel et al., 2014), recommendation systems (Selvi & Sivasankar, 2018; Vivek et al., 2018), bioinformatics (Mulia et al., 2018), and data mining (Anastasiu & Karypis, 2017; Paulose et al., 2018).

Tanimoto similarity can be calculated in two forms: set-based and vector-based. In the set-based Tanimoto similarity, the similarity between two sets is calculated by dividing the number of common elements (the intersection count) by the difference between the union count of the two sets and the intersection count, as shown in Equation 1. In the vector-based Tanimoto similarity, the similarity between two sequences or sets is measured by the ratio of the sum of the products of corresponding quantities in different sets to the difference between the sum of the squares of the individual quantities in each set, as demonstrated in Equation 2 (Bajusz et al., 2015).

P: $\{p_1, p_2, p_3 \ldots.. p_n\}$: First cluster, $Q\{q_1, q_2, q_3 \ldots.. q_n\}$: Second cluster, $P \cap Q$: The intersection of sets P and Q, $|P|$: The cardinality of set P, $|Q|$: The cardinality of set Q.

$$T(P,Q) = \frac{P \cap Q}{|P| + |Q| - P \cap Q} \tag{1}$$

$$T(P,Q) = \frac{P.Q}{\|P\|^2 + \|Q\|^2 - P * Q} = \frac{\sum_{i=1}^{n}(P_i * Q_i)}{\left(\sqrt{\left(\sum_{i=1}^{n}(P_j)^2\right)}\right)^2 + \left(\sqrt{\left(\sum_{i=1}^{n}(Q_j)^2\right)}\right)^2 - \sum_{i=1}^{n}(P_i * Q_i)} \tag{2}$$

Tanimoto similarity is metric offers several advantages over other similarity methods. First, Tanimoto similarity allows for the evaluation of common components between data points not only in terms of directional similarity but also considering magnitude differences (Zhang et al., 2015). For example, while cosine similarity measures the similarity between two vectors based on the angle between them (Mana & Sasipraba, 2021). Tanimoto similarity provides a more comprehensive comparison by considering both the intersection and the union of sets (Surendran et al., 2025). This characteristic ensures more accurate and reliable measurements, particularly in large datasets.

Another significant advantage of Tanimoto similarity is its ability to work with both binary data and vectors containing continuous variables (Bero et al., 2018). While methods like cosine similarity typically perform better with continuous vectors, and Jaccard similarity is mainly useful for set-based analysis (Zahrotun, 2016), Tanimoto similarity combines the strengths of both methods, making it applicable to both categorical and numerical data. In contrast to cosine similarity, which focuses only on the direction of vectors and disregards magnitude differences, Tanimoto similarity accounts for both direction and magnitude, offering a more holistic similarity analysis. This is especially beneficial when working with weighted vectors, as Tanimoto similarity allows for more accurate evaluations (Kryszkiewicz, 2013). Compared to Jaccard similarity, Tanimoto similarity is particularly stronger when working with continuous variables (Sankara et al., 2011). While Jaccard measures the proportion of common elements between sets, relying solely on presence/absence information, it can fall short in vector-based calculations (Kryszkiewicz, 2013). Tanimoto similarity, however, is compatible with numerical data and works effectively with both binary and continuous variables, giving it a broader range of applicability.

Euclidean distance, which measures the direct distance between two data points, is sensitive to different measurement scales (Dokmanic et al., 2015) and may not provide meaningful results in high-dimensional datasets. Tanimoto similarity, however, focuses on the density of shared components between datasets or vectors rather than direct distance, making it a more reliable comparison method in high-dimensional data (Lasek & Mei, 2019). It can produce more meaningful results, especially in large data analysis and compound similarity assessments, when compared to Euclidean distance.

Mahalanobis distance, which takes correlations between variables into account when calculating similarity (Iglesias & Kastner, 2013) requires high computational costs and may not be efficient with large datasets. Tanimoto similarity, on the other hand, offers a more scalable approach as it is based directly on the intersection and union of components, providing a faster and more effective similarity measure, especially in large-scale machine learning and bioinformatics applications (Baldi & Benz, 2008).

Minkowski distance, a general form of Euclidean distance that can be customized with different parameters (Xu et al., 2019), still compares vector magnitudes directly and does not consider the intersection-union relationship Tanimoto similarity, by considering both the distance between data points and the degree of overlap, provides more reliable results in object-based similarity analysis. Additionally, Tanimoto similarity offers scalability advantages when applied to large datasets, enabling efficient computations. The intersection and union-based calculation method ensures that similarity analysis can be performed without accuracy loss, even in datasets with numerous variables. Furthermore, Tanimoto similarity is more robust to noise. While other similarity metrics may show significant differences when there are minor deviations or missing data in a dataset, Tanimoto similarity provides a more stable measure, making it a valuable tool in biological data analysis (Mellor et al., 2019), chemical compound comparisons (Ma et al., 2011) and document similarity calculations. In conclusion, Tanimoto similarity stands out as a more flexible, comprehensive, and reliable method compared to other similarity metrics. Its ability to work with both binary and continuous data, scalability, robustness to noise, and precise measurement based on intersection-union ratios make it an effective analytical tool across various scientific fields.

A review of the literature reveals numerous studies focusing on Tanimoto similarity. Mohebbi et al. (2022) utilized Tanimoto similarity in the QSAR modeling of a ligand-based pharmacophore derived from Hepatitis B virus surface antigen inhibitors. Ying et al. (2021) applied Tanimoto similarity in improving the chemical structure elucidation process using Morgan Fingerprints. Kryszkiewicz (2021) employed Tanimoto similarity to identify similarity neighborhoods of real-valued vectors through triangle inequalities and length boundaries. Shan et al. (2025) evaluated ionic liquid toxicity using machine learning and structural similarity methods with Tanimoto similarity. Feldmann and Bajorath (2022) used Tanimoto similarity to calculate exact Shapley values for support vector machines. Yoon and Lee (2025) leveraged Tanimoto similarity in silico screening to discover new compounds for focal adhesion kinase activation using virtual screening, AI-based prediction, and molecular dynamics. Ahmad et al. (2025) applied Tanimoto similarity in developing a data mining and machine learning-based model for optimal materials for perovskite and organic solar cells. Yoshizawa et al. (2025) utilized Tanimoto similarity in creating a data-driven generative strategy to avoid reward manipulation in multi-target molecular design. Nowatzky et al. (2025) applied Tanimoto similarity for local neighborhood-based prediction of compound mass spectrometric data from a single fragmentation event. Feldmann et al. (2025) used Tanimoto similarity in the uncertainty analysis of neural fingerprint-based models.

2.3. Proposed Method (Tanimoto Contrast Approach-TCA)

In the determination of criteria weights, the distinctiveness and contrasts among criteria are fundamental in defining their inherent characteristics. The proposed method shares a conceptual similarity with the CRITIC method in its underlying logic. The CRITIC approach posits that a criterion's importance is directly proportional to its degree of contrast. Consequently, a criterion's significance increases with greater standard deviation and lower correlation with other criteria, indicating a higher degree of contrast (Ecer, 2020).

The proposed method emphasizes the uniqueness and oppositional nature of criteria, highlighting their distinguishing attributes. It employs Tanimoto similarity values to quantify the degree of contrast between criteria. Tanimoto similarity assesses the numerical proximity of criteria within a vector space. According to this principle, smaller differences within a criterion's numerical series imply closer proximity to other criteria in the vector space, resulting in a lower degree of contrast series (Bajusz et al., 2015). Conversely, the CRITIC method utilizes Pearson correlation coefficients, which rely on the proportional relationship between criteria's numerical series (Diakoulaki et al., 1995). For example, if a criterion with a sequence of relatively small values exhibits a similar progression to another criterion with larger values, a significant and positive correlation is inferred.

The CRITIC method determines each criterion's weight by multiplying its internal and external distributions. The internal distribution, representing a criterion's variability, is quantified by its standard deviation. The external distribution, reflecting a criterion's divergence from others, is measured by summing the differences between one and the Pearson correlation coefficients between the given criterion and all others (Diakoulaki et al., 1995). The fundamental formulation of the CRITIC weighting mechanism is expressed in Equations 3, 4, and 5 (Ayçin, 2019; Dinçer, 2019).

r_{ij}: Correlation coefficient between the $j-th$ and $j-th$ criteria

σj: Standard deviation of the $j-th$ criterion $(j = 1, 2, \ldots, n)$

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

p_{jk}: It indicates the correlation coefficient between any criterion *j* and criterion *k*.

$$p_{jk}=\frac{\sum_{i=1}^{m}(r_{ij}-\overline{r_j}).(r_{ik}-\overline{r_k})}{\sqrt{\sum_{i=1}^{m}(r_{ij}-\overline{r_j})^2.(r_{ik}-\overline{r_k})^2}}\ j,k=1,2,\ldots,n \tag{3}$$

$$\sigma_j=\sqrt{\frac{\sum_{i=1}^{m}(r_{ij}-\overline{r_j})^2}{m-1}} \tag{4}$$

$$C_j=\sigma_j.\sum_{i=1}^{m}\left(1-r_{ij}\right)\ j=1,2,\ldots,m \tag{5}$$

As shown in Equation 3, term σ_j represents the internal contrast of each criterion, reflecting the dissimilarity among its own values, while term $\sum_{i=1}^{m}\left(1-r_{ij}\right)$ represents the external contrast, indicating the dissimilarity of each criterion relative to all others. The product of σ_j and $\sum_{i=1}^{m}\left(1-r_{ij}\right)$ determines the spatial dispersion of each criterion, thereby establishing its weight (Diakoulaki et al., 1995). The proposed method employs a weighting mechanism conceptually aligned with the CRITIC approach. Specifically, internal contrast in the proposed method is measured by σ_j, and external contrast, representing dissimilarity with other criteria, is quantified by $\sum_{i=1}^{m}\left(1-r_{ij}\right)$ (Diakoulaki et al., 1995), consistent with the CRITIC method's logic. Therefore, in the proposed method, each criterion's weight is calculated by multiplying its internal distributions $\left(\sigma_j\right)$, with its external dispersion $\left[\sum_{i=1}^{m}\left(1-r_{ij}\right)\right]$, derived from the dissimilarity or distance based on Tanimoto similarity values (i.e., the external contrast among the criteria's own value distributions). The model illustrating the implementation steps of the proposed method within this scope is presented in Figure 1, while the corresponding mathematical procedures are meticulously detailed below.

GU J Sci, Part A 12(2) 445-478 (2025) 10.54287/gujsa.1673755

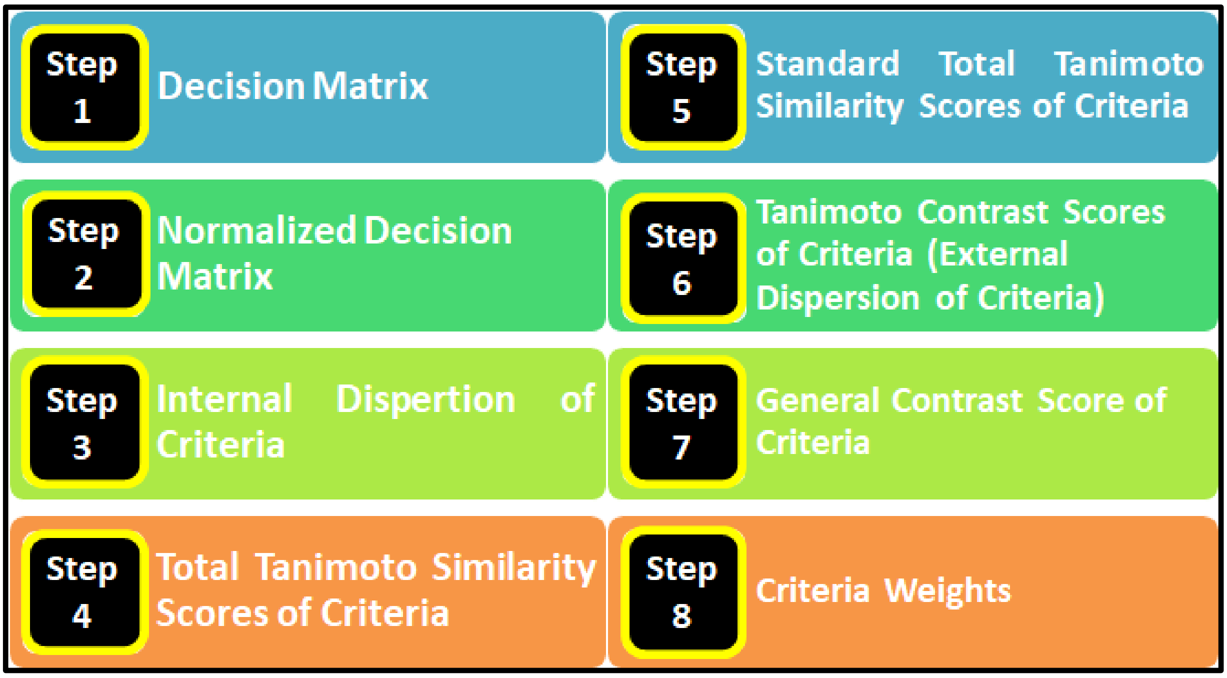

Figure 1. *TCA Model*

Step 1. Obtaining Decision Matrix (X)

In the first step of the proposed method, the decision matrix is constructed using Equation 6, similar to the CRITIC method.

$$DM = [d_{ij}]_{mxn} \begin{array}{c} ALT \\ ALT_1 \\ ALT_2 \\ \vdots \\ ALT_m \end{array} \begin{bmatrix} CRT_1 & CRT_2 & \dots & CRT_n \\ d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \dots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \quad (6)$$

Step 2: Calculation of Normalisation Values of Decision Matrix (d_{ij}^{*})

In the second step of the method, the normalization of the decision matrix values is achieved using Equation 7 for benefit-oriented criteria and Equation 8 for cost-oriented criteria. Subsequently, the normalized decision matrix is constructed using Equation 9, based on the direction of the criteria.

For benefit-oriented criteria:

$$d_{ij}^{*} = \frac{\min(d_{ij})}{d_{ij}} \quad (7)$$

For cost-oriented criteria:

$$d_{ij}^{*} = \frac{d_{ij}}{\max(d_{ij})} \quad (8)$$

Normalized matrix:

$$DM^* = \left[d_{ij}\right]^*_{mxn} = \begin{array}{c} ALT \\ ALT_1 \\ ALT_2 \\ \vdots \\ ALT_m \end{array} \begin{bmatrix} CRT_1 & CRT_2 & \dots & CRT_n \\ d^*_{11} & d^*_{12} & \dots & d^*_{1n} \\ d^*_{21} & d^*_{22} & \dots & d^*_{2n} \\ \vdots & \vdots & \dots & \vdots \\ d^*_{m1} & d^*_{m2} & \dots & d^*_{mn} \end{bmatrix} \quad (9)$$

Step 3: Calculation of Internal Distribution $(ID)_j$ of Critera

In this step, the standard deviation $(SD)_j$ values of each criterion are calculated using Equation 10 to measure the distribution of values within each criterion.

$$(ID)_j = (SD)_j = \sqrt{\frac{\sum_{i=1}^{m}(d^*_{ij} - \overline{d^*_{ij}})^2}{m-1}} \quad (10)$$

Step 4: Calculation of Total Tanimoto Similarity Scores of Criteria $(TTSS)_j$

In the third step, the Tanimoto Similarity Scores $\left((TSS)_{TAN_{CRT_j \to CRT_j}}\right)$ of each criterion with respect to the other criteria are first calculated using the equations provided below. These calculations are performed based on the normalized values and are determined using Equations 11, 12, 13, 14, and 15.

$$CRT \in \{CRT_1, CRT_2, CRT_3 \ldots\ldots CRT_n\} \quad (11)$$

$(1)\ for\ CRT_1$

$$\left(TAN_{CRT_1 \to CRT_2}\right) = \frac{CRT_1 \,.\, CRT_2}{\|CRT_1\| \,.\, \|CRT_2\| - (CRT_1 \,.\, CRT_2)} \quad (12)$$

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

$$\left(TAN_{CRT_1 \to CRT_n}\right) = \frac{CRT_1 \,.\, CRT_n}{\|CRT_1\| \,.\, \|CRT_n\| - (CRT_1 \,.\, CRT_2)} \quad (13)$$

$(n)\ for\ CRT_n$

$$\left(TAN_{CRT_n \to CRT_1}\right) = \frac{CRT_n \,.\, CRT_1}{\|CRT_n\| \,.\, \|CRT_1\| - (CRT_1 \,.\, CRT_2)} \quad (14)$$

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

$$\left(TAN_{CRT_n \to CRT_{n-1}}\right) = \frac{CRT_n \,.\, CRT_{n-1}}{\|CRT_n\| \,.\, \|CRT_{n-1}\| - (CRT_1 \,.\, CRT_2)} \quad (15)$$

Secondly, the Total Tanimoto Similarity Scores of Criteria $(TTSS)_j$ for each criterion are calculated using Equations 16 and 17.

$(1)\ for\ CRT_1$

$$(TTSS)_{CRT_1} = \sum_{j=1}^{(m-1)} \left[\left(TAN_{CRT_1 \to CRT_2} \right) + \cdots + \left(TAN_{CRT_1 \to CRT_n} \right) \right] \tag{16}$$

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

$(n)\ for\ CRT_n$

$$(TTSS)_{CRT_n} = \sum_{j=1}^{(m-1)} \left[\left(TAN_{CRT_n \to CRT_1} \right) + \cdots + \left(TAN_{CRT_n \to CRT_{n-1}} \right) \right] \tag{17}$$

Step 5: Calculation of Standard Total Tanimoto Similarity Scores of Criteria $(STTSS)_j$

In this step, the $(TTSS)_j$ values of each criterion are standardized to the [0,1] range using Equation 18.

$$(STTSS)_j = \frac{(TTSS)_j}{\sum_{j=1}^{n} (TTSS)_j} \tag{18}$$

Step 6: Calculation of Tanimoto Contrast Scores of Criteria $(TCS)_j$(External Dispersion of Criteria: ED_j)

In this step, the $(STTSS)_j$ of the criteria are converted into distance (contrast) values using the method proposed by Todeschini et al. (2007) and formulated in Equation 19. Accordingly, the relationship between similarity and distance is explained in Equation 20.

$$Similarity\ (S) = \frac{1}{1 + Distance\ (Contrast)} = Distance(Contrast) = \frac{1 - S}{S} \tag{19}$$

$$(TCS)_j = \frac{1 - (STTSS)_j}{(STTSS)_j} \tag{20}$$

The method presented in Equation 20 is not confined solely to the [0, 1] interval for similarity and distance measures but is also applicable to all positive similarity and distance metrics beyond this range (Bajusz et al., 2015). This inherent flexibility enables the proposed method to effectively transform similarity and distance values into a standardized [0, 1] scale, establishing it as a robust and comprehensive metric for similarity assessment. In the existing literature, conventional similarity and distance measures are typically restricted to the [0, 1] interval, with transformations predominantly achieved by subtracting the obtained value from 1 (Podani, 2000). However, this conventional approach can introduce metric inconsistencies, particularly in similarity assessments, thereby potentially compromising measurement accuracy. In this context, the transformation framework outlined in Equation 20 transcends the limitations of traditional methods based solely on the subtraction of 1. The proposed method not only addresses measurements within the [0, 1] range but also effectively accommodates a broader spectrum of positive values. Consequently, it provides a more inclusive and integrative perspective on the similarity-distance transformation process. Therefore, in comparison to conventional approaches, the proposed method not only encompasses a wider range of measurements but also facilitates a more accurate and coherent evaluation of the similarity-distance relationship. In this respect, the transformation methodology articulated in Equation 20 not only distinguishes itself from existing methods in the literature but also establishes a more comprehensive and theoretically sound foundation for similarity measurement.

Step 7: Calculation of General Contrast Score of Criteria $\left(GCS_j\right)$

In this step, the Standard Deviation $(SD)_j$ value of each criterion, measured using Equation 10, is multiplied by the TCS_j value presented in Equation 21 to calculate the General Contrast Score $\left(GCS_j\right)$ or External Dispersion values for each criterion. Similar to the weighting logic in the CRITIC method, in Equation 21, SD represents the standard deviation of the self-normalized values of each criterion (i.e., the internal distribution of each criterion's own values), while GCS_j, again as in the CRITIC method, indicates the contrast intensity $\sum_{i=1}^{m}\left(1\text{-}r_{ij}\right)$ of each criterion with respect to the other criteria. Within this scope, similar to the CRITIC method, the overall contrast value of the criteria is measured by multiplying the SD value of each criterion with the total contrast value of that criterion in relation to the other criteria.

$$GCS_j = (SD)_j * \left(GCS_j\right) \tag{21}$$

Step 8: Calculation of Criteria Weightings $\left(w_j\right)$

In the final step of the method, the weights of the criteria are calculated by determining the ratio of each criterion's GCS_j value to the total GCS_j value, as given in Equation 22.

$$w_j = \frac{GCS_j}{\sum_{j=1}^{m} GCS_{j_j}} \tag{22}$$

The proposed criterion weighting method offers an objective, data-driven, and mathematically grounded approach, providing significant advantages in decision-making processes. Its primary strength lies in the ability to determine criterion weights independently of the decision-maker's subjective judgments. As a result, the method can generate consistent and reliable outcomes across various applications. The proposed approach optimizes the weighting process by considering both similarities and dissimilarities among criteria. In this context, the Tanimoto similarity plays a pivotal role by measuring the degree of similarity and contrast between criteria. This prevents the excessive weighting of criteria with high uniqueness or dissimilarity, thereby ensuring a more balanced distribution of weights in terms of informational value. This balanced weighting contributes to a more meaningful and interpretable structure within the decision-making framework. The advantage provided by the Tanimoto similarity enables the method to produce more sensitive and robust results, particularly in MCDM problems. Furthermore, the scale-independence of the method allows for the normalization of criteria with different units of measurement, facilitating comparability and enhancing reliability across diverse data structures. This contributes to a more robust and accurate decision-making process. In addition, the high computational efficiency of the proposed method enables rapid and effective implementation, even on large datasets. Since the proposed method is conceptually based on the weighting logic of the CRITIC method, it has the potential to produce highly correlated results with other widely used objective weighting methods in the literature. This reinforces the reliability and scientific validity of the method. Moreover, its unique structure, which takes inter-criteria relationships into account, offers a novel perspective compared to existing methods and contributes meaningfully to the academic literature. In conclusion, when evaluated within a scientific and systematic framework, the proposed criterion weighting method can be regarded as a valuable approach that enhances objectivity, consistency, and accuracy in decision-making processes. By utilizing mathematical metrics such as Tanimoto similarity to analyze inter-criterion relationships, the method is considered to yield more realistic and reliable results in decision support systems.

Although the proposed criterion weighting method offers several advantages, it also presents certain limitations that may affect its applicability or pose challenges under specific conditions. First, the computational process of the method is relatively complex and requires more mathematical operations compared to traditional approaches. The integration of Tanimoto similarity and other associated calculations can lead to high computational costs, particularly when dealing with complex-scale datasets. This may render the method more time-consuming to implement and necessitate additional computational resources in big data environments. Second, the performance of the method can vary depending on the normalization techniques employed and the inherent characteristics of the dataset. For instance, in cases where an extremely high degree of similarity exists among the criteria, the discriminative power of Tanimoto similarity may diminish. As a result, the method may struggle to accurately reflect the relative importance of such criteria, potentially affecting the reliability of the weighting process. This limitation is particularly relevant in datasets where high correlations exist among multiple criteria, which can reduce the sensitivity of the method.

The proposed TCA method offers several advantages when compared to the widely used CRITIC method. One major limitation of the CRITIC approach lies in its reliance on the Pearson correlation coefficient to capture the contrast among criteria (Ayçin, 2019). The application of this coefficient is constrained by its underlying assumption of normally distributed data (Kilmen, 2015). If the dataset does not meet this assumption, the resulting correlation values may be misleading or incorrect (Kalaycı, 2014). In contrast, the Tanimoto Similarity employed in the TCA method is not subject to such restrictions. It can be effectively applied to datasets regardless of whether they follow a normal distribution, thus providing broader applicability. Secondly, while the Pearson correlation coefficient only measures linear relationships between variables ignoring potential nonlinear patterns (Karagöz, 2014; Özdamar, 2018). However, Tanimoto Similarity offers a more generalized similarity measure that accounts for both linear and nonlinear structures. This characteristic makes the TCA method more flexible and suitable for a wider range of applications, particularly in complex MCDM contexts. However, it is worth noting that the CRITIC method may yield more reliable results in cases where the relationships between criteria are strongly linear. In such scenarios, the use of TCA might introduce a risk of less accurate outcomes due to its sensitivity to complex or nonlinear patterns, whereas CRITIC maintains robustness due to its strong linear correlation-based structure (Diakoulaki et al., 1995). Moreover, the proposed TCA method shares conceptual similarities with the CRITIC approach in terms of its weighting logic. Both methods consider the contrast within individual criteria (internal dispersion) and the contrast between different criteria (external dispersion) in calculating the final criterion weights. This parallel highlights the methodological compatibility of TCA with established objective weighting approaches, while also emphasizing its unique advantages in terms of distributional flexibility and nonlinear relationship handling.

The ENTROPY method is inherently sensitive to negative and zero values due to its reliance on logarithmic calculations. To mitigate this issue, Zhang et al. (2014) proposed the use of Z-Score normalization to convert the dataset into positive values before applying the method. However, this pre-processing step introduces additional computational costs. In contrast, the proposed TCA method is not affected by zero or negative values, thus eliminating the need for such pre-processing and enhancing its computational efficiency. From a methodological perspective, the ENTROPY method evaluates each criterion based solely on its own entropy values, without considering the interrelationships or contrasts with other criteria (Ayçin, 2019). This lack of external interaction may limit its representational comprehensiveness. On the other hand, the TCA method incorporates both internal dispersion (measured via standard deviation) and external contrast between criteria (captured through Tanimoto Similarity). As a result, the TCA method offers a broader analytical scope compared to the ENTROPY method. Similarly, the SD and SVP methods also calculate criterion weights using only the intrinsic statistical properties of each individual criterion standard deviation for SD and variance for SVP (Demir et al., 2021). These approaches, while straightforward, do not account for inter-criterion contrasts. In this regard, the TCA method demonstrates a more comprehensive structure by integrating both intra-criterion and inter-criterion variability. Nevertheless, ENTROPY, SD, and SVP methods maintain an advantage in terms of computational simplicity (Ecer, 2020). Their ease of implementation makes them more practical for certain applications, and the risk of error during the weighting process tends to be lower compared to more complex approaches like TCA. Thus, while TCA offers greater analytical depth, traditional methods may be preferable in contexts where simplicity and efficiency are prioritized.

The LOPCOW method determines criterion weights based on logarithmic computations applied separately to each criterion, aiming to analyze the differences among them (Keleş, 2023). In contrast, the proposed TCA method considers both the similarity and contrast relationships between criteria, enabling a more comprehensive evaluation of their mutual interactions. However, due to its logarithmic formulation, the LOPCOW method is particularly sensitive to subtle differences among criteria (Ecer & Pamucar, 2022). As a result, it can more effectively distinguish between criteria with closely spaced values compared to the TCA method. This sensitivity allows LOPCOW to offer a finer differentiation in weight assignment when the criteria exhibit minimal variation. Therefore, while TCA provides a broader analysis by incorporating inter-criterion relationships, LOPCOW may outperform it in scenarios where a more granular distinction between closely related criteria is essential (Ecer & Pamucar, 2022).

The MEREC method determines criterion weights by analyzing the impact caused by the removal of each individual criterion. In other words, it considers the deviation in overall performance resulting from the exclusion of a specific criterion and computes this impact using a logarithmic function (Keshavarz-Ghorabaee et al., 2021). In contrast, the proposed TCA method does not rely on the removal effect but instead adopts a broader framework by integrating similarity (Tanimoto similarity) and contrast (Total Contrast Score) analyses to assess inter-criterion relationships. Furthermore, because MEREC evaluates the information loss due to the removal of a criterion, it tends to focus on linear dependencies. On the other hand, TCA captures both similarity and contrast simultaneously, enabling it to better model non-linear and more complex relationships among criteria. Additionally, similar to the ENTROPY method, MEREC is sensitive to zero and negative values due to its reliance on logarithmic calculations (Keshavarz-Ghorabaee et al., 2021). Nevertheless, MEREC offers a powerful mechanism for identifying critical criteria. If the removal of a criterion leads to significant changes in the system's performance, MEREC effectively highlights its importance [32]. By contrast, since TCA focuses on general similarity and contrast values, it may not emphasize the importance of such critical criteria as clearly. Finally, because MEREC directly demonstrates the change in the system when a criterion is removed, it provides a more intuitive and interpretable structure for decision-makers [32]. In contrast, the similarity and contrast-based approach of TCA may present interpretative challenges, as the underlying computations are less straightforward and may require additional explanation to fully understand the resulting weights.

2.4. Data Set

This study proposes a method based on Tanimoto similarity to evaluate the weights of criteria within the scope of decision-making problems. The dataset consists of the 2024 Global Innovation Index (GII) criterion values for seven selected countries with varying performance levels. These countries were chosen to ensure that the criterion values do not dominate the performance outcomes and that the differences among alternatives are not excessively large. Accordingly, there are no dominant values for any criterion within the dataset. In this context, the proposed method aims to reveal an ideal differentiation in the weights of the criteria. For clarity, the abbreviations of the countries and the GII criteria are explained in Table 1.

Table 1. *Data Set*

GII Criteria	**Abbreviations**
Institutions	CRT1
Human Capital and Research	CRT2
Infrastructure	CRT3
Market Sophistication	CRT4
Business Sophistication	CRT5
Knowledge and Technology Outputs	CRT6
Creative Outputs	CRT7
Countries/Alternatives (A)	**Abbreviations**
Hungary	ALT1
Türkiye	ALT2
Bulgaria	ALT3
India	ALT4
Poland	ALT5
Thailand	ALT6
Latvia	ALT7

3. RESULTS AND DISCUSSION

3.1. Computational Analysis

In the first step of the proposed method, the decision matrix was constructed using Equation 6, and in the second step, the normalized decision matrix was generated based on Equations 7 and 9. Accordingly, the calculated values are presented in Table 2.

In the third stage of the method, according to Equation 10, the standard deviations of each criterion based on their normalized values were calculated. Accordingly, the internal dispersion $(ID)_j$ of each criterion defined as the contrast among the values within the same criterion was determined through the measurement of these standard deviation values. In the fourth stage of the method, under the first case, the Tanimoto Similarity Scores$\left((TSS)_{TAN_{CRT_j \to CRT_j}}\right)$ between each criterion and the others were calculated using Equations 11, 12, 13, 14, and 15. In the second case, the Total Tanimoto Similarity Scores $(TTSS)_j$ of each criterion were computed using Equations 16 and 17. In the fifth stage, the $TTSS_j$ values of each criterion were standardized using Equation 18, resulting in the Standardized Tanimoto Similarity Scores $(STTSS)_j$. In the sixth stage, the Tanimoto Contrast Scores $(TCS)_j$ or External Dispersion values $(ED)_j$ of each criterion were calculated using

Equations 19 and 20. Subsequently, the General Contrast Scores $(GCS)_j$ for each criterion were computed using Equation 21. Finally, in the last stage of the method, the final criterion weights $(w)_j$ were derived using Equation 22. The calculated values for all these steps are presented in Table 3.

Table 2. *Decision and Normalized Decision Matrix*

Decision Matrix							
G7	**CRT1**	**CRT2**	**CRT3**	**CRT4**	**CRT5**	**CRT6**	**CRT7**
ALT1	52,2	42,9	51	34,1	46,3	35,6	32,1
ALT2	33,3	40	50,2	43,4	31,1	28,6	48,3
ALT3	41,8	32,3	54,4	37,7	32,1	31,7	42,9
ALT4	51,5	34,8	39	52,3	28,1	38,8	32,1
ALT5	44,9	42,6	45,8	33,6	38	28	38,1
ALT6	44,8	30,7	45,8	50,6	35,4	29,8	34,9
ALT7	57,9	39,2	51,3	36,6	35,9	24,2	32,8
Normalized Decision Matrix							
G7	**CRT1**	**CRT2**	**CRT3**	**CRT4**	**CRT5**	**CRT6**	**CRT7**
ALT1	0,638	0,716	0,765	0,985	0,607	0,680	1,000
ALT2	1,000	0,768	0,777	0,774	0,904	0,846	0,665
ALT3	0,797	0,950	0,717	0,891	0,875	0,763	0,748
ALT4	0,647	0,882	1,000	0,642	1,000	0,624	1,000
ALT5	0,742	0,721	0,852	1,000	0,739	0,864	0,843
ALT6	0,743	1,000	0,852	0,664	0,794	0,812	0,920
ALT7	0,575	0,783	0,760	0,918	0,783	1,000	0,979

According to the values presented in the table, the CRT4 criterion was identified as the most significant one, with a weight of 0.334. This was followed by CRT1 (0.127), CRT7 (0.123), CRT5 (0.114), CRT6 (0.112), CRT2 (0.101), and CRT3 (0.090), respectively. The incorporation of three distinct metrics (ID, ED, and GCS) in the determination of criterion weights demonstrates that the TCA method offers a balanced approach in the weighting process. In particular, the fact that CRT4 received the highest weight indicates that this criterion plays a pivotal role in the decision-making process within the TSA framework. Conversely, CRT3, having the lowest weight of 0.090, is shown to be relatively less influential in the evaluation. Within this context, the ranking of criteria based on the weights obtained through the TSA method is as follows: CRT4 > CRT1 > CRT7 > CRT5 > CRT6 > CRT2 > CRT3. This ranking, derived from computations performed on the decision matrix, provides a significant reference point for decision-makers in assessing the relative importance of the criteria involved. The mathematical calculation of the weight value of the CRT1 criterion, based on the proposed method, is presented below.

Table 3. *$SD_j = ID_j$, $TTSS_j$, $STTSS_j$, $TCS_j = ED_j$, GCS_j, and w_j Scores of Criteria*

	ID	ED			GCS_j	w_j	Rank
CRT	$SD_j = ID_j$	$TTSS_j$	$STTSS_j$	$TCS_j = ED_j$			
CRT1	0,140	5,501	0,145	5,888	0,822	0,127	2
CRT2	0,113	5,614	0,148	5,750	0,653	0,101	6
CRT3	0,094	5,262	0,139	6,202	0,585	0,090	7
CRT4	0,328	4,994	0,132	6,589	2,161	0,334	1
CRT5	0,127	5,554	0,147	5,823	0,737	0,114	4
CRT6	0,125	5,559	0,147	5,817	0,725	0,112	5
CRT7	0,132	5,412	0,143	6,002	0,795	0,123	3
Sum		37,895	Sum		6,479	----	-----

Step 2. Normalized Matrix (D^*)

$Equation\ 7$:

$$\frac{33{,}3}{52{,}2} = 0{,}638$$

Step 3. Internal distribution (SD Score) of Criteria $[(SD)_{CRT1} = (ID)_{CRT1}]$

$Equation\ 10$:

$$(SD)_{CRT1} = (ID)_{CRT1} = Equation\ 4 = \frac{[(0{,}638 - 0{,}734)^2 + .. + (0{,}575 - 0{,}734)^2]}{7-1} = 0{,}140$$

Step 4: Calculation of Total Tanimoto Similarity Scores of $CTR1$ $(TTSS)_{CRT1}$

Condition 1: Tanimoto Similarity Scores of $CTR1$ with Other Criteria $\left(TAN_{CTR1\rightarrow CTRj}\right)$

$Equation\ 11-15$:

$$TAN_{CTR1\rightarrow CTR2} = \frac{[(0{,}638*0{,}716)+\cdots+(0{,}575*0{,}783)]}{[(0{,}638)^2+\cdots+(0{,}575)^2]+[(0{,}716)^2+\cdots+(0{,}783)^2]-[(0{,}638*0{,}716)+\cdots+(0{,}575*0{,}783)]} = 0{,}945$$

$$TAN_{CTR1\rightarrow CTR3} = \frac{[(0{,}638*0{,}765)+\cdots+(0{,}575*0{,}760)]}{[(0{,}638)^2+\cdots+(0{,}575)^2]+[(0{,}765)^2+\cdots+(0{,}760)^2]-[(0{,}638*0{,}765)+\cdots+(0{,}575*0{,}760)]} = 0{,}943$$

$$TAN_{CTR1\rightarrow CTR4} = \frac{[(0{,}638*0{,}985)+\cdots+(0{,}575*0{,}918)]}{[(0{,}638)^2+\cdots+(0{,}575)^2]+[(0{,}985)^2+\cdots+(0{,}918)^2]-[(0{,}638*0{,}985)+\cdots+(0{,}575*0{,}918)]} = 0{,}824$$

$$TAN_{CTR1 \to CTR5} = \frac{[(0{,}638*0{,}607)+\cdots+(0{,}575*0{,}783)]}{[(0{,}638)^2+\cdots+(0{,}575)^2]+[(0{,}607)^2+\cdots+(0{,}783)^2]-[(0{,}638*0{,}607)+\cdots+(0{,}575*0{,}783)]} = 0{,}958$$

$$TAN_{CTR1 \to CTR6} = \frac{[(0{,}638*0{,}680)+\cdots+(0{,}575*1)]}{[(0{,}638)^2+\cdots+(0{,}575)^2]+[(0{,}680)^2+\cdots+(1)^2]-[(0{,}638*0{,}680)+\cdots+(0{,}575*1)]} = 0{,}948$$

$$TAN_{CTR1 \to CTR7} = \frac{[(0{,}638*1)+\cdots+(0{,}575*0{,}979)]}{[(0{,}638)^2+\cdots+(0{,}575)^2]+[(1)^2+\cdots+(0{,}979)^2]-[(0{,}638*1)+\cdots+(0{,}575*0{,}979)]} = 0{,}885$$

Condition 2: Total Tanimoto Similarity Scores of $CTR1$ $(TTSS_{(CTR1)})$

$Equation\ 16-17$:

$$(TTSS_{(CTR1)}) = 0{,}945 + 0{,}943 + 0{,}824 + 0{,}958 + 0{,}948 + 0{,}885 = 5{,}501$$

Step 5: Calculation of Standard Total Tanimoto Similarity Scores of CRT1 $(STTSS)_{CRT1}$

$Equation\ 18$:

$$(STTSS)_{CRT1} = \frac{5{,}501}{5{,}501 + (TTSS_{(CTR2)}) + (TTSS_{(CTR3)}) + \cdots (TTSS_{(CTRn)})} = 0{,}145$$

Step 6: Calculation of Tanimoto Contrast Score (TCS_{CRT1}) of CRT1 (External Dispersion of CRT1: ED_{CRT1})

$Equation\ 19-20$:

$$(ED_{CTR1} = TCS_{CTR1}) = \frac{(1-0{,}145)}{0{,}145} = 5{,}888$$

Step 7. General Contrast Score of CTR1 Criteria (GCS_{CTR1})

$Equation\ 21$:

$$GCS_{CTR1} = 0{,}140 * 5{,}888 = 0{,}822$$

Step 8. Weight Score of CTR1 (w_{CTR1})

$Equation\ 22$:

$$w_{CTR1} = \frac{0{,}822}{6{,}479} = 0{,}127$$

3.2. Sensitivity Analysis

Evaluating the resilience of MCDM methodologies often involves the introduction of supplementary criteria or the exclusion of suboptimal options from the initial dataset. Under such circumstances, a robust MCDM framework should exhibit stability, ensuring that the ordinal arrangement of criteria remains relatively consistent (Demir & Arslan, 2022). To scrutinize this particular facet, a sensitivity analysis was executed, commencing with the criteria identified as possessing the lowest relative importance according to the developed methodology. The resultant country rankings derived from this analytical procedure are tabulated in Table 4, and a corresponding visual representation is depicted in Figure 2.

Table 4. *Rank Reversal*

Criteria	S0	S1	S2	S3	S4	S5
GII7	7	0	0	0	0	0
GII5	6	6	0	0	0	0
GII1	5	5	4	0	0	0
GII2	4	4	5	4	0	0
GII4	3	3	3	3	3	0
GII6	2	2	2	2	2	2
GII3	1	1	1	1	1	1

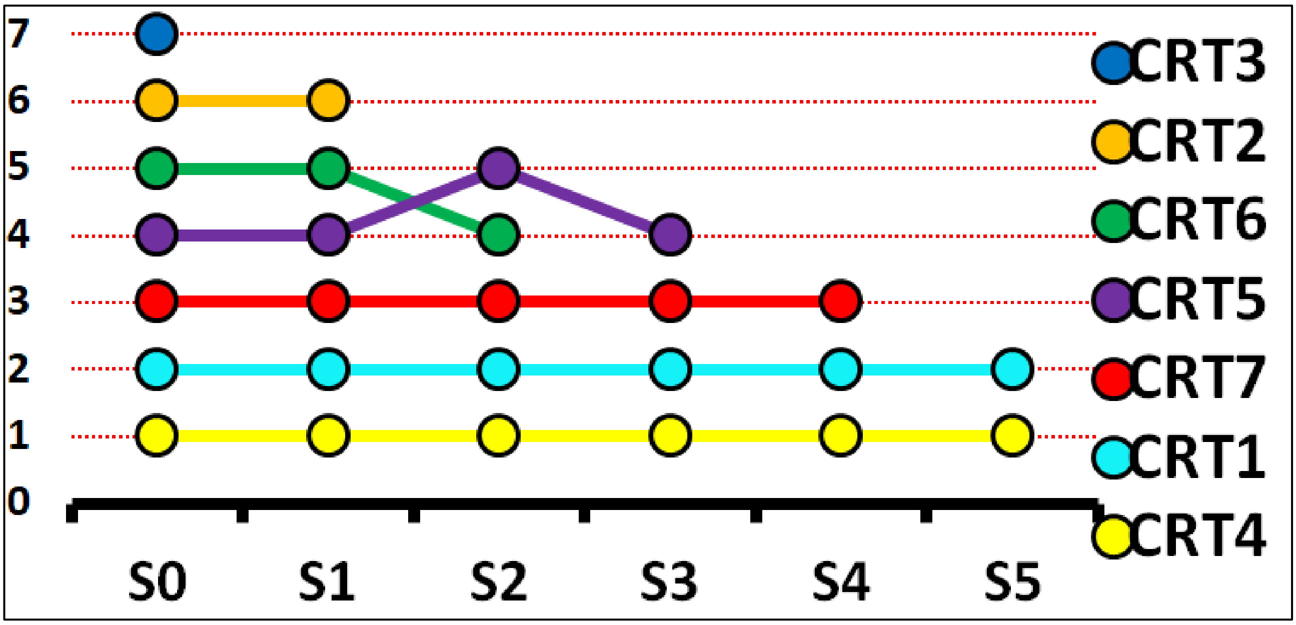

Figure 2. *Rank Reversal Chart*

When Table 4 and Figure 2 are evaluated together, it is observed that the ranking of criteria remains largely stable under certain scenarios. Specifically, in scenarios S1 (when CRT3 is removed), S3 (when CRT3, CRT2, and CRT6 are removed), S4 (when CRT3, CRT2, CRT6, and CRT5 are removed), and S5 (when CRT3, CRT2, CRT6, CRT5, and CRT7 are removed), the rankings of the criteria remain unchanged. This indicates that the proposed method provides a stable structure in terms of overall ranking. However, in scenario S2 (when CRT3 and CRT2 are removed), certain changes occur. In this scenario, the CRT5 criterion moves from the 4th to the 5th position, while the CRT6 criterion rises from the 5th to the 4th position. This change can be attributed to the relatively small difference in the weight values of these two criteria, as shown in Table 4. Therefore, the fact that the sensitivity analysis yields a different result only in scenario S2, while the overall ranking remains largely preserved, supports the robustness of the method in terms of ranking stability. In this context, it is concluded that the proposed TCA method exhibits an optimal level of sensitivity. The results of the sensitivity analysis demonstrate that the method shows only minor variations when specific criteria are removed, while the overall ranking structure remains largely intact. This finding underscores the robustness of the method and reinforces its reliability in decision-making processes.

3.3. Comparative Analysis

This comparative analysis scrutinizes the interrelationships and relative positions of the proposed methodology against established techniques for weight determination. The objective is to validate the proposed method's efficacy, reliability, and consistency with existing approaches, while demonstrating a robust and statistically significant correlation with diverse weighting methodologies (Keshavarz-Ghorabaee et al., 2021). Consequently, the initial stage of this comparative assessment involved the computation of criterion weights using ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC methods, all of which are commonly utilized in MCDM research. The resulting weight values for GII criteria, along with their corresponding rankings, as derived from these weighting methods, are presented in Table 5 and Figure 3.

The proposed TCA method's rankings, based on the Table 3 and Table 5, show varying degrees of consistency with different methods across various criteria. Notably, there is a complete alignment between the TCA and SVP rankings. This suggests that both TCA and SVP adopt a similar approach in determining the criteria weights.

Additionally, the rankings derived from the TCA method exhibit a high degree of consistency with those of the ENTROPY method. This indicates that the TCA method functions in parallel with the ENTROPY method's criterion weighting and ranking approach, producing generally similar results. In contrast, the rankings of the TCA method also exhibit a similar trend when compared to the MEREC method. However, when examining other methods, the TCA rankings show more distinct differences, particularly with CRITIC, SD, and LOPCOW. Specifically, the rankings of these methods diverge noticeably from those of TCA.

Both CRITIC and SD methods assign higher weights to certain criteria, while TCA ranks these criteria lower. In conclusion, the TCA method produces rankings that are more consistent with SVP, ENTROPY, and MEREC methods, while it shows noticeable differences in rankings compared to CRITIC, SD, and LOPCOW. These discrepancies are likely attributable to the different weighting techniques used by each method and the distinct importance assigned to the criteria.

Table 5. *Weight Scores According to Methods*

Criteria	ENTROPY	Rank	CRITIC	Rank	SD	Rank
CRT1	0,177	2	0,117	6	0,130	6
CRT2	0,101	6	0,137	4	0,160	2
CRT3	0,066	7	0,137	3	0,131	5
CRT4	0,199	1	0,191	1	0,164	1
CRT5	0,157	3	0,106	7	0,129	7
CRT6	0,144	5	0,127	5	0,134	4
CRT7	0,156	4	0,184	2	0,153	3
Criteria	**SVP**	**Rank**	**LOPCOW**	**Rank**	**MEREC**	**Rank**
CRT1	0,173	2	0,186	2	0,173	1
CRT2	0,117	6	0,152	3	0,097	7
CRT3	0,078	7	0,204	1	0,107	6
CRT4	0,195	1	0,098	6	0,172	2
CRT5	0,145	4	0,130	5	0,137	5
CRT6	0,143	5	0,151	4	0,160	3
CRT7	0,149	3	0,078	7	0,154	4

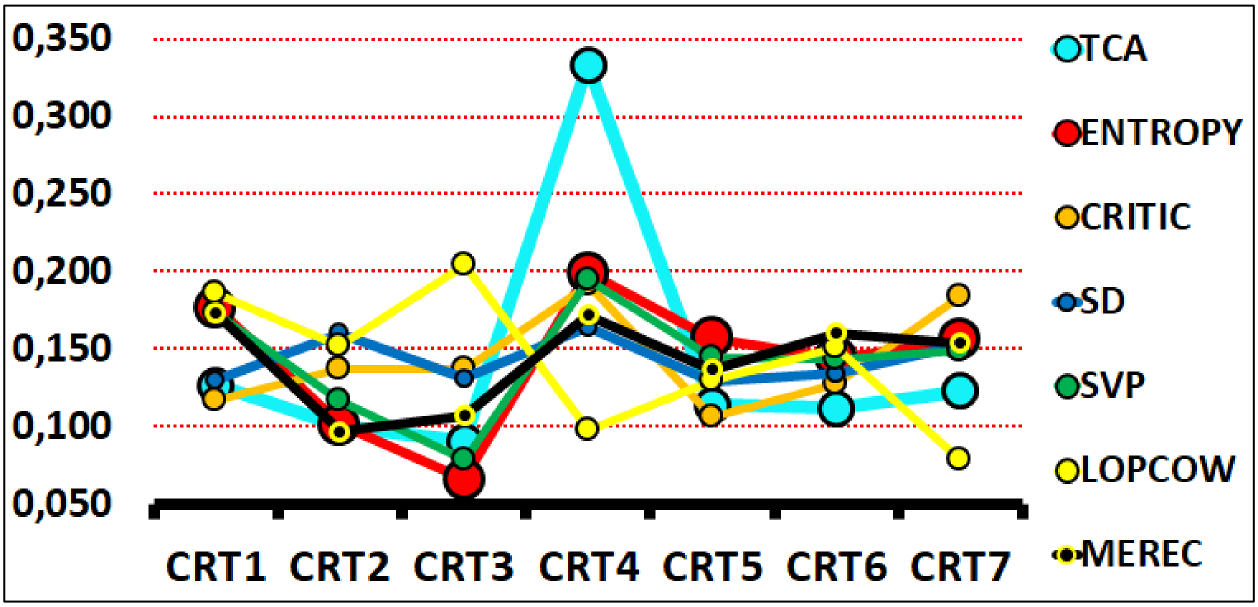

Figure 3. *Position of Methods*

A careful examination of Figure 3 reveals that the proposed TCA method generally exhibits a fluctuating pattern that aligns with other weighting methods (ENTROPY, SVP, and MEREC), with the exception of

LOPCOW, CRITIC, and SD. Specifically, the trends of increasing and decreasing criterion values show a clear parallelism between the TCA method and the other methods. This observation supports the hypothesis that, with the exception of LOPCOW, CRITIC, and SD, the TCA method demonstrates a significant, positive, and high correlation with the other methods. In this context, the correlation values between the TCA method and the other methods are presented in detail in Table 6. This correlation analysis is expected to enhance the understanding of the validity of the proposed method and its relationship with other widely used methods.

Table 6. *rho Correlation Scores-1*

Methods	TCA	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
TCA	1						
ENTROPY	0,964**	1					
CRITIC	0,198**	0,018	1				
SD	0,179**	0,036	0,883**	1			
SVP	0,998**	0,964**	0,198*	0,179	1		
LOPCOW	-0,571*	-0,500*	-0,396*	-0,393*	-0,571*	1	
MEREC	0,821**	0,786**	-0,018	-0,036	0,821**	-0,214	1

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

Upon examining Table 6, this analysis reveals that the TCA method exhibits a significant, high, and positive correlation with the ENTROPY, SVP, and MEREC methods (0.964, 0.998, and 0.821, respectively). This supports the observation in Figure 1 that the fluctuation patterns of the TCA method closely overlap with those of these methods. However, the correlation values between TCA and the CRITIC and SD methods are relatively lower, calculated at 0.198 and 0.179, respectively. These results indicate that the TCA method shows only a limited degree of similarity with these methods. On the other hand, a significant negative correlation (-0.571*) was found between the TCA method and the LOPCOW method. This finding, as seen in Figure 3, confirms that the general trends of the LOPCOW method significantly differ from those of the other methods and are not in parallel with the TCA method. Therefore, this correlation analysis demonstrates that the TCA method generally maintains a meaningful relationship with the ENTROPY, SVP, and MEREC methods, while exhibiting an inverse interaction with the LOPCOW method. This contributes to a better understanding of the compatibility of the proposed method with other commonly used methods. Consequently, the comparative analysis leads to the conclusion that the TCA method is reliable and credible, especially due to its high and significant correlations with the ENTROPY, SVP, and MEREC methods.

3.4. Simulation Analysis

To assess the reliability of the proposed method's findings, a simulation analysis was conducted wherein different values were assigned to the decision matrices to generate various scenarios. It is anticipated that as the number of scenarios increases, the method's results will progressively diverge from those of other criterion weighting methods. In the subsequent phase, the average variance values derived from the proposed method should exceed the variance values calculated by one or more comparative objective weighting techniques. This outcome would affirm the proposed method's capacity to better differentiate the relative importance of the criteria. Ultimately, the variances of the criterion weights measured across the scenarios are expected to demonstrate homogeneity (Keshavarz-Ghorabaee et al., 2021).

In this endeavor, ten distinct scenarios, represented as decision matrices, were initially formulated and partitioned into two discrete groups (First Group: Scenario1, Scenario2, Scenario3, Second Group: Scenario4, Scenario5, Scenario6, Scenario7, Scenario8, Scenario9, Scenario10). Subsequently, the correlation coefficients between the TCA method and other weighting methods were calculated for these scenarios. The results of these correlational analyses are presented in Table 7 and Figure 4.

When Figure 4 and Table 7 are evaluated together, it is observed that the correlation values of the TCA method under different scenarios gradually decrease in comparison to the other methods. Specifically, the initially high correlation values with the SVP, ENTROPY, and MEREC methods show a decline as the number of scenarios increases. In contrast, the correlation with the MEREC method remains generally positive, and although it decreases over time, it stabilizes at a certain level. This indicates that while SVP, ENTROPY, and MEREC provide relatively similar results with the TCA method initially, they begin to diverge as the scenarios increase. The correlation with the CRITIC and SD methods, on the other hand, remains consistently low from the outset. Moreover, a negative correlation is observed between the TCA method and the LOPCOW method. In conclusion, the correlations of the TCA method with other objective weighting methods decrease as the scenarios diversify. Particularly, the negative correlation with the LOPCOW method and the positive but decreasing correlation with SVP, ENTROPY, and MEREC suggest that the TCA method adopts a more characteristic and distinctive structure as the number of scenarios increases.

Table 7. *rho Correlation Scores-2*

Scenarios	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
Scenario1	0,988**	0,212	0,200	0,999**	-0,555*	0,855**
Scenario2	0,993**	0,244	0,209	0,999**	-0,533*	0,875**
Scenario3	0,921**	0,191	0,176	0,995**	-0,558*	0,809**
Scenario4	0,974**	0,182	0,165	0,998**	-0,544*	0,863**
Scenario5	0,908**	0,169	0,151	0,986**	-0,533*	0,843**
Scenario6	0,888**	0,155	0,136	0,974**	-0,505*	0,831**
Scenario7	0,873**	0,144	0,128	0,951**	-0,488*	0,811**
Scenario8	0,859**	0,132	0,125	0,933**	-0,451*	0,802**
Scenario9	0,837**	0,127	0,103	0,921**	-0,439*	0,788**
Scenario10	0,823**	0,118	0,089	0,909**	-0,421*	0,763**

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

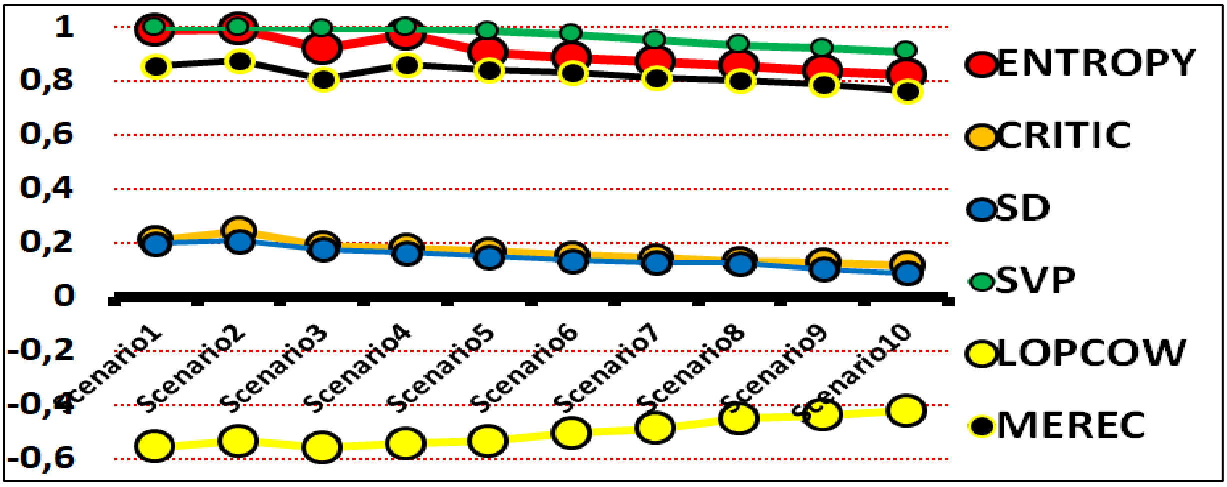

Figure 4. *Correlation Positions*

In the second phase of the simulation analysis, the variance value for each method was calculated under the respective scenarios, and the average variance values for each method were also determined. The relevant calculated values are presented in Table 8.

When the variance values provided in Table 8 are examined, it is observed that the average variance value of the TCA method is 0.00621, which is higher than the average variance values of all other weighting methods. This finding indicates that the TCA method has a greater capacity to distinguish between differences among the criteria. A high variance value for a weighting method implies that the method assigns weights with a broader distribution, thereby allowing for a clearer differentiation between the criteria. The fact that the variance values obtained by the TCA method are higher than those of other methods such as ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC demonstrates that this method can determine the relative importance levels of the criteria more sharply. In this context, the TCA method can be considered as an effective method for identifying the characteristic features of the criteria and revealing the differences between them, as much as other weighting methods. Particularly in analyses where the distinguishing power of the criteria needs to be enhanced, the use of the TCA method may be an appropriate approach.

In the concluding phase of the simulation analysis, the uniformity of variance exhibited by the criterion weights within the TCA methodology was appraised across the spectrum of Levene's test technique. This analytical approach furnishes a visual instrument for evaluating the consistency of variance. The graphical depiction is structured around three pivotal elements: the aggregate mean ADM (ANOM for variances based on Levene), serving as the central benchmark, and the upper decision limit (UDL) and lower decision limit (LDL), which define the boundaries of acceptable variation. Should the variance of any specific group or cluster transcend these decision limits, it signifies a statistically significant departure from the overall mean ADM, thereby indicating heterogeneity of variance. Conversely, if the variance of all clusters remain confined within the UDL and LDL thresholds, it validates the homogeneity of variance. Therefore, the homogeneity of the variances under the scenarios strengthens the robustness and stability of the method. (Keshavarz-Ghorabaee et al., 2021). Figure 5 illustrates the graphical outcomes of this ADM analysis.

Table 8. *Variance Scores of Methods in scope of Scenarios*

Criteria	TCA	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
Scenario1	0,00640	0,00180	0,00099	0,00025	0,00125	0,00189	0,00093
Scenario2	0,00690	0,00190	0,00093	0,00029	0,00129	0,00187	0,00089
Scenario3	0,00550	0,00156	0,00088	0,00016	0,00116	0,00171	0,00077
Scenario4	0,00580	0,00169	0,00079	0,00015	0,00118	0,00168	0,00071
Scenario5	0,00590	0,00181	0,00071	0,00017	0,00119	0,00166	0,00069
Scenario6	0,00530	0,00145	0,00069	0,00013	0,00132	0,00163	0,00078
Scenario7	0,00490	0,00249	0,00074	0,00013	0,00118	0,00165	0,00071
Scenario8	0,00740	0,00178	0,00129	0,00033	0,00135	0,00176	0,00096
Scenario9	0,00710	0,00197	0,00101	0,00031	0,00129	0,00188	0,00091
Scenario10	0,00690	0,00135	0,00122	0,00039	0,00131	0,00191	0,00093
Mean	0,00621	0,00178	0,00093	0,00023	0,00125	0,00180	0,00083

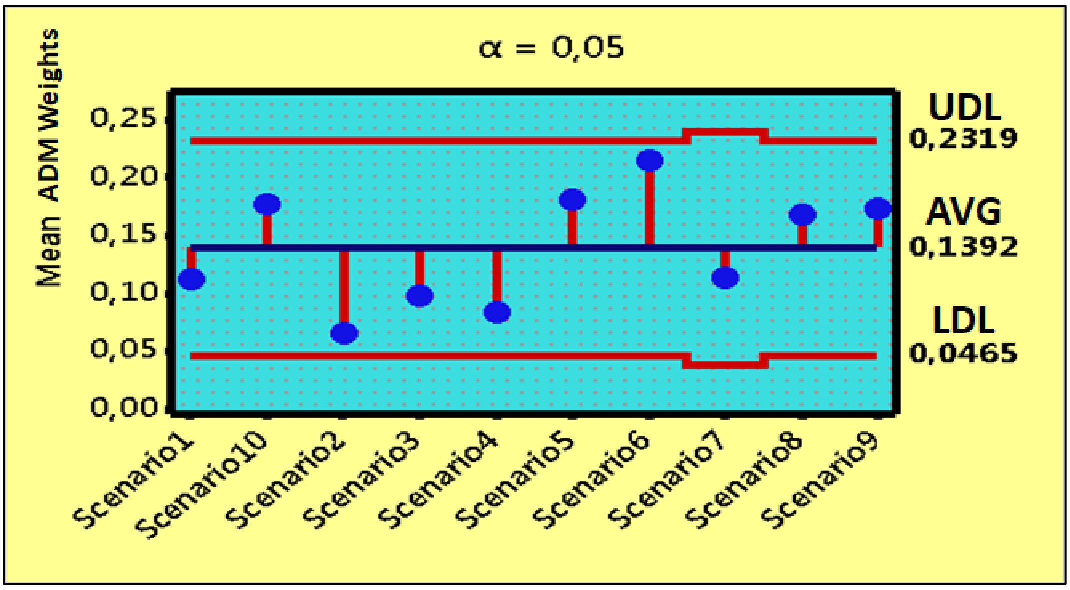

Figure 5. *ADM Chart*

Figure 5 illustrates the distribution of ADM weights calculated under different scenarios. In the graph, the mean ADM weights for each scenario are represented by blue dots, while the upper and lower confidence limits are indicated by red lines. Notably, the ADM weights for all scenarios remain below the Upper Decision Limit (UDL = 0.2319) and above the Lower Decision Limit (LDL = 0.0465). This observation indicates that the computed weights exhibit a stable distribution within the predefined decision boundaries. Additionally, it is evident that the weight values are predominantly concentrated around the Average (AVG = 0.1392) and do not display significant fluctuations. These findings demonstrate that the weighting process obtained through the TCA method does not produce extreme outliers and maintains a generally reliable weighting structure. The fact that the weight values remain consistently within the specified decision boundaries suggests that the method generates stable results across different scenarios and adheres to statistically acceptable variance levels. Accordingly, Levene's test was conducted to assess the homogeneity of variances across the scenarios. The results of the Levene's test are presented in Table 9.

Table 9. *Levene Statistic*

Levene Statistic	**df1**	**df2**	**Sig.**
0,163	2	10	0,241
p*<.05			

Upon examining Table 8, it is observed that the p-value (0.241) is greater than the significance level of 0.05 ($p > 0.05$). This finding confirms that the variance of criterion weights across the scenarios does not exhibit a statistically significant difference, thereby affirming the homogeneity of variances. The homogeneity of variances indicates that the weights calculated by the method do not exhibit substantial variations across different scenarios, ensuring a certain level of stability. Consequently, the simulation analysis concludes that the proposed TCA method demonstrates a robust and stable weighting structure. These findings validate that the method is not only applicable to specific datasets or particular cases but is also reliable for various data structures and scenarios, providing objective weight assignments. Notably, the method consistently produces meaningful results even when the dataset contains distinct similarities and differences. In conclusion, when the findings from both Figure 5 and Table 9 are evaluated together, it is evident that the proposed TCA method ensures statistical homogeneity, reliability, and consistency in determining criterion weights. The weights obtained under different scenarios remained within the defined decision boundaries and did not exhibit excessive fluctuations in terms of variability. The variance homogeneity confirmed by Levene's test supports the applicability of the method across diverse datasets and enhances its scientific credibility.

3.5. Discussion

In the sensitivity analysis of the TCA method, it was observed that changes in alternative rankings were minimal and did not lead to significant deviations in performance values. This finding highlights the method's capacity to produce reliable outcomes in decision-making processes. The success of the TCA method lies in its structure, which incorporates the similarities between criteria, and its balanced weighting process based on Tanimoto similarity. This allows the influence of highly similar criteria to be minimized, bringing forward criteria with higher informational value and resulting in a more stable model. Comparative analyses have assessed the similarities and differences between TCA and other methods such as CRITIC, ENTROPY, SD, SVP, LOPCOW, and MEREC. TCA showed strong positive correlations with ENTROPY, SVP, and MEREC, further supporting its reliability and robustness. In simulation analyses, although correlation values between TCA and other objective methods declined over time, the unique structural characteristics of TCA became more pronounced. The method effectively differentiates criterion weights through high average variance and maintains homogeneity across scenarios. These results demonstrate that TCA is a strong and stable method. Hence, the findings from sensitivity, comparative, and simulation analyses collectively confirm the applicability of the TCA method within the scope of MCDM.

The most prominent advantage of the TCA method lies in its ability to determine criterion weights independently of subjective judgments. This feature enables the production of consistent and reliable results across different applications. Furthermore, by utilizing Tanimoto similarity, the method quantifies the similarities between criteria, thereby preventing excessive weighting and promoting a more balanced weighting and decision-making process. The method's scale independence also allows criteria with different measurement units to be normalized and compared effectively. Additionally, TCA demonstrates high computational efficiency, enabling fast and effective application even with large datasets. However, the proposed criterion weighting method also has certain limitations. First, due to the inclusion of Tanimoto similarity and other computational steps, the method's calculation process can be complex and potentially costly for large datasets. Second, the performance of the method is dependent on the normalization techniques used and the structure of the dataset. Specifically, when criteria exhibit high degrees of similarity, the method's discriminative power may decrease, leading to potential accuracy issues in the weighting process.

Compared to the CRITIC method, the TCA approach does not require the assumption of normal distribution within the dataset and is capable of accounting for non-linear relationships. This characteristic allows TCA to offer a broader applicability, particularly within MCDM processes. While TCA considers contrasts between criteria similar to CRITIC's weighting mechanism, it differs in its theoretical foundations. Considering the Pearson correlation coefficient and its relation to linear regression (Kalaycı, 2014), CRITIC can be deemed more compatible with datasets that exhibit linear structures. On the other hand, the ENTROPY method is sensitive to negative and zero values (Ayçin, 2019), a limitation that does not affect TCA. TCA not only takes into account the individual values of the criteria but also considers the similarities between them. This enables TCA to provide a more comprehensive weighting approach compared to ENTROPY. The SD and SVP methods focus solely on the dispersion of criterion values (Demir et al., 2021), whereas TCA offers a more holistic evaluation by incorporating both similarity and contrast dimensions. Nonetheless, ENTROPY, SD, and SVP provide practical advantages due to their computational simplicity (Demir et al., 2021), while the more complex structure of the TCA method may increase the potential for calculation errors. The LOPCOW method analyzes differences between criteria (Ecer & Pamucar, 2022), while TCA captures both similarities and contrasts, allowing for a more extensive assessment of inter-criteria interactions. However, LOPCOW may be more sensitive to subtle differences between criteria (Ecer & Pamucar, 2022). MEREC, which evaluates the impact of removing each criterion from the system, offers a distinct approach (Keleş, 2023), while TCA combines similarity and contrast assessments to better accommodate non-linear relationships. Although MEREC may be more effective in identifying critical criteria (Keshavarz-Ghorabaee et al., 2021), TCA provides decision-makers with a deeper analytical framework. Additionally, since MEREC directly illustrates the system changes when a criterion is removed, it offers a more intuitive and interpretable structure for decision-makers (Keshavarz-Ghorabaee et al., 2021). In contrast, the similarity and contrast based analysis required by TCA may make it more challenging to clearly explain how results are derived.

The proposed TCA method offers an original contribution to the literature on objective weighting techniques. By utilizing spatial contrasts and Tanimoto similarity to determine criterion weights, TCA introduces a novel perspective distinct from existing methods. This approach enables a more comprehensive evaluation, particularly in complex decision-making scenarios, by modeling different dimensions of inter-criteria relationships. Moreover, by adapting Tanimoto similarity originally used in biology and chemistry to the MCDM domain, the method facilitates interdisciplinary knowledge transfer and incorporates spatial information embedded within the dataset into the evaluation process. In addition, as the proposed method is entirely data-driven, it enhances objectivity and consistency in decision-making processes, offering new opportunities for solving more complex problems. In summary, the proposed TCA method contributes to the literature by introducing a new objective weighting approach, offering a unique perspective on inter-criteria relationships, integrating a novel concept like Tanimoto similarity into the MCDM domain, and utilizing spatial data characteristics for enhanced evaluation. These contributions have the potential to open new avenues for modeling and solving real-world, complex decision-making problems. Furthermore, the TCA method significantly enriches the weighting literature within the scope of MCDM by incorporating a statistical concept Tanimoto similarity into a numerical weighting framework. This interdisciplinary integration strengthens the literature by combining numerical and statistical methodologies. Thus, the TCA method introduces a novel perspective to weighting processes and offers a multidisciplinary approach for addressing more complex and realistic problems, contributing meaningfully to both numerical methods and statistical literature.

4. CONCLUSION

As a result, the TCA method emerges as a scientifically grounded and practically applicable approach for objective criterion weighting in MCDM processes. By integrating the internal variation based on standard deviation with the external contrast structure derived from Tanimoto similarity, the method enables a more detailed and precise evaluation of the contribution of each criterion.

Its resilience to data changes, insensitivity to rank reversal, strong correlation with other objective weighting methods, and consistency observed in simulation environments further reinforce the methodological robustness of the approach. Furthermore, the comparative advantages of TCA over widely used methods in the literature, such as ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC, are noteworthy in terms of interpretability, stability, and comprehensiveness. Therefore, the TCA method can be recommended as an effective tool for decision-makers seeking robust and reliable weighting mechanisms. In conclusion, TCA offers a comprehensive approach among objective weighting methods, particularly excelling in the modeling success of inter-criterion similarities. The method provides decision-makers with a strong alternative, both in terms of its theoretical foundations and practical application outcomes. In this regard, it can be stated that TCA fills a significant gap in the multi-criteria decision-making literature and opens up new perspectives for future research.

Regarding the proposed method, the current study has been conducted on a sample decision problem that includes a limited number of criteria and alternatives. In future research, it would be valuable to test the performance of the TCA method on more complex and multidimensional decision-making problems across various sectors such as sustainability, healthcare, logistics, and public administration. In the logistics sector, the TCA method could be employed to address critical decision-making problems such as distribution center location selection, supply chain optimization, and routing challenges. Given the necessity to evaluate a multitude of alternatives while balancing conflicting criteria, the TCA method offers decision-makers a more objective and comprehensive analytical framework capable of capturing nuanced distinctions among alternatives. Similarly, in the realm of public policy, the TCA method holds significant promise for evaluating the effectiveness of policy alternatives, conducting risk assessments, and determining optimal resource allocation strategies. Considering the inherently multi-criteria nature of public administration processes, the TCA method’s ability to accommodate a broad range of measurement scales provides decision-makers with more granular and reliable insights. In the healthcare sector, the TCA method can serve as a robust tool for assessing healthcare service quality, comparing hospital performance, and optimizing healthcare delivery systems. This methodological approach is particularly valuable in reconciling conflicting criteria such as patient satisfaction, treatment duration, and cost-effectiveness, thereby offering a more holistic perspective in complex healthcare decision-making scenarios. Therefore, future research should focus on systematically exploring the practical applications of the TCA method across diverse sectors, utilizing complex, multi-dimensional decision-making contexts to rigorously validate its effectiveness and further extend its applicability. Such investigations would not only substantiate the method’s practical relevance but also contribute significantly to the broader body of decision-making literature by positioning the TCA method as a comprehensive and versatile decision-support framework. Secondly, subjecting the weights obtained by the TCA method to sensitivity analysis would be beneficial for understanding the stability of the proposed method under different data structures and increased scenario variations. Additionally, the applicability of the TCA method in decision-making environments characterized by uncertainty such as those involving fuzzy logic and grey system theory could be explored to assess its robustness in such contexts. Finally, the integration of TCA derived weights with different MCDM ranking algorithms (e.g., TOPSIS, VIKOR, MAUT, WASPAS, etc.) can be investigated. This would enable the development of more holistic decision support systems where both the weighting and ranking processes are jointly optimized.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

Ahmad, N., Ibrahim, M. A., Sayed, S. R., Shah, S. A., Tahir, M. H., & Zou, Y. (2025). Data mining and machine learning based search for optimal materials for perovskite and organic solar cells. *Solar Energy, 267*, 105-113. https://doi.org/10.1016/j.solener.2024.113223

Anastasiu, D. C., & Karypis, G. (2017). Efficient identification of Tanimoto nearest neighbors. *Int J Data Sci Anal, 4*, 153–172. https://doi.org/10.1007/s41060-017-0064-z

Ayçin, E. (2019). *Çok Kriterli Karar Verme.* Ankara: Nobel Yayın.

Aydemir, M. F. (2025). Evaluation of foreign direct investment attractiveness of BRICS-T countries: The critic-lopcow based aras approach. *Politik Ekonomik Kuram, 9*(1), 372-392. https://doi.org/10.30586/pek.1613421

Bajusz, D., Rácz, A., & Héberger, K. (2015). Why is Tanimoto index an appropriate choice for fingerprint-based similarity calculations? *Journal of Cheminformatics, 7*(20), 1-13. https://doi.org/10.1186/s13321-015-0069-3

Baldi, P., & Benz, R. W. (2008). BLASTing small molecules—statistics and extreme statistics of chemical similarity scores. *BIOINFORMATICS, 24*, 357-365. https://doi.org/10.1093/bioinformatics/btn187

Baş, F. (2021). *Çok Kriterli Karar Verme Yöntemlerinde Kriter Ağırlıklarının Belirlenmesi.* Ankara: Nobel Bilimsel.

Baydaş, M., Elma, O. E., & Stević, Ž. (2024). Proposal of an innovative MCDA evaluation methodology: knowledge discovery through rank reversal, standard deviation, and relationship with stock return. *Financial Innovation, 10*(4), 1-35. https://doi.org/10.1186/s40854-023-00526-x

Bero, S. A., Muda, A. K., Choo, Y. H., Muda, N. A., & Pratama, S. F. (2018). Similarity measure for molecular structure: A brief review. *IOP Conf. Series: Journal of Physics: Conf. Series*(892), 1-9. https://doi.org/10.1088/1742-6596/892/1/012015

Bircan, H. (2020). *Çok Kriterleri Karar Verme Problemlerinde Kriter Ağırlıklandırma Yöntemleri.* Ankara: Nobel Akademik.

Chung, N. C., Miasojedow, B., Startek, M., & Gambin, A. (2019). Jaccard/Tanimoto similarity test and estimation methods for biological presence-absence data. *BMC Bioinformatics, 20*(15), 1-11. https://doi.org/10.1186/s12859-019-3118-5

Demir, G., & Arslan, R. (2022). Sensitivity analysis in multi-criteria decision-making problems. *Ankara Hacı Bayram Veli Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 24*(3), 1025-1056.

Demir, G., Özyalçın, A. T., & Bircan, H. (2021). *Çok kriterli karar verme yöntemleri ve ÇKKV yazılımı ile problem çözümü.* Ankara: Nobel.

Dhara, A., Kaur, G., Kishan, P. M., Majumder, A., & Yadav, R. (2022). An efficient decision support system for selecting very light business jet using critic-topsis method. *Aircraft Engineering and Aerospace Technology, 94*(3), 458-472. https://doi.org/10.1108/AEAT-04-2021-013

Diakoulaki, D., Mavrotas, G., & Papayannakis , L. (1995). Determining objective weights in multiple criteria problems: The critic method. *Computers & Operations Research, 22*(7), 763-770.

Dinçer, S. E. (2019). *Çok Kriterli Karar Alma.* Ankara: Gece Akademi.

Dokmanic, I., Parhizkar, R., Ranieri, J., & Vetterli, M. (2015). Euclidean distance matrices: Essential theory, algorithms, and applications. *IEEE Signal Processing Magazine, 32*(6), 12-30. https://doi.org/10.1109/MSP.2015.2398954

Durdu, D. (2025). Evaluating financial performance with spc-lopcow-marcos hybrid methodology: A Case study for firms listed in BIST sustainability index. *Knowledge and Decision Systems with Applications, 1*, 92-111. http://www.doi.org/10.59543/kadsa.v1i.13879

Ecer, F. (2020). *Çok Kriterli Karar Verme.* Ankara: Seçkin Yayıncılık.

Ecer, F., & Pamucar, D. (2022). A novel lopcow-dobi multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. Omega, 1-35. https://doi.org/10.1016/j.omega.2022.102690

Eligüzel, İ. M., & Eligüzel, N. (2024). Evaluation of sustainable transportation in 25 European countries using gra and entropy mabac. *Journal of Transportation and Logistics, 9*(2), 245-259. https://doi.org/10.26650/JTL.2024.1437521

Feldmann, C. W., Sieg, J., & Mathea, M. (2025). Analysis of uncertainty of neural fingerprint-based models. *Faraday Discussions, 256*, 551-567. http://dx.doi.org/10.1039/D4FD00095A

Feldmann, C., & Bajorath, J. (2022). Calculation of exact Shapley values for support vector machines with Tanimoto kernel enables model interpretation. *iScience, 25*, 1-13. https://doi.org/10.1016/j.isci.2022.105023

Iglesias, F., & Kastner, W. (2013). Analysis of similarity measures in times series clustering for the discovery of building energy patterns. *Energies, 6*, 579-597. https://doi.org/10.3390/en6020579

Kalaycı, Ş. (2014). *SPSS Uygulamalı Çok Değişkenli İstatistik Teknikleri*. Ankara: Anı Yayın Dağıtım.

Karagöz, Y. (2014). *SPSS 21.1 Uygulamalı İstatistik Tıp, Eczacılık, DişHekimliği ve Sağlık Bilimleri İçin*. Ankara: Nobel Akademik Yayıncılık.

Keleş, N. (2023). *Uygulamalarla Klasik ve Güncel Karar Verme Yöntemleri.* Ankara: Nobel Bilimsel.

Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2021). Determination of objective weights using a new method based on the removal effects of criteria (MEREC). *Symmetry, 13*(525), 1-21. https://doi.org/10.3390/sym13040525

Kilmen, S. (2015). *Eğitim Araştırmacıları için SPSS uygulamalı istatistik*. Ankara: Edge Akademi.

Kryszkiewicz , M. (2013). Using non-zero dimensions for the cosine and tanimoto similarity search among real valued vectors. *Fundamenta Informaticae, 127*(1-4), 307-323. https://doi.org/10.3233/FI-2013-911

Kryszkiewicz, M. (2021). Determining Tanimoto Similarity Neighborhoods of Real-Valued Vectors by Means of the Triangle Inequality and Bounds on Lengths. In: S. C. Ramanna (Eds.), *Rough Sets. IJCRS Lecture Notes in Computer Science* (pp. 8–34). Singapore Springer.

Lasek, P., & Mei, Z. (2019). Clustering and visualization of a high-dimensional diabetes dataset. *Procedia Computer Science, 159*, 2179–2188. https://doi.org/10.1016/j.procs.2019.09.392

Lipkus, A. H. (1999). A proof of the triangle inequality for the tanimoto distance. *Journal of Mathematical Chemistry, 26*, 263–265. https://doi.org/10.1023/A:1019154432472

Ma, C., Wang, L., & Xie, X.-Q. (2011). GPU accelerated chemical similarity calculation for compound library comparison. *Journal of Chemical Information and Modeling, 51*(7), 1521–1527. https://doi.org/10.1021/ci1004948

Mana, S. C., & Sasipraba, T. (2021). Research on cosine similarity and pearson correlation based. *International Conference on Mathematical Sciences*(1770), 1-7. https://doi.org/10.1088/1742-6596/1770/1/012014

Mellor, C. L., Marchese, R. L., Robinson, Benigni, R., Ebbrell, D., Enoch, S. J., . . . Cronin, M. (2019). Molecular fingerprint derived similarity measures for toxicological read across: Recommendations for optimal use. *Regulatory Toxicology and Pharmacology, 101*, 121-134.

Mohebbi, A., Ebrahimi, M., Askari, F. S., Shaddel, R., Mirarab, A., & Oladnabi, M. (2022). QSAR modeling of a ligand-based pharmacophore derived from hepatitis B virus surface antigen ınhibitors. *ACTA MICROBIOLOGICA BULGARICA, 38*(3), 197-206.

Momena, A. F., Gazi, K. H., Rahaman, M., Sobczak, A., Salahshour, S., Mondal, S. P., & Ghosh, A. (2024). Ranking and challenges of supply chain companies using MCDM methodology. *Logistics, 8*, 1-32. https://doi.org/10.3390/logistics8030087

Mukhametzyanov, I. Z. (2021). Specific character of objective methods for determining weights of criteria in mcdm problems: Entropy, critic, sd. decision making. *Applications in Management and Engineering*, *4*(2), 76-105.

Mulia, I., Kusuma, W. A., & Afendi, F. M. (2018). Algorithm for predicting compound protein ınteraction using tanimoto similarity and klekota-roth fingerprint. *TELKOMNIKA, 16*(4), 1785-1792. https://doi.org/10.12928/TELKOMNIKA.v16i4.5916

Nasser, A. A., Alkhulaidi, A., Ali, M. N., Hankal, M., & Al-olofe, M. (2019). A study on the ımpact of multiple methods of the data normalization on the result of saw, wed and topsis ordering in healthcare multi-attributte decision making systems based on ew, entropy, critic and svp weighting approaches. *Indian Journal of Science and Technology, 12*(4), 1-21. https://doi.org/10.17485/ijst/2019/v12i4/140756

Nowatzky, Y., Russo, F. F., Lisec, J., Kister, A., Reinert, K., Muth, T., & Benner, P. (2025). FIORA: Local neighborhood-based prediction of compound mass spectra from single fragmentation events. *Nature Communications, 16*, 1-17. https://doi.org/10.1038/s41467-025-57422-

Özdamar, K. (2018). *Eğitim, Sağlık ve Sosyal Bilimler için SPSS Uygulamalı Temel İstatistik.* Bursa: Nisan Yayınevi.

Öztel, A., & Alp, İ. (2020). *Çok Kriterli Karar Verme Seçiminde Yeni Bir Yaklaşım.* İstanbul: Kriter Yayıncılık.

Paulose, R., Jegatheesan, K., & Balakrishnan, G. S. (2018). A big data approach with artificial neural network and molecular similarity for chemical data mining and endocrine disruption prediction. *Indian Journal of Pharmacology, 50*(4), 169-176. https://doi.org/10.4103/ijp.IJP_304_17

Podani, J. (2000). Introduction to the exploration of multivariate biological data. Leiden: Backhuys Publishers.

Popović, G., Pucar, D., & Smarandache, F. (2022). MEREC-COBRA approach in e-commerce development strategy selection. *Journal of Process Management and New Technologies, 10*(3-4), 66-74.

Sankara, R. A., Durga , B. S., Sobha , R. T., Raju , S. B., & Narahari , S. G. (2011). Study of Diversity and Similarity of Large Chemical Databases Using Tanimoto Measure. In: K. R. Venugopal & L. M. Patnaik (Eds.). *Communications in Computer and Information Science* (pp. 1-12. https://doi.org/10.1007/978-3-642-22786-8_5

Sehgal, K., Kaur, H., Kaur, S., Singh, S., Channi, H. K., & Stević, Ž. (2025). Cost-Effective optimization of hybrid renewable energy system for micro, small, and medium enterprises: A decision-making framework integrating merec and marcos. *Opportunities and Challenges in Sustainability, 4*(1), 17-32. https://doi.org/10.56578/ocs040102

Selvi, C., & Sivasankar, E. (2018). *A Novel Singularity Based Improved Tanimoto Similarity Measure for Effective Recommendation Using Collaborative Filtering*. In: Proceedings of the 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (NODIA, 2018)., (pp. 256-262).

Shan, R., Zhang, R., Gao, Y., Wang, W., Zhu, W., Xin, L., . . . Cui, P. (2025). Evaluating ionic liquid toxicity with machine learning and structural similarity methods. *Green Chemical Engineering, 6*, 249–262. https://doi.org/10.1016/j.gce.2024.08.008

Sharma, A., & Lal, S. P. (2011). Tanimoto based similarity measure for ıntrusion detection system. *Journal of Information Security, 2*, 195-201. https://doi.org/10.4236/jis.2011.24019

Sleem, A., Mostafa, N., & Elhenawy, I. (2023). Neutrosophic critic mcdm methodology for ranking factors and needs of customers in product's target demographic in virtual reality metaverse. *Neutrosophic Systems with Applications, 2*, 55-66. https://doi.org/10.61356/j.nswa.2023.10

Surendran, A., Zsigmond, K., López-Pérez, K., & Miranda-Quintana, R. A. (2025). Is Tanimoto a metric? *bioRxiv*, 1-12. https://doi.org/10.1101/2025.02.18.638904

Tayalı, H. A., & Timor, M. (2017). Ranking with Statistical variance procedure based analytic hierarchy process. *Acta Infologica, 1*(1), 31-38.

Thakkar, J. J. (2021). *Multi criteria decision making.* Springer Singapore.

Thiel, P., Sach-Peltason, L., Ottmann, C., & Kohlbacher, O. (2014). Blocked inverted indices for exact clustering of large chemical spaces. *Chem. Inf. Model, 54*(9), 2395–2401.

Todeschini , R., Ballabio , D., Consonni, V., Mauri, A., & Pavan, M. (2007). CAIMAN (Classification And Influence Matrix Analysis): A new approach to the classification based on leverage-scaled functions. *Chemometrics and Intelligent Laboratory Systems, 87*(1), 3-17. https://doi.org/10.1016/j.chemolab.2005.11.001

Uludağ, A. S., & Doğan, H. (2021). *Üretim Yönetiminde Çok Kriterli Karar Verme.* Ankara: Nobel.

Ulutaş, A., & Topal, A. (2020). *Bütünleştirilmiş Çok Kriterli Karar Verme Yöntemlerinin Üretim Sektörü Uygulamaları.* Ankara: Akademisyen Kitapevi.

Vivek, M. B., Manju, N., & Vijay, M. B. (2018). *Machine Learning Based Food Recipe Recommendation System*. In: Guru, D. S., Vasudev, T., Chethan, H. K., & Kumar, Y.S, In: Proceedings of International Conference on Cognition and Recognition (SINGAPORE 2018), (pp. 11-19).

Wang, C.-N., Nguyen, N.-A.-T., & Dang, T.-T. (2023). Sustainable evaluation of major third-party logistics providers: a framework of an mcdm-based entropy objective weighting method. *Mathematics, 11*, 1-27. https://doi.org/10.3390/math11194203

Xu, H., Zeng, W., Zeng, X., & Yen, G. (2019). An evolutionary algorithm based on minkowski distance for many objective optimization. *IEEE Transactions on Cybernetics, 49*(11), 3968-3979. https://doi.org/10.1109/TCYB.2018.2856208

Yasin, Y., Riaz, M., & Alsager, K. (2025). Synergy of machine learning and the einstein choquet integral with lopcowand fuzzy measures for sustainable solid waste management. *AIMS Mathematics, 10*(1), 460–498. https://doi.org/10.3934/math.2025022

Yazdi, A. K., Tan, Y., Birau, R., Frank, D., & Pamučar, D. (2025). Sustainable solutions: using mcdm to choose the best location for green energy projects. *International Journal of Energy Sector Management, 19*(1), 146-180. https://doi.org/10.1108/IJESM-01-2024-0005

Ying, C. Z., Leong, C. H., Alvin, L. W., & Yang, C. J. (2021). Improving the Workflow of Chemical Structure Elucidation with Morgan Fingerprints and the Tanimoto Coefficient. In: Guo, H, Ren, H & Kim, N (Eds.). *IRC-SET 2020* (pp. 13-24). Singapore Springer.

Yoon, D., & Lee, H. (2025). In silico discovery of novel compounds for fak activation using virtual screening, AI based prediction, and molecular dynamics. *Computational Biology and Chemistry, 117*, https://doi.org/10.1016/j.compbiolchem.2025.108420

Yoshizawa, T., Ishida, S., Sato, T., Ohta, M., Honma, T., & Terayama, K. (2025). A data-driven generative strategy to avoid reward hacking in multi-objective molecular design. *Nature Communications, 16*, 1-12. https://doi.org/10.1038/s41467-025-57582-3

Zahrotun, L. (2016). Comparison jaccard similarity, cosine similarity and combined both of the data clustering with shared nearest neighbor method. *Computer Engineering and Applications, 5*(1), 11-18.

Zainudin, S., & Nurjana, N. R. (2018). Comparison of similarity method to improve retrieval performance for chemical data. *Jurnal Teknologi Maklumat dan Multimedia Asia-Pasifik, 7*(1), 91-98. https://doi.org/10.17576/apjitm-2018-0701-08.

Zardari, N. H., Ahmed, K., Shirazi, S. M., & Yusop, Z. B. (2014). *Weighting Methods and their Effects on Multi Criteria Decision Making Model Outcomes in Water Resources Management.* Springer Nature.

Zhang, B., Vogt, M., Maggiora, G. M., & Bajorath, J. (2015). Design of chemical space networks using a Tanimoto similarity variant based upon maximum common substructures. *J Comput Aided Mol Des, 29*, 937–950. https://doi.org/10.1007/s10822-015-9872-1

Zhang, X., Wang, C., Li, E., & Xu, C. (2014). Assessment model of ecoenvironmental vulnerability based on improved entropy weight method. *Scientific World Journal, 2014*, 1-7. http://dx.doi.org/10.1155/2014/797814