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A Hybrid MADM Approach Based on Simple Additive Weighting and TOPSIS: An Application on Comparison of Innovation Performances of the EU Countries

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Keywords

Convex Optimization

Innovation

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Abstract

This study aims to objectively compare the long-term innovation performances of the EU countries. In this context, we propose a hybrid multi-attribute decision-making (MADM) approach combining Simple Additive Weighting (SAW) and TOPSIS. The proposed approach (CST) uses the alternatives' quadratic utility functions considering the weighted sum value and distance to the positive ideal solution. It also uniquely determines the criteria weight vector using a strictly concave maximization problem. Using the Summary Innovation Index (SII) data for the 2016-2023 period, CST reveals that Sweden, Denmark, and the Netherlands are in the first three ranks. In contrast, Romania, Bulgaria, and Latvia are in the last three ranks.

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1. INTRODUCTION

Innovation is the word of our age. An original or substantially upgraded product offered to the market or the initiation within a business of an original or substantially upgraded process is called innovation. That is, two main types of innovation are product innovation and process innovation. Product innovation is related to goods or services. Process innovation may have organizational or marketing aspects (Eurostat, 2023). European Innovation Scoreboard (EIS) can measure countries' innovation performances. EIS has four dimensions, twelve sub-dimensions, and thirty-two indicators. Based on EIS, selected countries have a total innovation score called the Summary Innovation Index (SII). SII is an important tool for monitoring and comparing countries' innovation performances and helps evaluate the effectiveness of the EU's innovation policies (European Commission, 2023).

Comparing the innovation performances of countries is of great importance in evaluating and improving the effectiveness of policies. These comparisons help countries identify their strengths and weaknesses and make strategic decisions accordingly (Anderson & Stejskal, 2019). Although it is a very important subject, few studies have compared the countries with respect to their innovation performances. This is because there are already some important and reliable innovation indices, such as the Global Innovation Index, Summary Innovation Index, Bloomberg Innovation Index, etc. Kaynak et al. (2017) compare the EU candidate countries using TOPSIS. Brodny et al. (2023) compare the EU countries using EDAS. Ozkaya et al. (2021) compare many countries using different methods. Namazi and Mohammadi (2018) compare many countries using DEA-based TOPSIS. Ecer and Aycin (2023) compare G7 countries using different methods. Aytekin et al. (2022) compare the EU member and candidate countries using DEA-EATWIOS. Satı (2024) compares the EU

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member and candidate countries using TOPSIS. Do Carmo Silva et al. (2020) compare many countries using TOPSIS and PROMETHEE. Erdin and Caglar (2023) compare the OECD countries using a DEA-based approach. Murat (2020) compares the OECD countries using DEA. Jeon et al. (2022) and Selvaraj and Jeon (2021) compare the OECD countries using a fuzzy approach. Anderson and Stejskal (2019) and Jurickova et al. (2019) compare the EU member countries using DEA. Kabadurmuş and Karaman Kabadurmuş (2019) compare the Eastern Europe and Central Asia countries using TOPSIS. Chen et al. (2011) compare many countries using DEA.

SAW is one of the most used MADM methods (Taherdoost, 2023). Similarly, TOPSIS is widely used since it is an understandable method with a strong mathematical structure. On the other hand, the issue of determining criteria weights is a matter of criticism for TOPSIS. Because the results obtained with it depend significantly on the criteria weights (Bouslah et al., 2023). One of the motivations of this study is to combine SAW and TOPSIS with a hybrid approach, which also determines the criteria weights inherently. Thus, we propose a hybrid MADM approach combining SAW and TOPSIS. We call it CST. Another motivation for this study is to provide a different perspective for innovation-based analyses. Thus, this study aims to compare the long-term innovation performances of the EU countries using an objective approach. Due to its objectivity, we use CST to achieve this aim. This study differs from the above studies and existing innovation index reports since it directly makes a long-term analysis using SII's yearly data, whereas the studies in the literature consider many criteria using a specific year's data for each analysis. This study also differs from them by analyzing the annual progress of the countries. Thus, the originality of the paper comes from the long-term analysis and the annual progress analysis in addition to the proposed MADM approach.

The rest of the paper is organized as follows. Section 2 gives the steps of SAW and TOPSIS. It also presents the theory of CST. Section 3 illustrates CST by comparing the innovation performances of the EU countries for the 2016-2023 period based on SII (EIS, 2023). It also presents and discusses the results of the innovation performance comparisons. Section 4 concludes the paper.

2. MATERIAL AND METHOD

Many normalization techniques can be used in SAW. We prefer the vector normalization. Then, the steps of SAW can be given as follows (Vafaei et al., 2022; Taherdoost, 2023).

Step 1: The decision matrix $A_{nxm}=(a_{ij})$ is formed, where a_{ij} is the positive value of the i^{th} alternative for the j^{th} criterion, n is the number of alternatives, and m is the number of criteria.

Step 2: The normalized decision matrix $B_{nxm}=(b_{ij})$ is formed using (1a) for the benefit criterion and (1b) for the cost criterion (Acuña-Soto et al., 2021).

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{n} a_{ij}^2}} \tag{1a}$$

$$b_{ij} = \frac{1/a_{ij}}{\sqrt{\sum_{i=1}^{n} 1/a_{ij}^2}} \tag{1b}$$

Step 3: The criteria weight vector $w=(w_j)$ is determined using an approach.

Step 4: The alternatives' weighted sum vector $p=(p_i)$ is determined using the equation $p=Bw$.

Step 5: The alternatives are ranked in descending order using the p_i values.

Different normalization techniques can be used in TOPSIS, which uses Euclidean distance (Acuña-Soto et al., 2021). We prefer (1a)-(1b) for normalization. Then, the first three steps of TOPSIS are identical to the first three steps of SAW. The other steps of TOPSIS are as follows (Acuña-Soto et al., 2021; Bouslah et al., 2023).

Step 4: Let the maximum element of the j^{th} row of B is β_j, whereas the minimum element of the j^{th} row of B is α_j. The positive ideal solution $x=(x_j)$ is determined using the equation $x_j=w_j\beta_j$ for all j. The negative ideal solution $y=(y_j)$ is determined using the equation $y_j=w_j\alpha_j$ for all j.

Step 5: The i^{th} alternative's relative proximity to the ideal solution is calculated as in (2). The numerator term equals the alternative's distance to the negative ideal solution. The denominator term equals the sum of the alternative's distance to the negative ideal solution and the alternative's distance to the positive ideal solution.

$$s_i = \frac{\sqrt{\sum_{j=1}^{m} w_j^2 \left(b_{ij} - \alpha_j\right)^2}}{\sqrt{\sum_{j=1}^{m} w_j^2 \left(b_{ij} - \alpha_j\right)^2} + \sqrt{\sum_{j=1}^{m} w_j^2 \left(\beta_j - b_{ij}\right)^2}} \tag{2}$$

Step 6: The alternatives are ranked in descending order using the s_i values.

To combine SAW and TOPSIS, we assume that the quadratic utility function of the i^{th} alternative is as in (3), which considers two objectives: higher weighted sum value and lower distance to the positive ideal solution. We ignore the distance to the negative ideal solution since it is not a concave function. On the other hand, these distances generally give similar rankings. Thus, we believe that the loss of information is ignorable.

$$U_i(w) = \sum_{j=1}^{m} w_j b_{ij} - m \sum_{j=1}^{m} w_j^2 \left(\beta_j - b_{ij}\right)^2 \tag{3}$$

Then, we form the following concave maximization problem, which determines the criteria weight vector (w) by maximizing the worst alternative's utility. Clearly, y is a variable associated with the worst alternative.

$$\begin{aligned} &\max y \\ &\text{s.t. } y - \left(\sum_{j=1}^{m} w_j b_{ij} - m \sum_{j=1}^{m} w_j^2 \left(\beta_j - b_{ij}\right)^2 \right) \le 0, \forall i \\ &\quad \sum_{j=1}^{m} w_j = 1 \\ &\quad w_j \ge 0, \forall j \end{aligned} \tag{4}$$

Since (4) is a concave maximization problem, its optimal solution set is convex. The optimal solution closest to the origin can be found approximately using Tikhonov's regularized problem, which gives a unique solution (Boyd & Vandenberghe, 2004; Beck & Sabach, 2014). Thus, we use Tikhonov's regularized problem given in (5) instead of (4), where ε is a positive constant close to 0. We take $\varepsilon=2^{-23}$ in this study. Since (5) is a concave maximization problem, it can be solved with MATLAB software CVX (Grant & Boyd, 2008).

$$\begin{aligned} &\max y - 0.5\varepsilon \sum_{j=1}^{m} w_j^2 \\ &\text{s.t. } y - \left(\sum_{j=1}^{m} w_j b_{ij} - m \sum_{j=1}^{m} w_j^2 \left(\beta_j - b_{ij}\right)^2 \right) \le 0, \forall i \\ &\quad \sum_{j=1}^{m} w_j = 1 \\ &\quad w_j \ge 0, \forall j \end{aligned} \tag{5}$$

The first two steps of CST are identical to the first two steps of SAW. The other steps of CST are as follows.

Step 3: The squared difference matrix $D=(d_{ij})$ is formed using the equation $d_{ij}=(\beta_j-b_{ij})^2$ for all i and j, where β_j is the maximum element of the j^{th} row of B.

Remark: When the criteria weights are equal, the i^th^ alternative's utility is as in (6).

$$U_i = \frac{\sum_{j=1}^{m}\left(b_{ij} - d_{ij}\right)}{m} \tag{6}$$

Step 4: (5) is solved using suitable software to determine the criteria weight vector (w) uniquely. (It can also be used to find the criteria weights in SAW and TOPSIS.) The CVX code for (5) is given in (7).

```
cvx_solver mosek
cvx_begin
variables w(m) y;
maximize(y - 0.5*eps("single")*transpose(w)*w);
subject to                                                        (7)
    y*ones(n,1) - (B*w - m*D*(w.^2)) <= zeros(n,1);
    ones(1,m)*w == 1;
    w >= zeros(m,1);
cvx_end
```

Step 5: (3) is calculated for each alternative. Then, the alternatives are ranked in descending order using them.

3. RESULTS AND DISCUSSION

In this section, we use SAW, TOPSIS, and CST to compare the innovation performances of the EU countries for the 2016-2023 period based on SII. Any country's innovation performance increases with the increase in SII. We use SII for each year as a criterion, whereas the EU countries are the alternatives. We apply CST with the following steps.

Step 1: We form the decision matrix A=(a_{ij}) as in Table 1 using SII data of the EU countries for the 2016-2023 period.

Table 1. *The decision matrix*

	2023	**2022**	**2021**	**2020**	**2019**	**2018**	**2017**	**2016**
Austria	130.00	129.40	124.58	124.01	124.31	122.97	123.96	123.60
Belgium	136.44	136.92	136.00	127.60	129.26	125.94	123.69	122.35
Bulgaria	50.63	44.58	45.07	46.90	46.31	44.77	45.90	46.28
South Cyprus	114.29	113.70	108.41	88.70	84.54	82.23	79.09	78.67
Czechia	102.73	92.27	89.10	85.73	83.24	82.11	81.71	81.75
Germany	127.79	129.04	127.06	122.07	121.61	121.12	120.41	120.16
Denmark	149.24	146.47	144.53	140.06	137.79	134.16	134.52	133.25
Estonia	107.00	118.39	114.10	98.78	96.41	77.84	78.83	77.72
Greece	86.22	85.73	80.69	75.21	72.19	64.89	64.75	63.98
Spain	96.80	92.84	91.77	91.94	90.47	89.02	88.16	87.08
Finland	145.63	141.68	137.66	134.42	133.03	125.83	125.66	127.32
France	114.21	115.55	113.12	114.71	114.24	116.43	115.57	115.84

Table 2. *continued*

	2023	2022	2021	2020	2019	2018	2017	2016
Croatia	75.44	74.30	69.83	61.91	60.06	55.79	61.45	60.66
Hungary	76.31	73.87	70.42	67.96	66.92	68.52	68.48	68.57
Ireland	125.61	121.68	118.40	120.78	123.23	125.10	123.88	123.32
Italy	97.99	103.63	101.96	92.94	89.87	84.40	83.56	82.37
Lithuania	90.92	87.18	82.06	84.09	81.71	74.13	73.89	74.19
Luxembourg	127.15	126.17	125.87	128.45	129.71	128.47	128.76	128.68
Latvia	56.97	56.37	54.68	55.95	56.29	53.32	52.98	53.44
Malta	93.11	95.70	98.98	95.96	94.17	91.06	84.25	82.23
Netherlands	139.56	138.55	135.41	137.81	137.17	133.66	132.34	130.96
Poland	68.09	62.87	60.98	58.34	58.87	56.54	56.43	54.79
Portugal	92.88	89.90	87.53	96.97	93.75	83.91	85.02	85.15
Romania	35.85	38.27	37.36	33.79	31.91	34.51	35.42	34.41
Sweden	145.92	147.31	145.16	138.19	138.18	138.34	137.66	135.49
Slovenia	103.10	99.84	96.40	91.53	92.40	97.38	98.08	100.17
Slovakia	71.18	66.97	65.63	66.69	65.99	63.23	66.08	64.81

Step 2: We form the normalized decision matrix $B=(b_{ij})$ as in Table 2 using (1a).

Table 2. *The normalized decision matrix*

	2023	2022	2021	2020	2019	2018	2017	2016
Austria	0.2346	0.2356	0.2322	0.2382	0.2408	0.2448	0.2477	0.2482
Belgium	0.2462	0.2493	0.2535	0.2450	0.2504	0.2507	0.2471	0.2457
Bulgaria	0.0914	0.0812	0.0840	0.0901	0.0897	0.0891	0.0917	0.0929
South Cyprus	0.2063	0.2070	0.2021	0.1703	0.1637	0.1637	0.1580	0.1580
Czechia	0.1854	0.1680	0.1661	0.1646	0.1612	0.1634	0.1633	0.1641
Germany	0.2306	0.2350	0.2368	0.2344	0.2355	0.2411	0.2406	0.2413
Denmark	0.2693	0.2667	0.2694	0.2690	0.2669	0.2671	0.2688	0.2676
Estonia	0.1931	0.2155	0.2127	0.1897	0.1867	0.1550	0.1575	0.1560
Greece	0.1556	0.1561	0.1504	0.1444	0.1398	0.1292	0.1294	0.1285
Spain	0.1747	0.1690	0.1710	0.1766	0.1752	0.1772	0.1761	0.1749
Finland	0.2628	0.2580	0.2566	0.2582	0.2577	0.2505	0.2511	0.2556
France	0.2061	0.2104	0.2108	0.2203	0.2213	0.2318	0.2309	0.2326
Croatia	0.1361	0.1353	0.1301	0.1189	0.1163	0.1111	0.1228	0.1218
Hungary	0.1377	0.1345	0.1312	0.1305	0.1296	0.1364	0.1368	0.1377
Ireland	0.2267	0.2215	0.2207	0.2320	0.2387	0.2490	0.2475	0.2476
Italy	0.1768	0.1887	0.1900	0.1785	0.1741	0.1680	0.1670	0.1654
Lithuania	0.1641	0.1587	0.1529	0.1615	0.1583	0.1476	0.1476	0.1490
Luxembourg	0.2295	0.2297	0.2346	0.2467	0.2512	0.2557	0.2573	0.2584

Table 2. continued

	2023	2022	2021	2020	2019	2018	2017	2016
Latvia	0.1028	0.1026	0.1019	0.1075	0.1090	0.1061	0.1059	0.1073
Malta	0.1680	0.1742	0.1845	0.1843	0.1824	0.1813	0.1683	0.1651
Netherlands	0.2518	0.2523	0.2524	0.2647	0.2657	0.2661	0.2644	0.2630
Poland	0.1229	0.1145	0.1136	0.1120	0.1140	0.1125	0.1127	0.1100
Portugal	0.1676	0.1637	0.1631	0.1862	0.1816	0.1670	0.1699	0.1710
Romania	0.0647	0.0697	0.0696	0.0649	0.0618	0.0687	0.0708	0.0691
Sweden	0.2633	0.2682	0.2705	0.2654	0.2676	0.2754	0.2751	0.2720
Slovenia	0.1861	0.1818	0.1797	0.1758	0.1790	0.1938	0.1960	0.2011
Slovakia	0.1285	0.1219	0.1223	0.1281	0.1278	0.1259	0.1320	0.1301

Step 3: We form the $\beta=(\beta_j)$ vector as $(0.2693, 0.2682, 0.2705, 0.2690, 0.2676, 0.2754, 0.2751, 0.2720)^T$. Then, we determine the squared difference matrix $D=(d_{ij})$ matrix as in Table 3 using the equation $d_{ij}=(\beta_j-b_{ij})^2$.

Table 3. *The squared difference matrix*

	2023	2022	2021	2020	2019	2018	2017	2016
Austria	0.0012	0.0011	0.0015	0.0010	0.0007	0.0009	0.0007	0.0006
Belgium	0.0005	0.0004	0.0003	0.0006	0.0003	0.0006	0.0008	0.0007
Bulgaria	0.0317	0.0350	0.0348	0.0320	0.0317	0.0347	0.0336	0.0321
South Cyprus	0.0040	0.0037	0.0047	0.0097	0.0108	0.0125	0.0137	0.0130
Czechia	0.0070	0.0100	0.0109	0.0109	0.0113	0.0125	0.0125	0.0116
Germany	0.0015	0.0011	0.0011	0.0012	0.0010	0.0012	0.0012	0.0009
Denmark	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Estonia	0.0058	0.0028	0.0033	0.0063	0.0065	0.0145	0.0138	0.0135
Greece	0.0129	0.0126	0.0144	0.0155	0.0163	0.0214	0.0212	0.0206
Spain	0.0090	0.0098	0.0099	0.0085	0.0085	0.0096	0.0098	0.0094
Finland	0.0000	0.0001	0.0002	0.0001	0.0001	0.0006	0.0006	0.0003
France	0.0040	0.0033	0.0036	0.0024	0.0022	0.0019	0.0019	0.0016
Croatia	0.0177	0.0177	0.0197	0.0225	0.0229	0.0270	0.0232	0.0226
Hungary	0.0173	0.0179	0.0194	0.0192	0.0190	0.0193	0.0191	0.0181
Ireland	0.0018	0.0022	0.0025	0.0014	0.0008	0.0007	0.0008	0.0006
Italy	0.0086	0.0063	0.0065	0.0082	0.0088	0.0115	0.0117	0.0114
Lithuania	0.0111	0.0120	0.0138	0.0116	0.0120	0.0163	0.0162	0.0151
Luxembourg	0.0016	0.0015	0.0013	0.0005	0.0003	0.0004	0.0003	0.0002
Latvia	0.0277	0.0274	0.0284	0.0261	0.0252	0.0286	0.0286	0.0271
Malta	0.0103	0.0088	0.0074	0.0072	0.0073	0.0089	0.0114	0.0114
Netherlands	0.0003	0.0003	0.0003	0.0000	0.0000	0.0001	0.0001	0.0001
Poland	0.0214	0.0236	0.0246	0.0246	0.0236	0.0265	0.0263	0.0263
Portugal	0.0103	0.0109	0.0115	0.0068	0.0074	0.0117	0.0111	0.0102

Table 3. *continued*

	2023	2022	2021	2020	2019	2018	2017	2016
Romania	0.0419	0.0394	0.0404	0.0416	0.0424	0.0427	0.0417	0.0412
Sweden	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Slovenia	0.0069	0.0075	0.0083	0.0087	0.0079	0.0066	0.0063	0.0050
Slovakia	0.0198	0.0214	0.0220	0.0199	0.0195	0.0224	0.0205	0.0201

Step 4: We uniquely find $w=(0.1195, 0.1348, 0.1315, 0.1204, 0.1138, 0.1229, 0.1289, 0.1281)^T$ using the CVX code given in (7). That is, CST objectively determines the criteria weights as follows. The 2023's weight is 0.1195, the 2022's weight is 0.1348, the 2021's weight is 0.1315, the 2020's weight is 0.1204, the 2019's weight is 0.1138, the 2018's weight is 0.1229, the 2017's weight is 0.1289, and the 2016's weight is 0.1281.

Step 5: We find the EU countries' utilities as in Table 4 using the quadratic utility function given in (3) and the criteria weight vector (w) given in Step 4. We also rank them in descending order. We find the first three ranks as Sweden, Denmark, and the Netherlands, respectively, whereas Romania is at the last rank.

Table 4. *The innovation performances of the EU countries for the 2016-2023 period*

	SAW		TOPSIS		CST	
	p_i	Rank	s_i	Rank	U_i	Rank
Austria	0.2402	7	0.8474	7	0.2393	7
Belgium	0.2485	5	0.8883	5	0.2480	5
Bulgaria	0.0886	26	0.1057	26	0.0553	26
South Cyprus	0.1790	13	0.5464	13	0.1701	13
Czechia	0.1670	18	0.4883	18	0.1561	18
Germany	0.2370	8	0.8328	8	0.2358	8
Denmark	0.2681	2	0.9800	2	0.2681	2
Estonia	0.1835	12	0.5662	12	0.1752	12
Greece	0.1417	20	0.3665	20	0.1248	20
Spain	0.1743	16	0.5239	16	0.1648	16
Finland	0.2562	4	0.9216	4	0.2560	4
France	0.2205	10	0.7494	10	0.2179	10
Croatia	0.1243	23	0.2810	23	0.1026	23
Hungary	0.1344	21	0.3284	21	0.1157	21
Ireland	0.2353	9	0.8191	9	0.2339	9
Italy	0.1762	14	0.5341	14	0.1671	14
Lithuania	0.1548	19	0.4286	19	0.1412	19
Luxembourg	0.2452	6	0.8648	6	0.2445	6
Latvia	0.1053	25	0.1858	25	0.0778	25
Malta	0.1759	15	0.5318	15	0.1668	15
Netherlands	0.2599	3	0.9390	3	0.2597	3
Poland	0.1140	24	0.2286	24	0.0892	24

Table 4. *continued*

	SAW		TOPSIS		CST	
	p_i	Rank	s_i	Rank	U_i	Rank
Portugal	0.1710	17	0.5069	17	0.1608	17
Romania	0.0675	27	0.0000	27	0.0261	27
Sweden	0.2698	1	0.9884	1	0.2698	1
Slovenia	0.1868	11	0.5860	11	0.1796	11
Slovakia	0.1270	22	0.2921	22	0.1062	22

Table 4 also presents the results obtained with SAW and TOPSIS when the criteria weight vector (w) is found with (5). We see that CST determines the same rank as SAW and TOPSIS. We also compare the annual progress of the EU countries using these methods. Criterion 1 equals SII 2023 minus SII 2022. Criterion 2, 3, 4, 5, 6, and 7 are determined similarly. Then, the criteria weights found with CST are 0.1699, 0.3058, 0.0849, 0.1009, 0.0761, 0.0930, and 0.1692, respectively. Furthermore, we find the annual progress rankings as in Table 5. South Cyprus is at the first rank based on the annual progress, whereas Luxembourg is at the last rank. The Spearman rank correlation between the CST and SAW results equals 0.9206, whereas the Spearman rank correlation between the CST and TOPSIS results equals 0.9640. CST incorporates SAW and TOPSIS using convex optimization and worst-case analysis. Thus, as in this study, the CST results may be similar to their results when the same criteria weights are used.

Table 5. *The annual progress rankings of the EU countries for the 2017-2023 period*

	SAW		TOPSIS		CST	
	p_i	Rank	s_i	Rank	U_i	Rank
Austria	0.1000	13	0.5872	9	-0.0407	12
Belgium	0.0859	17	0.5411	17	-0.0714	17
Bulgaria	0.0230	25	0.4882	23	-0.1869	24
South Cyprus	0.2426	1	0.6881	1	0.1609	1
Czechia	0.1815	3	0.6705	2	0.0892	3
Germany	0.0599	21	0.5145	19	-0.1054	19
Denmark	0.1371	5	0.6087	7	0.0267	5
Estonia	0.1293	8	0.5186	18	-0.1212	20
Greece	0.1877	2	0.6547	3	0.0926	2
Spain	0.1093	11	0.5840	10	-0.0175	8
Finland	0.1015	12	0.5697	14	-0.0582	14
France	0.0298	23	0.4927	22	-0.1583	22
Croatia	0.1182	9	0.5830	11	-0.0355	10
Hungary	0.0946	15	0.5799	12	-0.0384	11
Ireland	0.0841	18	0.5893	8	-0.0518	13
Italy	0.0988	14	0.5144	20	-0.0855	18
Lithuania	0.1595	4	0.6391	4	0.0505	4
Luxembourg	-0.0027	27	0.4537	27	-0.2162	27
Latvia	0.0274	24	0.4879	24	-0.1584	23

Table 5. continued

	SAW		TOPSIS		CST	
	p_i	**Rank**	**s_i**	**Rank**	**U_i**	**Rank**
Malta	0.0707	20	0.4787	26	-0.2162	25
Netherlands	0.1298	7	0.6132	6	0.0176	7
Poland	0.1337	6	0.6242	5	0.0249	6
Portugal	0.0911	16	0.5555	16	-0.0617	15
Romania	0.0414	22	0.4816	25	-0.1566	21
Sweden	0.1171	10	0.5773	13	-0.0260	9
Slovenia	0.0126	26	0.5005	21	-0.2162	26
Slovakia	0.0830	19	0.5600	15	-0.0681	16

Brodny et al. (2023) compare the EU countries' innovation performances for the 2013-2020 period by making a separate EDAS analysis for each year in this period. They find that Luxembourg, Sweden, Finland, Denmark, Germany, and the Netherlands have the highest performances, whereas Poland, Latvia, Romania, and Bulgaria have the lowest performances. We find similar results, except that Belgium and Austria have higher innovation performances than Germany in our results. The less similar results are also given in the literature. Based on the Global Innovation Index 2020 data, Aytekin et al. (2022) find that the Netherlands, Germany, and Sweden have the highest performances, whereas Lithuania and Greece have the lowest performances. Using the Global Innovation Index 2021 data and many other data, Satı (2024) finds that Austria, Denmark, and Germany have the highest performances, whereas Croatia has the lowest performance. Jurickova et al. (2019) compare the EU countries' innovation performances for the 2015-2016 period by making a separate DEA analysis for each year in this period. They find efficient countries such as Cyprus, Luxembourg, Malta, and Romania. Anderson and Stejskal (2019) compare the EU countries using the European Innovation Scoreboard data collated in 2018. They find that many countries (including Luxembourg, the Netherlands, Ireland, Bulgaria, Romania, etc.) are efficient decision-making units.

Table 4 and Table 5 give some important results about the EU countries' long-term innovation performances. We use a further analysis with the following procedure to integrate and discuss these results.

1. The average U_i value in Table 4 and the average U_i value in Table 5 are calculated. We show them with the x and y values, respectively.
2. If a country's U_i value in Table 4 is lower (higher) than the x value i.e. $-x+U_i$ is negative (positive), then we call that this country has innovation performance below (above) the average.
3. If a country's U_i value in Table 5 is lower (higher) than the y value i.e. $-y+U_i$ is negative (positive), then we call that this country has annual progress below (above) the average.
4. Countries are divided into four categories.
   - If a country is below (above) the average with respect to these two different analyses, then we call it as a problematic (star) country.
   - If a country is above the average with respect to innovation performance and below the average with respect to annual progress, then we call it as a question mark country.
   - If a country is below the average with respect to innovation performance and above the average with respect to annual progress, then we call it as a climbing country.

Based on the above procedure and information given in Table 4 and Table 5, we divide the EU countries into four categories as in Table 6.

Table 6 shows that the star countries are Austria, Denmark, Finland, Ireland, Netherlands, and Sweden. Austria (Ireland) has the seventh (ninth) rank based on innovation performance, whereas the other four countries are in the first four ranks. This information is compatible with the fact that continuous improvement is necessary to stay at the top. The problematic countries are Bulgaria, Italy, Latvia, Malta, Portugal, Romania, and

Slovakia. Since both their innovation performances and annual progress are below the average, these countries should take immediate and serious actions to increase their innovation performances. In addition, the EU should support these actions. These countries could determine the star countries as the guiding countries. Belgium, Germany, Estonia, France, Luxembourg, and Slovenia are the question mark countries. They should deeply analyze themselves and then take necessary actions. The climbing countries are South Cyprus, Czechia, Greece, Spain, Croatia, Hungary, Lithuania, and Poland. These countries could surpass some of the question marks countries in the future if they continue their progress.

Table 6. *Categorization of the EU countries based on further analysis*

	$-x+U_i$	$-y+U_i$	Category
Austria	0.0669	0.0196	Star
Belgium	0.0757	-0.0111	Question Mark
Bulgaria	-0.1170	-0.1266	Problematic
South Cyprus	-0.0022	0.2212	Climbing
Czechia	-0.0162	0.1494	Climbing
Germany	0.0635	-0.0451	Question Mark
Denmark	0.0958	0.0870	Star
Estonia	0.0029	-0.0609	Question Mark
Greece	-0.0475	0.1529	Climbing
Spain	-0.0075	0.0428	Climbing
Finland	0.0837	0.0021	Star
France	0.0455	-0.0980	Question Mark
Croatia	-0.0697	0.0247	Climbing
Hungary	-0.0567	0.0219	Climbing
Ireland	0.0616	0.0085	Star
Italy	-0.0052	-0.0252	Problematic
Lithuania	-0.0311	0.1108	Climbing
Luxembourg	0.0722	-0.1559	Question Mark
Latvia	-0.0946	-0.0981	Problematic
Malta	-0.0055	-0.1559	Problematic
Netherlands	0.0874	0.0779	Star
Poland	-0.0831	0.0852	Climbing
Portugal	-0.0115	-0.0014	Problematic
Romania	-0.1462	-0.0963	Problematic
Sweden	0.0975	0.0343	Star
Slovenia	0.0073	-0.1559	Question Mark
Slovakia	-0.0661	-0.0078	Problematic

4. CONCLUSION

This study proposes a hybrid MADM approach called CST. Since it combines SAW and TOPSIS using convex optimization and worst-case analysis, it has strong properties of these methods. CST also has two superiorities. It objectively determines the criteria weight vector and conveys more information than SAW or TOPSIS. Its main limitation is that the information is restricted to the total information derived with SAW and TOPSIS. In addition, it does not consider the distance to the negative ideal solution, unlike TOPSIS. Furthermore, it finds the approximate result since it uses Tikhonov's regularized problem instead of the original problem. Moreover, special software is needed for its implementation, unlike SAW and TOPSIS.

This study objectively compares the EU countries' innovation performances for the 2016-2023 period using CST. Sweden has the maximum innovation performance for this period, whereas Romania has the minimum innovation performance. This study also compares the annual progress of the EU countries in the 2017-2023 period. The annual progress is maximum for South Cyprus and minimum for Luxembourg in this period. Based on these separate analyses, we divide the EU countries into four categories. Denmark, Finland, Ireland, Netherlands, and Sweden are the star countries corresponding to the best category. Belgium, Germany, Estonia, France, Luxembourg, and Slovenia are the question mark countries corresponding to the second-best category. South Cyprus, Czechia, Greece, Spain, Croatia, Hungary, Lithuania, and Poland are the climbing countries corresponding to the second-worst category. Bulgaria, Italy, Latvia, Malta, Portugal, Romania, and Slovakia are the problematic countries corresponding to the worst category. The main limitation of this study is that we only compare the EU countries using the Summary Innovation Index (SII). Future research could increase the number of countries and used innovation indices. Furthermore, CST could be used for other MADM problems.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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