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Re-evaluation of the TÜBİTAK Entrepreneurial and Innovative University Index using objective weighting methods

Seda Karakaş Geyik [1]

[1] Asst. Prof., Department of Econometrics, Faculty of Economics, İstanbul University, İstanbul, Türkiye

Abstract

Today, the performance of universities is evaluated not only based on their academic outputs but also on their collaboration, intellectual property production, and economic and social contributions. In this context, the Entrepreneurial and Innovative University Index (EIUI), developed by the Scientific and Technological Research Council of Türkiye (TÜBİTAK), evaluates universities in Türkiye according to four dimensions and 23 indicators. The EIUI methodology is based on subjective weights determined by expert opinions and policy priorities; however, in multi-criteria decision-making (MCDM) problems, results are often sensitive to the weighting approach employed. This study uses objective weighting methods such as CRITIC (Criterion Importance Through Correlation of Criteria), SD (Standard Deviation), CILOS (Criterion Impact Loss of Significance), and LOPCOW (Logarithmic Percentage Change Objective Weighting). Based on these weights, university rankings were re-established through the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and ARAS (Additive Ratio Assessment) methods and compared with the original TÜBİTAK ranking. Ranking consistency was examined using Spearman's rank correlation analysis, and it was found that all correlations were statistically significant (p-value < 0.05), and that the highest correlation was observed between the TÜBİTAK ranking and the LOPCOW–ARAS method (ρ=0.985). The findings were supported by visualization tools such as heatmaps and radar charts. The highest variation in criterion weights among the methods was observed for Net Sales Revenue of Companies Owned by Students/Graduates, Number of BİGG Companies, Net Sales Revenue of Companies Owned by Academics, and Number of Faculty Members/Students with Mobility. In the ranking results, Middle East Technical University and Istanbul Technical University frequently occupy the top positions. In general, universities in the top and bottom ranks exhibit consistent positions across different methods, while universities in the middle ranks are more sensitive to methodological choices. This highlights the importance of considering alternative weighting and ranking approaches in university performance evaluations.

Keywords Objective Weighting Methods, TÜBİTAK Entrepreneurial and Innovative University Index, TOPSIS, ARAS, Visualization Tools

Jel Codes C39, C44, D81, I23

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Correspondence

S. Karakaş Geyik
kseda@istanbul.edu.tr

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ORCID

S. Karakaş Geyik 0000-0003-2218-6689

1. Introduction

Global university rankings have become a significant phenomenon, influencing higher education worldwide (Hazelkorn, 2015). Today, universities make significant efforts to improve their positions in global rankings. To enhance their rankings each year, they develop policies and transform their higher education strategies in this direction. There are various ranking systems developed to appropriately rank universities, including key ones such as the Academic Ranking of World Universities (ARWU), Leiden University Ranking, Quacquarelli Symonds (QS), Times Higher Education (THE), and Webometrics (Fauzi et al., 2020).

Rankings of higher education institutes and programs are a global trend, related to the demand for transparent information on the quality of teaching provision and the standing of higher education institutes offering it (Marginson & van der Wende, 2007). Initially developed as a transparency tool, rankings now serve as indicators of institutional reputation and national competitiveness in the global knowledge economy (Hazelkorn, 2021). Rankings have faced widespread criticism from various sources, addressing concerns related to methodology, pragmatics, ethics, and philosophy, making the ranking of higher education a highly controversial topic (Harvey, 2008). Various university ranking systems have been developed using different methods. However, some of these systems face criticism, especially regarding the indicators they include. While some rankings are mainly based on research performance, others focus on specific fields such as science and technology. As a result, institutions in the arts and social sciences may be underrepresented (Fauzi et al., 2020). Salmi (2009) and Altbach & Salmi (2011) have defined being a world-class university as a concept that goes beyond the limited methodologies of international ranking systems. Aside from this conceptual critique, the methodological, pragmatic, moral, and philosophical foundations of higher education ranking systems have also been criticized in various studies (Harvey, 2008). One of the biggest debates is about the methods used to create rankings, with survey-based ones facing a lot of criticism. Survey-based reputation scores in university rankings are often criticized for being methodologically flawed, as they tend to reflect anchoring effects from prior rankings rather than independent evaluations (Bowman & Bastedo, 2011).

In addition to methodological concerns, the following issues are also debated in this context: critics of ranking selection of indicators, handling missing values, weighting of indicators, reliability, formula changes, and statistical insignificance (Harvey, 2008). Marginson & van der Wende (2007) criticize both the ARWU and THE rankings for not providing any guidance on teaching quality. The ARWU ranking assigns 30% of its weight to Nobel Prizes and Fields Medals. It is frequently criticized for being elitist in terms of the indicators it uses to measure international recognition. Altbach (2006) explains that using international recognition, such as Nobel Prizes, as a proxy for excellence downplays the social sciences and humanities, fields in which Nobels are not awarded, and further disadvantages developing countries and smaller universities worldwide. Similar criticisms are also applicable to other ranking systems. QS is criticized for its subjective survey methodology used to assess reputation (Huang, 2012). Altbach (2006) also emphasizes that using citation counts as an indicator of excellence creates significant issues. The widespread availability of English-language materials and the presence of journals easily accessible in larger academic systems may unfairly benefit certain institutions, artificially boosting their rankings. As a result, universities in major English-speaking centers of academia, particularly those in the United States and the United Kingdom, are likely to see an increase in their reputation. Altbach (2006) also highlights that higher education institutions with medical schools have a significant advantage due to their ability to generate more external funding and the fact that researchers in these fields publish more papers. The combination of indicators used in rankings is criticized for further privileging already advantaged institutions and for favoring certain academic disciplines over others. Rankings are also criticized for overlooking important academic roles, such as teaching, and for failing to assess how students' academic experiences are impacted. These critiques in the literature have led to the suggestion that alternative ranking systems, which compare universities' achievements across different areas, should also be considered by higher education stakeholders such as students, families, academics, university administrators, and employers (Uslu et al., 2020).

In the competitive and market-driven academic world of the 21st century, rankings are inevitable and likely necessary. However, the academic-focused approach of current rankings fails to reflect changing societal and industrial trends, putting universities that focus on practical impact at a disadvantage. Moreover, existing ranking systems are mostly based on quantitative data from the past, which leads institutions to follow a path that fails to guide them toward the future and disadvantages universities that make heavy investments in innovation with long-term perspectives. Therefore, World University Rankings that value innovation, differentiation, and long-term impact on industry and society are being proposed. One of the main examples is the World's Universities with Real Impact (WURI) Top 50 ranking, which ranks universities based on innovation and has been published since 2020, following discussions at the first Hanseatic League of Universities Conference in 2018 (WURI, 2025). Clarivate's Global Innovators Top 50 University analysis, which aims to highlight the significant contributions of independent academic research institutions to the global innovation landscape, is also one of the respected rankings in this field (Clarivate, 2025). Additionally, the "Most Innovative Schools" rankings published by UK News are also noteworthy in the area of innovation.

Another key concept associated with innovation is entrepreneurship. In his pioneering work, Clark (1998) defines the concept of the entrepreneurial university as one that actively plays a role in promoting economic development and societal benefit by integrating innovative research, social interaction, and a culture of entrepreneurship. In Türkiye, the EIUI was created by TÜBİTAK to measure and rank the entrepreneurship and innovation performance of universities, and has been published since 2012. Various studies in the literature evaluate TÜBİTAK EIUI in detail in all its dimensions. However, there is no clear and objective consensus on which criteria should be used in these evaluations and how the impact of these criteria on the overall performance of universities should be weighted. In fact, the TÜBİTAK EIUI structure aims to rank universities' entrepreneurship and innovation performance according to multiple criteria, which can itself be considered an MCDM problem. The weights related to TÜBİTAK EIUI dimensions were determined based on policy priorities and expert opinion. However, it is also possible to determine these weights using objective MCDM methods. Although there are studies aimed at re-obtaining rankings related to the index based on existing weights in the literature or obtaining rankings based on the aforementioned weights by selecting an objective weighting method, studies that comprehensively evaluate the weights related to TÜBİTAK EIUI criteria by considering multiple objective weighting methods together are quite limited. The main objective of this study is to recalculate the weights of the criteria included in the TÜBİTAK EIUI using objective weighting methods, and to generate new university rankings based on these weights. Another aim of the study is to analyze and interpret the differences and similarities in criteria weights and university rankings across different weighting and decision-making methods. In this context, the study seeks to answer the following research questions: "How do the weights of the criteria used within the scope of TÜBİTAK EIUI change according to different objective weighting methods?" and "How do the university rankings obtained using different objective weighting methods differ from the TÜBİTAK EIUI ranking?".

The novelty and contributions of this study lie in the simultaneous use of objective weighting methods and the use of methods such as LOPCOW and CILOS, which have relatively limited application for EIUI, in addition to the objective methods used in previous studies to calculate weights related to the EIUI. Unlike previous studies, criterion weights are evaluated separately based on both indicators and dimensions. Furthermore, the separate evaluation of the results of universities ranked at the top, middle, and bottom of the index provides another valuable contribution. This study presents new and objective findings regarding the evaluation of university performance by obtaining and comparatively analyzing TOPSIS and ARAS rankings based on objective weights derived using CRITIC, SD, LOPCOW, and CILOS methods. In this respect, the study provides guidance for both researchers and policymakers. Additionally, this study differs from many studies in the literature because it was conducted using the most up-to-date data published by TÜBİTAK EIUI, and it re-evaluates existing findings from a current perspective. Another contribution of the study is that the analyses were performed using the Julia programming language and the JMcDM package. This provides an alternative computational environment to similar studies in the literature that are predominantly conducted in other software environments, and presents an open and programmable application example that supports the reproducibility of the analyses. In this context, the following sections will first present a literature review on the TÜBİTAK EIUI. Then, the concept and methodological structure of the index will be explained. Finally, the selected MCDM methods will be introduced, followed by the analysis and comparative interpretation of the results.

2. Research Background and Literature Review

In the literature, most of the studies on the TÜBİTAK EIUI include analyses based on MCDM methodologies. There are also theoretical studies on measuring the entrepreneurship and innovation efforts of universities. Uslu et al. (2020) conducted a theoretical study evaluating the compatibility between EIUI indicators and entrepreneurial university activity areas. The studies in the literature were compared using the meta-synthesis method. As a result, some indicators were criticized for directly overlapping with entrepreneurial university activity areas, while others were found to have only limited relationships.

When the empirical studies on EIUI are examined, the analysis of 2016 data with Entropy-based MAUT and SAW methods was carried out by Ömürbek & Karataş (2018). As a result of the analysis, intellectual property rights were observed to be the criterion with the highest weight among the weights calculated with the objective weighting method. When the university rankings in the same study are examined, it is seen that Sabancı University is in the first place and Middle East Technical University is in the second place. In addition, studies by Çınaroğlu (2021) and Satıcı (2022) can be examined. The ranking of universities using the CRITIC-based MARCOS method was carried out by Çınaroğlu (2021) based on 2020 EIUI data. It was observed that the criterion with the highest weight among the weights obtained by applying the CRITIC method was "intellectual property pool". As a result of the ranking obtained, it was revealed that Middle East Technical University, Bilkent University and Istanbul Technical University shared the first three places, respectively. In the analysis of 2021 data, the study by Satıcı (2022) is noteworthy. As a result of the analysis carried out with the MEREC-based

WASPAS method, the most effective indicator was obtained as “Collaboration and Interaction” and was determined as the highest performing criterion. The university rankings were carried out in such a way that Middle East Technical University, Sabancı University and Istanbul Technical University were in the first three places. The consistency of the ranking results was also confirmed by SAW and MAUT methods. One of the analyses conducted on TÜBİTAK EIUI was the study of Karahan & Kızkapan (2022). The study used the PROMETHEE GAIA method for the 2021 EIUI data. As a result of the analysis, Middle East Technical University, Sabancı University, Istanbul Technical University, Bilkent and Yıldız Universities were ranked top, respectively. In addition, the study provided examples on the sensitivity of the EIUI criteria by taking advantage of the walking weights feature of the PROMETHEE method. Elevli & Elevli (2024) ranked and compared universities in Türkiye using Grey Relational Analysis (GRA) and the PROMETHEE based on the 2022 EIUI data. In addition to the existing criterion weights of the EIUI, entropy-based weights and equal weights were used in the study. The study concluded that METU and Sabancı University remained unchanged in their rankings as the most entrepreneurial and innovative universities, holding the first and second positions respectively.

According to the EIUI results, the top 50 most successful universities are announced. However, some of the studies were carried out on a certain number of universities. Studies conducted by Yıldırım & Kuzu Yıldırım (2020) and Oğuz (2022) can be cited as examples. Oğuz (2022) conducted a study on the ten most successful universities in Türkiye in terms of entrepreneurship and innovation performance. In this study, which was conducted using 2018 EIUI data, the weights for the indicators were obtained using the Entropy method. The rankings were obtained using the EDAS method and validated using the TOPSIS method. To reveal the consistency of the rankings obtained using MCDM methods, it is important to also provide results related to rankings obtained using a different method in addition to the proposed method. As a result of the analysis, Middle East Technical University ranked first. Unlike other empirical studies, Yıldırım & Kuzu Yıldırım (2020) aimed to examine the change in a certain year period instead of evaluating the index for a single year. They examined the performances of universities between 2012-2017 through the data they integrated with a Grey system theory approach. In this study, a different method was not used to calculate the weights, and the rankings were obtained with the ARAS-G method using the weights in the original TÜBİTAK methodology, and validated using the TOPSIS-G method. As a result of the analysis, it was revealed that Sabancı University and Middle East Technical University were the universities with the highest performance during the selected period.

In the literature, there are also studies that use methods other than MCDM methods in the analysis of the TÜBİTAK EIUI. Yenilmez (2024) evaluated the productivity and effectiveness of universities together using balanced panel data analysis with four-year data and index values from the 2019-2022 period. Çoban (2024) clustered universities by performing a classification analysis based on artificial intelligence methods using the EIUI scores of universities. In the classification of universities, evaluations were made according to EIUI scores, URAP ranking score, research university status, and state or foundation university status, and traditional methods such as Decision Tree and K-Nearest Neighbor (k-NN) and artificial intelligence-based methods such as Support Vector Machines (SVM) and Random Forest were used.

3. Methodology

This study focuses on re-evaluating the TÜBİTAK EIUI ranking using objective weight-based MCDM methods. For this purpose, this section first introduces the methodology of TÜBİTAK EIUI and then discusses the theoretical foundations of the methods used in data analysis. Figure 1 below shows a flowchart illustrating the steps of the research methodology.

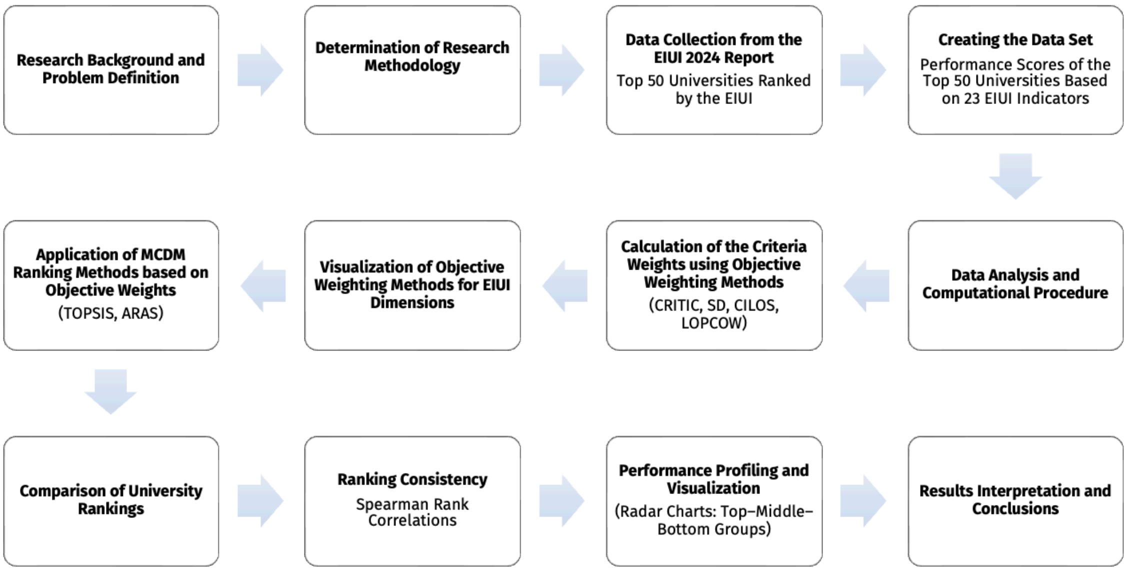

Figure 1. Flowchart of the research methodology

This flowchart summarizes the main stages of the study, including defining the research methodology, data collection and creation of the dataset, objective weighting of criteria, application of MCDM ranking methods, conducting consistency analysis of the rankings, visualizing performance, and interpreting the results.

3.1. Research Design and Data Collection

The most recent EIUI report released by TÜBİTAK provided the data used in this study. This data includes the 2024 results of universities. Table 1 displays the ranking of the top 50 universities. These universities will be referred to in the study using the codes listed in Table 1.

Table 1. Top 50 Universities Ranked by the EIUI

Rank	University	Rank	University
U1	Orta Doğu Techinal University	U26	Dokuz Eylül University
U2	Istanbul Techinal University	U27	Bursa Technical University
U3	Yıldız Techinal University	U28	Hasan Kalyoncu University
U4	Sabancı University	U29	Çukurova University
U5	Ihsan Doğramaci Bilkent University	U30	Atatürk University
U6	Özyeğin University	U31	Yeditepe University
U7	Koç University	U32	Sakarya University
U8	Izmir Institute of Technology	U33	Kocaeli University
U9	Boğaziçi University	U34	Fırat University

Rank	University	Rank	University
U10	Bahçeşehir University	U35	Eskişehir Osmangazi University
U11	Istanbul University	U36	Kadir Has University
U12	Gebze Techinal University	U37	Ondokuz Mayıs University
U13	Ege University	U38	Istinye University
U14	Erciyes University	U39	Yaşar University
U15	Hacettepe University	U40	Sivas Cumhuriyet University
U16	TOBB University of Economics & Technology	U41	Konya Techinal University
U17	Istanbul University-Cerrahpaşa	U42	Pamukkale University
U18	Marmara University	U43	Atılım University
U19	Ankara University	U44	Çanakkale Onsekiz Mart University
U20	Gazi University	U45	İzmir University of Economics
U21	Karadeniz Techinal University	U46	Selçuk University
U22	Eskişehir Techinal University	U47	Abdullah Gül University
U23	Akdeniz University	U48	Düzce University
U24	Bursa Uludağ University	U49	Süleyman Demirel University
U25	Istanbul Medipol University	U50	Başkent University

EIUI is a national index published by TÜBİTAK since 2012 to evaluate universities based on their entrepreneurship and innovation characteristics. This index has four main dimensions: Scientific and Technological Research Competence (STRC: 6 indicators), Intellectual Property Pool (IPP: 4 indicators), Collaboration and Interaction (CI: 6 indicators) and Economic and Social Contribution (ESC: 7 indicators) (TÜBİTAK, 2024a) . Table 2 shows the performance scores of the top 50 universities for the 23 indicators related to the dimensions of EIUI. The indicators denoted as C1-C23 in Table 2 are detailed in Table 3. The indicator weights are subjective weights based on expert opinions and higher education policy priorities (TÜBİTAK, 2024b).

Table 2. Performance Scores of the Top 50 Universities Based on 23 EIUI Indicators

	STRC (C1-C6)						IPP (C7-C10)				CI (C11-C16)						ESC (C17-C23)						
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**	**C21**	**C22**	**C23**
U1	85	84	94	96	85	78	70	41	70	83	86	93	96	99	84	45	82	99	78	84	50	47	44
U2	87	85	87	89	93	64	76	24	66	99	72	94	88	91	86	45	86	92	80	90	52	62	0
U3	81	79	82	80	48	66	71	40	88	76	76	79	73	86	78	59	66	74	74	95	97	64	60
U4	84	88	95	96	87	51	67	0	80	95	92	98	94	96	90	92	65	56	79	56	92	0	0
U5	77	80	89	96	91	45	59	0	79	81	56	84	86	97	85	40	43	70	71	91	77	0	53
U6	45	58	80	80	69	30	86	43	77	100	71	88	77	88	70	71	62	58	69	50	72	0	60
U7	93	91	94	99	100	48	45	0	70	78	47	72	92	99	86	65	51	56	87	77	47	0	0
U8	73	66	89	90	68	49	82	23	83	39	74	94	85	94	76	51	82	73	68	58	0	62	0
U9	67	76	82	87	67	55	49	19	53	16	71	97	82	89	93	29	69	74	83	77	28	73	0
U10	52	65	61	61	14	47	52	19	70	35	47	64	39	68	77	34	52	76	95	81	100	72	0
U11	65	74	72	73	34	74	77	67	37	43	44	74	58	75	81	37	39	57	58	69	73	57	0
U12	86	78	84	81	55	55	49	0	61	0	67	92	64	76	75	56	74	72	76	64	34	0	0
U13	70	74	86	82	32	74	58	54	56	19	67	87	78	84	78	45	52	43	64	54	0	58	53

	STRC (C1-C6)						IPP (C7-C10)				CI (C11-C16)						ESC (C17-C23)						
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**	**C21**	**C22**	**C23**
U14	70	77	74	76	66	67	70	24	69	12	59	73	53	66	69	43	52	42	73	72	69	0	57
U15	81	88	83	82	41	77	41	0	50	12	64	76	77	86	72	36	56	44	65	73	0	41	0
U16	44	58	71	83	0	32	75	23	68	54	65	98	44	74	63	0	53	49	62	40	40	62	0
U17	73	76	68	72	11	72	94	61	49	46	42	87	50	63	59	25	38	37	71	52	21	44	0
U18	58	69	74	73	27	74	42	31	44	12	60	81	79	86	85	42	45	46	66	59	57	0	0
U19	73	77	81	80	27	85	35	22	55	12	59	89	74	79	76	54	47	34	68	55	0	0	0
U20	72	73	72	72	31	79	42	39	52	25	58	73	53	64	66	36	40	52	56	61	29	0	0
U21	62	68	75	75	12	68	58	60	54	13	53	72	59	72	71	33	42	29	57	51	22	78	0
U22	49	57	73	75	0	51	49	29	64	16	66	78	56	72	65	62	51	31	79	43	0	0	100
U23	62	68	72	71	19	68	38	29	39	32	52	80	54	73	72	17	45	31	67	43	31	61	0
U24	54	60	66	70	0	71	47	15	70	0	69	86	44	76	58	78	42	41	61	52	20	0	0
U25	53	55	66	68	34	48	84	100	100	92	46	59	58	81	67	23	27	0	72	0	0	0	0
U26	61	66	74	82	28	68	52	0	49	30	48	78	67	77	65	29	33	26	60	44	29	0	0
U27	52	56	73	67	0	32	49	41	62	20	68	70	56	73	58	83	51	30	59	33	0	60	0
U28	38	53	56	48	25	55	44	67	17	0	29	71	37	53	52	0	64	55	88	52	77	0	0
U29	65	67	71	75	0	66	41	16	47	0	69	84	68	77	69	38	47	20	67	32	0	45	0
U30	71	75	70	70	36	69	49	42	77	25	37	65	43	62	54	36	41	23	55	32	20	0	38
U31	46	52	63	67	41	56	50	34	59	97	46	74	62	72	81	24	0	41	0	50	0	0	0
U32	60	68	64	61	12	64	30	24	49	0	44	68	41	68	71	22	47	49	58	61	0	0	42
U33	59	62	62	62	0	62	40	16	17	0	58	65	41	61	65	35	57	50	74	63	0	0	0
U34	67	74	76	74	32	63	44	16	24	13	46	61	41	49	60	0	51	29	69	35	21	63	59
U35	55	59	67	70	0	63	38	31	34	13	54	82	60	73	59	0	43	36	63	46	0	0	0
U36	60	55	84	86	51	35	0	0	17	0	61	83	76	90	80	59	25	36	54	63	0	0	0
U37	59	63	70	64	11	67	59	23	56	0	43	68	48	64	57	0	25	40	49	43	0	43	57
U38	91	70	60	61	16	0	0	0	62	0	42	73	41	49	63	0	72	58	73	60	0	0	0
U39	33	58	49	57	0	33	46	50	53	40	26	49	54	76	74	29	22	54	38	49	0	0	0
U40	56	61	57	65	0	53	17	0	24	0	27	53	51	72	72	0	30	46	100	55	0	0	42
U41	56	62	67	66	19	47	22	0	32	0	72	67	35	80	56	0	47	36	75	39	0	0	0
U42	46	49	57	60	0	60	29	16	24	0	38	54	48	66	63	25	39	43	61	51	0	44	41
U43	50	58	56	57	0	38	60	33	43	34	50	71	52	70	44	27	0	46	0	46	62	0	0
U44	46	52	69	67	11	51	39	34	21	0	41	66	51	62	61	0	48	24	64	46	0	0	40
U45	36	48	61	68	18	26	35	22	51	0	34	40	60	84	77	0	35	20	65	30	0	58	0
U46	66	70	64	67	0	70	30	0	23	0	50	72	44	71	51	21	28	31	52	39	0	0	0
U47	69	70	69	70	68	38	0	0	0	0	41	68	48	54	69	0	40	29	71	32	0	79	0
U48	56	64	57	57	13	50	32	33	29	0	32	44	38	47	57	24	17	43	50	49	0	49	46
U49	49	62	59	57	20	64	17	24	52	0	35	49	49	63	61	0	34	21	67	46	0	0	0
U50	48	49	49	49	0	47	36	36	17	0	26	53	42	55	54	0	31	37	61	70	0	0	0

3.2. Data Analysis

This section will provide the theoretical foundations of the methods to be used in data analysis and information about the stages of analysis. CRITIC, SD, CILOS, and LOPCOW techniques will be used to recalculate the weights of the criteria based on the 2024 EIUI data in data analysis. Then, rankings will be generated using TOPSIS and ARAS according to the weights obtained.

In MCDM problems, the weighting of criteria can lead to significant changes in the results. Therefore, the weighting process is extremely important (Belton & Stewart, 2002). In the majority of MCDM models, assigning weights to the evaluation criteria is an important step. For that, various weighting methods have been proposed in the literature and applied for solving different MCDM problems. These weighting methods are classified in different ways: algebraic or statistical, decomposed or holistic, direct or indirect, and compensatory or non-compensatory (Zardari et al., 2014). Within the scope of the study's objectives, MCDM methods with different theoretical foundations were selected to ensure high representativeness in the analysis. Furthermore, considering the literature review given in Section 2, in addition to classical methods such as CRITIC and SD, which have been used previously for similar purposes, relatively newer methods such as CILOS and LOPCOW, whose use in calculating EIUI criterion weights is limited, were also included in the analysis. These methods have specific advantages and limitations. The CRITIC method (Diakoulaki et al., 1995) offers a method with high information content by considering the standard deviations of the criteria and the correlation between the criteria. However, it is criticized for its sensitivity to correlation structure. The SD method (Jahan et al., 2012) has the advantage of offering ease of calculation; however, its disregard for relationships between criteria is considered a significant limitation. The CILOS method (Zavadskas & Podvezko, 2016) determines weights by considering the relative losses of criteria compared to ideal values, thus producing results sensitive to reference points. However, its dependence on the determination of ideal values can increase the sensitivity of the method. The LOPCOW method (Ecer & Pamucar, 2022), with its logarithmic percentage change-based structure, evaluates the total contribution of the criteria in a balanced manner and reduces the effect of extreme values. By considering these advantages and disadvantages, a comprehensive assessment of the impact of different theoretical approaches has been ensured. The re-obtaining of the ranking of alternatives is addressed within the scope of a supporting analysis that complements the main focus of the study. Therefore, the choice of ranking method has been limited, and two methods with different theoretical foundations, commonly used in the literature, have been adopted. In this context, the distance-based TOPSIS method (Hwang & Yoon, 1981) and the ratio-based ARAS method (Zavadskas & Turskis, 2010) were used. The next section will cover the theoretical foundations of the methods and the procedural steps.

3.2.1. CRITIC Method

The CRITIC method proposed by Diakoulaki et al. (1995) is an objective weighting method used to determine the contrasts between criteria. The method is mainly based on the correlations between criteria. The steps of the method are as follows.

The x_ij values represent the elements of the decision matrix. The benefit and cost criteria are normalised using Eq. 1 and Eq. 2, respectively.

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad i = 1, ..., m \quad j = 1, ..., n \quad \text{Benefit Criteria} \tag{1}$$

$$r_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \quad i = 1, ..., m \quad j = 1, ..., n \quad \text{Cost Criteria} \tag{2}$$

After obtaining the normalized decision matrix, the correlation coefficients between the criteria (ρ_{jk}) and standard deviation values of the criteria (σ_j). Then, based on these values, the inter-criteria contrast values are calculated using Eq. 3.

$$c_j = \sigma_j \sum_{k=1}^{n} \left(1 - \rho_{jk}\right) \quad j = 1, ..., n \tag{3}$$

Subsequently, the weights w_j are obtained as a function of the c_j values by Eq. 4 (Jahan et al., 2012).

$$w_j = \frac{c_j}{\sum_{k=1}^{n} c_k} \quad j = 1, ..., n \tag{4}$$

3.2.2. SD Method

The SD method is based on the basic principle of assigning a small weight to criteria that have similar values across alternatives. In this method, the weights of the criteria are determined by Eq. 6 using the standard deviation values (σ_j) given in Eq. 5 (Jahan et al., 2012).

$$\sigma_j = \frac{\sum_{j=1}^{m} \left(x_{ij} - \overline{x_j}\right)^2}{m} \quad j = 1, ..., n \tag{5}$$

$$w_j = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j} \quad j = 1, ..., n \tag{6}$$

3.2.3. CILOS Method

The CILOS method was developed by Zavadskas & Podvezko (2016) based on the work of Mirkin (1974). The basic idea behind the method is that the smaller the loss suffered by a criterion, the higher its weight should be. The steps of the CILOS method are given below.

Once a multi-criteria decision matrix is established, the cost criteria are transformed using Eq. 7. No transformation is applied to the benefit criteria.

$$x_{ij} = \frac{\min_i r_{ij}}{r_{ij}} \tag{7}$$

Subsequently, the highest value of each criterion is calculated using the formula $x_{ij} = \max_i x_{ij} = x_{k_j j}$, where k_j denotes the row number of the j_{th} column where the largest value is obtained. The next steps involve constructing the square matrix A ($A = \| a_{ij} \|, a_{ii} = a_{ij}, a_{ij} = x_{k_i j}$ $i, j : 1, 2, ..., m$ m is the number of criteria and the relative loss matrix $P = \| p_{ij} \|$. The relative loss matrix is formed by Equation (8).

$$p_{ij} = \frac{x_j - a_{ij}}{x_j} = \frac{a_{ii} - a_{ij}}{a_{ii}} \quad , \qquad p_{ii} = 0; i, j = 1, 2, ..., m \tag{8}$$

The diagonal elements of the matrix P are 0. The elements of p_{ij} in the matrix P show the relative loss of the j_{th}criterion, if the i_{th} criterion is selected to the best. According to this method, if the relative loss in criteria significance is low, the criterion is assigned a higher weight. The weights are obtained by solving the system of linear equations given by Eq. 9, where q represents the weight vector and the matrix F is defined as shown in Equation (10).

$$Fq^t = 0 \tag{9}$$

$$F = \begin{bmatrix} -\sum_{i=1}^{m} p_{i1} & p_{12} & \cdots & p_{1m} \\ p_{21} & -\sum_{i=1}^{m} p_{i2} & \cdots & p_{2m} \\ \vdots & p_{m1} & \ddots & \vdots \\ p_{m2} & \cdots & \cdots & -\sum_{i=1}^{m} p_{im} \end{bmatrix} \tag{10}$$

The weight vector is, hence, determined by normalizing the values so that $\sum_{i=1}^{m} q_i = 1$ (Zavadskas & Podvezko, 2016).

3.2.4. LOPCOW Method

The LOPCOW method, presented by Ecer & Pamucar (2022), is another objective weighting technique for MCDM problems. This method is notable for features such as not being affected by the size of the data or negative values, and not requiring limitations for the criteria. The steps of this method are as follows.

In the first step of the method, a multi-criteria decision matrix is established, followed by normalization. Similar to the CRITIC method, for benefit criteria, Eq. 1 is used, while for cost criteria, Eq. 2 is applied. Let r_{ij} denote the elements of the obtained normalized matrix. The PV_{ij} values, calculated as a function of the standard deviations of the criteria to eliminate differences arising from data size, are obtained as Eq. 11.

$$PV_{ij} = \left| \ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^2}{m}}}{\sigma} \right) \cdot 100 \right| \tag{11}$$

Here, σ and m represent the standard deviation and the number of alternatives, respectively. In the next step, the criteria weights w_j are obtained with the formula given by Eq. 12 (Ecer & Pamucar, 2022).

$$w_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}} \tag{12}$$

3.2.5. TOPSIS Method

TOPSIS method was developed by Hwang & Yoon (1981). This method, which is widely used among multi-criteria decision-making methods, is based on ranking alternatives according to their relative closeness to the ideal solution. The stages of the method are as follows: normalizing the decision matrix, obtaining the weighted decision matrix, obtaining the ideal solution vectors as separation criteria, calculating the distances to the ideal solutions and obtaining the scores. Formulas and definitions for the steps of the method are given below.

The x_{ij} values represent the elements of the decision matrix. In the first step, the normalized decision matrix is obtained using Eq. 13 for both benefit-oriented and cost-oriented criteria

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \; ; \; i = 1, ..., m \; j = 1, ..., n \tag{13}$$

Then, the weighted normalized decision matrix is obtained as follows using the predefined weights: $v_{ij} = w_j \cdot r_{ij}$ where $\sum_{j=1}^{n} w_j = 1$. Alternatives involving ideal solutions are determined. Positive ideal solution (A^*) and negative ideal solution (A^-) vectors are created using Eq. 14 and Eq. 15 according to the benefit criteria and cost criteria sets, respectively.

$$A^* = \left\{ (\max_i v_{ij} \mid j \in J), \left(\min_i v_{ij} | \, j \in J' \right), i = 1, 2, 3, ..., m \right\} = (v_{1*}, v_{2*}, ..., v_{j*}) \tag{14}$$

$$A^- = \{ (\min_i v_{ij} \mid j \in J), \left(\max_i v_{ij} \mid j \in J', i = 1, 2, 3, ..., m \right\} = (v_{1-}, v_{2-}, ..., v_{j^-}) \tag{15}$$

The measures of separation from positive ideal (S_{i^*}) and negative ideal solutions (S_{i^-}) are calculated using the Euclidean distance, as shown in Eq. 16 and Eq. 17, respectively.

$$S_{i^*} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_{j^*})^2} \; ; i = 1, 2, 3, ..., m \tag{16}$$

$$S_{i^-} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_{j^-})^2}; \;\; i = 1, 2, 3, ..., m \tag{17}$$

In the final step, scores (C_{i^*}) are obtained using Eq. 18 as a measure of relative closeness to the ideal alternative (Triantaphyllou, 2000).

$$C_{i*} = \frac{S_{i^-}}{S_{i^*} + S_{i^-}} \; ; 1 \geq C_{i^*} \geq 0 \text{ and } i = 1, 2, 3, ..., m \tag{18}$$

3.2.6. ARAS Method

The ARAS method is a MCDM technique developed by Zavadskas & Turskis (2010) based on evaluating alternatives included in the analysis relative to an optimal alternative. The steps of the method are summarized below.

Where *m* denotes the number of alternatives and *n* denotes the number of criteria, and x_{ij} , $i = 0, 1, 2, ..., m$ and $j = 1, 2, ..., n$ represents the elements of the decision matrix. Following the construction of the decision matrix, optimal values for the criteria are determined.
The optimal value of criterion *j* is denoted as x_{0j}, where $x_{0j} = \max_i x_{ij}$ if the criterion is beneficial, $x_{0j} = \min_i x_{ij}$ if the criterion is cost. The decision matrix is reformulated by incorporating the optimal alternative, and the normalization procedure is then applied to the updated matrix. The normalization process is performed as follows according to Eq. 19, Eq. 20 and Eq. 21.

For benefit criteria:

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{19}$$

Cost criteria are normalized by applying two stage procedure: x_{ij}^* represents the value of the cost-oriented criterion.

$$x_{ij} = \frac{1}{x_{ij}^*} \tag{20}$$

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{21}$$

$\overline{x}_{ij}$ denote the elements of the normalized decision matrix and w_j represent the weights assigned to the criteria. Then, the normalized-weighted values of all the criteria ($\hat{x}_{ij}$), are calculated using the following formula given in Eq. 22.

$$\hat{x}_{ij} = \overline{x}_{ij} w_j \cdot \hat{x}_{ij} \tag{22}$$

The determination of the optimality function values (S_i) is carried out by using the normalized weighted values through Eq. 23;

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}; \quad i = 0, 1, 2, ..., m \tag{23}$$

S_i represents the value of the optimality function for the ith alternative. The utility degree of an alternative K_i is determined by comparing the analyzed variant to the ideally best alternative, denoted as S_0, and is calculated according to the formula given in Eq. 24.

$$K_i = \frac{S_i}{S_0}; \quad i = 0, 1, 2, ..., m \tag{24}$$

The calculated K_i values represent scores in the range [0, 1] and reflect the desired preference priority (Zavadskas et al., 2010).

3.3. Computational Procedure

This section explains the computational process used to obtain the study findings. The calculation of objective criteria weights and the ranking of alternatives using MCDM methods were performed using the Julia programming language (Bezanson et al., 2017) and the JMcDM package (Satman et al., 2021).

JMcDM was designed to provide a developer-friendly library for solving multi-criteria decision-making problems using the Julia programming language (Satman et al., 2021). This tool was chosen for this study due to its programmable structure, free accessibility, and ability to ensure comparability of results. Appendix 1 is an example application showing both the calculation of criterion weights and the ranking of alternatives using the package. All methods given in Section 3.2 can be run in a similar way.

In this context, as shown in Appendix 1, sample code is provided for the analysis to be performed using the CRITIC method to calculate the weights and the TOPSIS method to obtain the rankings using CRITIC-based weights. Here, the decision matrix presented in Table 2 of the `eiui_data.csv` file is used to calculate criterion weights using the CRITIC method; based on these weights, the scores and rankings of the alternatives are obtained using the TOPSIS method and reported. Similarly, it is possible to obtain all ranking results reported in Table 3-6 by modifying the weighting and ranking functions in the relevant code with the desired methods.

When implementing the computational procedure, several technical points should be considered.The direction of the criteria is defined using the `fns` vector, where benefit-type criteria are specified with `maximum` and cost-type criteria with `minimum`. Depending on the version of the JMcDM package, the computed weight vector may be stored under different field names such as `w` or `weights`, which should be taken into account during implementation.In the example code provided in Appendix 1, different weighting and ranking methods can be applied by changing the corresponding method names. However, some methods require additional parameter adjustments in the code; therefore, the normalization structure of the selected method should be taken into account. For instance, due to its scale sensitivity, the SD method requires that weights be computed without normalization; accordingly, when applying the SD method, the line `w = critic(X, fns).w` given in Appendix A should be replaced with `w = sd(X, fns; normalization = Normalizations.nullnormalization).weights`. Finally, alternative rankings are obtained by sorting the score vector in descending order; in cases where equal scores occur, the ranking behavior may vary, and a stable sorting algorithm can be used if needed. The same implementation approach can be followed for the remaining weighting and ranking methods.

4. Findings

Two main findings of the study are presented in this section. First, the criteria weights calculated using the CRITIC, SD, CILOS, and LOPCOW methods are presented and analyzed in comparison with the original TÜBİTAK criteria weights. Second, university rankings were re-evaluated and analyzed using the TOPSIS and ARAS methods with the calculated objective criteria weights. In addition to the statistical analyses used in this section, visualization tools such as heatmaps and radar charts were employed to enhance the interpretability of the findings.

4.1. Differences in Criteria Weights Across Objective Methods

The weights for each indicator used in EIUI were calculated using the CRITIC, SD, CILOS, and LOPCOW methods and summarized below. The weights calculated for each indicator according to the selected objective weighting method are presented in Table 3. Calculations related to the methods used to calculate criterion weights and rank alternatives throughout the analysis were performed as described in Section 3.3.

Table 3. The Weights of EIUI Indicators Based on Different Weighting Method

		EIUI	TÜBİTAK	CRITIC	SD	CILOS	LOPCOW	σ
STRC	C1	*Number of Scientific Publications*	0.0250	0.0399	0.0325	0.0513	0.0482	0.0109
	C2	*Number of Citations*	0.0350	0.0388	0.0244	0.0675	0.0413	0.0159
	C3	*Number of Projects*	0.0200	0.0323	0.0257	0.0633	0.0468	0.0175
	C4	*Project Funding Amount*	0.0300	0.0314	0.0268	0.0727	0.0493	0.0193

		EIUI	TÜBİTAK	CRITIC	SD	CILOS	LOPCOW	σ
	C5	*Number of Awards*	0.0150	0.0430	0.0654	0.0277	0.0214	0.0201
	C6	*Number of Doctoral Graduates*	0.0250	0.0447	0.0369	0.0468	0.0756	0.0187
IPP	C7	*Number of National Patent Documents*	0.0520	0.0404	0.0478	0.0431	0.0531	0.0055
	C8	*Number of Utility Model Certificates*	0.0300	0.0596	0.0483	0.0230	0.0270	0.0157
	C9	*Number of International Patent Applications*	0.0500	0.0374	0.0486	0.0532	0.0557	0.0070
	C10	*Number of International Patent Documents*	0.0680	0.0547	0.0730	0.0381	0.0154	0.0235
CI	C11	*Number of Industry-Collaborative Projects*	0.0500	0.0363	0.0350	0.0264	0.0421	0.0088
	C12	*Industry-Collaborative Project Funding Amount*	0.0600	0.0383	0.0319	0.0473	0.0565	0.0119
	C13	*Number of International Collaborative Projects*	0.0500	0.0389	0.0376	0.0352	0.0334	0.0065
	C14	*International Collaborative Project Funding Amount*	0.0600	0.0392	0.0297	0.0555	0.0488	0.0123
	C15	*Number of Mobility Faculty Members/Students*	0.0144	0.0357	0.0250	0.0826	0.0536	0.0268
	C16	*Number of Students Registered in the Industry PhD Program*	0.0156	0.0449	0.0548	0.0182	0.0287	0.0170
ESC	C17	*Number of Academician-Owned Firms*	0.0568	0.0350	0.0407	0.0222	0.0593	0.0155
	C18	*Number of Student/Alumni-Owned Firms*	0.0757	0.0322	0.0429	0.0156	0.0561	0.0229
	C19	*Net Sales Revenue of Academician-Owned Firms*	0.0757	0.0375	0.0394	0.1045	0.0802	0.0287
	C20	*Net Sales Revenue of Student/Alumni-Owned Firms*	0.1041	0.0330	0.0400	0.0251	0.0693	0.0325
	C21	*Number of Licensed Patents*	0.0378	0.0554	0.0697	0.0290	0.0139	0.0219
	C22	*Number of BİGG Firms*	0.0300	0.0876	0.0666	0.0303	0.0150	0.0301
	C23	*Number of 4004-4005 Projects*	0.0200	0.0638	0.0573	0.0214	0.0092	0.0245

Table 3 shows the EIUI criterion codes (C1-C23), criterion descriptions, and weights related to the TÜBİTAK methodology. The standard deviation (σ) values in the last column of the table are presented as a measure of the method-based variability of the weights. This measure provides an indicator of the sensitivity of the criterion weights to the applied weighting method. Higher σ values indicate that certain criteria are more sensitive to the weighting approach. For a visual representation of the sensitivity of the criteria to different weighting methods, the heatmap analysis given in Figure 2 is presented. Figure 2 shows the heatmap of the weights obtained with different weighting methods for EIUI indicators. The color gradient in the heatmap represents the magnitude of the weights, with lighter colors representing lower weights and darker colors representing higher weights.

When the results obtained from Figure 2 and Table 3 are examined together, significant differences in criterion weights across different weighting methods indicate varying levels of sensitivity at the criteria level between different weighting methods (TÜBİTAK, CRITIC, SD, CILOS, LOPCOW). The highest variability and weight sensitivity was observed for the C20 and C22 criteria. The value obtained using the TÜBİTAK method for the C20 criterion and CRITIC method for C22 are significantly higher than the others. The standard deviation values (σ) for C20 and C22 are respectively 0.0325 and 0.0301 further support this sensitivity-related finding. The fact that these two criteria belong to the ESC dimension, which has the highest weight in the TÜBİTAK methodology, supports this situation. In the TÜBİTAK EIUI methodology, the C20 criterion has the highest weight with a value of 0.1041, and this value differs significantly from all other criterion weights.

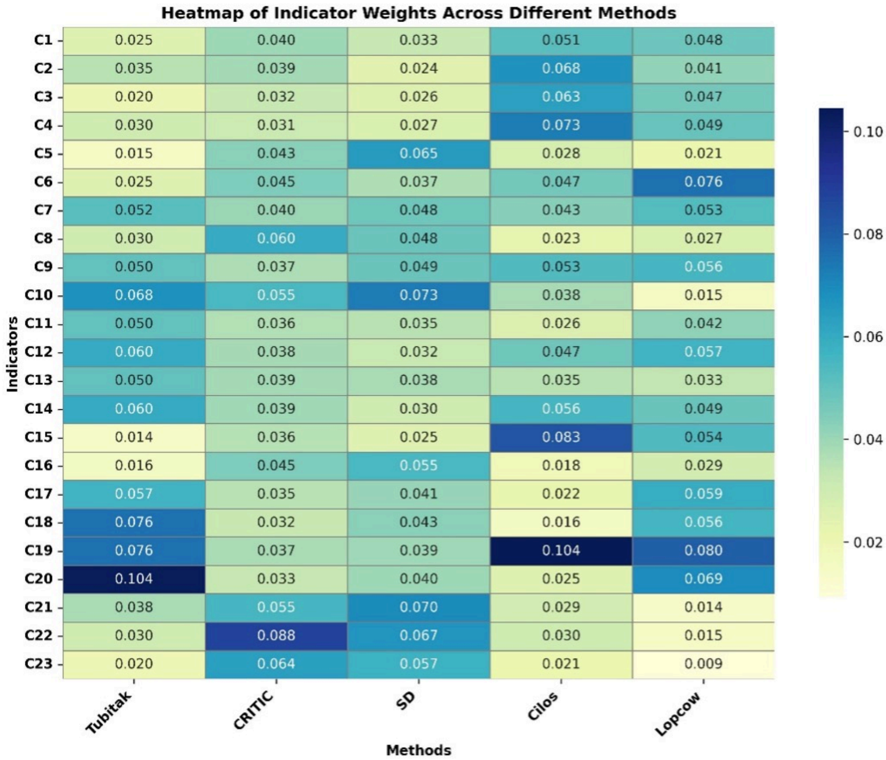

Figure 2. Heatmap representation of objective weighting methods for EIUI indicators

Similarly, other criteria showing high sensitivity to the weighting method, such as C19, C15, C23, C10, C18, C21, and C5, are noticeable. For the C19 and C15 criteria, the CILOS method assigns the highest weights of 0.104 and 0.083, respectively, while the LOPCOW method also assigns high weights to the criteria in a similar way, but the CRITIC and SD methods assign relatively lower weights. The standard deviation values of C19 (σ=0.0287) and C15 (σ=0.0268) also support this variability. For the C23 criterion (σ=0.0245), higher weights assigned by the CRITIC and SD methods and lower weights assigned by CILOS, LOPCOW, and TÜBİTAK. Similarly, while the CRITIC and SD methods assign higher weights to the C21 (σ=0.0219) and C5 (σ=0.0201) criteria, the other methods assign relatively lower weights. The C18 (σ=0.0229) criterion, on the other hand, is only considered significantly lower by the CILOS method. The C10 criterion (σ=0.0235) received the lowest weight from the LOPCOW method, while other methods assigned relatively higher values. In contrast, there is very little variation in the weights assigned by the methods for the C11, C9, C13, C7, and C1 criteria. This indicates that these criteria are less sensitive to the selection of weighting methods and exhibit a more stable contribution to the ranking results.

It is also possible to aggregate the changes in weights obtained from different weighting methods for the dimensions of the EIUI. Table 4 shows the aggregated results obtained from weighting methods for the four basic dimensions of the EIUI. Similar to the interpretation of criterion-based changes, visualization tools and standard deviation values were also used to express the sensitivity of aggregate weights to the methods.

Table 4. Aggregated weights of EIUI dimensions based on different weighting methods

	TÜBİTAK	CRITIC	SD	CILOS	LOPCOW	σ
STRC	0.1500	0.2302	0.2117	0.3294	0.2827	0.0686
IPP	0.2000	0.1921	0.2178	0.1574	0.1511	0.0285
CI	0.2500	0.2333	0.2139	0.2651	0.2632	0.0216
ESC	0.4001	0.3445	0.3566	0.2481	0.3029	0.0576

The radar chart in Figure 3 shows the change in the total weights of the four main dimensions of EIUI, namely STRC, IPP, CI, and ESC, across different weighting methods.

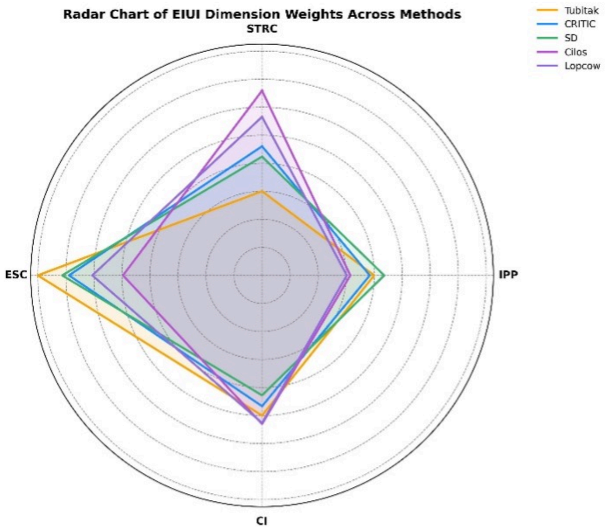

Figure 3. Radar chart visualization of objective weighting methods for EIUI dimensions

When Figure 3 and Table 4 are evaluated together, it can be seen that the weights assigned by different weighting methods have a balanced variability for the CI dimension. In this case, it can be said that the CI dimension shows poor sensitivity (σ=0.0216) to weighting methods. The IPP dimension also exhibits relatively balanced variability. While TÜBİTAK, CRITIC, and SD methods assign similar weights for the IPP dimension, CILOS and LOPCOW methods assign more different values. It can be said that this dimension shows limited but noticeable sensitivity (σ=0.0285) among the methods. However, the differences between the methods are more noticeable for the STRC and ESC dimensions. TÜBİTAK assigns a significantly lower importance to the STRC dimension (0.15) compared to other methods. Objective methods assign higher values than TÜBİTAK for the STRC dimension, with the CILOS method in particular standing out from other methods by assigning a value of 0.3294. Furthermore, this dimension shows the highest variability with its standard deviation value (σ=0.0686). Another dimension with high variability (σ=0.0576) is the ESC dimension. This dimension has the highest weight in the TÜBİTAK methodology, and other methods assign similarly higher weights, although not as many as TÜBİTAK. In contrast, the CILOS method assigns significantly lower weights to the ESC dimension compared to all other methods. This sensitivity is also clearly visible on the radar chart. Visualization tools such as heatmaps and radar charts, used to increase the interpretability of method-based variability, were created using the matplotlib (Hunter, 2007) and seaborn (Waskom, 2021) libraries in Python programming language.

4.2. Application of MCDM Ranking Methods based on Objective Weights

In this section, the TOPSIS and ARAS methods based on objective weighting methods were used to rank universities. In order to show the effects of different weighting-ranking method combinations on the results, an analysis was performed using 8 different MCDM methods: CRITIC–TOPSIS, SD–TOPSIS, CILOS–TOPSIS, LOPCOW–TOPSIS, CRITIC–ARAS, SD–ARAS, CILOS–ARAS, and LOPCOW–ARAS. The corresponding scores are presented in Table 5.

Table 5. Scores of alternatives obtained by different MCDM methods

	CRITIC TOPSIS	SD TOPSIS	CILOS TOPSIS	LOPCOW TOPSIS	CRITIC ARAS	SD ARAS	CILOS ARAS	LOPCOW ARAS
U1	0.5864	0.6238	0.7205	0.7721	0.6917	0.6997	0.7870	0.8178
U2	0.5126	0.5673	0.6824	0.7386	0.6398	0.6615	0.7612	0.7901
U3	0.6599	0.6772	0.7176	0.7383	0.7299	0.7319	0.7718	0.7741
U4	0.4450	0.5420	0.6511	0.6496	0.5711	0.6242	0.7414	0.7401
U5	0.4691	0.5563	0.6345	0.6250	0.5774	0.6146	0.7064	0.6934
U6	0.5336	0.6114	0.6254	0.6107	0.6162	0.6511	0.6868	0.6748
U7	0.3866	0.4762	0.6149	0.6126	0.4869	0.5275	0.6771	0.6773
U8	0.4281	0.4384	0.5765	0.6587	0.5122	0.5059	0.6424	0.6938
U9	0.4284	0.4211	0.5706	0.6337	0.5046	0.4874	0.6319	0.6691
U10	0.4597	0.4701	0.5693	0.5977	0.5092	0.5072	0.5942	0.6065
U11	0.4776	0.4739	0.5402	0.5852	0.5303	0.5177	0.6060	0.6207
U12	0.3023	0.3485	0.5082	0.6046	0.3769	0.3882	0.5520	0.6204
U13	0.4912	0.4306	0.5429	0.5871	0.5381	0.4946	0.6117	0.6308
U14	0.4329	0.4705	0.5587	0.5997	0.5010	0.5101	0.6030	0.6222
U15	0.3160	0.3117	0.4843	0.5571	0.3841	0.3648	0.5402	0.5847
U16	0.3874	0.3768	0.4922	0.4959	0.4253	0.4080	0.5329	0.5319
U17	0.3987	0.3775	0.5246	0.5543	0.4404	0.4175	0.5545	0.5745
U18	0.3106	0.3368	0.4806	0.5394	0.3802	0.3797	0.5286	0.5659
U19	0.2722	0.2824	0.4743	0.5394	0.3354	0.3240	0.5113	0.5617
U20	0.2962	0.3146	0.4492	0.5342	0.3603	0.3591	0.4984	0.5462
U21	0.4344	0.3751	0.4786	0.5146	0.4546	0.4111	0.5350	0.5515
U22	0.4446	0.4152	0.4998	0.5125	0.4571	0.4289	0.5307	0.5423
U23	0.3703	0.3380	0.4716	0.4760	0.4112	0.3836	0.5166	0.5163
U24	0.2755	0.2971	0.4309	0.5207	0.3144	0.3089	0.4582	0.5248
U25	0.4125	0.4233	0.5440	0.4798	0.4112	0.4113	0.5488	0.5200
U26	0.2434	0.2737	0.4398	0.4593	0.3130	0.3163	0.4784	0.4916
U27	0.3824	0.3534	0.4328	0.4647	0.4005	0.3711	0.4799	0.5077
U28	0.3462	0.3573	0.4503	0.4995	0.3412	0.3404	0.4399	0.4822
U29	0.2963	0.2631	0.4368	0.4621	0.3347	0.2976	0.4709	0.4959
U30	0.3418	0.3471	0.4604	0.4783	0.3921	0.3839	0.5002	0.5083
U31	0.3190	0.3702	0.3777	0.3977	0.3417	0.3554	0.4504	0.4508
U32	0.2850	0.2720	0.4002	0.4807	0.3247	0.3023	0.4395	0.4836
U33	0.2185	0.2253	0.3970	0.4874	0.2554	0.2405	0.4026	0.4715

	CRITIC TOPSIS	SD TOPSIS	CILOS TOPSIS	LOPCOW TOPSIS	CRITIC ARAS	SD ARAS	CILOS ARAS	LOPCOW ARAS
U34	0.4309	0.3756	0.4585	0.4427	0.4476	0.4073	0.5056	0.4836
U35	0.2170	0.2086	0.3885	0.4448	0.2580	0.2371	0.4120	0.4529
U36	0.2285	0.2599	0.3722	0.4042	0.2725	0.2688	0.4261	0.4558
U37	0.3741	0.3229	0.4093	0.4462	0.3885	0.3459	0.4611	0.4698
U38	0.1988	0.2190	0.3939	0.4428	0.2202	0.2137	0.3843	0.4289
U39	0.2631	0.2696	0.3446	0.4016	0.2802	0.2729	0.3918	0.4210
U40	0.2478	0.2337	0.4440	0.4400	0.2644	0.2393	0.4111	0.4221
U41	0.1774	0.1849	0.3861	0.4130	0.2188	0.2058	0.3848	0.4183
U42	0.3273	0.2807	0.3727	0.4203	0.3436	0.3049	0.4101	0.4324
U43	0.2795	0.3120	0.2927	0.3532	0.3073	0.3112	0.3824	0.3992
U44	0.2679	0.2438	0.3740	0.4074	0.2917	0.2644	0.4006	0.4223
U45	0.3001	0.2544	0.3938	0.3627	0.2958	0.2609	0.4068	0.3962
U46	0.1737	0.1694	0.3353	0.3902	0.2135	0.1943	0.3661	0.4023
U47	0.3527	0.3184	0.4003	0.3617	0.3286	0.2951	0.4242	0.4040
U48	0.3619	0.3047	0.3502	0.3811	0.3629	0.3222	0.4056	0.4113
U49	0.1925	0.1924	0.3785	0.4079	0.2239	0.2083	0.3746	0.4012
U50	0.1997	0.1914	0.3282	0.4010	0.2089	0.1902	0.3296	0.3784

Table 6 shows the ranking results for the methods along with TÜBİTAK's original ranking. Examining the rankings in Table 6 reveals that the methods have different impacts on the ranking of the alternatives.

Table 6. Rankings of alternatives obtained by different MCDM methods

	TÜBİTAK	CRITIC TOPSIS	SD TOPSIS	CILOS TOPSIS	LOPCOW TOPSIS	CRITIC ARAS	SD ARAS	CILOS ARAS	LOPCOW ARAS
U1	1	3	3	1	1	3	3	1	1
U2	2	1	1	3	2	1	1	3	2
U3	3	6	6	2	3	2	2	2	3
U4	4	2	2	4	8	6	6	4	4
U5	5	13	5	5	4	5	4	5	8
U6	6	11	4	6	9	4	5	6	5
U7	7	5	7	7	5	13	7	7	7
U8	8	10	11	8	7	11	11	8	6
U9	9	4	14	9	6	8	14	9	9
U10	10	22	10	10	12	10	10	13	13
U11	11	21	8	14	14	9	8	11	14
U12	12	14	13	25	10	14	13	14	11
U13	13	34	25	13	13	7	9	10	12
U14	14	9	9	11	11	22	22	17	10
U15	15	8	22	17	15	21	17	12	15
U16	16	25	17	12	17	34	25	25	17

	TÜBİTAK	CRITIC TOPSIS	SD TOPSIS	CILOS TOPSIS	LOPCOW TOPSIS	CRITIC ARAS	SD ARAS	CILOS ARAS	LOPCOW ARAS
U17	17	17	16	22	19	17	21	15	18
U18	18	16	34	16	18	16	16	21	19
U19	19	7	21	15	20	25	34	16	21
U20	20	27	31	18	24	23	12	22	20
U21	21	37	28	21	21	27	30	18	22
U22	22	23	27	19	22	30	23	23	16
U23	23	48	12	23	28	37	18	19	24
U24	24	47	30	30	16	15	27	34	25
U25	25	28	23	34	33	18	15	30	23
U26	26	30	18	28	32	12	20	20	30
U27	27	42	37	20	25	48	31	27	27
U28	28	31	47	40	30	20	37	26	29
U29	29	15	20	26	23	42	28	29	26
U30	30	18	43	29	27	31	19	37	34
U31	31	12	15	27	29	28	48	24	32
U32	32	45	48	24	26	19	26	31	28
U33	33	29	24	37	37	29	43	28	33
U34	34	20	19	47	35	47	24	32	37
U35	35	32	42	32	38	32	42	36	36
U36	36	43	26	33	34	24	32	47	35
U37	37	24	32	38	40	26	29	35	31
U38	38	19	39	45	42	43	47	40	42
U39	39	44	29	35	41	45	39	42	38
U40	40	39	36	41	49	44	36	45	44
U41	41	40	45	49	44	39	44	48	40
U42	42	26	44	31	36	36	45	33	39
U43	43	36	40	44	39	40	33	44	41
U44	44	33	33	42	50	35	40	39	48
U45	45	35	38	36	31	33	35	41	47
U46	46	50	35	48	46	49	38	38	46
U47	47	38	49	39	48	38	49	43	49
U48	48	49	50	46	45	41	41	49	43
U49	49	41	41	50	47	46	46	46	45
U50	50	46	46	43	43	50	50	50	50

4.3. Ranking Stability Based on Different Ranking Methods

In many complex decision environments, the robustness and reliability of the ranking scores of alternatives are examined by comparing the result of one model with other available and established methods (Demir & Arslan, 2022). In this study, ranking stability is evaluated through a comparative analysis based on multi-criteria decision-making methods employing different ranking methodologies. In this context, Spearman rank correlation analysis results are also presented to demonstrate the consistency of the rankings between methods. Subsequently, to visually assess the sensitivity of alternatives to method-based rankings, universities were grouped into sets of five, and separate evaluations were conducted using radar charts for the top, middle, and bottom groups of the ranking.

4.3.1. Ranking Consistency of Different Ranking Methods

The Spearman rank correlation coefficient is commonly used to assess the consistency of rankings obtained from different MCDM methods. High correlation values between rankings indicate a stronger similarity between methods. Low correlations may indicate significant differences between rankings (Triantaphyllou, 2000). If the coefficients are more excellent than 0,80, the relationship between the methods is considered to be high (Yazdani et al., 2019). In addition to the TÜBİTAK methodology, eight different ranking methods were used in the study: CRITIC-TOPSIS, SD-TOPSIS, CILOS-TOPSIS, LOPCOW-TOPSIS, CRITIC-ARAS, SD-ARAS, CILOS-ARAS, and LOPCOW-ARAS. To reveal the consistency of the ranking, the Spearman correlation coefficients given in Table 7 were calculated.

Table 7. Spearman rank correlation coefficients between ranking methods

	TÜBİTAK	CRITIC TOPSIS	SD TOPSIS	CILOS TOPSIS	LOPCOW TOPSIS	CRITIC ARAS	SD ARAS	CILOS ARAS	LOPCOW ARAS
TÜBİTAK	1.000	0.748	0.847	0.936	0.958	0.855	0.899	0.957	0.985
CRITIC-TOPSIS	0.748	1.000	0.710	0.701	0.726	0.633	0.611	0.761	0.733
SD-TOPSIS	0.847	0.710	1.000	0.777	0.788	0.685	0.772	0.843	0.826
CILOS-TOPSIS	0.936	0.701	0.777	1.000	0.937	0.795	0.827	0.912	0.932
LOPCOW-TOPSIS	0.958	0.726	0.788	0.937	1.000	0.829	0.862	0.916	0.957
CRITIC-ARAS	0.855	0.633	0.685	0.795	0.829	1.000	0.816	0.831	0.846
SD-ARAS	0.899	0.611	0.772	0.827	0.862	0.816	1.000	0.845	0.890
CILOS-ARAS	0.957	0.761	0.843	0.912	0.916	0.831	0.845	1.000	0.942
LOPCOW-ARAS	0.985	0.733	0.826	0.932	0.957	0.846	0.890	0.942	1.000

The results of the analysis showed that all correlation coefficients were statistically significant ($p < 0.05$). Table 7 reveals high levels of positive correlations between the methods. The highest correlation was observed between the TÜBİTAK and LOPCOW–ARAS (ρ= 0.985) rankings, followed by the TÜBİTAK and LOPCOW–TOPSIS (ρ = 0,958) and TÜBİTAK and CILOS–ARAS (ρ = 0.957) rankings. The lowest correlation between TÜBİTAK ranking and the other methods is CRITIC-TOPSIS (ρ = 0.748). For all methods the lowest correlation was found between CRITIC–TOPSIS and SD-ARAS (ρ = 0.611), indicating a relatively weaker relationship compared to the other pairs.

4.3.2. Visual Stability Assessment of Different Ranking Methods

This section presents the ranking stability of university performance according to different MCDM methods using radar charts. To illustrate the sensitivity of alternatives (U1-U50) across different ranking approaches, universities were evaluated in groups of five. Separate analyses were conducted for universities ranked at the top, middle, and bottom of the TÜBİTAK EIUI ranking, making it possible to conduct a comparative assessment of university performance profiles.

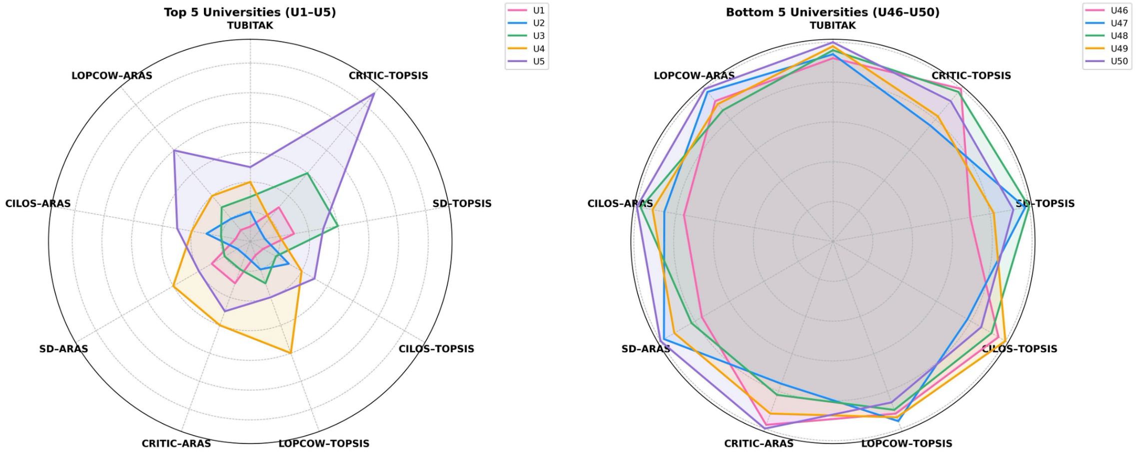

Figure 4. Radar charts of the top five (U1–U5) and bottom five (U46–U50) universities across different MCDM methods

Figure 4 presents radar charts showing the rankings of the top five (U1–U5) and bottom five (U46–U50) alternatives according to different methods. Upon examining Figure 4, it is evident that alternatives U1 and U2 consistently rank at the top in all ranking approaches and demonstrate a high level of consistency against methodological variability. Although the U3 alternative has a generally stable ranking, it shows a distinct difference compared to other methods in the CRITIC–TOPSIS and SD–TOPSIS methods. Similarly, alternatives U4 and U5 show consistent rankings in general. However, they show slight variability in some specific methods. U5 is more significantly affected in the CRITIC–TOPSIS method, while U4 is more significantly affected in the LOPCOW–TOPSIS method. For the alternatives at the bottom of the rankings in particular U46–U50 high ranking consistency has been observed.

Figure 5 shows the radar charts that reveal the ranking stability of the alternatives (U6–U45) in the middle ranks, as determined by different MCDM methods. When the radar charts are examined, it is observed that the rankings in U6-U45 groups are more balanced compared to the alternatives at the top and bottom ranks. In particular, universities such as U13, U16, U19, U23, U24, U27, U28, U31, U32, U34, U38 and U42 exhibit significant ranking variability across methods. The main reason for this difference can be explained by the fact that the dimension-based performance of middle rank universities shows high variability, unlike the universities at the top or bottom of the list.

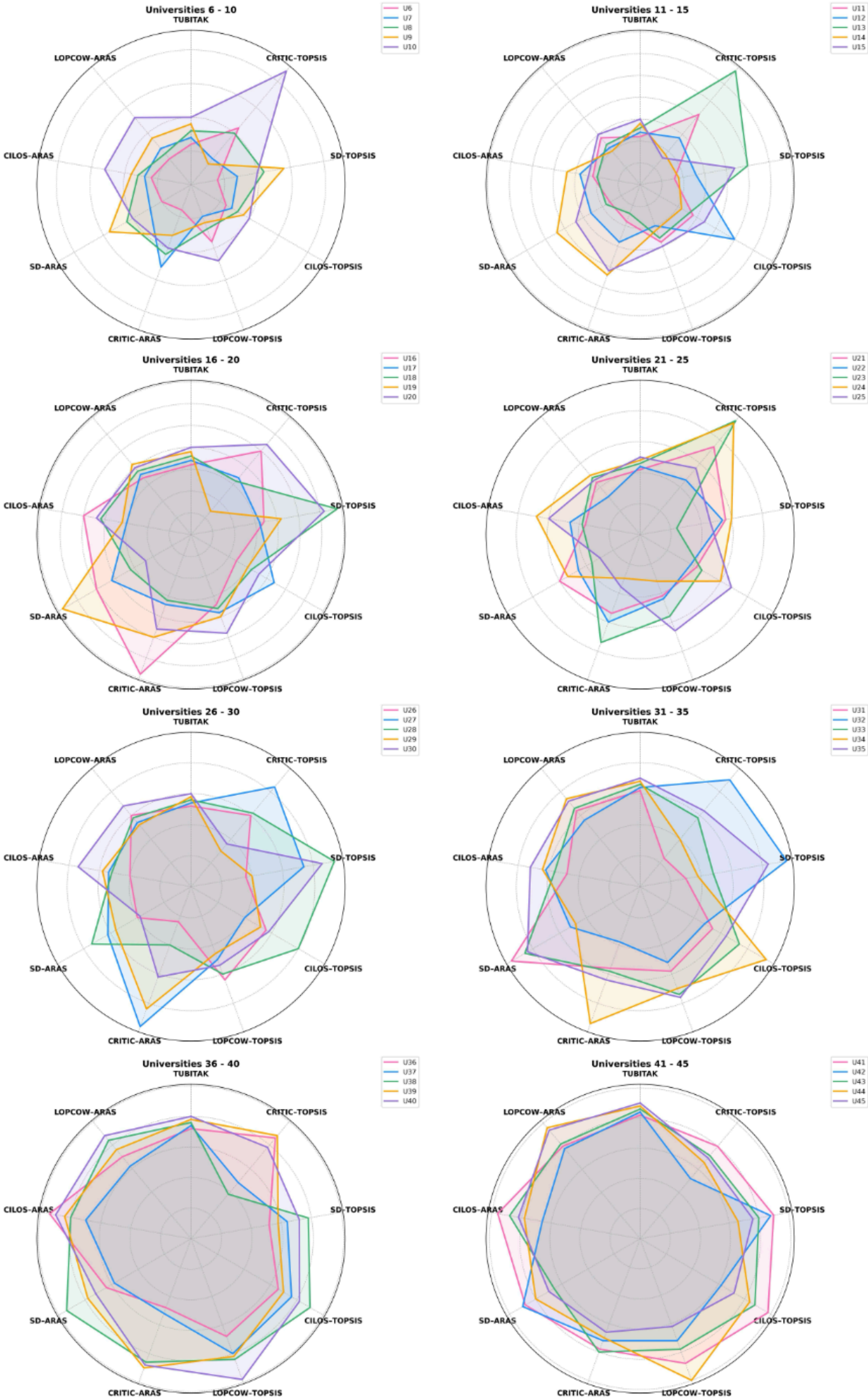

Figure 5. Radar charts of the U6–U46 universities across different MCDM method

5. Discussion and Conclusion

The criteria weights in the EIUI are based on higher education policy priorities and expert opinions. Although determining these weights in line with policy priorities is a reasonable and consistent approach from an institutional and strategic perspective, it is also important to re-evaluate them using different objective methods and analyze how alternative weighting structures may influence ranking results, especially for comparative purposes. In this study, the weights of the 23 indicators included in the EIUI were recalculated using four different objective weighting methods: CRITIC, SD, CILOS, and LOPCOW. Most of the studies in the literature focus on weighting analysis only at the dimension level. The originality of this study can be expressed in the detailed analysis of university performance not only at the level of four main dimensions (STRC, IPP, CI, ESC) but also at the level of each indicator (C1–C23). In this way, a more comprehensive and comparative framework was presented for all indicators. Additionally, using the 2024 EIUI results increases the validity of the results by providing a current perspective on university performance. However, the findings are supported not only by numerical results but also by visual tools such as heatmaps and radar charts that help increase the interpretability of differences between methods.

The analysis results show that there are notable differences between the original criteria weights defined by TÜBİTAK and the weights calculated using objective methods (CRITIC, SD, CILOS, and LOPCOW). In particular, some indicators related to entrepreneurship and university-industry collaboration such as Net Sales Revenue of Student/Alumni-Owned Firms (C20), Number of BİGG Firms (C22), Net Sales Revenue of Academician-Owned Firms (C19), and Number of Mobility Faculty Members/Students (C15) had relatively high standard deviation values. These results suggest that the weights for these indicators vary more depending on the method used. On the other hand, some IPP and CI dimensions indicators such as Number of Industry-Collaborative Projects (C11), Number of International Patent Applications (C9), Number of International Collaborative Projects (C13) and Number of National Patent Documents (C7) were evaluated with very similar weights across all methods, which means that the differences in these criteria were minimal. When the four main dimensions STRC, IPP, CI and ESC are compared, it is seen that the total weights assigned to these dimensions by the methods show significant differences. While the ESC dimension is evaluated with a weight of 40% in the TÜBİTAK method, this rate decreases to 24.81% in the CILOS method. The STRC dimension is evaluated higher compared to TÜBİTAK in all methods, and in particular, the CILOS method assigns a notably higher weight to this dimension compared to the other methods. While the objective methods consistently assign weights in the range of 21% to 33% to the STRC dimension, it is noteworthy that this dimension is assigned a weight of only 15% in the TÜBİTAK methodology. In this context, the relatively higher weight given to the ESC dimension compared to the STRC in the TÜBİTAK methodology may indirectly emphasize the policy priorities of the index. Universities aiming to rank higher in the EIUI ranking may take this into account when determining their strategic priorities. On the other hand, the CI dimension produces relatively consistent values in most methods, generally varying between 21% and 26%. Similarly, the IPP dimension also exhibits relatively balanced; only the CILOS and LOPCOW methods differ at this point. When the weighting methods are compared, it is observed that the CILOS method, unlike all other methods, assigns the highest weight to the STRC dimension rather than the ESC dimension. This finding is supportive for policymakers and researchers who argue that the impact of the STRC dimension on entrepreneurial and innovative university performance should be strengthened.

Another important finding of the study is the obtaining of university rankings based on recalculated objective weights. Using these weights, university rankings were recalculated with two common MCDM methods, namely TOPSIS and ARAS. After that, new rankings for method combinations such as CRITIC–TOPSIS, SD–TOPSIS, CILOS–TOPSIS, LOPCOW–TOPSIS, CRITIC–ARAS, SD–ARAS, CILOS–ARAS and LOPCOW–ARAS were obtained and compared with the original ranking of TÜBİTAK. As a result, it was revealed that the methods produced consistent results and the correlations were found to be statistically significant. In general, all methods showed stronger correlations with the TÜBİTAK rankings. However, methods based on the CRITIC approach exhibit relatively lower correlations compared to the others. The highest correlation with the TÜBİTAK ranking was obtained using the LOPCOW–ARAS method (ρ= 0.985), while the lowest correlation with the TÜBİTAK ranking was observed for the CRITIC–TOPSIS method (ρ = 0.748). Except for the CRITIC–TOPSIS approach, all other methods show correlation values greater than 0.80 with the TÜBİTAK ranking. Moreover, methods based on CILOS and LOPCOW generally demonstrate higher correlations both with the TÜBİTAK ranking and with other ranking methods. These findings indicate that the combination of the weighting method and the decision-making model significantly affects ranking results, suggesting that method selection is a critical issue in MCDM analysis. In addition, radar charts were used to visually assess the stability and method-related sensitivity of ranking results across different combinations of weighting and ranking methods, with universities evaluated in groups of five. The results showed that the universities at the top and bottom of the list exhibited a consistent structure. In particular top two universities Middle East Technical University (METU) and Istanbul Technical University (ITU) have demonstrated a high level of stability in terms of ranking by remaining their top positions across all methods and decision models. Yıldız Technical University, Sabancı University and İhsan Doğramacı Bilkent University, which are ranked third, fourth and fifth, respectively, according to the TÜBİTAK ranking, also ranked relatively high in other decision models. Although there is no study in the literature regarding 2024 EIUI data, the results obtained substantially support the findings of previous studies summarized in the literature section, such as those by Çınaroğlu (2021), Satıcı (2022), Oğuz (2022), Karahan & Kızkapan (2022). Similarly, universities in the bottom group U41–U50, particularly U45-U50 underperformed regardless of the method used, but the same consistency was not observed for universities in the middle of the ranking. This shows that the positions of the universities in the middle ranks are more sensitive to the decision model and weighting method used. Therefore, it is important for these universities to carefully analyze which indicators they should prioritize and structure their strategic policies accordingly to increase their stability in the rankings.

The findings of the study indicate that the criteria included in the TÜBİTAK EIUI index and university rankings are sensitive to the selected weighting and ranking methods. This situation indicates that, in order to increase transparency and balance in performance evaluation, it would be beneficial to periodically test the current weighting structure of the EIUI not only within the framework of policy priorities but also using objective methods. In this context, comparing the EIUI with weights obtained from objective methods could contribute to the success of the index for policymakers. The results show that universities at the top and bottom of the ranking demonstrate relatively stable performance, but universities in the middle of the ranking are more sensitive to methodological choices. This situation offers important strategic management implications, particularly for universities seeking to improve their rankings.University administrators can prioritize indicators that are more sensitive to weight changes (e.g., university-industry collaboration, entrepreneurial income, and mobility indicators) as strategic areas to enhance entrepreneurship and innovation performance. Furthermore, rather than relying on a single ranking result in performance evaluation, evaluating results obtained using different methodological approaches can help managers make more robust and sustainable decisions.

This study has certain limitations. The analysis was conducted for a single year using the most recently published data from the EIUI. Changes over time in the entrepreneurship and innovation performance of universities were not examined. Furthermore, institutional differences such as geographic region, research university status, and public or private university status were not included in the analysis. The study examined ranking stability through method-based comparisons and visualization analyses. Future studies could examine the stability and robustness of ranking results in greater detail by incorporating rank reversal analysis and sensitivity analysis based on systematic weight adjustment. The proposed framework can be expanded by including multi-year data, institutional characteristics of universities, hybrid weighting approaches, and additional MCDM methods.

Declarations

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

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Appendix

Appendix 1. Illustrative Julia Code for the Computational Procedure

```
using CSV, DataFrames, JMcDM

df = CSV.read("eiui_data.csv", DataFrame;
              delim=';', decimal=',', header=false)
X = Matrix{Float64}(df)

fns = fill(maximum, size(X,2))

w = critic(X, fns).w

res    = topsis(X, w, fns)
scores = res.scores
order  = sortperm(scores; rev=true)

n = length(scores)

println("CRITIC weights:")
show(DataFrame(Weight = w), allrows=true, allcols=true)
println("\n")

println("TOPSIS scores (A1–A$n):")
show(DataFrame(Alternative = 1:n, Score = scores),
     allrows=true, allcols=true)
println("\n")

println("TOPSIS ranking:")
show(DataFrame(Alternative = order,
               Score = scores[order]),
     allrows=true, allcols=true)
```