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DEVELOPMENT OF RAMDOE: A NEW METHOD FOR RAPIDLY RANKING ALTERNATIVES WITH SUPPLEMENTARY OPTIONS AND CONSIDERING CHANGES IN CRITERIA VALUES

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This paper delves into the development and validation of the RAMDOE method, a pioneering approach in multi-criteria decision making (MCDM) that seamlessly integrates the root assessment method (RAM) and design of experiments (DOE) techniques, addressing the inflexibility of traditional MCDM methods in accommodating adjustments in criteria ranges and the addition of new alternatives without necessitating a complete overhaul of the decision framework. Through empirical analysis, the study demonstrates the RAMDOE method's remarkable efficacy in precisely ranking alternatives, as illustrated through a practical case study focused on the selection of a supplier from a pool of seven candidates. One of the most notable aspects of the RAMDOE method lies in its capacity to formulate a regression equation that accurately captures the intricate relationship between alternative scores and criteria values, enabling decision-makers to seamlessly integrate new alternatives into the decision-making process without the cumbersome task of recalibration, thereby distinguishing it from conventional MCDM techniques such as TOPSIS (technique for order of preference by similarity to ideal solution), COPRAS (complex proportional assessment), MOORA (multiobjective optimization on the basis of ratio analysis), EDAS (evaluation based on distance from average solution) and CODAS (combinative distance-based assessment). The practical implications of these findings are profound, offering decision-makers across various domains a more efficient and adaptable framework to navigate complex decision scenarios. Particularly in contexts like supplier selection, where criteria ranges may vary significantly, the RAMDOE method provides decision-makers with a robust toolset to make informed decisions, presenting a promising avenue for addressing the dynamic nature of decision-making environments and enhancing the overall robustness and flexibility of MCDM processes in real-world applications

Keywords: multi-criteria decision making, RAMDOE method, RAM method, DOE method

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1. Introduction

The research topic of multi-criteria decision-making techniques holds increasing significance in contemporary times, attracting attention from numerous scientists. With over 200 different MCDM (multi-criteria decision making) methods proposed by researchers [1], the field presents a diverse array of methodologies, all excelling in identifying the optimal choice among alternatives [2–4]. However, as the number of alternatives grows, the need for recalculations from scratch becomes evident, posing challenges, especially in urgent decision-making scenarios.

In today's complex and fast-paced world, decision-making processes are constantly challenged by a myriad of options and variables, from business strategies to public policy formulation. Multi-criteria decision-making techniques offer a structured framework to navigate through this complexity, aiding in the identification of optimal solutions amidst competing objectives and constraints. Moreover, the practical value of research in this field is profound, enhancing our understanding of decision-making processes and offering efficient methodologies to tackle complex scenarios. These insights directly contribute to improving decision-making practices across diverse domains, empowering decision-makers to navigate uncertainty and make informed choices. Therefore, the quest for a novel approach capable of swiftly and accurately handling the escalating number of alternatives becomes imperative.

2. Literature review and problem statement

Multi-criteria decision-making (MCDM) involves making a decision based on multiple criteria. This decision-making process aims to provide users with the best option among several available alternatives [5, 6]. The essence of this approach lies in ranking the alternatives to identify the top-ranked option, which is referred to as the best alternative. However, using traditional MCDM methods alone requires recalculating the entire process when the number of alternatives changes (due to additions or removals). To address this issue, a combination of design of experiments (DOE) and MCDM methods has been implemented. This integration of DOE with MCDM aims to construct a regression equation that reflects the relationship between the scores of alternatives and the criteria. Consequently, if the number of alternatives to be ranked changes, one can simply use the regression equation to calculate the scores for the alternatives without having to repeat all the steps of the traditional MCDM method.

In [7], DOE was combined with the SAW method (simple additive weighting). This combination has been confirmed as successful and has been applied to rank alternatives when the number of alternatives changes in the field of non-ferrous metals, in the field of metal cutting, and in evaluating air quality in office spaces. However, this study has not considered the case where the values of the criteria in the additional option fall outside the range of values of the criteria in the existing options. To explain this further, if in the existing options, the value of criterion j lies within the range $C_j \in [x, y]$, then the additional options must also have the value of C_j satisfying $C_j \in [x, y]$. This is perhaps something that the authors of this study have not fully anticipated, that there may be additional options whose criterion j does not fall within the range from x to y.

In [8], DOE was integrated with the MARCOS method (measurement alternatives and ranking according to compromise solution). This combination has been affirmed as successful in ranking alternatives when the number of alternatives changes in the selection of cutting tool materials and in a numerical example. However, during the research process, there was also no consideration given to the possibility that the values of the additional criteria might lie outside the range of values of the criteria in the existing options. This could also be an aspect that researchers have not meticulously calculated, namely, the existence of supplementary options where the value of C_j does not fall within the range from x to y.

In [9], DOE was combined with the PIV method (proximity indexed value). This combination has also been affirmed as successful in selecting metal milling methods, choosing suppliers for the steel industry in India, selecting logistics services, and selecting robots. In each of these problems, cases where the number of alternatives to be ranked changes were considered. Nevertheless, one aspect that researchers have also failed to meticulously calculate is the existence of supplementary options where the value of C_j does not fall within the range from x to y.

In [10], DOE was combined with the MABAC (multi-attributive border approximation area comparison) method. This combination has also been affirmed as successful in selecting suppliers for the steel industry in India when the number of alternatives to be ranked changes. However, during the research process, there was also no consideration given to the possibility that the additional criteria might exceed the range of values of the criteria in the existing options. This could also be an aspect that researchers have not sufficiently deliberated on, namely, the existence of supplementary options where the value of C_j does not fall within the range from x to y.

In [11], the combination of DOE with the EDAS method (evaluation based on distance from average solution) has been demonstrated as successful in selecting the best material types when the number of material types changes in two different fields: gear manufacturing materials and shock-absorbing materials for automobiles. However, during the research process, there was also no consideration given to the possibility of newly added criteria exceeding the range of values of the criteria in the existing options. This could also be an aspect that researchers have not taken into account.

In [12], the combination of DOE with the EDAS method has also been verified as successful in selecting office spaces with the best air quality, selecting non-ferrous metal machining methods, and selecting metal grinding methods. In each of these cases, the number of alternatives to be ranked has also changed. The case where the criteria C_j in the additional options lie outside the range from x to y is also a matter not considered in this paper. Perhaps the authors of this paper did not anticipate that this issue could entirely occur.

All of the aforementioned studies have demonstrated that the combination of DOE with MCDM methods has been successful in ranking alternatives in various fields when the number of alternatives changes. However, in all of these studies, the varying values of criteria have not been taken into account. If, for the additional alternatives, the value of criterion j is less than x or greater than y (i.e., $C_j < x$ or $C_j > y$), then the pure combination of DOE and MCDM methods cannot be applied. To address this limitation, this study proposes a solution to rank alternatives considering the adjustment of criterion values in the additional alternatives. The root assessment method (RAM) method is used to combine with DOE in this study because it is a newly emerging method as of September 2023 and has the advantage of balancing beneficial and non-beneficial criteria [13]. The combination of the RAM method with DOE is referred to as the RAMDOE method. The RAMDOE method can quickly rank options when the number of options changes, and notably, this method takes into account the changing values of criteria in newly added options to the list of options needing ranking.

3. The aim and objectives of the study

The aim of this study is to introduce a novel method called RAMDOE (multi-criteria decision making and design of experiments), which enables rapid ranking of alternative options when additional alternatives are incorporated into the list with adjusted criterion values compared to previously existing options. Evaluating the effectiveness of the RAMDOE method involves comparing the ranking outcomes of alternatives using the RAMDOE method against those using the original RAM method and other MCDM methods.

To achieve this aim, the following objectives need to be accomplished:

– to compare the effectiveness of the RAMDOE method in ranking alternatives with the RAM method;

– to compare the effectiveness of the RAMDOE method in ranking alternatives with the other MCDM methods.

4. Materials and methods

4. 1. The Root Assessment Method (RAM) method

The steps to rank alternatives using the RAM method are as follows [13]:

Step 1: construct the decision matrix X with m rows and n columns, where m and n are the number of alternatives to be ranked and the number of criteria for each alternative, respectively. Let x_{ij} denote the value of criterion j for alternative i, with $j=1$ to n and $i=1$ to m:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}. \quad (1)$$

Step 2: normalize the data according to formula (2):

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}. \quad (2)$$

Step 3: calculate the normalized values considering the weights of the criteria according to formula (3):

$$y_{ij} = w_j \cdot r_{ij}. \quad (3)$$

Here, w_j represents the weight of criterion j.

Step 4: compute the total normalized score considering the weights of the criteria according to formulas (4), (5). Here, letters B and C are used to denote the corresponding criteria for profit and cost:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \text{ if } j \in B; \quad (4)$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \text{ if } j \in C. \quad (5)$$

Step 5: calculate the score of each alternative according to formula (6):

$$RI_i = \sqrt[2+S_{-i}]{2+S_{+i}}. \quad (6)$$

Step 6: rank the alternatives in descending order of their scores.

4. 2. The Root Assessment Method-Design of Experiments (RAMDOE) method

The proposed method in this paper, which is based on the integration of the RAM and DOE methods, is named the RAMDOE method. The eight steps to rank alternatives using the RAMDOE method are as follows:

Step 1: same as Step 1 of RAM.

Step 2: specify the allowed limits of the criteria, including $\min(C'_j)$ and $\max(C'_j)$. This implies that in the existing alternatives, if the value of criterion j falls within the range $C_j \in [x, y]$, then $\min(C'_j) < x$ and $\max(C'_j) > y$. This represents a complete departure from previous studies. Specifically, when integrating an MCDM method with a DOE method, previous studies only considered the case where $C_j \in [x, y]$. However, in the RAMDOE method, the range of C_j has been expanded, meaning $C_j \in \left[\min(C'_j), \max(C'_j)\right]$.

Step 3: construct the table of limit values of the criteria after adjusting their values as in Table 1.

Table 1

Illustration of limit values of criteria after adjustment

C_1	$\min(C'_1)$	$\max(C'_1)$
C_2	$\min(C'_2)$	$\max(C'_2)$
C_j	$\min(C'_j)$	$\max(C'_j)$
C_n	$\min(C'_n)$	$\max(C'_n)$

Step 4: use the DOE method to construct a full factorial orthogonal matrix with 2^n experiments.

Step 5: calculate scores for each experiment using the RAM method.

Step 6: construct a regression equation showing the relationship between the scores of experiments and the criteria.

Step 7: use the regression equation to calculate scores for the alternatives to be ranked, including the additional ones.

Step 8: rank the alternatives.

5. Evaluating the performance of the RAMDOE method in multi-criteria decision making: a comparative analysis

5. 1. Comparing the RAM and RAMDOE methods

The ranking of alternatives was conducted using a dataset from a recently published study [14]. This was done to reduce data collection time. Furthermore, the ranking of alternatives in this case has also been performed using other MCDM methods. The ranking results obtained from those MCDM methods will be used as a basis for evaluating the effectiveness of both the RAM and RAMDOE methods.

Five criteria were used to describe each provider, including warehouse capacity (C_1), service cost (C_2), batch size (C_3), flexibility (C_4), and technology utilization (C_5). The values of these criteria for each provider, along with their types and weights, are compiled in Table 2.

Table 2

Summarizes seven logistics service providers in France [14]

Alt.	C_1	C_2	C_3	C_4	C_5
Weights	0.036	0.192	0.326	0.326	0.12
Type	*B*	*C*	*B*	*B*	*B*
A1	60	0.4	2,540	500	990
A2	6.35	0.15	1,016	3,000	1,041
A3	6.8	0.1	1727.2	1,500	1,676
A4	10	0.2	1,000	2,000	965
A5	2.5	0.1	560	500	915
A6	4.5	0.08	1,016	350	508
A7	3	0.1	1,778	1,000	920

A scenario is as follows: initially, only the ranking of the five alternatives, namely A3, A4, A5, A6, and A7, needs to be conducted. After ranking these five alternatives, two additional alternatives, A1 and A2, are added to the list of alternatives to be ranked. This scenario is created to demonstrate the advantages of the RAMDOE method over the RAM method and other existing MCDM methods.

The application of the RAM method to rank the five alternatives is as follows: the decision matrix is presented in Table 3.

All calculations in this study are conducted using Excel software. Normalized values were calculated according to (2), resulting in Table 4.

Normalized values considering the weights of the criteria were calculated according to (3), resulting in Table 5.

Table 3

Decision matrix for the five alternatives

Alt.	C_1	C_2	C_3	C_4	C_5
A3	6.8	0.1	1727.2	1,500	1,676
A4	10	0.2	1,000	2,000	965
A5	2.5	0.1	560	500	915
A6	4.5	0.08	1,016	350	508
A7	3	0.1	1,778	1,000	920

Table 4

Normalized values

Alt.	C_1	C_2	C_3	C_4	C_5
A3	0.25373	0.17241	0.28402	0.28037	0.33628
A4	0.37313	0.34483	0.16444	0.37383	0.19362
A5	0.09328	0.17241	0.09209	0.09346	0.18359
A6	0.16791	0.13793	0.16707	0.06542	0.10193
A7	0.11194	0.17241	0.29238	0.18692	0.18459

Table 5

Normalized values considering the weights of the criteria

Alt.	C_1	C_2	C_3	C_4	C_5
A3	0.00913	0.03310	0.09259	0.09140	0.04035
A4	0.01343	0.06621	0.05361	0.12187	0.02323
A5	0.00336	0.03310	0.03002	0.03047	0.02203
A6	0.00604	0.02648	0.05447	0.02133	0.01223
A7	0.00403	0.03310	0.09531	0.06093	0.02215

The values of S_{+i}, S_{-i}, and RI_i were calculated using the corresponding formulas (4), (5), and (6). All calculated values are summarized in Table 6. The ranking results of the alternatives are also placed in the last column of Table 6.

Table 6

Some parameters in RAM and the ranking of alternatives

Alt.	S_{+i}	S_{-i}	RI_i	Rank
A3	0.23348	0.03310	1.48474	1
A4	0.21214	0.06621	1.46853	2
A5	0.08588	0.03310	1.43564	5
A6	0.09407	0.02648	1.44012	4
A7	0.18243	0.03310	1.46795	3

So, when using the RAM method to rank the alternatives, the ranking of the alternatives increases in the order of A3>A4>A7>A6>A5. Right after this, the ranking of alternatives using the RAMDOE method will be conducted.

Initially, the ranking was applied to the five alternatives A3, A4, A5, A6, and A7. Therefore, the decision matrix in this case is the same as the one generated when applying the RAM method (Table 3).

Setting the allowable limits for the criteria is carried out as follows. From Table 3, it can be observed that $C_1 \in [2.5, 10]$, $C_2 \in [0.08, 0.2]$, $C_3 \in [560, 1{,}778]$, $C_4 \in [350, 2{,}000]$, and $C_5 \in [508, 1{,}676]$. Therefore, we need to determine the limit values for the criteria such that $\min(C_1') < 2.5$, $\min(C_2') < 0.08$, $\min(C_3') < 560$, $\min(C_4') < 350$, $\min(C_5') < 508$, $\max(C_1') < 10$, $\min(C_2') < 2$, $\max(C_3') < 1{,}778$, $\max(C_4') < 2{,}000$, $\min(C_5') < 1{,}676$. Thus, the limit values for the criteria are determined as shown in Table 7. This means that only additional alternatives whose criterion values fall within the range specified in Table 7 are added to the list of alternatives to be ranked.

With five criteria and their minimum and maximum limit values as shown in Table 7, a full factorial experimental matrix consisting of 32 experiments is established as shown in Table 8.

Table 7

Allowable limit values for the criteria

C_j	$\min(C_j')$	$\max(C_j')$
C_1	2	65
C_2	0.05	0.5
C_3	550	2,550
C_4	340	3,100
C_5	500	1,700

Table 8

Experimental matrix

Exp.	C_1	C_2	C_3	C_4	C_5	$RI_i^{(e)}$
#1	2	0.05	2,550	340	1,700	1.42262
#2	2	0.05	2,550	3,100	1,700	1.42835
#3	65	0.5	550	340	500	1.41489
#4	65	0.5	2,550	3,100	1,700	1.42660
#5	2	0.5	550	3,100	500	1.41987
#6	65	0.05	550	340	500	1.41730
#7	2	0.05	550	340	1,700	1.41800
#8	2	0.5	550	340	1,700	1.41558
#9	2	0.05	2,550	3,100	500	1.42692
#10	2	0.05	550	340	500	1.41656
#11	2	0.5	2,550	340	500	1.41875
#12	65	0.5	2,550	340	500	1.41949
#13	2	0.05	2,550	340	500	1.42119
#14	65	0.5	550	3,100	500	1.42061
#15	65	0.05	2,550	3,100	1,700	1.42909
#16	65	0.5	550	340	1,700	1.41632
#17	65	0.5	550	3,100	1,700	1.42203
#18	65	0.05	550	3,100	500	1.42305
#19	2	0.5	2,550	340	1,700	1.42018
#20	2	0.05	550	3,100	1,700	1.42375
#21	65	0.05	550	340	1,700	1.41875
#22	65	0.05	550	3,100	1,700	1.42449
#23	2	0.5	2,550	3,100	1,700	1.42587
#24	2	0.5	550	3,100	1,700	1.42129
#25	65	0.05	2,550	340	1,700	1.42337
#26	2	0.5	550	340	500	1.41415
#27	65	0.05	2,550	3,100	500	1.42766
#28	65	0.05	2,550	340	500	1.42193
#29	65	0.5	2,550	340	1,700	1.42092
#30	2	0.5	2,550	3,100	500	1.42445
#31	2	0.05	550	3,100	500	1.42231
#32	65	0.5	2,550	3,100	500	1.42518

The scores for each experiment ($RI_i^{(e)}$) are then calculated using the steps of the RAM method and are also summarized in the last column of Table 8.

From the data in Table 8, a regression equation is established as (7):

$$RI_i^{(e)} = 1.41427 + 1.18 \cdot 10^{-5} \cdot C_1 - 0.00544 \cdot C_2 + \\ +2.3 \cdot 10^{-6} \cdot C_3 + 2.07 \cdot 10^{-6} \cdot C_4 + 1.19 \cdot 10^{-6} \cdot C_5. \quad (7)$$

The equation (7) has two coefficients R^2 and $R^2(adj)$ corresponding to 0.999988 and 0.999986, respectively. Both of these values are very close to 1, indicating that (7) has very high accuracy [15, 16].

Using (7) to recalculate the scores for the five alternatives in Table 3 to rank these alternatives. All calculated values are summarized in Table 9.

Table 9

Ranking results of the five alternatives using the RAMDOE method

Alt.	C_1	C_2	C_3	C_4	C_5	$RI_i^{(e)}$	Rank
A3	6.8	0.1	1727.2	1,500	1,676	1.42288	1
A4	10	0.2	1,000	2,000	965	1.42089	3
A5	2.5	0.1	560	500	915	1.41717	5
A6	4.5	0.08	1,016	350	508	1.41755	4
A7	3	0.1	1,778	1,000	920	1.42102	2

Thus, the ranking of the five alternatives using both the RAM and RAMDOE methods has been completed. The summarized data are presented in Table 10.

Table 10

Ranking results of the five alternatives using both the RAM and RAMDOE methods

Alt.	RAM	RAMDOE
A3	1	1
A4	2	3
A5	5	5
A6	4	4
A7	3	2

According to the data in Table 10, when both the RAM and RAMDOE methods are applied, both indicate that A3 is ranked 1st and A5 is ranked 5th. This preliminary observation suggests that the proposed RAMDOE method has a comparable effect to the original RAM method in identifying the best alternative among the available options.

However, this is only a scenario deliberately created, while in reality, seven alternatives in Table 2 need to be ranked. It should be noted that the values of the five criteria for the two additional alternatives A1 and A2 fall within the predetermined limit range as shown in Table 7. At this point, the difference between the RAM and RAMDOE methods can be clearly demonstrated. Specifically, to rank the seven alternatives in Table 2 using the RAM method, it is necessary to start over by applying the six formulas from (1) to (6). Meanwhile, if the RAMDOE method is used, only formula (7) needs to be applied. This is a notable advantage of the RAMDOE method over the RAM method and all other current MCDM methods.

Applying the six formulas from (1) to (6) to calculate the scores RI_i for each alternative to rank them using the RAM method. Applying only formula (7) to calculate the scores $RI_i^{(e)}$ for each alternative and ranking them using the RAMDOE method. All calculated values are summarized in Table 11.

Table 11

Ranking of seven alternatives using RAM and RAMDOE methods

Alt.	RAM		RAMDOE	
	RI_i	Rank	$RI_i^{(e)}$	Rank
A1	1.44615	5	1.42086	5
A2	1.46431	1	1.42331	1
A3	1.45987	2	1.42288	2
A4	1.44955	3	1.42089	4
A5	1.42883	7	1.41717	7
A6	1.43098	6	1.41755	6
A7	1.44934	4	1.42102	3

The ranking of alternatives using both the RAM and RAMDOE methods has been completed. Comparisons of the effectiveness of the RAMDOE method with other MCDM methods will be conducted in the next section.

5. 2. Comparing the RAMDOE method with other methods

In Table 12, the ranking results of alternatives using both the RAM and RAMDOE methods conducted in this study have been summarized, along with those using the TOPSIS (technique for order of preference by similarity to ideal solution), COPRAS (complex proportional assessment), MOORA (multiobjective optimization on the basis of ratio analysis), EDAS (evaluation based on distance from average solution) and CODAS (combinative distance-based assessment) methods in the previously published research [14].

Table 12

Ranking of seven alternatives using various methods

Alt.	RAM	RAM-DOE	TOP-SIS	CO-PRAS	MOORA	EDAS	CODAS
A1	5	5	5	3	5	4	4
A2	1	1	1	1	1	1	1
A3	2	2	2	2	2	3	2
A4	3	4	3	5	4	2	5
A5	7	7	7	7	7	5	7
A6	6	6	6	6	6	7	6
A7	4	3	4	4	3	6	3

The synthesis of ranking results of alternatives using various MCDM methods has been completed. The next chapter of this paper will discuss the achieved results.

6. Discussion on the effectiveness of using the RAMDOE method

Observing Table 10 reveals that when ranking the five options from A3 to A7, both the RAM and RAMDOE methods indicate that A3 is the best option and A5 is the worst. This suggests that RAMDOE is as effective as RAM in identifying the best option.

Table 11 demonstrates that when using both the RAM and RAMDOE methods together, they both identify A2 as the best alternative and A3 as the second-ranked alternative.

This once again confirms that the RAMDOE method is equivalent to the original RAM method.

Examining Table 12 shows that all seven methods, including RAM, RAMDOE, TOPSIS, COPRAS, MOORA, EDAS, and CODAS, unanimously identify A2 as the best option. This further confirms that the proposed RAMDOE method is equally effective as other MCDM methods in identifying the best option among the available alternatives. Moreover, according to Table 12, the ranking of options using the RAMDOE method closely matches the rankings obtained using the MOORA method, a well-known technique. This further emphasizes the accuracy of the proposed RAMDOE method.

It is noteworthy that when ranking options with the addition of new alternatives using the RAMDOE method, only equation (7) needs to be applied. In contrast, other methods require recalculating the entire process from scratch. For instance, using the RAM method would necessitate reapplication of the six equations sequentially from (1) to (6). This stands out as a significant advantage of the proposed RAMDOE method over existing MCDM methods.

The limitation of this study is that it only compares the ranking results of alternatives using the RAMDOE method with other MCDM methods through the ranking of alternatives. The comparison results would become clearer if considering the sensitivity when ranking alternatives in different scenarios. Different scenarios can be created by varying the weights for the criteria. To analyze sensitivity, the Spearman's rank correlation coefficient of alternatives can be used in this case [17, 18]. This is the work to be done in the near future.

The disadvantage of this study is the failure to consider cases where the normalization method available in the RAM approach cannot be used. Looking back at equation (2), it can be observed that if the total value of alternatives under a criterion equals zero, this formula cannot be applied. To overcome this limitation, alternative normalization methods need to be employed. Some alternative normalization methods can be found in recently published studies [19, 20].

7. Conclusions

1. The RAMDOE method consistently identifies the best alternative, just like when using the original RAM method.

2. By employing RAMDOE, a novel approach merging RAM and DOE methods, this study consistently identifies optimal choices akin to established MCDM methodologies (including TOPSIS, COPRAS, MOORA, EDAS, CODAS, and the original RAM method). This consistency underscores RAMDOE's potential as a robust decision-making tool, particularly valuable in scenarios with fluctuating option counts, ensuring both precision and expediency in decision processes.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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