ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

Estuscience – Se, 2024, 25 [3] pp. 456-470, DOI: 10.18038/estubtda.1483766

RESEARCH ARTICLE

IMPACT OF THE OBJECTIVE ATTRIBUTE WEIGHTING ON FIVE POPULAR MULTI-CRITERIA DECISION-MAKING METHODS: AN EMPIRICAL STUDY

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Abstract

In a Multi Criteria Decision Making (MCDM) problem, it is rarely possible to optimize all objectives simultaneously, since they can be contradictory, ambiguous or may involve other types of inconsistencies or uncertainties. Therefore, when trying to choose from a number of available alternatives, a decision maker is expected to assign weights to attributes whose values are utilized to evaluate the alternative under consideration for ranking. Attributes can be qualitative or quantitative, and their weights can be assigned by the decision maker in a somewhat subjective manner or algorithmically. In this paper, the impact of attribute weighting approaches on the ranking results across a number of widely used MCDM methods are discussed. That is, it examines how different weighting methods affect the results on the same multi-criteria decision-making methods when making a rating. In doing so, consider five MCDM methods, namely, Evamix, Aras, Topsis, Vikor, Waspas, under three different objective attribute weight assignment procedures, namely, Critic, Entropy, and Standart Deviation (SD). Results indicate that, in some cases, the employed attribute weight-assignment mechanism influences the rating results more heavily than the MCDM method itself. In other words, different MCDM methods tend to yield similar results under the same weight assignment method whereas, the same method produces more distinguishable results under different weighting schemes.

Keywords

Multi-Criteria Decision Making (Mcdm),
Critic,
Entropy,
Evamix,
Topsis,

Time Scale of Article

Received :14 May 2024
Accepted : 18 Septembert 2024
Online date :30 September 2024

1. INTRODUCTION

Decision making has been becoming an increasingly more complex process in today's social and business environments where information and technology keep changing rapidly, thus, giving rise to more challenging problems across many diverse fields of study. Decision makers (DMs) who want to find the most effective option among a number of available alternatives need to consider multiple criteria that characterize an alternative for evaluation against the others. In doing so, a DM usually employs the following basic steps of decision analysis; defining the problem, listing all possible options, constructing the decision table showing the results of each option for each event, choosing a decision model, applying the model, and finally, choosing an option [47]. A decisive step in this process is the determination of the degree of importance of each criterion, since the ranking of the alternatives is heavily influenced by them. For this reason, a DM first should look at the nature of the problem in order to specify the most appropriate criteria and then determine the importance levels of the criteria by assigning weights to them. Basically, there are two ways to assign weights to criteria (also called attributes); the DM either assigns them drawing upon his personal experience and preferences, or uses an algorithm for the task. The first type of approaches is called subjective methods for obvious reasons. In contrast, the second

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type of so-called objective methods does not need any direct input from the DM, assuming that the required information to assign weights already exists in the decision matrix.

In this paper, when making a rating, it is examined how different weighting methods affect the results in the same multi-criteria decision-making methods. As the weight ratios and ranking methodology change, changes to the rankings are discussed. Three well-known objective weighting methods are used to assign weights to the selection criteria, namely CRITIC, Entropy and standard deviation (SD) methods. Then, using these weights, EVAMIX, ARAS, TOPSIS, VIKOR, and WASPAS methods are utilized for ranking the available alternatives. The data in the article are taken from Raymond Bissdorf's study titled "The Euro 2004 Best Poster Award (EBPA): Choosing The Best Poster in a Scientific Conference" [8]. This article is structured as follows: Section 2 and Section 3 briefly introduce the methods used in the study. Section 4 presents the Case study. Finally, Section 5 includes a discussion of the results and conclusions.

2. OBJECTIVE WEIGHT ASSIGNMENT METHODS

Before going into the details of the methods, first discuss what makes a criterion more important compared to the others. Intuitively, a criterion is more valuable to the DM if it helps her to remove a larger uncertainty towards a solution and, this happens only when the attribute values are well dispersed. Let us give an example to illustrate this point better. Suppose that you want to buy a house and your real-estate agent presents you with five alternatives, with price tags (all expressed in thousands of dollars) given as A = (900, 700, 500, 300, 100). Depending on your budget, this set of values helps you a great deal (removes a lot uncertainty) in your analysis towards a decision. Now, assume that the price tags are presented as B = (900, 895, 905, 910, 890). Since the values are not so much different, you obviously want to have a closer look at the values of the other attributes (number of rooms, number of bathrooms, distance to your work, distance to city center, quality of the district, etc.) before making a decision. In other words, the price attribute values of B do not remove as much uncertainty as the price attribute values of A. In general, all the objective weight assignment methods addressed in this paper, and most others, uses the capacity of the attribute to remove uncertainty (measured one way or the other) to assign weights; the higher the uncertainty removal capacity, the higher the weight. Note that, in the following we always use the normalized attribute values, so that commensurability holds to an acceptable degree across different value ranges.

Standard Deviation (SD) is a simple method that tries to measure the uncertainty removal capacity of a given attribute using standard deviation of the values, the expectation is being that a set of values with higher standard deviation values have a wider spread. Consequently, it assigns smaller weights to attributes with smaller standard deviation values. However, this expectation is not always justified and, its violation may lead to unexpected consequences, as we will demonstrate shortly.

Entropy was first defined by Rudolf Clausius in 1965 as a measure of disorder and uncertainty in a system [57].Entropy is used to measure the amount of useful information provided by existing data [53]. The main feature of the entropy method is that it can make an objective weighting that can be acted upon directly on the data without the need for the judgments of the decision makers. However, it may not be as robust as expected.

CRITIC (The Criteria Importance Through Intercriteria Correlation) method was first introduced in [24]. It calculates weights by scaling the standard deviation of the attributes with the linear correlation coefficient between the alternatives in a multiplicative aggregation formulation. Despite its popularity, it is not a silver-bullet solution for all cases either. We will not discuss this subject here any further, but simply indicate that it extends the weight assignment problem beyond the sole domain of a single attribute to a more holistic level where correlation is involved.

Going back to our house-buying example, let us discuss further cases to demonstrate certain weaknesses in SD and Entropy methods. Note that, the formulation of entropy, as stated in the communication theory, uses only the probability of occurrences, not the actual values themselves, and, since in both cases there are five distinct values, their entropy will be the same. The dispersion characteristics of the actual values simply cannot be captured by this definition the entropy. For this reason, MCDM methods use normalized attribute values, instead of probability of occurrences. Consequently,

$$\begin{aligned} Entropy(A) &= Entropy\,([\,0.36 \;\; 0.28 \;\; 0.20 \;\; 0.12 \;\; 0.04)] \\ &= -\frac{1}{ln\,5}(0.36 \times ln0.36 + 0.28 \times ln0.28 + 0.20 \times ln0.20 + 0.12 \times ln0.12 + 0.04 \times ln0.04) \\ &= \;\; 0.88807 \end{aligned}$$

In the same manner, we calculate Entropy(B)= 0.99998. Since weights are calculated according to (1 – Entropy) values, the highest weight goes to case A, as expected. Using the SD method, we calculate std(A)=0.11314 and std(B)= 0.0015713, indicating that the case A deserves much more weight; a result which complies with our expectations.

However, consider another case C = (900, 905, 500, 110, 100). A human quickly recognizes three groups in the data, which offers actually three choices; two homes approximately at 900, one home at 500 and two homes around 100 price range. Therefore, she can easily surmise that the case C is more helpful than case B but less so than case A. Consequently, we expect that the highest weight to be assigned to the attribute at case A, a lesser weight at case C and even lesser weight at case B. However, since the standard deviation of case C is std(C)= 0.14182, the highest weight goes to the case C. On the other hand, it is not a completely unexpected result if you are aware of the following fact from statistics: for bimodal distributions with two peaks, the standard deviation will increase as the spacing between peaks increases and, this is exactly what we did in case C. Similarly, Entropy(C) = 0.82066, again assigning the highest weight to the case C. Both results simply contradict the basic premise of understanding of the uncertainty removal capacity; the higher the weight, the better the dispersion.

The point of this discussion is to re-emphasize the fact that weighting is a difficult problem, which involves controversy and uncertainty [15]. So far, no overarching solution method has been proposed that can deliver optimum results in all possible cases. To address this issue, some authors have proposed hybrid or integrated approaches that combine the preferences of DMs with a decision matrix for obtaining the criteria weights, in order to take advantage of both method types. Others advocated solving MCDM scenarios initially without weights, and employing them only when the DM reckons that they are necessary in some criteria [38]. In any case, they seem to be claiming that the intervention of a DM is compulsory since the weight assignment process is an overly complex task, which cannot be fully automated.

3. MCDM METHODS

In this section, the five MCDM methods used in this article will be briefly introduced. Some references are provided to their various applications and refer the interested reader to Alinezhad's book where their mathematical formulations and numerical examples are conveniently provided in a single source [1].

EVAMIX (The EVAluation of MIXed data) method, introduced in 1982 by Voogd, has been applied to a diverse set of MCDM problems ever since [52]. Qureshi et al. [41] established a model for environmental and natural resource management using weighted total, expected value and EVAMIX methods. [34], Hajkowicz and Higgins [27] and Chung and Lee [20] analyzed water resources management projects with the EVAMIX method. Andalecio [2] evaluated seven different fishing strategies proposed by the municipality in the Philippines using Regime and EVAMIX methods. Chatterjee et al. [11] used COPRAS and EVAMIX methods in the complex material selection problem.

Dosal et al. [25] used EVAMIX, weighted total, ELECTRE II and Regime methods in site selection for recycling businesses. Chatterjee and Chakraborty [13] applied the EVAMIX method to select the non-traditional manufacturing process. Darji and Rao [21] used AHP and EVAMIX methods for appropriate material selection. Darji and Rao [22] solved the material selection problem in the sugar industry with the improved TODIM, ARAS, OCRA and EVAMIX methods. Chatterjee and Chakraborty [14] selected the best flexible manufacturing system for a manufacturing company with six MCDM methods, including EVAMIX.

ARAS (The Additive Ratio ASsessment) introduced by Zavadskas et al. [54] who modeled location selection problem for ports using Analytical Hierarchy Process (AHP) and Fuzzy ARAS methods. Medineckiene et al. [37] evaluated the sustainability of the buildings with ARAS. Stanujkic et al. [45] conducted studies with TOPSIS, VIKOR, MOORA, SAW, Gray Relational Analysis, COPRAS and ARAS methods. Turskis and Zavadskas [49] extended the ARAS method with Gray System Theory. Chatterjee and Chakraborty [12] handled the material selection decision problem using COPRAS and ARAS methods in their study. Reza and Majid [42] evaluated the use of Reliable Online Banking at the scale of financial institutions, using ARAS and Analytical Network Process (ANP) methods. Bakshi and Sarkar [6] used AHP and ARAS methods in their project selection performance evaluation decision problem. Ghadikolaei and Esbouei [26] used Fuzzy AHP and Fuzzy ARAS methods together for financial performance evaluation in their studies. Baležentis et al. [3] evaluated the sectors in the Lithuanian economy on the scale of financial ratios by using Fuzzy VIKOR, Fuzzy TOPSIS and Fuzzy ARAS methods. Sliogerience et al. [44] dealt with the problem of analysis and selection of energy production alternatives using AHP and ARAS methods. Shariati et al. [43] modeled the ARAS method for waste dump site selection in their study. They solved the decision problem by integrating fuzzy logic into a model named GARAS. Baležentis and Streimikienė [5] used TOPSIS and ARAS methods to determine the priorities of sustainable growth strategies for Lithuania. Kaklauskas et al. [29] developed a knowledge-based model for a standard home renovation and used the ARAS method to select the most ideal renovation project. Keršulienė and Turskis [30] used the Fuzzy ARAS method in the accounting department chief selection process for a business. Balezentiene and Kusta [4] determine the fuel type that will provide the most ideal gas emission for green houses by using the ARAS method. Stanujkic and Jovanovic [46] used the ARAS method for faculty web page quality measurement and evaluation.

TOPSIS (Technique of Order Preference by Similarity to the Ideal Solution) method is one of the most common methods among the MCDM, which has been applied for; evaluating the organizational performance of banks in capital management [16], multi-purpose inventory planning [17], evaluating the performance of insurance companies [28], the evaluation of the service quality of the banking sector [35], evaluating the service quality of hotel businesses [7], data mining [23] and, determining the facility location selection [18].

VIKOR (VlseKriterijuska Optimizacija I Komoromisno Resenje) method was first proposed by Opricovic and Tzeng [39] for multi-criteria optimization of complex systems. Tzeng et al. [51] used TOPSIS and VIKOR methods to evaluate bus fuels to be used in public transportation in Taiwan. Chu et al. [19] compared three methods: simple weighted average method (SAW), TOPSIS and VIKOR and discussed the applicability of these methods in group decision analysis in information societies. Opricovic and Tzeng [40] compared the extended VIKOR method with the TOPSIS, PROMETHEE and ELECTRE methods. Tong et al. [48] proposed the VIKOR method, which can take into account the variation in quality losses, for the optimization of multi-response processes. Liu and Yan [32] consider the VIKOR method to evaluate construction project proposals.

WASPAS (The Weighted Aggregates Sum Product Assessment) method has been applied in the solution of many decision-making problems due to its convenience. Zolfani et al. [58] proposed an integrated method based on SWARA and WASPAS methods for shopping mall location evaluation. Zavadskas et al. [56] evaluated the facade alternatives of four public and commercial buildings with

WASPAS and ratio method, reference point method and MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) method based on multiplicative system. Madic et al. [33] made a multi-criteria economic analysis of various machine processes with WASPAS. Lashgari et al. [31] listed the outsourcing strategies in health care and selected the best of these strategies with the Quantitative Strategic Planning Matrix and WASPAS methods. Chakraborty and Zavadskas [10] have solved eight real selection problems that arise in production with the WASPAS method. Turskis et al. [50] combined fuzzy set theory with WASPAS. Chakraborty et al. [9] solved the parameter selection problems of non-traditional machine processes with the WASPAS method. Zavadskas et al. [55] solved the site selection problem for the waste incineration plant with a method called WASPAS-SVNS. Mathew et al. [36] used the WASPAS method in the selection of industrial robots

4. CASE STUDY

In this section, the effect of weighting methods in MCDM methods is discussed. The problem definition and relevant input data are taken from a study where 13 posters {P1, P2, P3, …, P12, P13} are evaluated against four criteria {Scientific Quality (SQ), Contribution to OR Theory and/or Practice (TP), Originality (OR), Presentation Quality (PQ)} by five jury members {J1, J2, J3, J4, J5} for choosing the best poster in a scientific conference [8]. The scores given by the jury members are presented in Table 1. Note that, some scores are unevaluated by the jury members, which are denoted by a dash in the table

Table 1. The evaluation sheet used by the jury members.

Poster ID	Scientific Quality **(SQ)**					Contribution to Theory and/or Practice **(TP)**					Originality **(OR)**					Presentation Quality **(PQ)**				
	j_1	j_2	j_3	j_4	j_5	j_1	j_2	j_3	j_4	j_5	j_1	j_2	j_3	j_4	j_5	j_1	j_2	j_3	j_4	j_5
P1	4	7	5	5	3	4	7	6	5	3	4	6	6	7	3	4	7	5	6	2
P2	-	1	6	2	-	-	1	7	3	-	-	1	8	3	-	-	3	9	7	-
P3	6	6	7	6	2	8	9	7	6	4	6	7	7	7	5	6	6	9	7	5
P4	8	9	9	8	6	7	8	6	7	4	8	8	7	7	4	8	6	7	7	6
P5	8	6	8	7	2	8	7	9	7	0	8	5	7	7	2	8	8	8	6	5
P6	5	5	5	6	2	5	7	5	5	0	5	5	5	6	2	5	7	6	5	5
P7	6	5	6	6	-	7	8	7	6	-	6	5	5	6	-	8	8	5	3	-
P8	4	-	5	6	2	4	-	5	6	0	4	-	7	5	2	7	-	10	5	4
P9	-	-	5	3	-	-	-	5	3	-	-	-	7	3	-	-	-	10	3	-
P10	9	9	8	8	4	9	9	9	7	6	9	9	9	7	7	9	10	10	8	7
P11	6	9	8	7	5	6	8	6	6	5	6	9	7	8	5	8	9	8	7	3
P12	4	5	7	5	-	4	5	7	5	-	4	3	7	5	-	4	5	3	3	-
P13	4	8	8	8	8	4	8	8	7	10	4	6	7	7	8	4	9	9	8	10

Based on the evaluation sheet by the jury members, the author creates the decision matrix given in Table 2. An order of importance of the criteria was taken into consideration (SQ=0.4. TP=0.3. OR=0.2. PQ=0.1) and the score given by each jury member to each criterion is multiplied by these numbers. For the unevaluated values in Table 1, the arithmetic average of the scores given to each criterion by the other jury members is taken. Note that, this a decision matrix in which scores are already weighted. After an elaborate evaluation process, the author presents the ranking result as a partially ordered set (poset) in which p10 is the best , p9 is the worst and, the posters in the same equivalence class are denoted in curly braces: (p10, {p3, p4, p5, p12, p13}, p7, {p1, p6, p8, p11}, p2, p9).

Table 2. Decision Matrix

Poster ID	Scientific Quality					Contribution to Theory or Practice of OR					Originality					Presentation Quality				
	j_1	j_2	j_3	j_4	j_5	j_1	j_2	j_3	j_4	j_5	j_1	j_2	j_3	j_4	j_5	j_1	j_2	j_3	j_4	j_5
P1	1,6	2,8	2	2	1,2	1,2	2,1	1,8	1,5	0,9	0,8	1,2	1,2	1,4	0,6	0,4	0,7	0,5	0,6	0,2
P2	0,72	0,4	2,4	0,8	0,72	0,66	0,3	2,1	0,9	0,66	0,48	0,2	1,6	0,6	0,48	0,24	0,3	0,9	0,7	0,24
P3	2,4	2,4	2,8	2,4	0,8	2,4	2,7	2,1	1,8	1,2	1,2	1,4	1,4	1,4	1	0,6	0,6	0,9	0,7	0,5
P4	3,2	3,6	3,6	3,2	2,4	2,1	2,4	1,8	2,1	1,2	1,6	1,6	1,4	1,4	0,8	0,8	0,6	0,7	0,7	0,6
P5	3,2	2,4	3,2	2,8	0,8	2,4	2,1	2,7	2,1	0	1,6	1	1,4	1,4	0,4	0,8	0,8	0,8	0,6	0,5
P6	2	2	2	2,4	0,8	1,5	2,1	1,5	1,5	0	1	1	1	1,2	0,4	0,5	0,7	0,6	0,5	0,5
P7	2,4	2	2,4	2,4	1,84	2,1	2,4	2,1	1,8	1,68	1,2	1	1	1,2	0,88	0,8	0,8	0,5	0,3	0,42
P8	1,6	1,36	2	2,4	0,8	1,2	0,9	1,5	1,8	0	0,8	0,72	1,4	1	0,4	0,7	0,5	1	0,5	0,4
P9	0,64	0,64	2	1,2	0,64	0,48	0,48	1,5	0,9	0,48	0,4	0,4	1,4	0,6	0,4	0,2	0,2	1	0,3	0,2
P10	3,6	3,6	3,2	3,2	1,6	2,7	2,7	2,7	2,1	1,8	1,8	1,8	1,8	1,4	1,4	0,9	1	1	0,8	0,7
P11	2,4	3,6	3,2	2,8	2	1,8	2,4	1,8	1,8	1,5	1,2	1,8	1,4	1,6	1	0,8	0,9	0,8	0,7	0,3
P12	1,6	2	2,8	2	1,68	1,2	1,5	2,1	1,5	1,26	0,8	0,6	1,4	1	0,76	0,4	0,5	0,3	0,3	0,24
P13	1,6	3,2	3,2	3,2	3,2	1,2	2,4	2,4	2,1	3	0,8	1,2	1,4	1,4	1,6	0,4	0,9	0,9	0,8	1

At this stage, the ready weighted decision matrix is taken and the importance weights of the criteria for each jury member are calculated using Standard Deviation (SD), Entropy and Critic methods (Table 3).

Table 2. Decision Matrix

		j1	j2	j3	j4	j5
SD	SQ	0,91182	1,06725	0,57467	0,73867	0,78665
	TP	0,69621	0,82323	0,41324	0,41602	0,85928
	OR	0,43155	0,50442	0,21363	0,31622	0,39416
	PQ	0,23706	0,23669	0,22560	0,18327	0,22983
Entropy	SQ	0,27135	0,28248	0,22080	0,30439	0,18288
	TP	0,2631	0,27351	0,19886	0,18331	0,50303
	OR	0,22672	0,27885	0,11777	0,21219	0,15524
	PQ	0,23881	0,16515	0,46255	0,30010	0,15883
CRITIC	SQ	0.16316	0.22459	0.27536	0.16951	0.25211
	TP	0.25408	0.2525	0.26064	0.19844	0.19686
	OR	0.17441	0.23028	0.16456	0.19165	0.20837
	PQ	0.40835	0.29263	0.29944	0.4404	0.34266

Table 3. Importance weights of criteria by objective methods.

At this point, recall the basic operating principle of all objective weight assignment methods; objective methods are utilized to prevent human-made instabilities and obtain results that are more realistic. The objective methods use mathematical models and only data within the decision matrix assuming that all the required information to assign weights properly already exists in the decision matrix, thus without needing to consider the preferences of decision makers. While the decision matrix is constructed, an order of importance of the criteria is imposed upon the alternatives. Therefore, when weights are assigned to attributes using the Standard Deviation, Entropy and Critic methods, one would expect the already imposed importance pattern (SQ > TP > OR > PQ) to emerge more clearly in the result. Table 4 which summarizes the results in Table 3, shows that this is not always the case.

Table 4. Order of importance according to the three objective weighting methods

	j1	j2	j3	j4	j5
SD	**SQ** > **TP** > **OR** > **PQ**	**SQ** > **TP** > **OR** > **PQ**	**SQ** > **TP** > **OR** > **PQ**	**SQ** > **TP** > **OR** > **PQ**	TP > SQ > **OR** > **PQ**
Entropy	**SQ** > **TP** > PQ > OR	**SQ** > OR > TP > **PQ**	PQ > SQ > TP > OR	**SQ** > PQ > OR > TP	TP > SQ > PQ > OR
CRITIC	PQ > **TP** > **OR** > SQ	PQ > **TP** > **OR** > SQ	PQ > SQ > TP > OR	PQ > **TP** > **OR** > SQ	PQ > SQ > **OR** > TP

The Standard Deviation, Entropy and Critic methods have quite different indicators about the relative importance of the four criteria. Whatever importance information already present in the raw data or imposed by the multiplication operation seemed to be caught only by the SD method in a consistent manner. The minor discrepancy observed for J5 (TP and SQ switched places) can be attributed to the fact J5 did not specify any scores for many attributes and those are replaced by the averages. For Entropy method, three of the four criteria are indicated by the scores of different jurors as the most important one, with the exception of OR. Critic method has the greatest consistency, regarding the most important criterion, which is indicated as PQ by all five jurors. Since multiplication coefficient for PQ was the smallest (0.1), It is suspected that there must be a strong correlation between the alternatives for such a result to occur. Now apply the five MCDM methods, for a discussion of the magnitude of possible effects of weighting on them. First starts with no weighting condition (in fact, all four criteria are assigned a weight of 0.25 equally to avoid duplicating the code).

Table 5. Ranking of alternatives with no weights

Order / Method	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**11th**	**12th**	**13th**
EVAMIX	P8	P2	P10	P9	P6	P11	P3	P5	P1	P13	P4	P7	P12
ARAS	P10	P13	P4	P11	P3	P5	P7	P1	P6	P12	P8	P2	P9
TOPSIS	P10	P13	P4	P11	P5	P3	P7	P1	P6	P8	P12	P2	P9
WIKOR	P10	P13	P4	P11	P5	P3	P7	P1	P6	P8	P12	P2	P9
WASPAS	P10	P13	P4	P11	P3	P5	P7	P1	P6	P12	P8	P2	P9

In this case, all methods seem to be in complete agreement, with the exception Evamix method. In fact, they are exactly the same if allow only two of them to switch the places of the 5th and 6th posters, and places of the 10th and 11th posters. Recall the ranking poset that was produced by Bisdorff, which was (p10, {p3, p4, p5, p12, p13}, p7, {p1, p6, p8, p11}, p2, p9). Reordering the posters in the equivalence classes as (p10, {p13, p4, p5, p12, p3}, p7, {p1, p6, p8, p11}, p2, p9. You see that the first three and last two posters are the same. At this point It can be state that four out of five MCDM methods give very close results, and any inconsistencies that may arise later can be attributed to the feature weighting method used, which will be discussed in the next section.

First, apply the SD method (Table 6).

Table 6. Ranking of alternatives by SD method

Order / Method	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**11th**	**12th**	**13th**
EVAMIX	P13	P10	P1	P4	P3	P11	P5	P2	P7	P12	P6	P8	P9
ARAS	P10	P13	P4	P11	P5	P3	P7	P1	P12	P6	P8	P2	P9
TOPSIS	P10	P13	P4	P11	P5	P3	P7	P12	P1	P6	P8	P2	P9
WIKOR	P10	P13	P4	P11	P5	P3	P7	P12	P1	P6	P8	P2	P9
WASPAS	P10	P13	P4	P11	P5	P3	P7	P1	P6	P12	P8	P2	P9

The SD method increased the uniformity among the results of the four methods even further. Now we have a complete match in 10 places out of 13. Even the Evamix agrees about last place. In short, SD method served to diminish the differences between methods.
Next, apply the Entropy method (Table 7).

Table 7. Ranking of alternatives by the Entropy method

Order / Method	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
EVAMIX	P10	P13	P4	P11	P5	P3	P7	P1	P8	P6	P12	P2	P9
ARAS	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9
TOPSIS	P10	P13	P11	P4	P3	P5	P7	P1	P6	P8	P12	P2	P9
WIKOR	P10	P13	P11	P4	P3	P5	P7	P1	P6	P8	P12	P2	P9
WASPAS	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9

The overall agreement between the results becomes even more pronounced. Aras-Waspas and Topsis-Vikor pairs exhibit a complete match between themselves. The most striking difference is observed in the behavior of Evamix that matches the rankings of the other four methods in 7 out of 13 places. Allowing four pair wise switching of places in three methods, the consensus among the methods will be complete. In other words, the methods will deliver the most similar rankings using the weights produces by the Entropy method.

Lastly, apply the Critic method (Table 8).

Table 8. Ranking of alternatives by the CRITIC method

Order / Method	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
EVAMIX	P10	P13	P4	P5	P11	P3	P7	P8	P6	P1	P2	P12	P9
ARAS	P10	P13	P4	P11	P5	P3	P7	P1	P6	P8	P12	P2	P9
TOPSIS	P10	P13	P4	P11	P5	P3	P7	P6	P8	P1	P12	P2	P9
WIKOR	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9
WASPAS	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9

The weights calculated by the Critic method allow all methods, without exception, to deliver equal rankings in the top three places. This implies the existence of some underlying correlation between the alternatives, which only the Critic method is able to extract from the decision matrix.

So far, some changes in the behavior of MCDM methods resulting from the use of different weighting methods have been observed. It will now be discussed how their significance compares with the significance of the differences that may arise in the rankings of a particular MCDM method under SD, Entropy and Critical method. (Table 9, Table 10, Table 11, Table 12, Table 13).

Table 9. EVAMIX

EVAMIX

Order / Method	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
CRITIC	P10	P13	P4	P5	P11	P3	P7	P8	P6	P1	P2	P12	P9
ENTROPY	P10	P13	P4	P11	P5	P3	P7	P1	P8	P6	P12	P2	P9
SD	P13	P10	P1	P4	P3	P11	P5	P2	P7	P12	P6	P8	P9

Table 10. ARAS

ARAS

Method \ Order	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
CRITIC	P10	P13	P4	P11	P5	P3	P7	P1	P6	P8	P12	P2	P9
ENTROPY	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9
SD	P10	P13	P4	P11	P5	P3	P7	P1	P12	P6	P8	P2	P9

Table 11. TOPSIS

TOPSIS

Method \ Order	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
CRITIC	P10	P13	P4	P11	P5	P3	P7	P6	P8	P1	P12	P2	P9
ENTROPY	P10	P13	P11	P4	P3	P5	P7	P1	P6	P8	P12	P2	P9
SD	P10	P13	P4	P11	P5	P3	P7	P12	P1	P6	P8	P2	P9

Table 12. VIKOR

VIKOR

Method \ Order	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
CRITIC	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9
ENTROPY	P10	P13	P11	P4	P3	P5	P7	P1	P6	P8	P12	P2	P9
SD	P10	P13	P4	P11	P5	P3	P7	P12	P1	P6	P8	P2	P9

Table 13. WASPAS

WASPAS

Method \ Order	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
CRITIC	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9
ENTROPY	P10	P13	P4	P11	P3	P5	P7	P1	P6	P8	P12	P2	P9
SD	P10	P13	P4	P11	P5	P3	P7	P1	P6	P12	P8	P2	P9

Examination of Tables 9-13 reveals the following observations:

- Evamix has only one match across its own rankings under three weighting methods (Table 9). Thus, it is the most sensitive method to the selected weighting assignment mechanism.
- Aras and Waspas exhibit no significant changes in rankings under three weighting methods (Table 10 and Table 13). Its rankings are more similar to each other under the Entropy and Critic methods, while SD ranking differs from these to a greater extent.
- The agreement between the rankings of Aras and Vikor are less than those of Aras and Waspas (5 places vs. 8 and 9). Interestingly, the Critic ranking of Topsis agrees with its SD ranking at four more places, as opposed to Entropy. This behavior is unique among the cases considered here.

5. CONCLUSION

This article considers five potential preference ranking-based methods and compares ranking performances and the effect of criterion weights on preferences for ranking posters at a scientific conference. The performance tests conducted for ranking performance comparison and to measure the degree of concordance between the rankings in a quantitative manner are provided in the Appendix. Based on these test results, it can be stated that objective attribute weighting methods have a strong impact on the rankings produced by different MCDM methods, albeit some are more sensitive than the others are. In almost all cases (with a single exception), all MCDM-weighting method combinations agree on that P10 is the best poster, and (without any exception) P9 is the worst one. If one is only interested in finding the best or worst alternative, there is no difference between combinations. However, if whole ranking is important, we propose that DM should construct the Table 4 for its own data and inspect the order of importance implied therein to choose those MCDM-weighting method combinations that matches best to the order of importance that she has in mind. Such an approach produces more rational and justified rankings.

ACKNOWLEDGEMENTS

The author expresses his gratitude to the editor for providing valuable assistance throughout the publication process.

CONFLICT OF INTEREST

The author stated that there are no conflicts of interest regarding the publication of this article.

CRediT AUTHOR STATEMENT

Hamiyet Merkepçi: Formal analysis, Visualization, Writing, Original Draft, Review & Editing, Conceptualization.

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APPENDIX: Performance tests conducted for ranking performance comparison and for measuring the degree of concordance between the rankings.

Tests are conducted using the methodology described in [14] .The test results are provided in the form of value tuples where

(a) Spearman's rank correlation coefficient: Using Spearman's rank correlation coefficient (rs) value, the similarity between two sets of rankings can be measured. Usually, its value lies between –1 and +1, where the value of +1 denotes a perfect match between two rank orderings.

(b) Agreement between the top three ranked alternatives: Here, a result of (1,2,3) means the first, second and third ranks match; (1,2,#) means the first and second ranks match; (1,#,#) means only the first ranks match; and (#,#,#) means no match.

(c) (c) The last test is performed with respect to the number of ranks matched, expressed as the percentage of the number of alternatives considered.

Test 1: (For Table 6)

Method	Aras	Topsis	Vikor	Waspas
Evamix	0.96704, (1,2,3),53.8	0.98352, (1,2,3),53.8	0.98352, (1,2,3), 76.9	0.95605, (1,2,3), 46.2
Aras		0.98352, (1,2,3), 76.9	0.98352, (1,2,3), 53.8	**0.99451,(1,2,3), 84.6**
Topsis			0.98352, (1,2,3), 53.8	0.97528,(1,2,3), 61.5
Vikor				0.97253,(1,2,3), 46.2

Test 2: (For Table 7)

Method	Aras	Topsis	Vikor	Waspas
Evamix	0.98902, (1,2,3), 69.2	0.98352, (1,2,#), 53.8	0.98352, (1,2,#), 53.8	0.98902, (1,2,3), 69.2
Aras		0.99451, (1,2,#), 84.6	0.99451, (1,2,#), 84.6	**1,(1,2,3), 100**
Topsis			**1, (1,2,3), 100**	0.99451,(1,2,#), 84.6
Vikor				0.99451,(1,2,#), 84.6

Test 3: (For Table 8)

Method	Aras	Topsis	Vikor	Waspas
Evamix	0.83517, (#,#,#), 7.69	0.79671, (#,#,#), 7.69	0.79671, (#,#,#), 7.69	0.82968, (#,#,#), 15.3
Aras		0.99451, (1,2,3), 84.6	0.99451, (1,2,3), 84.6	0.99451,(1,2,3), 84.6
Topsis			**1, (1,2,3), 100**	0.98352,(1,2,3), 76.9
Vikor				0.98352,(1,2,3), 76.9

Test 4: (For Table 9)

Method	Entropy	SD
Critic	**0.97252, (1,2,3), 46,15**	0.72527, (#,#,#), 7,69
Entropy		0.81318,(#,#,#), 7,69

Test 5: (For Table 10)

Method	Entropy	SD
Critic	**0.99746, (1,2,3), 84,61**	0.98351, (1,2,3), 76,92
Entropy		0.97802,(1,2,3), 61,53

Test 6: (For Table 11)

Method	Entropy	SD
Critic	**0.97252**, (1,2,#), 46,15	0.95054, **(1,2,3), 69,23**
Entropy		0.95604,(1,2,#), 38,46

Test 7: (For Table 12)

Method	Entropy	SD
Critic	**0.99450**, (1,2,#), **84,61**	0.96153, **(1,2,3)**, 53,84
Entropy		0.95604,(1,2,#), 38,46

Test 8: (For Table 13)

Method	Entropy	SD
Critic	**1 (1,2,3), 100**	0.98901, (1,2,3), 69,23
Entropy		0.98901,(1,2,3), 69,23