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A novel approach to weighting criteria based on rank stability

Osman PALA[1*]

[1]International trade and business, Karamanoğlu Mehmetbey University, **70000** Karaman, osmanpala@kmu.edu.tr, ORCID No: https://orcid.org/0000-0002-2634-2653

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Abstract

In Multi-Criteria Decision Making (MCDM), the weighting of the criteria is at least as important as the normalization of the decision matrix and the procedure for ranking the alternatives. The slightest uncertainty in the weights of criteria poses a major problem for decision-makers, especially when there is little difference between the assessments of alternatives. One crucial question is which approaches should be applied to a given MCDM problem? This question may be answered by considering the insensitivity of rankings of the alternatives to changes in the weights of criteria. I propose a novel approach to criteria weighting that focuses solely on the insensitivity of rankings to changes in the weights of criteria. Simulations reveal that this approach is superior to other existing methods in terms of ranking stability. A real-life example concerning the digital readiness of the European Union reveals that this new approach yields beneficial results in different aspects of decision-making.

1. Introduction

Decision-making is a phenomenon that is frequently realized and has significant consequences for the stakeholders affected by the decision. Some decisions need to be made on a daily basis, while others need to be made with strategic thinking (Pala, 2022). Strategic decision making is defined in terms of the magnitude of actions, the allocation of resources, and the significance of the results (Eisenhardt & Zbaracki, 1992). Decision-making science has recently developed as a branch of operations research, especially due to the importance of strategic decision-making.

In the decision-making process, in cases where evaluation should be made according to more than one criterion, the problem is analyzed with Multi-Criteria Decision Making (MCDM) methods. These approaches simply break the problem into parts and evaluate the alternatives based on criteria (Mardani et al., 2015). MCDM techniques and approaches have been utilized to solve problems in various fields such as project management (Chen et al. 2019), military (Çarman & Şakar, 2019), education (Kazancoglu & Özen, 2019), health (Liou et al., 2017), information systems (Esangbedo, et al., 2021), tourism planning (Alptekin & Büyüközkan, 2011), city planning (Özbekler & Akgül, 2025), agriculture systems (Radmehr et al., 2022), energy sources (Lee & Chang, 2018), environment plans (Chen et al., 2010), supply chain management (Büyüközkan & Güler, 2021), logistics systems (Tzeng & Huang, 2012), finance (Baydaş & Elma, 2021), quality management (Akdag et al., 2014), vendor selection (Lin et al., 2010), mechanical process (Chatterjee et al., 2017), material selection (Anojkumar et al., 2014), supplier selection (Karsak & Dursun, 2015) and (Soygüder & Geçer, 2023).

MCDM problem consists of a finite number of alternatives and criteria. Selection of the best alternative (or ranking of all alternatives) depends on the evaluation of alternatives in terms of criteria. In MCDM, criteria are symbolized through a performance value that is most desired in selecting alternatives (Zeleny, 1998). The process of assigning criteria weights is a very susceptible issue as it directly affects alternative rankings. Two major and different trends have been prevailed in determining the weights of the criteria: subjective and objective approaches. Subjective methods reveal criteria importance levels based only on the opinion of the decision maker or expert. However, it is not possible to know the accuracy of this subjective evaluation. Additionally there would be a precisionism problem about these values (Jessop, 2004). Some failures in assigning criteria weights may occur due to the cognitive deficiency of people in decision-making (Danielson & Ekenberg, 2017). Objective weighting methods that rely solely on the decision matrix attempt to address these concerns. However, no matter how it is acquired (subjectively or objectively), an agreement cannot be achieved completely on the weights of the criteria. Accordingly, the alternative rankings should remain indifferent to the weight changes of the criteria as possible as (Wang & Luo, 2010) and (Pala, 2023).

In this study, a weighting method that focuses on robustness (insensitivity) in alternative rankings against changes in criteria weights, as in (Wang & Luo, 2010) and (Pala, 2023), but does not require optimization processes like them and also does not include functions such as logarithms and exponentials but only four basic operations in the calculation stages, is proposed. I evaluated each criterion by extracting one by one from the model and examined their affects to robustness. Hence, the criterion that provides more robustness comes to the fore in weighting process. Accordingly, the proposed approach RRC (Robustness to Removing Criteria) provides decision-makers and practitioners an easy tool to implement and outputs more reliable rankings.

The rest of the paper is organized as follows. Section 2 contains preliminaries which are required to compare the RCC method with the state of art methods. In Section 3, I briefly described the RRC method. In Section 4, I compared RRC with the widely used and respected objective weighting methods. Section 5 consists of implementing RRC to a real life application based on digital readiness of European Union (EU) countries. Finally, I provided an overview evaluation in the conclusions.

2. Preliminaries

I ensured the accuracy of RRC by comparing it with the most important, widely used and respected objective criteria weighting methods, such as the Equal Weight Model (EWM), Entropy (Hwang & Yoon, 1981), CRITIC (Criteria Importance through Correlation between Criteria) and SD (Standard Deviation) methods (Diakoulaki et al., 1995) and MEREC (Method Based on the Removal Effects of Criteria) (Keshavarz-Ghorabaee et al., 2021), as in the studies by Vinogradova-Zinkevič (2024), Pala (2024), Uyala (2024), and Su et al. (2025). In EWM, all criteria weights are equal and can be calculated with $w_j = 1/m$. Here, I can describe the rest of the methods as follows.

2.1 Entropy Method

Objective weighting can be done in MCDM by measuring the contrast intensity in the criteria with the entropy function. The phases of the entropy method are as follows (Wang & Lee, 2009);

Phase 1: The decision matrix $D = \|d_{ij}\|_{(n*m)}$ has to be normalized according to Eq. (1);

$$z_{ij} = \frac{d_{ij}}{\sum_{i=1}^{n} d_{ij}} \tag{1}$$

Phase 2: Entropy values of each criterion can be evaluated by Eq. (2);

$$e_j = \frac{-1}{\ln(n)} \sum_{i=1}^{n} d_{ij} \ln d_{ij} \tag{2}$$

Phase 3: Acquiring criteria weights through the entropy can be done by Eq. (3);

$$we_j = \frac{1 - e_j}{m - \sum_{j=1}^{m} e_j} \tag{3}$$

2.2 MEREC Method

The decision matrix $D = \|d_{ij}\|_{(nxm)}$ can be normalized by Eq. (4) and (5) in MEREC (Keshavarz-Ghorabaee et al., 2021) ;

$$z_{ij} = \frac{d_{ij}}{d_j^{\max}} \quad \text{for cost criteria} \tag{4}$$

$$z_{ij} = \frac{d_j^{\min}}{d_{ij}} \quad \textit{for benefit criteria} \tag{5}$$

While the performance scores of alternatives can be calculated by all criteria included in Eq. (6), the alternative scores are obtained with Eq. (7) by removing the criterion j from the model.

$$S_i = \ln\left(1 + \frac{1}{m}\sum_{j=1}^{m}\left(\left|\ln(z_{ij})\right|\right)\right), \quad i = 1,\dots,n \tag{6}$$

$$S_{ij}^* = \ln\left(1 + \frac{1}{m}\sum_{k=1,k\neq j}^{m}\left(\left|\ln(z_{ik})\right|\right)\right), \quad i = 1,\dots,n \quad j = 1,\dots,m \tag{7}$$

E_j, which represents the change in alternative scores when the criterion is removed, can be obtained by Eq. (8) and is used to determine the criterion weights via Eq. (9).

$$E_j = \sum_{i=1}^{n}\left|S_{ij}^* - S_i\right|, \quad j = 1,\dots,m \tag{8}$$

$$w_j = \frac{E_j}{\sum_{j=1}^{m} E_j} \quad j = 1,...,m \tag{9}$$

2.3 CRITIC Method

The decision matrix $D = \left\|d_{ij}\right\|_{(n*m)}$ has to be normalized using Eqs. (10) and (11) in CRITIC (Diakoulaki et al., 1995);

$$; \ z_{ij} = \frac{d_{ij} - d_j^{\min}}{d_j^{\max} - d_j^{\min}} \quad \text{for benefit criteria} \tag{10}$$

$$z_{ij} = \frac{d_j^{\max} - d_{ij}}{d_j^{\max} - d_j^{\min}} \quad \text{for cost criteria} \tag{11}$$

The correlation coefficients and standard deviations can be obtained via Eqs. (12) and (13), respectively.

$$\rho_{jk} = \frac{\sum_{i=1}^{n}(z_{ij} - \bar{z}_j)(z_{ik} - \bar{z}_k)}{\sqrt{\sum_{i=1}^{n}(z_{ij} - \bar{z}_j)^2 . \sum_{i=1}^{n}(z_{ik} - \bar{z}_k)^2}}, \ j,k = 1,...,m \tag{12}$$

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_{ij} - \bar{z}_j)^2} \ , \ j = 1,...,m. \tag{13}$$

The criteria weights are acquired by Eqs. (14) and (15);

$$c_j = \sigma_j \sum_{k=1}^{m}(1 - \rho_{jk}), \ \ j = 1,...,m. \tag{14}$$

$$w_j = \frac{c_j}{\sum_{k=1}^{m} c_k}, \ \ j = 1,...,m. \tag{15}$$

2.4 SD Method

Diakoulaki et al. (1995) stated that the criteria weight according to SD can be evaluated by Eq. (16) as follows;

$$w_j = \frac{\sigma_j}{\sum_{k=1}^{m} \sigma_k}, \ \ j = 1,...,m. \tag{16}$$

3. Robustness to Removing Criteria Method

The Decision matrix is beneficial in defining the MCDM problems. Assume that the decision matrix $D = d_{ij(n*m)}$ contains n alternatives as $A_1,,,A_n$ and m criteria $C_1,,,C_m$ where d_{ij} denotes the importance of A_i in terms of C_j. We have to assess the weight of each criterion w_j to calculate the importance of each alternative. While all w_j must be nonnegative, they must also add up to 1. In addition, alternative values can have different scales in terms of criteria, and criteria can be either based on benefit or cost. To overwhelm these two issues we can simply normalize the decision matrix. The most widespread normalization method can be performed by employing Eqs. (17) and (18) where $d_j^{\min}$ and $d_j^{\max}$ are lowest and highest values of criterion j, respectively.

$$z_{ij} = \frac{d_{ij} - d_j^{\min}}{d_j^{\max} - d_j^{\min}} \quad \text{for benefit criteria} \tag{17}$$

$$z_{ij} = \frac{d_j^{\max} - d_{ij}}{d_j^{\max} - d_j^{\min}} \quad \text{for cost criteria} \tag{18}$$

After obtaining the w_j and z_{ij}, we can assess the alternatives scores using an assessment MCDM method.

The most basic and broadly applied Weighted Sum Model (WSM) evaluates the S_i, the final score of the alternative i, using Eq. (19) (Fishburn, 1967):

$$S_i = \sum_{j=1}^{m} w_j z_{ij}, \quad i = 1,...,n \tag{19}$$

Determining all w_j can vary without any alteration in the alternative rankings can be evaluated for the WSM method, using Eq. (20) and η^* denotes the stability interval ratio that all criteria weight can vary without occurring ranking changes among any alternatives (Wang & Luo, 2010);

$$\eta^* = \min\left\{ \left. \frac{\sum_{j=1}^{m}\left(z_{ij} - z_{kj}\right)w_j}{\sum_{j=1}^{m}\left|z_{ij} - z_{kj}\right|w_j} \right| \ where\ i = t, k = t+1, t = 1,...,n-1\ and\ S_t > S_{t+1} > ... > S_n \right\} \tag{20}$$

This η^* value is evaluated in terms of all criteria, and just as a chain is as strong as its weakest link, the strength of the model's stability is as strong as the criterion with the weakest stability. Accordingly, this η^*, evaluated and obtained on the weakest stable criterion, is desired to be as high as possible in order to ensure the stability of the whole model.

If we sought to examine stability for each pairwise rankings like $S_t > S_{t+1}$ and $S_{n-1} > S_n$, we can evaluate the stability intervals for each pair using equal values for all w_j as in Eq. (21). The η_{ik} denotes the stability interval ratio of all w_j can vary without occurring ranking changes between alternatives i and k with respect to their overall scores.

$$\eta_{ik} = \left\{ \frac{\sum_{j=1}^{m}\left(z_{ij}-z_{kj}\right)w_j}{\sum_{j=1}^{m}\left|z_{ij}-z_{kj}\right|w_j} \;\middle|\; where\; i=t, k=t+1, t=1,\dots,n-1 \; and \; S_t > S_{t+1} > \dots > S_n \right\} \tag{21}$$

Accordingly, the singular contribution of the relevant criteria to the stability of rankings can be measured from the stability values that will be obtained when each criterion is removed from the decision matrix. So, we can evaluate the WSM scores when the criterion j is removed and the rest of the criteria weights are equal, as in Eq. (22);

$$S_{ij} = \sum_{h=1,h\neq j}^{m} w_h z_{ih}, \quad i=1,\dots,n,\; j=1,\dots,m \tag{22}$$

Using S_{ij} values we can evaluate η_j^{ave} (the average ratio that a criterion changes without altering each ranking of alternatives when the j criterion discarded from model) and η^*_j (the maximum ratio that a criterion changes without altering any ranking of alternative when the j criterion discarded from model) for each criterion as in Eq. (23) and Eq. (24), respectively.

$$\eta_{ave}{}^{j} = \frac{\sum_{i=1}^{n-1}\left\{ \frac{\sum_{h=1,h\neq j}^{m}\left(z_{ih}-z_{kh}\right)w_h}{\sum_{h=1,h\neq j}^{m}\left|z_{ih}-z_{kh}\right|w_h} \;\middle|\; where\; i=t, k=t+1, t=1,\dots,n-1,\; j=1,\dots,m \; and \; S_{tj} > S_{(t+1)j} > \dots > S_{nj} \right\}}{n-1} \tag{23}$$

$$\eta^*{}_j = \min\left\{ \frac{\sum_{h=1,h\neq j}^{m}\left(z_{ih}-z_{kh}\right)w_h}{\sum_{h=1,h\neq j}^{m}\left|z_{ih}-z_{kh}\right|w_h} \;\middle|\; where\; i=t, k=t+1, t=1,\dots,n-1,\; j=1,\dots,m \; and \; S_{tj} > S_{(t+1)j} > \dots > S_{nj} \right\} \tag{24}$$

Evaluating both the η_j^{ave} and $\eta^*{}_j$, we can assess the singular contribution of each criterion in the stability of rankings. If the η_j^{ave} and $\eta^*{}_j$ values increase when the criterion j is removed, less weight should be given for the criterion and these values should be normalized as follows:

$$z\eta_j^{ave} = -\eta_j^{ave} + \eta_{\max}{}^{ave} + \eta_{\min}{}^{ave} \tag{25}$$

$$z\eta^*{}_j = -\eta^*{}_j + \eta^*{}_{\max} + \eta^*{}_{\min} \tag{26}$$

In RRC, we can obtain w_j^* according to $z\eta_j^{ave}$ and $z\eta^*{}_j$ for each criterion as in Eq. (27).

$$w_j^* = \frac{\frac{z\eta_j^{ave}}{\sum_{j=1}^{m} z\eta_j^{ave}} + \frac{z\eta^*{}_j}{\sum_{j=1}^{m} z\eta^*{}_j}}{2} \qquad j=1,\dots,m \tag{27}$$

In determining criteria weights, using only the $\eta^*{}_j$ values yields the disperences between weight values quite higher. Conversely, employing only the average of η_j^{ave} in the same manner causes decreasing effects on the stability intervals. So, the combination of these two variable produces more balanced results.

Employing WSM in ranking alternatives with RRC's criteria weight would be beneficial in two ways. First, due to RRC acquiring stability values via WSM, these two methods merge effectively. The other one is the decision-maker can obtain stability intervals and examine sensitivity in detail.

A numerical example of using RRC method, as follows. Suppose we have a decision matrix (DM) with five alternatives and six benefit criteria (28) as follows;

$$DM = \begin{bmatrix} 1000 & 5 & 5 & 5 & 500 & 1000 \\ 10 & 990 & 10 & 10 & 600 & 1000 \\ 5 & 1000 & 990 & 20 & 900 & 1000 \\ 5 & 1000 & 1000 & 25 & 1000 & 999 \\ 10 & 980 & 1000 & 15 & 600 & 1000 \end{bmatrix} \tag{28}$$

I can acquire z_{ij} via Eq. (17), as follows.

```
Zij=  [1.0000  0       0       0       0       1.0000
        0.0050  0.9899  0.0050  0.2500  0.2000  1.0000
        0       1.0000  0.9899  0.7500  0.8000  1.0000
        0       1.0000  1.0000  1.0000  1.0000  0
        0.0050  0.9799  1.0000  0.5000  0.2000  1.0000];
```

Then, I can obtain S_{ij} via Eq. (22), as follows.

```
Sij= [ 0.2000  0.4000  0.4000  0.4000  0.4000  0.2000
       0.4890  0.2920  0.4890  0.4400  0.4500  0.2900
       0.9080  0.7080  0.7100  0.7580  0.7480  0.7080
       0.8000  0.6000  0.6000  0.6000  0.6000  0.8000
       0.7360  0.5410  0.5370  0.6370  0.6970  0.5370];
```

Afterwards, we can acquire η_j^{ave} and η^*_j via using Eq. (23) and (24), respectively.

η_j^{ave} = [0.6229 0.2829 0.4051 0.3575 0.3989 0.7836]

η^*_j = [0.1380 0.1280 0.1355 0.0913 0.1116 0.18449]

Then, $z\eta_j^{ave}$ and $z\eta^*_j$ can be obtained by employing Eq. (25) and (26), respectively.

$z\eta_j^{ave}$ = [0.4436 0.7836 0.6615 0.7091 0.6676 0.2829]

$z\eta^*_j$ = [0.1380 0.1280 0.1355 0.0913 0.1116 0.1844]

Finally, the w_j^* can be acquired via Eq. (27).

w_j^* = [0.1421 0.1958 0.1742 0.2064 0.1889 0.0926]

4. Comparative Analysis of Objective Weighting Methods

I compared RRC with well-known approaches through the simulations where I randomly generated 1000 samples via uniform distribution in the range [1-100] for each different size of matrix. I have presented in Table 1 how many times the RRC method outperforms other methods in terms of η^* scores in each sample. For example, the value of 801 in the first row and first column reveals in how many cases out of 1000 different 3*3 matrices RCC provides better stability than EWM.
The first and last values presented in matrix size refer to the number of alternatives and the number of criteria, respectively, represented in the Table 1-3.
According to Table1, RRC outperformed all methods in the range of 853 to 706 in the 3-by-3 decision matrices. Although the degree of superiority decreased as the size of the matrix increased, the superiority of RRC over other methods continued even in the 20 by 20 matrices. In overall I generated 10000 decision matrices (one thousand times for each of ten different sizes) and RRC outperformed EWM, Entropy, MEREC, CRITIC, and SD by 61.18%, 60.29%, 56.64%, 64.67% and 60.48%, respectively.

Table 1. Number of times the RRC method outperforms other methods in terms of stability

Matrix Size	EWM	Entropy	MEREC	CRITIC	SD
3*3	801	816	706	853	802
4*4	688	667	590	750	668
5*5	626	652	567	708	632
6*6	621	592	558	664	598
7*7	617	589	572	613	611
8*8	571	559	536	605	570
9*9	564	535	551	585	542
10*10	587	542	554	590	554
15*15	519	536	512	541	532
20*20	524	541	518	558	539

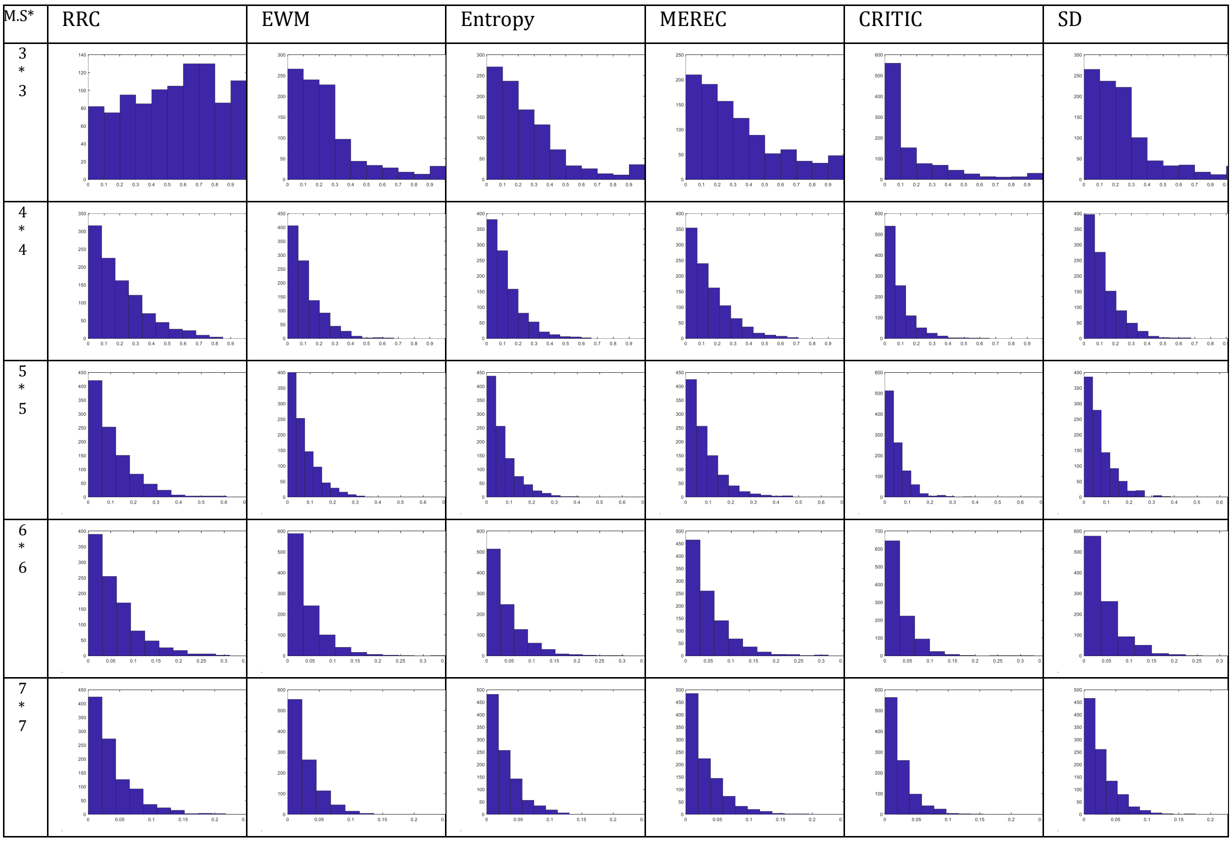
The average η^* values of 1000 samples for different matrix size are represented in Table 2. RRC outperformed all other methods in terms of stability degrees in each matrix size. I also conducted statistical comparisons according to average η^* values, considering a 5% significance level were applied and the RRC statistically outperformed the EWM, Entropy, MEREC, CRITIC, and SD with the same p-values (0.001). In overall average η^* values methods are ranked as RRC (0.0992), MEREC (0.0692), Entropy (0.0563), SD (0.0558), EWM (0.0550), and CRITIC (0.0417). In general, it is observed that all methods except RRC have similar values, while RRC differs positively from the others.

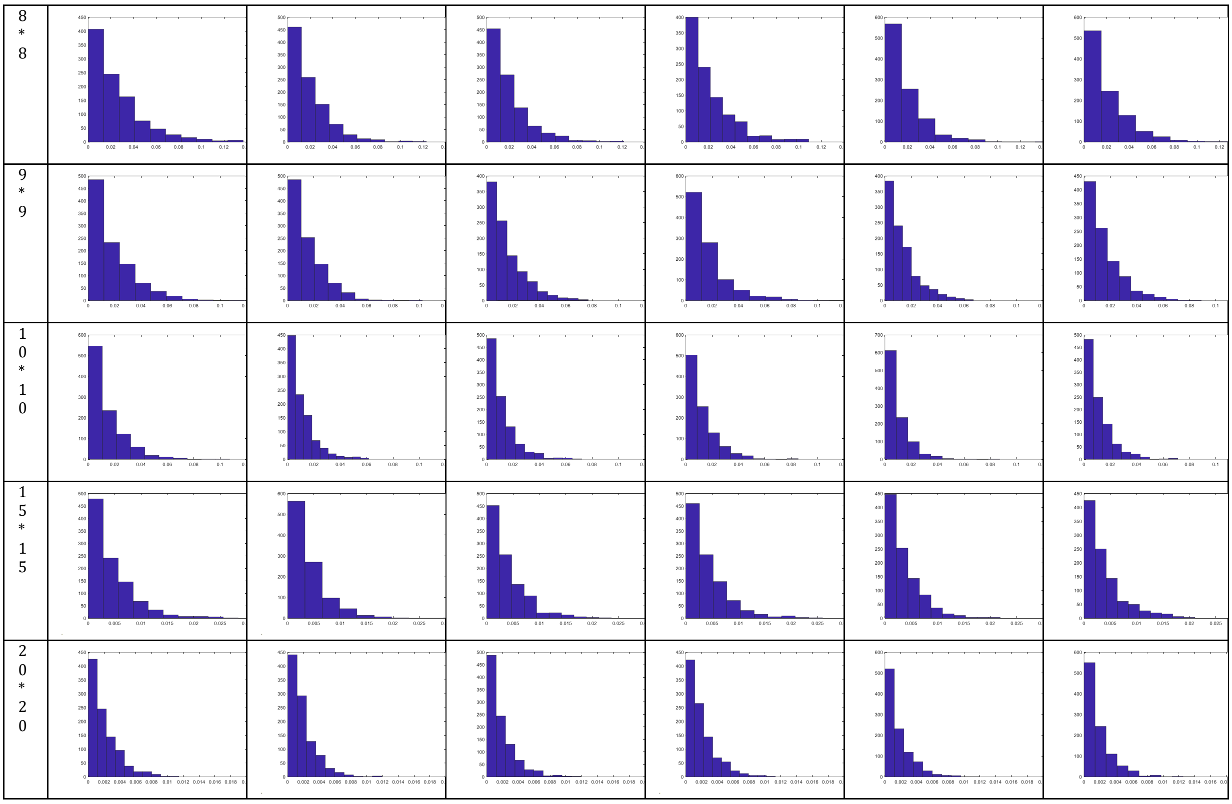
Table 2. The average η^* values (1000 samples) of each weighting method.

Matrix Size	RRC	EWM	Entropy	MEREC	CRITIC	SD
3*3	0.5337	0.2518	0.2570	0.3301	0.1792	0.2547
4*4	0.1959	0.1134	0.1191	0.1467	0.0853	0.1157
5*5	0.1059	0.0693	0.0679	0.0822	0.0526	0.0687
6*6	0.0574	0.0397	0.0419	0.0477	0.0322	0.0417
7*7	0.0369	0.0266	0.0268	0.0305	0.0232	0.0265
8*8	0.0249	0.0184	0.0190	0.0211	0.0169	0.0196
9*9	0.0178	0.0144	0.0148	0.0159	0.0131	0.0146
10*10	0.0136	0.0104	0.0109	0.0117	0.0092	0.0106
15*15	0.0043	0.0038	0.0038	0.0040	0.0035	0.0038
20*20	0.0020	0.0018	0.0018	0.0019	0.0017	0.0018

In Fig. 1, I represented the histogram of η^* values for each method and matrix size. Although the superiority of RRC in the 3*3 matrix is obvious in terms of η^*, it also has superiority in the others. The increasing number of η^* values towards the right in the histogram indicates that higher η^* values are obtained more frequently with the relevant method.
To examine the performances further I defined a threshold ratio for η^* as % 1, which means ranking is stable when any of criterion changes up to %1. I evaluated each method according to the threshold limit and the results are listed in Table 3.

Fig. 1 . The histogram of η^* for each method





* M.S. refers to matrix size

Table 3. Number of η^* values above the threshold rate in 1000 samples.

Matrix Size	RRC	EWM	Entropy	MEREC	CRITIC	SD
3*3	994	977	981	973	918	968
4*4	954	925	926	948	903	943
5*5	920	879	883	919	847	900
6*6	868	774	790	820	745	802
7*7	797	708	705	740	677	703
8*8	679	601	608	635	567	614
9*9	581	521	524	547	489	524
10*10	471	408	394	428	328	406
15*15	336	279	271	298	248	269
20*20	75	49	63	74	54	63

Considering the results in Table 3, for the threshold ratio of 1% that will create significant robustness, RRC provided significant robustness in more cases in all matrix dimensions compared to other methods, at sample numbers where η^* exceeded this threshold ratio. As the matrix size increases, the decrease in the stability value and the lower number of cases above the limit value is not a coincidence because the possible average weight value per criterion is becoming smaller. Accordingly, a fairer comparison was made by considering this limit value as 0.5% for matrices 15*15 and 20*20. Considering the significant stability values, it has been observed that RRC continues to be useful even as the matrix sizes increase.

4. A Real Life Application

This study aims to examine the digital readiness of EU countries. In recent years, the Digital Readiness Index (DRI) developed by CISCO (A leading company in digital communications technology) has become a golden standard in evaluation of digital readiness. I carried out the analysis of the DRI data for 2021. Table 4 contains the DRI data of 27 EU member states over 7 benefit-oriented criteria.

Table 4. The DRI values of EU Countries in 2021

EU Country	CRITERIA						
	Basic Needs	Business & Government Investment	Ease of Doing Business	Human Capital	Start-Up Environment	Technology Adoption	Technology Infrastructure
Austria	0.86	1.57	1.44	1.06	-0.18	1.02	0.91
Belgium	0.86	1.22	0.46	0.95	0.13	0.78	0.94
Bulgaria	0.61	-0.04	-0.69	0.32	0.30	0.17	0.95
Croatia	0.63	0.11	0.67	0.52	-0.07	0.21	0.68
Cyprus	0.85	0.09	0.51	1.05	1.54	0.87	1.10
Czech Republic	0.79	0.41	1.00	1.12	-0.07	0.63	1.15
Denmark	0.83	1.60	1.84	1.29	0.81	1.19	3.44
Estonia	0.77	0.57	1.25	1.39	2.79	0.98	1.78
Finland	0.88	2.22	1.65	1.30	0.31	1.16	1.74
France	0.89	1.00	0.98	0.78	0.39	0.76	1.17
Germany	0.85	1.60	1.47	1.29	0.08	1.18	1.60
Greece	0.88	-0.02	0.53	0.48	-0.40	0.35	0.72
Hungary	0.70	0.40	-0.52	0.78	-0.26	0.35	0.73
Ireland	0.84	2.05	1.34	1.30	0.98	1.23	1.61
Italy	0.93	0.55	0.37	0.42	-0.15	0.66	0.59
Latvia	0.62	0.27	0.96	1.14	0.27	0.43	0.99
Lithuania	0.63	0.19	1.19	1.13	0.04	1.12	1.03
Luxembourg	0.89	1.31	1.16	0.87	5.78	2.16	1.27
Malta	0.86	0.35	0.33	0.64	1.24	1.20	1.05
Netherlands	0.88	2.18	1.09	1.36	0.57	1.20	2.21
Poland	0.75	0.53	0.46	1.07	-0.40	0.68	1.34
Portugal	0.87	0.79	0.96	0.73	0.24	0.46	0.79
Romania	0.64	-0.07	0.20	0.32	0.03	0.33	0.67
Slovakia	0.70	0.16	0.68	0.82	-0.10	0.72	0.71
Slovenia	0.86	0.44	1.05	1.12	-0.12	0.70	0.94
Spain	0.93	1.80	0.91	0.83	-0.17	0.82	0.93
Sweden	0.91	3.44	1.51	1.38	1.93	1.33	1.34

Source: CISCO Digital Readiness Index (https://www.cisco.com)

Employing the data in Table 4 as decision matrix, I obtained the normalized matrix by using Eq. (17) and represented in Table 5.

Table 5. The Normalized DRI values of EU Countries in 2021

Country	Basic Needs	Business & Government Investment	Ease of Doing Business	Human Capital	Start-Up Environment	Technology Adoption	Technology Infrastructure
Austria	0.7812	0.4672	0.8419	0.6916	0.0356	0.4271	0.1123
Belgium	0.7812	0.3675	0.4545	0.5888	0.0858	0.3065	0.1228
Bulgaria	0	0.0085	0	0	0.1133	0	0.1263
Croatia	0.0625	0.0513	0.5375	0.1869	0.0534	0.0201	0.0316
Cyprus	0.75	0.0456	0.4743	0.6822	0.3139	0.3518	0.1789
Czech Republic	0.5625	0.1368	0.668	0.7477	0.0534	0.2312	0.1965
Denmark	0.6875	0.4758	1	0.9065	0.1958	0.5126	1

Estonia	0.5	0.1823	0.7668	1	0.5162	0.407	0.4175
Finland	0.8437	0.6524	0.9249	0.9159	0.1149	0.4975	0.4035
France	0.875	0.3048	0.6601	0.4299	0.1278	0.2965	0.2035
Germany	0.75	0.4758	0.8538	0.9065	0.0777	0.5075	0.3544
Greece	0.8437	0.0142	0.4822	0.1495	0	0.0905	0.0456
Hungary	0.2812	0.1339	0.0672	0.4299	0.0227	0.0905	0.0491
Ireland	0.7187	0.604	0.8024	0.9159	0.2233	0.5327	0.3579
Italy	1	0.1766	0.419	0.0935	0.0405	0.2462	0
Latvia	0.0313	0.0969	0.6522	0.7664	0.1084	0.1307	0.1404
Lithuania	0.0625	0.0741	0.7431	0.757	0.0712	0.4774	0.1544
Luxembourg	0.875	0.3932	0.7312	0.514	1	1	0.2386
Malta	0.7812	0.1197	0.4032	0.2991	0.2654	0.5176	0.1614
Netherlands	0.8437	0.641	0.7036	0.972	0.157	0.5176	0.5684
Poland	0.4375	0.1709	0.4545	0.7009	0	0.2563	0.2632
Portugal	0.8125	0.245	0.6522	0.3832	0.1036	0.1457	0.0702
Romania	0.0938	0	0.3518	0	0.0696	0.0804	0.0281
Slovakia	0.2812	0.0655	0.5415	0.4673	0.0485	0.2764	0.0421
Slovenia	0.7812	0.1453	0.6877	0.7477	0.0453	0.2663	0.1228
Spain	1	0.5328	0.6324	0.4766	0.0372	0.3266	0.1193
Sweden	0.9375	1	0.8696	0.9907	0.377	0.5829	0.2632

According to Eq. (22), the S_{ij} values (see in the Table 6) when the criterion j is removed can be acquired where S_{12} denotes the WSM scores of the first alternative when the second criteria is eliminated from the decision model.

Table 6. The Sij Values

	Basic Needs	Business & Government Investment	Ease of Doing Business	Human Capital	Start-Up Environment	Technology Adoption	Technology Infrastructure
Austria	0.4293	0.4816	0.4192	0.4442	0.5536	0.4883	0.5408
Belgium	0.321	0.3899	0.3754	0.3531	0.4369	0.4001	0.4307
Bulgaria	0.0414	0.0399	0.0414	0.0414	0.0225	0.0414	0.0203
Croatia	0.1468	0.1487	0.0676	0.1261	0.1483	0.1539	0.152
Cyprus	0.3411	0.4585	0.3871	0.3524	0.4138	0.4075	0.4363
Czech Republic	0.3389	0.4099	0.3213	0.308	0.4238	0.3941	0.3999
Denmark	0.6818	0.7171	0.6297	0.6453	0.7637	0.7109	0.6297
Estonia	0.5483	0.6013	0.5038	0.465	0.5456	0.5638	0.5621
Finland	0.5848	0.6167	0.5713	0.5728	0.7063	0.6426	0.6582
France	0.3371	0.4321	0.3729	0.4113	0.4616	0.4335	0.449
Germany	0.5293	0.575	0.512	0.5032	0.6413	0.5697	0.5952
Greece	0.1303	0.2686	0.1906	0.246	0.271	0.2559	0.2634
Hungary	0.1322	0.1568	0.1679	0.1074	0.1753	0.164	0.1709
Ireland	0.5727	0.5918	0.5587	0.5398	0.6553	0.6037	0.6328
Italy	0.1626	0.2999	0.2595	0.3137	0.3225	0.2883	0.3293
Latvia	0.3158	0.3049	0.2123	0.1933	0.3029	0.2992	0.2976
Lithuania	0.3795	0.3776	0.2661	0.2638	0.3781	0.3104	0.3642
Luxembourg	0.6462	0.7265	0.6701	0.7063	0.6253	0.6253	0.7522
Malta	0.2944	0.4046	0.3574	0.3747	0.3804	0.3383	0.3977
Netherlands	0.5933	0.627	0.6166	0.5719	0.7077	0.6476	0.6391

Poland	0.3076	0.3521	0.3048	0.2637	0.3806	0.3378	0.3367
Portugal	0.2666	0.3612	0.2934	0.3382	0.3848	0.3778	0.3904
Romania	0.0883	0.1039	0.0453	0.1039	0.0923	0.0905	0.0993
Slovakia	0.2402	0.2762	0.1968	0.2092	0.279	0.241	0.2801
Slovenia	0.3359	0.4419	0.3514	0.3415	0.4585	0.4217	0.4456
Spain	0.3542	0.432	0.4154	0.4414	0.5146	0.4664	0.5009
Sweden	0.6806	0.6701	0.6919	0.6717	0.774	0.7396	0.7929

Based on Eq. (23) and (24), I evaluated the η_j^{ave} and η^*_j values for each criterion and afterwards I obtained $z\eta_j^{ave}$, $z\eta^*_j$, and w_j^* via Eq. (25), (26), and (27), respectively. The results are represented in Table 7. According to RRC, the most prominent criterion is Human Capital and the least one is Ease of Doing Business.

Table 7. The Criteria Weights obtained by RRC

	Basic Needs	Business & Government Investment	Ease of Doing Business	Human Capital	Start-Up Environment	Technology Adoption	Technology Infrastructure
η_{ave}^{j}	0.2024	0.1937	0.2203	0.2027	0.2121	0.2223	0.2086
η^*_j	0.0043	0.0015	0.0188	0.0002	0.001	0.0023	0.0092
$z\eta_{ave}^{j}$	0.1473	0.1533	0.1350	0.1471	0.1406	0.1336	0.1430
$z\eta^*_j$	0.154	0.1829	0.0018	0.1970	0.1881	0.1743	0.1019
w_j^*	0.1507	0.1681	0.0684	0.1720	0.1644	0.1539	0.1225

I also compared RRC with other prominent objective weighting methods in evaluating the criteria of DRI, and the criteria weights based on these methods are given in Table 8. Zhang et al. (2014) stated that if there is a negative value in decision matrix, the Z score approach can be applied in normalization process of entropy method. Accordingly, I performed this approach in the entropy method.

Incidentally, it causes problems in practice if the difference between the most and the least important criteria is enormous (Zavadskas & Podvezko, 2016) and (Ecer & Pamucar, 2022). Accordingly, it is desired that the ratio difference between them should not be as large as possible. While this ratio is naturally 1 for EWM, I calculated the ratio for RRC, Entropy, MEREC, CRITIC and SD as 2.5146, 1.673, 14.8607, 2.2863, and 1.5696, respectively. Acceptable results were acquired with all methods except MEREC. Conversely, if this ratio is close to 1, there will be no differentiation between criteria. The RRC come to the fore with its more balanced ratio regarding these two issues.

Table 8. The criteria weights obtained by objective weighting methods

	Basic Needs	Business & Government Investment	Ease of Doing Business	Human Capital	Start-Up Environment	Technology Adoption	Technology Infrastructure
EWM	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
Entropy	0.1640	0.1296	0.1852	0.1569	0.1107	0.1361	0.1175
MEREC	0.0201	0.2987	0.2455	0.0756	0.2042	0.1101	0.0458
CRITIC	0.2204	0.1264	0.1162	0.1654	0.1521	0.0964	0.1232
SD	0.1849	0.1433	0.1342	0.1771	0.1178	0.1238	0.1189

According to the rankings in Table 9, it can be thought that all methods are quite similar to each other except MEREC, while the values of Spearman Rank Correlations given in Table 10 clearly reveal this argument. Meanwhile, the RRC's ranking is highly correlated with other methods.

Table 9. Rankings of Countries acquired by each weighting approach via WSM

	RRC		EWM		Entropy		MEREC		CRITIC		SD	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank

Austria	0.4582	9	0.4796	9	0.5284	9	0.4737	9	0.5039	9	0.5173	9
Belgium	0.3882	13	0.3867	14	0.418	14	0.3385	12	0.4265	14	0.425	14
Bulgaria	0.0355	27	0.0354	27	0.0285	27	0.0315	27	0.0339	27	0.0296	27
Croatia	0.1027	25	0.1348	25	0.1581	25	0.1772	23	0.1276	25	0.1367	25
Cyprus	0.3981	11	0.3995	12	0.4275	13	0.3077	17	0.4427	12	0.4315	13
Czech Republic	0.3505	16	0.3708	15	0.4115	15	0.318	16	0.3971	15	0.4039	15
Denmark	0.6415	3	0.6826	2	0.7108	2	0.6122	3	0.6802	3	0.6955	2
Estonia	0.5291	8	0.5414	8	0.5662	8	0.4977	8	0.5569	8	0.5594	8
Finland	0.6025	5	0.6218	5	0.6658	4	0.6049	4	0.6425	5	0.6589	5
France	0.3938	12	0.414	11	0.4511	11	0.3713	11	0.4523	11	0.4461	11
Germany	0.5416	7	0.5608	7	0.6043	7	0.5233	7	0.579	7	0.5961	7
Greece	0.2077	23	0.2323	23	0.2707	23	0.163	24	0.2829	21	0.2659	22
Hungary	0.1671	24	0.1535	24	0.164	24	0.1115	26	0.176	24	0.1761	24
Ireland	0.5848	6	0.5936	6	0.6277	6	0.5817	5	0.6088	6	0.6241	6
Italy	0.2696	20	0.2823	20	0.3171	20	0.2182	22	0.3367	19	0.3182	20
Latvia	0.2526	21	0.2752	21	0.305	21	0.2905	19	0.268	22	0.2885	21
Lithuania	0.307	19	0.3342	18	0.3673	18	0.3372	13	0.3106	20	0.3418	19
Luxembourg	0.6839	2	0.6789	3	0.6854	3	0.6786	2	0.6904	2	0.6773	3
Malta	0.3599	15	0.3639	16	0.384	17	0.2916	18	0.3937	16	0.3832	16
Netherlands	0.6253	4	0.629	4	0.6589	5	0.5697	6	0.6532	4	0.6646	4
Poland	0.318	18	0.3262	19	0.3539	19	0.2647	20	0.3439	18	0.3536	18
Portugal	0.3222	17	0.3446	17	0.3854	16	0.319	15	0.3876	17	0.3793	17
Romania	0.0654	26	0.0891	26	0.1025	26	0.1126	25	0.0833	26	0.086	26
Slovakia	0.2265	22	0.2461	22	0.2762	22	0.2358	21	0.2497	23	0.2618	23
Slovenia	0.3813	14	0.3995	13	0.4473	12	0.3287	14	0.4418	13	0.4429	12
Spain	0.4365	10	0.4464	10	0.4875	10	0.4196	10	0.4919	10	0.4895	10
Sweden	0.7232	1	0.7173	1	0.7518	1	0.7591	1	0.7438	1	0.7566	1

Table 10. Correlation between the rankings based on each approach

	RRC	EWM	Entropy	MEREC	CRITIC	SD
RRC	1	0.9969	0.9933	0.9646	0.9957	0.9951
EWM	0.9969	1	0.9982	0.9719	0.9957	0.9982
Entropy	0.9933	0.9982	1	0.9768	0.9939	0.9976
MEREC	0.9646	0.9719	0.9768	1	0.9579	0.9676
CRITIC	0.9957	0.9957	0.9939	0.9579	1	0.9976
SD	0.9951	0.9982	0.9976	0.9676	0.9976	1

However, the stability values which are indications of the robustness of the rankings to the criteria weights, differs according the weighting methods. I obtained η^* values as 0.0214, 0.0004, 0.0090, 0.0055, 0.0079, and 0.0200 for RRC, EWM, Entropy Method, MEREC, CRITIC, and SD respectively. While RRC provides more robustness than any of these methods, SD achieved 2nd place. The effectiveness of RRCD in problem solving has emerged as alternative ranking is similar to other methods and provides additional robustness.

5. Conclusions

MCDM is an important methodology used in various fields. Criteria weighting is a vital part of MCDM. The objective criteria weighting approach, which provides criteria weighting based on decision matrix values instead of expert opinions, has a solid foundation in the MCDM field. Any doubt on the criteria weights would raises question marks about the MCDM's results. However, there is always room for error in the alternative scores measured for each criterion. Any small change in the criterion scores of the alternatives, whether or not caused by measurement errors, can significantly affect criteria weights obtained by objective criteria weighting methods. According to (Wang & Luo, 2010), this point peculiarly causes objective approaches to receive significant criticism. To tide over this problem, especially small changes in the weights of the criteria should not affect the ranking. This η^* ratio can be considered as a value that compensates the possible error margin in the weight values of the criteria.

In this study, to address this concern, I proposed an objective criteria weighting approach that aims to increase the stability of rankings to the criteria weight changes. The proposed RRC, which focuses primarily on the criteria removal effect on robustness, was compared with EWM, Entropy Method, MEREC, CRITIC, and SD via simulations. In simulation-based analysis, the RRC outperformed all methods on every matrix size in average robustness and pairwise comparisons.

The digital readiness of the EU member states were evaluated with the RRC method, which is easy to calculate and developed from a different point of view than existing methods. While only the proposed RRC and SD were able to exceed the previously determined limit value (1%) with 2.14% and 2%, the RRC prevailed against SD with a ratio of 2.5146 to 1.5696 in differentiating the criteria.

The validity of the model was ensured because there was no significant difference between the maximum and minimum criteria weight values, the stability value was higher than other methods, and the ranking correlations were high with other methods. On the other hand, as managerial insights, countries' prioritization of Human Capital and subsequent focus on Business & Government Investment and Start-Up Environment will lead to an increase in digital readiness processes.

I employed the η^*_j and η_j^{ave} to concern the robustness of ranking to the criteria changes. Future research can explore employing various robustness indicators like the correlation of stability values between criteria, the covariance of criteria, and ranking correlations. Moreover, the RRC approach can be extended by using different types of MCDMs than WSM. The integration of RRC with other existing weighting methods would be another direction of future studies. While extending RRC by applying it in a fuzzy environment can be beneficial in fuzzy decision-making, employing different normalization techniques can explore more fields in capability of the proposed approach.

Contributions of Authors

Osman PALA: Investigation, Methodology, Writing – original draft, Conceptualization, Supervision, Writing - review and editing.

Conflict of interest

No conflict of interest was declared by the authors.

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