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A new method for measuring the performance of alternatives: Cosine similarity approach

Alternatiflerin performanslarinin ölçülmesinde yeni bir yöntem: Kosinüs benzerliği yaklaşımı

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A New Method for Measuring the Performance of Alternatives: Cosine Similarity Approach

Highlights

- *A new method based on cosine similarity for decision problems in Multi-Criteria Decision-Making(MCDM) has been proposed.*
- *The sensitivity analysis confirmed that the proposed method exhibits ideal sensitivity.*
- *The comparative analysis revealed that the proposed method is credible and reliable.*
- *According to the simulation analysis, it was concluded that the proposed method is stable and robust.*

Graphical Abstract

A new method based on Cosine Similarity within the framework of MCDM has been developed in this study.

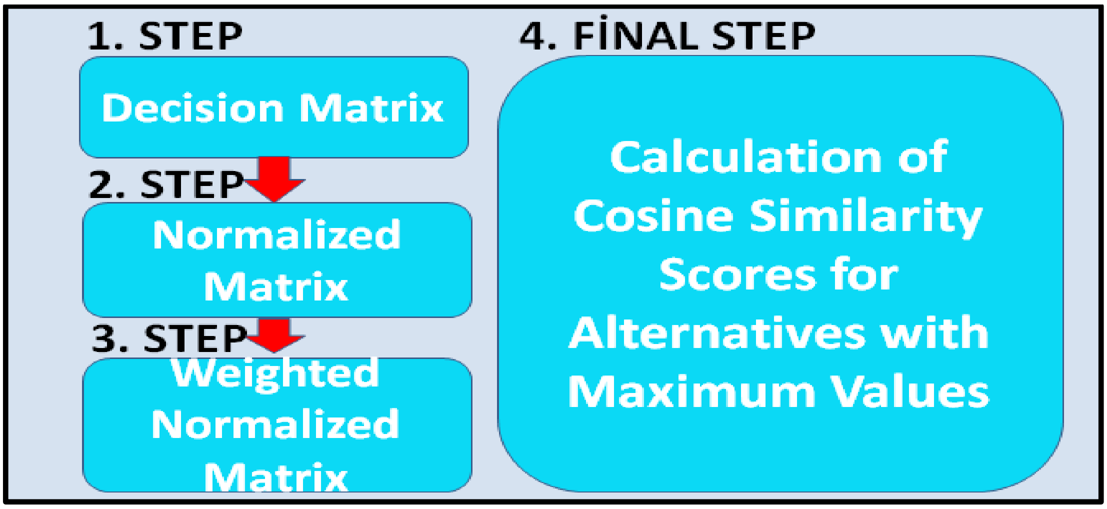

Figure. Proposed method diagram

Aim

The aim of this study is to demonstrate the applicability of a newly proposed method based on cosine Similarity for evaluating alternative performances in selection problems.

Design & Methodology

The method was applied using the criteria values of seven selected countries from the Global Innovation Index-2024, with necessary measurements taken accordingly.

Originality

A review of the literature revealed no existing studies based on cosine similarity, making this research original.

Findings

According to the findings, the proposed method is ideal in terms of sensitivity analysis, credible and reliable in comparative analysis, and stable and robust in simulation analysis.

Conclusion

Based on sensitivity, comparative, and simulation analyses, the proposed method is deemed applicable for selection problems and performance evaluation of decision alternatives.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission..

A New Method for Measuring the Performance of Alternatives: Cosine Similarity Approach

Araştırma Makalesi / Research Article

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ABSTRACT

The development of new methods within the scope of Multi-Criteria Decision Making (MCDM) provides decision-makers with alternative solution approaches in various scenarios, enabling more flexible and effective decision-making processes. This study aims to demonstrate the applicability of a newly proposed method based on cosine similarity (Cosine Similarity Approach) for evaluating the performance of alternatives in selection problems. The proposed method was tested using the criterion values of seven selected countries from the Global Innovation Index-2024, and the necessary measurements were conducted accordingly. A review of the literature revealed that no prior studies have been conducted based on cosine similarity, establishing the originality of this research. The findings indicate that the proposed method demonstrates optimal sensitivity, high reliability and consistency in comparative analyses, and strong stability and robustness in simulation analyses. In this context, the proposed method is concluded to be a practical and applicable tool for decision-makers in solving selection problems.

Keywords: MCDM, cosine similarity, alternative performance, selection problems.

Alternatiflerin Performanslarının Ölçülmesinde Yeni Bir Yöntem: Kosinüs Benzerliği Yaklaşımı

ÖZ

Çok Kriterli Karar Verme (MCDM) kapsamında yeni yöntemlerin geliştirilmesi, karar vericilere farklı durumlarda alternatif çözüm yaklaşımları sunarak daha esnek ve etkili karar alma süreçleri sağlamaktadır. Bu çalışma, seçim problemlerinde alternatif performanslarının değerlendirilmesi için kosinüs benzerliği temelli yeni bir yöntemin (Kosinüs Benzerliği Yaklaşımı) uygulanabilirliğini ortaya koymayı amaçlamaktadır. Çalışma kapsamında önerilen yöntem, Global İnovasyon Endeksi-2024'ten seçilen yedi ülkenin kriter değerleri kullanılarak test edilmiş ve gerekli ölçümler gerçekleştirilmiştir. Literatür incelemesi, kosinüs benzerliğine dayalı bir yöntemin daha önce çalışılmadığını ortaya koymuş ve bu durum araştırmayı özgün kılmıştır. Bulgular, önerilen yöntemin duyarlılık analizi açısından ideal, karşılaştırmalı analizlerde güvenilir ve tutarlı, simülasyon analizlerinde ise kararlı ve sağlam olduğunu göstermektedir. Bu bağlamda, önerilen yöntemin seçim problemlerinde karar vericiler için pratik ve uygulanabilir bir araç olduğu sonucuna ulaşılmıştır..

Anahtar Kelimeler: ÇKKV, kosinüs benzerliği, alternative performansı, seçim problemleri.

1. INTRODUCTION

Multi-Criteria Decision-Making (MCDM) methods evaluate multiple criteria to determine the best alternative by assessing each alternative through specific computational techniques [1]. These methods quantify alternatives based on various criteria and compare their performances according to the weights assigned to each criterion. Therefore, the core principle of MCDM lies in achieving quantitative superiority within its unique computational framework to solve selection problems or identify the best alternative [2].

Developing new methods in MCDM is crucial for evaluating alternatives and solving decision-making problems [3]. While existing methods yield effective results under certain conditions, exploring alternative approaches enables more comprehensive analyses by considering diverse criteria and constraints. Such approaches make decision-making processes more flexible and adaptable, contributing to more robust and efficient solutions [4].

The primary objective of this study is to demonstrate the applicability of a cosine similarity-based method in evaluating alternative performances within the context of MCDM. In this regard, the study aims to provide a detailed analysis of the proposed method’s practicality, computational efficiency, and advantages for decision-makers compared to conventional methods. Additionally, the primary motivation of the study is to assess the sensitivity of the CSA method using sensitivity analysis. The second motivation is to evaluate its reliability and validity through comparative analysis. Finally, the third motivation is to determine the method's robustness and stability via simulation analysis. Accordingly, the proposed method was applied to evaluate the innovation performances of seven countries based on the 2024 Global Innovation Index (GII) criteria. The findings indicate that the CSA method is ideal in terms of sensitivity analysis, reliable and consistent in comparative analyses, and stable and robust in simulation analyses. Based on these findings, it has been concluded that the method offers a practical

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and applicable tool for decision-makers in selection problems. In this context, the literature section of the study summarizes the fundamental characteristics of various MCDM methods, while the methodology section details the dataset, cosine similarity, and the proposed approach. The results section presents quantitative evaluations, and the discussion section examines the applicability of the CSA method..

2. MATERIAL VE METOD

2.1. Various MCDM Approaches in the Literature and Their Distinctive Features

A review of the MCDM literature reveals that a variety of methods are employed to select decision alternatives or assess their performance levels [3]. The aforementioned MCDM methods are interrelated, yet each possesses its own unique techniques [5]. Consequently, it becomes evident that researchers frequently employ techniques such as Simple Additive Weighting (SAW) [6,7], the Weighted Product Method (WPM) [8,9], the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [10–12], the Weighted Aggregated Sum Product Assessment (WASPAS) [13,14], the Additive Ratio Assessment (ARAS) [15,16], the Multiple Attribute Utility Theory (MAUT) [17,18], the Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) [19,20], and the Complex Proportional Assessment (COPRAS) [21,22] in their evaluations.

SAW, also known as the weighted linear combination or scoring method, requires the data to be numerical and comparable for proper application [23,24]. The method begins with the construction of a decision matrix as the initial step in evaluating the performance of decision alternatives or addressing selection problems. Following this, the values within the decision matrix are normalized. In the subsequent step, a weighted normalized decision matrix is generated. Finally, the normalized decision matrix values corresponding to each decision alternative are aggregated, and the resulting sums are ranked in descending order [25,26].

WPM evaluates each decision alternative by multiplying several ratios corresponding to each criterion, with one ratio assigned to each alternative. Given the exponential structure of the method, it is essential that the sum of the criterion weights equals [27,28]. The first step of the method involves constructing a decision matrix. In the second step, the values in the decision matrix are normalized. During the third step, the exponential form of the normalized values is weighted by the respective criterion weights. Finally, criterion-specific values are multiplied to generate new scores for each decision alternative, and the resulting performance scores are ranked in descending order [29,30].

WASPAS is a technique that integrates the principles of SAW and WPM. Within this approach, the combined optimality coefficient and the total relative importance score are calculated. The total relative importance score represents the performance of decision alternatives or identifies the preferred alternative in decision-making problems [31-32]. The first step in the WASPAS method is the preparation of the decision matrix. In the second step, the values of the decision matrix are normalized. The third step involves determining the relative importance scores of alternatives using both SAW and WPM methods. Finally, the combined optimality score for the decision alternatives is computed, and the alternatives are ranked in descending order based on these values [33,34].

In the TOPSIS method, decision alternatives are evaluated based on their proximity to the positive ideal solution and their distance from the negative ideal solution. The positive ideal solution represents the best values for the criteria, while the negative ideal solution represents the worst values [35,36]. An optimal alternative is one that is closest to the positive ideal solution or exhibits the highest aggregated criterion values compared to others. Method begins with the creation of a decision matrix, followed by normalization of its values. In the third step, weights are applied to the normalized matrix. The positive and negative ideal values for each criterion are then identified in the fourth step. In the fifth step, the distances of each alternative from these ideal solutions are calculated. Finally, the relative closeness of each alternative to the positive ideal solution is determined, and alternatives are ranked in descending order of these values [37,38].

The MAUT method is a decision-making approach based on a real-valued utility function that aims to maximize utility in scenarios involving multiple conflicting criteria. Preferences are represented as utility functions for each criterion [39]. The method begins by constructing a decision matrix, followed by normalizing its values. In the next step, the normalized values for each criterion are multiplied by their respective weights, and the weighted values are summed to calculate the total utility score for each decision alternative. Finally, alternatives are ranked in descending order based on their utility scores [40,41].

The COPRAS method distinguishes between benefit-oriented and cost-oriented criteria to evaluate decision alternatives through percentage comparisons [42,43]. It starts with creating a decision matrix, normalizing its values, and applying weights. Benefit and cost-oriented criteria are then aggregated separately using the weighted normalized values. The relative significance of each alternative is determined based on these aggregated values, and a performance index is calculated. Alternatives are ranked in descending order of their performance indices [32,44].

In the ARAS method, decision alternatives are evaluated and selected by analyzing their benefit levels, with each alternative's optimality value compared to that of a reference alternative [45]. The method begins with the creation of a decision matrix, followed by normalization of its values. Weights are then assigned to the normalized matrix values, and the optimality function value for each alternative is calculated using the weighted normalized values. Finally, the benefit levels or performance scores are determined by comparing each alternative's optimality function value to the reference alternative, and alternatives are ranked in descending order [46,47].

The MARCOS method ranks alternatives based on a compromise solution that considers their proximity to both ideal and anti-ideal solutions. Utility functions are determined, and alternatives are ranked based on their distances from the ideal (AI) and anti-ideal (AAI) solutions [48-49]. The alternative closest to AI and furthest from AAI is preferred. After normalizing and weighting the decision matrix, the sum of criteria values for each alternative is calculated. Benefit degrees are determined by dividing these values by the ideal (maximum) and anti-ideal (minimum) solution values. In the final step, performance scores are calculated by equally considering both ideal and anti-ideal solutions using a ratio-based approach [50,51].

In this context, the quantitative superiority of alternatives in SAW and WPM methods is determined by higher normalized criterion scores and their corresponding weights [6,8]. In the WASPAS method, it is linked to the combination of these scores and weights, integrating the principles of SAW and WPM [33]. For the TOPSIS method, superiority is based on the proximity of weighted normalized scores to positive ideal (maximum value) or negative ideal distances (minimum value) [37]. In the MAUT method, it depends on higher normalized scores and their marginal utility values [40]. The COPRAS method evaluates superiority through changes in weighted normalized scores that maximize benefit criteria [32]. In ARAS, superiority is tied to the proximity of weighted normalized scores to maximum values [46]. Lastly, in MARCOS, it relies on the closeness of weighted normalized scores to makximum values and their distance from minimum values [51]..

2.2. Cosine Similarity

Cosine similarity measures the similarity between two vectors by calculating the cosine of the angle between them. The angle indicates whether the vectors point in the same or different directions [52-54]. This technique is widely used in text mining and information retrieval to compare documents or term vectors [55].

A cosine similarity value close to 1 indicates a high similarity, as the vectors are nearly parallel and point in the same direction [56]. Conversely, a value near -1 implies the vectors point in opposite directions, representing dissimilarity [57]. A value of 0 signifies orthogonality, meaning no similarity or relationship between the vectors [58]. Hence, the smaller the angle between two vectors, the greater their similarity [59]. A visual representation of this concept is shown in Figure 1

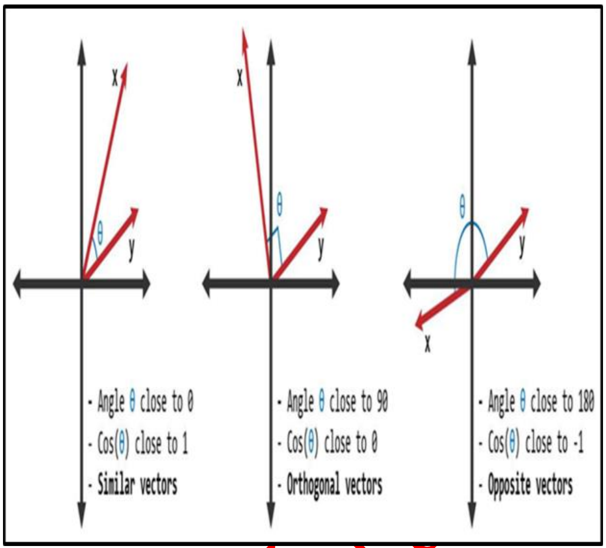

Figure 1. Cosine similarity positions

Reference: [60]

The cosine between two non-zero vectors can be determined using the Euclidean dot product method, as illustrated in Equation 1 [61-62].

$$A\,.\,B = \|A\|\,.\,\|B\|\cos\theta \tag{1}$$

The cosine similarity, cos θ, between two n-dimensional attribute vectors, A and B, can be expressed using their dot product and magnitudes, as presented in Equation 2 [63].

$$\cos\theta = \frac{A\,.B}{\|A\|\,.\|B\|} = \frac{\sum_{i=1}^{n} A_i.B_i}{\sqrt{\sum_i^n A_i^2}\,.\sqrt{\sum_i^n B_i^2}} \tag{2}$$

The literature reveals numerous studies based on the cosine similarity method. Ye (2014) [64] proposed new method using the cosine similarity measure for Simplified Neutrosophic Sets (SNS), a subset of neutrosophic sets. In this approach, alternatives are ranked based on their cosine similarity to the ideal alternative. Wojke and Bewley (2018) [65] demonstrated that optimizing cosine similarity within a traditional softmax classification framework enhances generalization on test sets compared to networks trained with triplet loss. Similarly, Elfakir et al. (2020) [66] introduced the "floating distance" concept, which combines linear regression and cosine distance to improve threshold selection in decision-making, outperforming conventional methods in word recognition systems. Huang et al. (2020) [67] also leveraged cosine similarity in Curricular Face, a face recognition system, achieving superior performance in benchmark tests. Singh et al. (2020) [68] employed cosine similarity and k-nearest neighbors (KNN) to develop a content-based recommendation system tailored to users based on movie popularity or genre, leveraging deep learning approaches. Yu et al. (2020) [69] applied cosine similarity in neural interaction models for cross-lingual information retrieval (CLIR) using cross-lingual word embeddings (CLWEs), identifying different neural architectures and query-document interaction representations. Zhang et al. (2020) [70] proposed a similarity-guidance network for one-shot segmentation, utilizing cosine Similarity to relate pixel features and guidance features in query images, demonstrating strong correlations. Sattler et al. (2021) [71]. developed a clustered federated learning (CFL) framework, leveraging cosine similarity between client gradient updates to group clients with similar data distributions, facilitating effective multitask learning. Duan et al. (2024) [72]. introduced FedGroup, a clustering-based federated learning framework that groups clients based on optimization similarities, improving absolute test accuracy by cosine similarity. Huang et al. (2024) [73]. used cosine similarity in SVAML, a multi-LSTM network guided by semantic and visual attention, for precise multi-label classification by effectively designing a label discriminator module.

2.3. Data Set and Analysis of Study

The study presents a cosine similarity-based method for measuring the performance of alternatives in selection problems. The dataset comprises the 2024 Global Innovation Index (GI) criterion values of seven countries with distinct performances. These countries were selected due to the variation in their criterion values. For convenience, the abbreviations of the GI criteria are explained in Table 1.

Table 1. Abbrevations of global innovation criteria

GI Criteria	Abbreviations
Institutions	GI1 (Benefit Orientied)
Human Capital and Research	GI2 (Benefit Orientied)
Infrastructure	GI3 (Benefit Orientied)
Market Sophistication	GI4 (Benefit Orientied)
Business Sophistication	GI5 (Benefit Orientied)
Knowledge and Technology Outputs	GI6 (Benefit Orientied)
Creative Outputs	GI7 (Benefit Orientied)

Reference: WIPO, 2024

2.4. Proposed Method (Cosine Similarity Approach-CSA)

The calculation of the quantitative superiority levels of alternatives in MCDM methods typically begins after constructing the weighted normalized decision matrix [75]. This matrix provides a structure for evaluating each alternative under various criteria [76]. Once the weighted normalized decision matrix is formed, distinct MCDM techniques are employed to calculate the superiority levels of alternatives based on their unique characteristics [77]. At this stage, evaluations using maximum values can highlight differences in alternative performances more clearly [78]. An alternative's proximity to maximum criterion values serves as a key indicator of its performance compared to others. Such comparisons help identify the alternatives with superior performance. In this context, the cosine similarity method offers an effective tool for measuring similarities among alternatives. By analyzing the proximity between alternatives, it facilitates the identification of the highest-performing alternative. The steps of the proposed method are detailed below.

A: Alternative

C: Criteria

Cj: $j-th$ evaluation criterion

p: number of alternatives

r: number of criteria

d_{ij}: value of the $i-th$ alternative according to the $j-th$ evaluation criterion

$max(d_{ij})$: maximum value of the decision alternatives according to the $j-th$ criterion

$\min(d_{ij})$: minimum value of the decision alternatives according to the $j-th$ criterion

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

Step 1. Obtaining Decision Matrix (D)

In the first step of the proposed method, the decision matrix is constructed using Equation 3

$$D = \begin{array}{c} A \\ A_1 \\ A_2 \\ \vdots \\ A_p \end{array} \begin{bmatrix} C_1 & C_2 & \cdots & C_r \\ d_{11} & d_{12} & & d_{1r} \\ d_{21} & d_{22} & \cdots & d_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ d_{p1} & d_{p2} & \cdots & d_{pr} \end{bmatrix} \tag{3}$$

Step 2. Calculation of Normalisation Values of Decision Matrix (d^*_{ij})

In the second step of the process, the decision matrix values are normalized by applying Equation 4 for criteria that are benefit-oriented and Equation 5 for criteria that are cost-oriented.

For benefit-oriented criteria:

$$d^*_{ij} = \frac{d_{ij}-\max(d_{ij})}{\max(d_{ij})-\min(d_{ij})} \tag{4}$$

For cost-oriented criteria:

$$d^*_{ij} = \frac{\min(d_{ij})-d_{ij}}{\max(d_{ij})-\min(d_{ij})} \tag{5}$$

Step 3: Calculation of Weighted Normalisation Values of Decision Matrix (WD)

In this step, the normalized values from the second step are weighted, and the maximum values for each criterion are identified. A matrix is then formed with the help of Equation 6.

$$WD = \begin{array}{c} A \\ w \\ A_1 \\ A_2 \\ \vdots \\ A_P \\ A_{max} \end{array} \begin{bmatrix} C_1 & C_2 & C_{...} & C_r \\ w_1 & w_2 & \cdots & w_r \\ wd^*_{11} & wd^*_{12} & \cdots & wd^*_{1r} \\ wd^*_{21} & wd^*_{22} & \cdots & wd^*_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ wd^*_{p1} & wd^*_{p2} & \cdots & wd^*_{Pr} \\ A_{max_{C_1}} & A_{max_{C_2}} & \cdots & A_{max_{C_r}} \end{bmatrix} \quad (6)$$

Step 5: Calculation of Cosine Similarity Values of Alternatives with Maximum Scores $\left(cos_{wA_i \leftrightarrow A_{max.}} \theta\right)$

In the fourth step, using the weighted normalized values calculated in the third step and the maximum values for each criterion, the cosine similarity values between the weighted normalized alternative values (number series) and the maximum weighted normalized alternative values for each criterion are calculated with the help of Equation 7 and Equation 8.

$$A \in \{wA_1, wA_2, wA_3 \ldots\ldots wA_P, A_{max.}\} \quad (7)$$

$$\left(cos_{wA_i \leftrightarrow A_{max.}} \theta\right) = \frac{wA_i \,.A_{max.}}{\|wA_i\| \,.\|A_{max}\|} \quad (8)$$

Based on the calculation steps of the proposed method described above, the model of the suggested approach is illustrated in Figure 2.

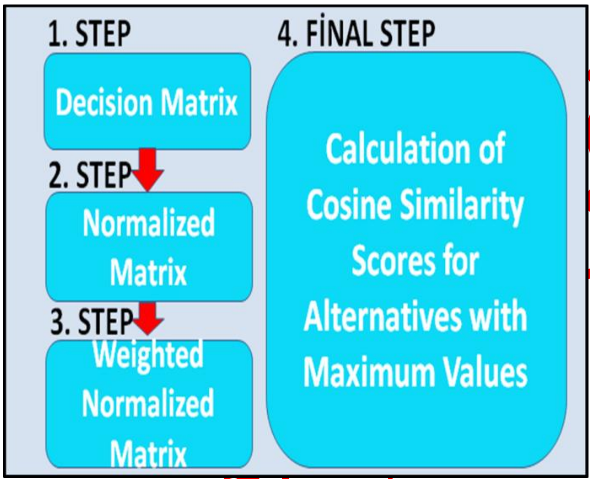

Figure 2. Model of proposed method

The proposed Cosine similarity Approach (CSA) stands out among other MCDM methods due to its ability to provide high accuracy and flexibility while relying on basic mathematical operations. This approach effectively evaluates the performance of alternatives without requiring complex mathematical models. In traditional MCDM methods, the evaluation of decision alternatives typically involves complex matrix operations, optimization algorithms, or iterative procedures. In contrast, since the CSA method is based directly on similarity computation, it is computationally more efficient and straightforward. The most distinctive feature of CSA is its direct calculation of similarities between alternatives using the cosine similarity method. Unlike traditional MCDM methods, CSA analyzes the geometric proximity of alternatives only to the criteria with maximum values, offering clearer comparisons. This enables decision-makers to better understand the performance of alternatives. Another significant advantage of the proposed method is its ability to process data directly after constructing the weighted decision matrix without requiring additional transformations. This feature ensures a realistic and straightforward approach, preserving the originality of the data and leading to more reliable results. Particularly in cases where minimal data manipulation is desired, this characteristic provides a substantial advantage. Additionally, the method is well-suited for handling high-dimensional and complex datasets with numerous criteria and alternatives. By mathematically calculating similarities between alternatives with precision, it enhances clarity and accuracy in decision-making processes.

In this regard, CSA offers an objective perspective for evaluating alternative performance, helping decision-makers interpret results more easily and strengthening the scientific basis of the decision-making process. Furthermore, another practical advantage of the CSA method is its simplicity and clarity in evaluating the performance of decision alternatives. While traditional methods determine ideal and anti-ideal solutions and compute distances accordingly, CSA directly measures the similarity of alternatives to the criteria with the highest values, generating a performance score without requiring complex distance calculations. This approach allows decision-makers to interpret results more easily and to distinguish differences between alternatives more clearly.The main limitation of the method is its disregard for minimum values, which makes it less comprehensive compared to certain MCDM methods (e.g., ARAS, COPRAS, MARCOS).

3. COMPUTATIONAL ANALYSIS AND RESULTS

In the study, the decision matrix was first obtained using Equation 3. In this regard, the criterion values of countries under the GII framework (the values presented in Table 2: Decision Matrix) have been obtained from the WIPO-2024report (WIPO, 2024). The GII objectively measures countries' innovation performance, assigning scores ranging from 1 to 100 [74]. A review of the literature on MCDM and innovation reveals that numerous researchers have employed MCDM methods to assess countries' innovation performance [79-80]. The selection of the countries examined in this study is based on the fact that their innovation performance is relatively similar to one another compared to other countries. This approach is expected to enhance the ability of the proposed method to effectively differentiate between alternatives. Subsequently, in the second step of the method, the normalized values were calculated using Equation 4. The corresponding values are presented in Table 2.

Table 2. Decision and normalized decision matrices

Decision Matrix							
Countries	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	**G7**
Argentina	21.7	33.9	36.7	23	27.7	18.6	29.9
Australia	77	58.7	55.4	53.8	48.2	33.1	42.1
China	57.6	50.3	62.4	55.8	58	61.7	50
India	51.5	34.8	39	52.3	28.1	38.8	32.1
Indonesia	59.5	25.2	41.2	44.3	24.2	19.9	24.8
Italy	51.2	45.4	52.5	43.1	38.7	41.4	47.5
S.Africa	36.5	26.8	37.1	37.8	28.6	21.4	25.3
Normalized Decision Matrix							
Countries	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
Argentina	0.000	0.260	0.000	0.000	0.104	0.000	0.202
Australia	1.000	1.000	0.728	0.939	0.710	0.336	0.687
China	0.649	0.749	1.000	1.000	1.000	1.000	1.000
India	0.539	0.287	0.089	0.893	0.115	0.469	0.290
Indonesia	0.684	0.000	0.175	0.649	0.000	0.030	0.000
Italy	0.533	0.603	0.615	0.613	0.429	0.529	0.901
S.Africa	0.268	0.048	0.016	0.451	0.130	0.065	0.020

In the third step, the weighted values of the criteria for decision alternatives were calculated using Equation 6 based on the normalized decision matrix values. These weights were previously determined using the ENTROPY method. The corresponding values are shown in Table 3.

In the fourth step, the cosine similarity values (performance of decision alternatives) were calculated using Equation 5, based on the weighted values of the decision alternatives and the maximum values of these weighted criteria. The cosine similarity values and the rankings of the decision alternatives relative to the maximum values are presented in Table 4.

An example application based on the results calculated in Table 4 is provided below.

Normalized Score of Argentina-GI1:

$$Equation\ 4 = \frac{(21.7 - 21.7)}{(59.5 - 21.7)} = 0$$

Weighted Normalized Score of Argentina-GI1:

$$Equation\ 6 = 0.173 * \ 0 = 0$$

Cosine Similarity Score of Argentina:

$$Equation\ 7\ and\ 8 = \left(cos_{wA_{Argentina} \leftrightarrow A_{max.}} \theta\right) =$$

$$\frac{(0x0.173)+(0.034x0.133)+(0x0.064)+(0x0.097)+(0.016x0.154)+(0x0.269)+(0.023x0.111)}{\sqrt{[(0)^2+(0.034)^2+(0)^2+(0)^2+(0.016)^2+(0)^2+(0.023)^2]x[(0.173)^2+(0.133)^2+(0.064)^2+(0.097)^2+(0.154)^2+(0.269)^2+(0.111)^2]}} =$$

0.525

In scope of sensitivity analysis, an effective way to assess the robustness of MCDM methods is by introducing new alternative to the original set or removing less favorable ones.

In such scenarios, the MCDM method should maintain stability, ensuring that the ranking of alternative does not change or undergo significant changes [81]. Since the criterion values will change when each alternative is removed from the dataset, the scores of the alternatives may also change. To address this issue, a sensitivity analysis was conducted, beginning with the alternative identified as the weakest by the proposed method. The resulting country rankings from this analysis are summarized in Table 5, while a graphical representation is shown in Figure 3.

Table 3. Weighted normalized matrix

Countries	**GI1**	**GI2**	**GI3**	**GI4**	**GI5**	**GI6**	**GI7**
w (Entropy)	**0.173**	**0.133**	**0.064**	**0.097**	**0.154**	**0.269**	**0.111**
Argentina	0.000	0.034	0.000	0.000	0.016	0.000	0.023
Australia	0.173	0.133	0.047	0.091	0.109	0.090	0.076
China	0.112	0.099	0.064	0.097	0.154	0.269	0.111
India	0.093	0.038	0.006	0.087	0.018	0.126	0.032
Indonesia	0.118	0.000	0.011	0.063	0.000	0.008	0.000
Italy	0.092	0.080	0.039	0.060	0.066	0.142	0.100
S.Africa	0.046	0.006	0.001	0.044	0.020	0.017	0.002
Maximum	0.173	0.133	0.064	0.097	0.154	0.269	0.111

Table 4. Cosine similarity scores (performance scores) of alternatives and ranking

Countries	Score	rank
Argentina↔Maximum Scores	0.525	7
Australia↔Maximum Scores	0.914	3
China↔Maximum Scores	0.988	1
India↔Maximum Scores	0.912	4
Indonesia↔Maximum Scores	0.531	6
Italy↔Maximum Scores	0.981	2
S.Africa↔Maximum Scores	0.742	5

Table 5. Rank reversal matrix

CSA	S0 (Rank)	S1 (Rank)	S2 (Rank)	S3 (Rank)	S4 (Rank)	S5 (Rank)	S6 (Rank)
Argentina	7						
Indonesia	6	6					
S.Africa	5	5	5				
India	4	4	4	4			
Australia	3	3	3	3	3		
Italy	2	2	2	2	2	2	
China	1	1	1	1	1	1	1

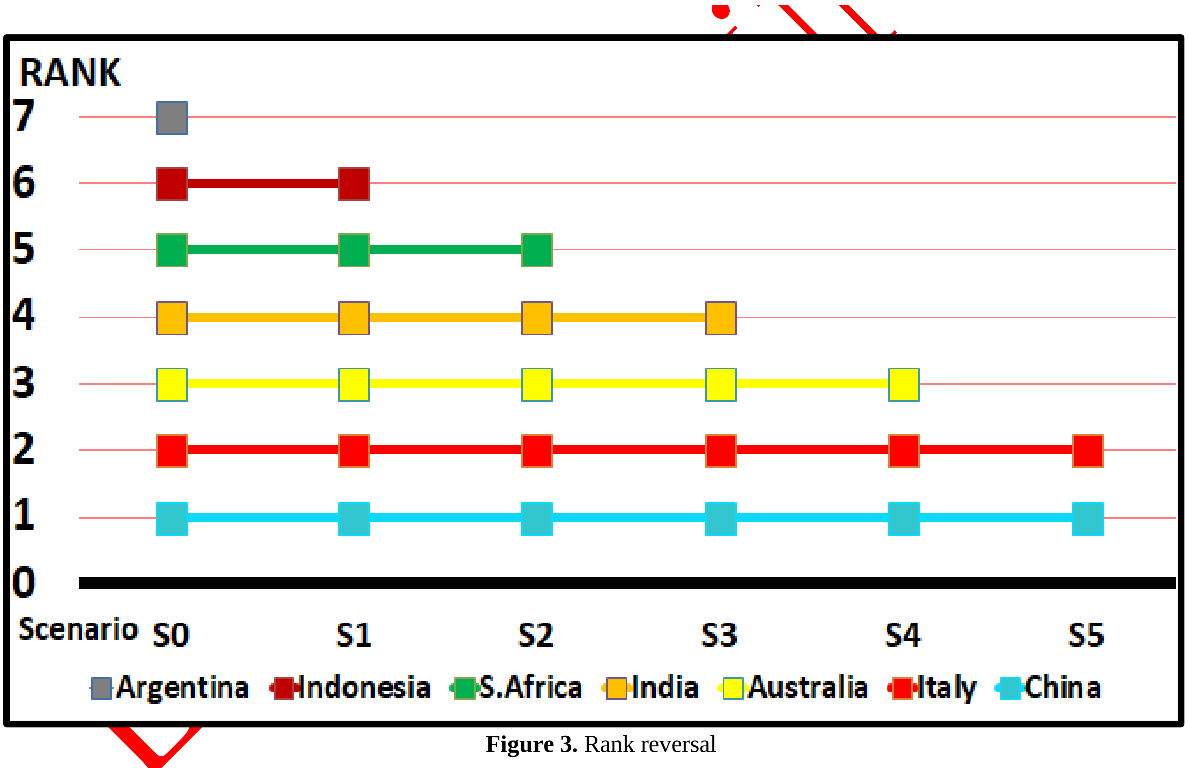

Figure 3. Rank reversal

A review of Table 5 and Figure 3 indicates that the rankings of countries based on performance remain relatively consistent across various scenarios analyzed using the rank reversal method for sensitivity testing. Similarly, an examination of Table 5 and Figure 3 shows that when the alternative (Countries) are progressively removed, starting from the least performance to the most performance, the rankings of the alternative ranks remain stable throughout the all scenarios. Consequently, as no changes are observed in the rankings under the rank reversal method, the proposed approach is deemed to exhibit optimal sensitivity. The comparative analysis investigates the relationships and relative standings of the proposed approach in comparison to other methods utilized for calculating MCDM outcomes. The objective is to validate the proposed method's reliability, consistency, and alignment with established techniques, while also demonstrating a robust and statistically significant correlation with various MCDM methods [82]. The performance of the alternatives (countries) has been assessed using commonly employed MCDM methods in the literature, such as SAW, WPM, TOPSIS, WASPAS, ARAS, MAUT, COPRAS, and MARCOS. The calculated values and rankings for these methods are presented in Table 6 and Figure 4.

Table 6. ENTROPY based the other MCDM method scores

Methods	SAW		WPM		TOPSIS		WASPAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Argentina	0.424	7	0.404	7	0.078	7	0.414	7
Australia	0.821	2	0.798	2	0.578	2	0.809	2
China	0.938	1	0.932	1	0.833	1	0.935	1
India	0.640	4	0.631	4	0.448	4	0.635	4
Indonesia	0.516	5	0.485	5	0.293	5	0.500	5
Italy	0.735	3	0.729	3	0.538	3	0.732	3
S.Africa	0.471	6	0.461	6	0.158	6	0.467	6
Methods	**ARAS**		**MAUT**		**MARCOS**		**COPRAS**	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Argentina	0.416	7	0.009	7	0.298	7	0.093	7
Australia	0.806	2	0.530	2	0.597	2	0.179	2
China	0.939	1	0.809	1	0.670	1	0.210	1
India	0.635	4	0.156	4	0.462	4	0.142	4
Indonesia	0.502	5	0.091	5	0.380	5	0.111	5
Italy	0.729	3	0.261	3	0.525	3	0.162	3
S.Africa	0.462	6	0.023	6	0.339	6	0.103	6

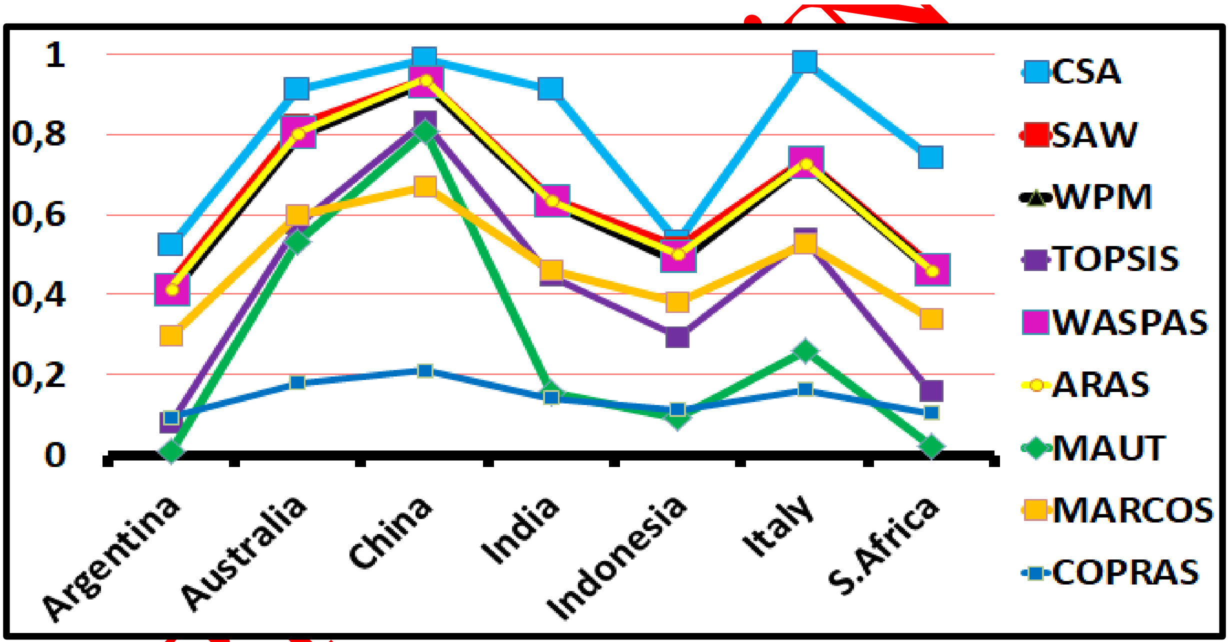

Figure 4. Position of MCDM methods

When Table 6 and Figure 4 are examined together, it is observed that the performance trends of countries using the CSA method are generally consistent with those of other methods. Accordingly, the correlation values between the performance values of countries calculated by the proposed method and those determined by other ENTROPY-based MCDM methods are presented in Table 7.

Table 7. Correlation scores of the ENTROPY-based CSA method with other ENTROPY-based MCDM methods

Methods	SAW	WPM	TOPSIS	WASPAS
CSA	0.846**	0.864**	0.830**	0.855**
	ARAS	**MAUT**	**MARCOS**	**COPRAS**
	0.849**	0.694**	0.839**	0.850**

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

Upon examining Table 7, it is observed that the correlation values of the CSA method with other methods are significant, positive, and high (Only the MAUT method is close to high correlation). Additionally, considering the performance rankings according to the methods, the correlation value (rho) between the CSA method and the other methods was calculated as 0.929 (p**<.01). Therefore, the findings of the comparative analysis suggest that the proposed method is stable and reliable for measuring the performance of alternatives. For the simulation analysis, multiple scenarios were developed by assigning unique values to the decision matrices. To validate the robustness of the results generated by the proposed method, it is expected that its outcomes will deviate more from those of other methods as the number of scenarios increases. In the subsequent phase, the average variance values derived from the proposed method across the scenarios should surpass those of one or more alternative methods. This would indicate that the proposed method is comparatively more effective in distinguishing the score of the alternative. Finally, it is essential to verify the consistency of variances in alternative across various methods within these scenarios [82]. In this regard, 10 scenarios (decision matrices) were initially generated and divided into two groups. Following this, the correlation coefficients between the CSA method and other MCDM methods were computed for these scenarios. The resulting correlation values are displayed in Table 8.

Table 8. Correlation scores of CSA methot with other MCDM methods in scope of scenarios

Group	**Scenarios**	**SAW**	**WPM**	**TOPSIS**	**WASPAS**
First Group	Scenario1	0.888**	0.905**	0.855**	0.897**
	Scenario2	0.879**	0.898**	0.843***	0.878**
	Scenario3	0.890**	0.895**	0.837**	0.885**
Second Group	Scenario4	0.855**	0.862**	0.826**	0.859**
	Scenario5	0.768**	0.788**	0.732**	0.779**
	Scenario6	0.736**	0.751**	0.705**	0.744**
	Scenario7	0.789**	0.801**	0.745**	0.794**
	Scenario8	0.677**	0.700**	0.651**	0.685**
	Scenario9	0.643**	0.667**	0.637**	0.652**
	Scenario10	0.638**	0.654**	0.629**	0.649**
Group	**Scenarios**	**ARAS**	**MAUT**	**MARCOS**	**COPRAS**
First Group	Scenario1	0.892**	0.729**	0.859**	0.894**
	Scenario2	0.884**	0.705**	0.847**	0.887**
	Scenario3	0.907**	0.733**	0.840**	0.915**
Second Group	Scenario4	0.863**	0.700**	0.835**	0.871**
	Scenario5	0.775**	0.656**	0.747**	0.779**
	Scenario6	0.749**	0.624**	0.724**	0.766**
	Scenario7	0.796**	0.679**	0.768**	0.799**
	Scenario8	0.681**	0.588*	0.663**	0.689**
	Scenario9	0.652**	0.574**	0.645**	0.665**
	Scenario10	0.647**	0.568*	0.636**	0.642**

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

As shown in Table 8, the correlation values of the CSA method with other methods decrease as the number of scenarios increases. The graphical representation of these values is provided in Figure 5.

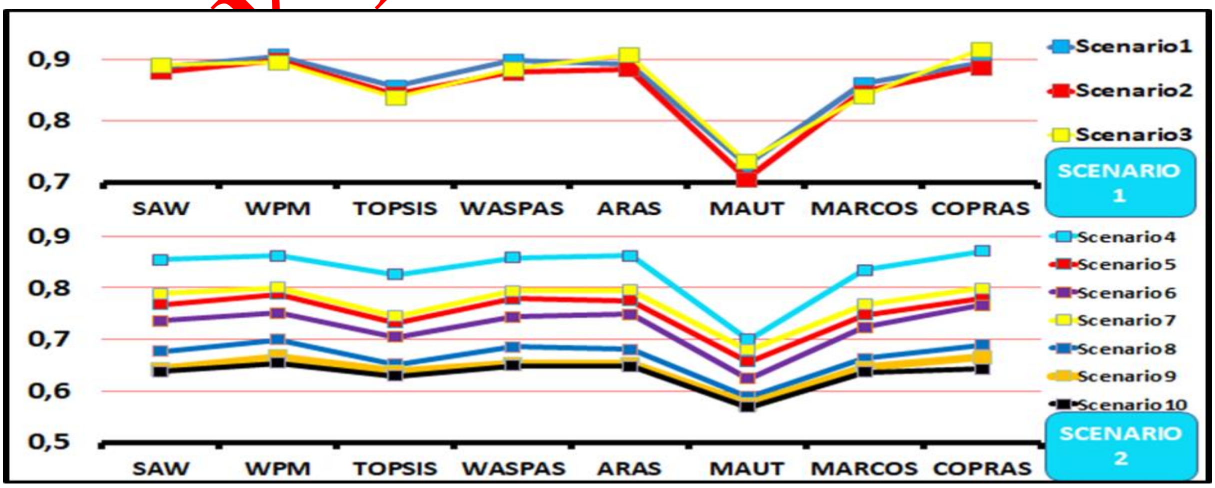

Figure 5. Correlation positions of CSA method

In the continuation of the simulation analysis, the variance values for each method were computed across the different scenarios. These variance values are displayed in Table 9.

Table 9. Variance score of methods in scope of scenarios

Scenarios	CSA	SAW	WPM	TOPSIS	WASPAS
Scenario1	0.037	0.027	0.028	0.054	0.033
Scenario2	0.039	0.028	0.029	0.056	0.028
Scenario3	0.041	0.030	0.031	0.058	0.037
Scenario4	0.043	0.031	0.033	0.060	0.030
Scenario5	0.045	0.032	0.035	0.062	0.035
Scenario6	0.045	0.034	0.037	0.064	0.032
Scenario7	0.041	0.035	0.039	0.066	0.034
Scenario8	0.039	0.036	0.041	0.068	0.029
Scenario9	0.043	0.038	0.043	0.070	0.036
Scenario10	0.047	0.039	0.045	0.072	0.031
Mean	**0.042**	**0.033**	**0.036**	**0.063**	**0.033**
Countries	**ARAS**	**MAUT**	**MARCOS**	**COPRAS**	
Scenario1	0.031	0.078	0.014	0.005	
Scenario2	0.035	0.072	0.018	0.004	
Scenario3	0.029	0.079	0.022	0.007	
Scenario4	0.033	0.073	0.021	0.006	
Scenario5	0.037	0.075	0.019	0.008	
Scenario6	0.032	0.074	0.024	0.005	
Scenario7	0.030	0.077	0.015	0.006	
Scenario8	0.036	0.076	0.020	0.004	
Scenario9	0.034	0.071	0.016	0.007	
Scenario10	0.031	0.080	0.023	0.005	
Mean	**0.033**	**0.076**	**0.019**	**0.006**	

Table 9 reveals that the CSA method has higher average variance values compared to SAW, WPM, WASPAS, ARAS, MARCOS, and COPRAS, indicating its ability to better distinguish alternatives through more distinct performance scores. In the final step of the simulation analysis, ADM (ANOM for variances based on Levene) was used to evaluate the homogeneity of variances in the CSA scores across multiple scenarios. ADM provides a graphical assessment of variance consistency, featuring the overall average (central line), upper decision limit (UDL), and lower decision limit (LDL). A finding of variance heterogeneity occurs if the standard deviation of any group (or cluster) exceeds the decision limits; conversely, variance homogeneity is confirmed when all standard deviations are contained within the defined bounds. The ADM analysis results are illustrated in Figure 6.

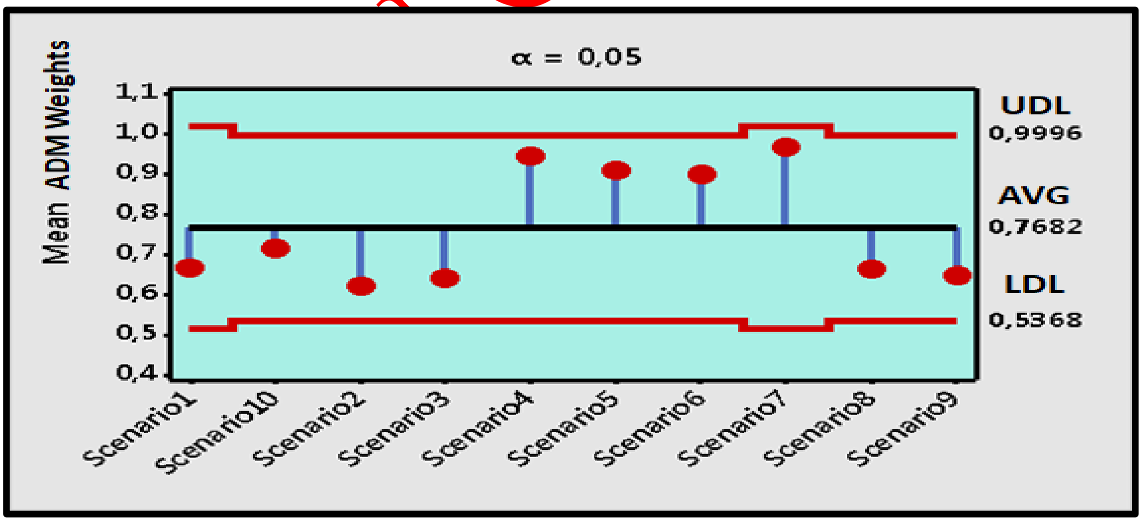

Figure 6. ADM chart

As shown in Figure 6, the ADM values calculated for each scenario fall between the upper decision limit (UDL) and the lower decision limit (LDL). Consequently, the variances in the assigned weights across all scenarios exhibit homogeneity. This finding was further corroborated through the application of the Levene Test. The relevant statistics from the Levene Test are provided in Table 10.

Table 10. Levene statistic

Levene Statistic	df1	df2	Sig. (p)
0.144	2	10	0.222

p**<.05

As shown in Table 10, the p-value is greater than the significance level of 0.05, indicating that the criterion weights exhibit homogeneity of variances across the scenarios. In conclusion, the findings from the simulation analysis demonstrate the reliability and credibility of the CSA method.

4. DISCUSSION

The proposed method is grounded in cosine similarity, which, unlike proportional approaches, works based on the quantitative similarity of alternatives. In this method, each decision alternative's values for the criteria are compared to their own maximum values using cosine s

similarity. The alternative most similar to the maximum values is selected as the best. The findings of the research, based on decision matrix values and various scenarios, show that the proposed method is ideal in sensitivity analysis, reliable and credible in comparative analysis, and robust and stable in simulation analysis. In conclusion, the proposed method is expected to provide benefits for decision-makers in measuring the performance of alternatives and managing the operational process. In conclusion, the proposed method offers valuable benefits for decision-makers in measuring alternative performance and managing operational processes. By utilizing cosine similarity, it provides a streamlined approach to performance evaluation. This method not only considers individual criteria but also their interrelationships, enabling a more comprehensive and balanced assessment. Additionally, its simplicity and applicability to large datasets make it particularly advantageous in complex MCDM scenarios, ultimately supporting more informed and effective decision-making. Therefore, the proposed method is considered to contribute to the MCDM literature. In particular, based on the sensitivity and comparative simulation results, the method has been found to be stable, robust, and reliable. Consequently, it is evaluated that decision-makers can utilize the proposed method in real-life decision-making or selection problems. The primary limitation of this study is that the quantitative values of the alternatives for the criteria have been assessed based on their similarity to the maximum values observed among the alternatives, while the minimum values have been disregarded. To develop a more comprehensive framework for the proposed method, the similarity of the alternatives to the minimum values could also be incorporated.

The proposed method distinguishes itself by evaluating alternatives based on their similarity to maximum values, diverging from methods like SAW, WPM, and WASPAS, which rely solely on individual data series [27, 75]. Unlike EDAS, TOPSIS, VIKOR, and TODIM, which consider inter-alternative relationships, this method prioritizes simplicity and directness through the application of cosine similarity [32, 76]. In contrast to TOPSIS, which employs Euclidean distance to ideal solutions, the proposed method offers a standardized [-1, 1] scale, thereby simplifying the analysis of large datasets [36, 37]. While TOPSIS provides a comprehensive evaluation, this method accelerates the decision-making process by focusing on similarities to maximum values. Differing from ARAS, which utilizes a summative optimality function and may exhibit reduced sensitivity in proportional comparisons, this method employs cosine similarity to achieve a more heterogeneous data structure [45, 46]. Although ARAS offers balanced relative performance, this method provides simpler calculations. Compared to MARCOS, which considers both ideal and anti-ideal solutions for a risk-benefit balanced evaluation, this method simplifies the process by focusing exclusively on similarities to maximum values [48, 49, 50]. Despite MARCOS's broader analytical scope, this method prioritizes simplicity and practicality.

Upon reviewing the literature, it is evident that no research has been found that measures the performance of alternatives using cosine similarity, which makes the present study unique. Additionally, cosine similarity has been employed in various studies within the literature: Ye (2014) [64] used it in the analysis of Simplified Neutrosophic Sets (SNS), Wojke and Bewley (2018) [65] applied it in optimizing traditional softmax classification, Elfakir et al. (2020) [66] utilized it in the development of a new word recognition system, and Huang et al. (2020) [67] employed it in the implementation of the Curricular Face, a face recognition system. Furthermore, Yu et al. (2020) [69] used cosine similarity to identify different neural architectures and query-document interaction representations, Zhang et al. (2020) [70] introduced a similarity-guided network for one-shot segmentation, leveraging cosine similarity to relate pixel features, and finally, Sattler et al. (2021) [71] utilized it in facilitating effective multitask learning through clustered federated learning (CFL). More recently, Duan et al. (2024) [72] incorporated cosine similarity in the creation of a federated learning framework, and Huang et al. (2024) [73] applied it to improve multi-label classification accuracy. Therefore, cosine similarity has acquired a multidisciplinary character, and this study expands its application domain. In this regard, the study contributes both to the MCDM and cosine similarity literature.

Future research could expand the proposed method by incorporating the minimum and average values of decision alternatives, thus enabling a more balanced evaluation of their performance. Additionally, analyzing the interactions between criteria could provide a key development direction. The flexibility and scalability of the method may be further enhanced by considering the size and diversity of data sets in various sectors. Sensitivity analyses could also assess the method's reliability under more different decision-making scenarios. Finally, optimizing the computational processes and applying algorithmic improvements for faster performance evaluations could facilitate the application of the method to large data sets. These advancements would broaden the method's applicability, especially in complex, MCDM problems.

5. CONCLUSION

The measurement of alternative performances is a critical step in decision-making problems, where decision-makers identify the best option. MCDM methods facilitate objective and rational decisions by balancing different criteria. MCDM offers a comprehensive framework for evaluating the overall performance of alternatives, considering multiple criteria rather than optimizing a single one. Since each method has its own assumptions, computational approach, and advantages, the diversity of MCDM methods provides more flexible and suitable solutions for various problems. The development of different methods helps overcome the limitations of existing techniques, enabling more accurate and reliable results tailored to the nature of the problem. This diversity allows for a more thorough and precise evaluation of alternatives, offering decision-makers a broader perspective and supporting optimal decision-making. In this context, a new approach based on the cosine similarity method, suitable for performance measurement and selection problems, is proposed.

DECLARATION OF ETHICAL STANDARDS

The author of this article declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Furkan Fahri ALTINTAŞ: The author has made a full (100%) contribution to the entirety of the study.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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