Novel Comprehensive MEREC Weighting-Based Score Aggregation Model for Measuring Innovation Performance: The Case of G7 Countries

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Abstract. Innovation can be the greatest hope of overcoming economic challenges. This paper aims to evaluate countries concerning their innovation performances. We introduce an innovation performance evaluation methodology by considering objective factors and applying seven reliable MCDM methods: MEREC, CODAS, MABAC, MARCOS, CoCoSo, WASPAS, and MAIRCA. MEREC calculates the relative weights of indicators considered, while the other techniques decide the ranking order of G7 countries. The Borda rule is then employed to gain an aggregated ranking order. "Business sophistication" is the most critical indicator, whereas the US has the best position regarding the overall ranking. Sensitivity control is as well conducted.

Key words: innovation, MCDM, innovation measurement, Borda rule, G7 countries, score aggregation model.

1. Introduction

Innovation is a strategy that can help countries keep their competitive advantage. Moreover, it is among the major components of a country's economic and sustainable development (Huang *et al.*, 2021). Dutta *et al.* (2020) claimed that it assists countries in overcoming their chronic problems. A huge body of literature such as Brenner and Broekel (2011), Ivanov and Avasilcǎi (2014), Smith (2005), Banu (2018), Walker *et al.* (2002), Kim *et al.* (2020), Cirera and Muzi (2020), Ligardo-Herrera *et al.* (2019), Blažek and Kadlec (2019), Furková (2022), and Yu *et al.* (2021), among others, emphasizes the importance of this issue. Further, the existing literature reviews demonstrate the growing interest of researchers in this subject (see Wolfe, 1994; Cooper, 1999; Becheikh *et al.*, 2006; Bloch and Bugge, 2013; Dziallas and Blind, 2019; Haefner *et al.*, 2021; Vrontis and Christofi, 2021).

Policymakers, scholars and authorities widely accept the significance of measuring innovation to highlight general trends, settle performance objectives and form policy scenarios (Garcia-Bernabeu *et al.*, 2020). So far, there has been an ongoing divergence of

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opinion on the measurement of innovation performance. For such a measurement, Garcia-Bernabeu *et al.* (2020) argued that there are three views in the current literature: using single indicators, composite innovation indices, and multiple indicators. In terms of policy-making, in deciding innovation performance, the last may offer a more inclusive approach (Capello and Lenzi, 2013; Navarro *et al.*, 2009).

According to Grupp and Schubert (2010), innovation indicators are statistical values that describe different parts of innovation and they fail to describe innovation as a whole if they are used alone. As pillars of innovation, therefore, this work considers institutions, human capital and research, infrastructure, market sophistication, business sophistication, knowledge and technology outputs, and creative outputs. It is well shown in the literature that these indicators affect the innovation level of countries (see Özkaya *et al.*, 2021; do Carmo Silva *et al.*, 2019; Garcia-Bernabeu *et al.*, 2020). Notwithstanding, up to now, an agreed method or methodology could not be developed to measure innovation (Grupp and Schubert, 2010). Consequently, this paper proposes an alternative framework capable of making such a measurement.

Since innovation is widely accepted as one of the critical aspects of sustainable economic growth, measuring innovation at the national level is significant (Grupp and Schubert, 2010). Measuring innovation can guide policymakers and decision-makers to specify the finest innovative countries and clarify the most important innovation indicators for innovation evaluations. Considering the reality that the concept of innovation covers varied affecting factors that could be conflicting, the MCDM terminology can ensure effective vehicles to assess the innovation level of countries. It is obvious that each MCDM technique, no matter how famous it is, has its weaknesses. Thus, unlike results might be obtained even for the same problem since each method has its own specific mathematical structures, normalization methods, and aggregation functions. To cope with this problem encountered frequently, a set of MCDM techniques with some ranking combination methods like the Borda rule may be applied for obtaining an overall ranking. This useful approach has earlier been handled in various studies like smart cities (Mokarrari and Torabi, 2021), battery electric vehicles (Ecer, 2021), innovation systems (Paredes-Frigolett *et al.*, 2021), cryptocurrencies (Ecer *et al.*, 2022), and research and technology organizations (Varmazyar *et al.*, 2016).

As of 2020, the G7 countries account for a little over 50 percent of global net wealth ($418 trillion), 32 to 46 percent of global GDP, and about 770 million people or 10 percent of the world's population (World Bank, 2020). In today's globalizing competitive environment, it is seen that new policies have been developed to increase the innovation performance of these major advanced economies. In this context, G7 countries should give more importance to infrastructure, R&D, and technology necessary for innovation activities. Innovation indexes can be described as a simple quantitative indicator of the innovation capacity of countries in selected fields of research. It measures, monitors, and promotes progress in innovation performance. Further, an innovation index provides significant insights into a country's potential to sustain productivity growth and competitiveness. The performance of countries measured with various criteria could provide guidelines for policymakers to allocate resources that lead to improvements. To the authors'

knowledge, no earlier work has collaboratively applied many reliable MCDM techniques to address a comprehensive innovation performance of G7 countries. In order to fill this remarkable gap in the relevant literature, the vital indicators of innovative countries are investigated and the proper assessment methods are reviewed in this study. The most vital motivation to choose G7 countries for this study relies on the importance of determining their innovation performance and availability of real-life data such as innovation indexes for computational purposes. Moreover, unlike in other papers, a comprehensive evaluation methodology is developed to measure the importance level of indicators determined and the innovation level of countries through a collection of MCDM techniques i.e. MEREC, CODAS, MABAC, MARCOS, CoCoSo, WASPAS, and MAIRCA. Last but not least, an overall ranking of countries employing their innovativeness is determined by the Borda rule, which is a reliable compromise strategy. The proposed framework takes advantage of various robust MCDM methods simultaneously. Thus, it is aimed to gain more accurate and reliable results for the decision-making process. The other advantages of the introduced approach are ease of understanding and problem-solving, and there is no requirement for specific software.

Finally, the answers to the following research questions are sought: How can the level of G7 countries be measured? Is it possible to use MEREC, CODAS, MABAC, MARCOS, CoCoSo, WASPAS, and MAIRCA together in the process of innovation measurement? The combined usage of these techniques seems to be promising because MEREC ensures a practical and trustworthy path to evaluate criteria weight values, whereas CODAS, MABAC, MARCOS, CoCoSo, WASPAS, and MAIRCA are convenient vehicles to employ such criteria weight values taking into consideration how the dissimilar criteria can be consolidated. As a result, below highlights the original contributions of this paper.

- To perform a comprehensive innovation measurement of countries through a set of MCDM techniques.
- To utilize a set of innovation indicators for the ranking aim, which fits the context of any country.
- To conduct a new objective MCDM method named MEREC to extract the weight values of indicators.
- To apply a real case study and measure the innovation levels of G7 countries.

Overall, this paper is organized as follows: Section 2 reviews the studies and MCDM usage in the innovation field. Section 3 provides the research methodology for this study. Section 4 serves the application as well as highlights the validity of the results. Section 5 discusses the outcomes gathered briefly and summarizes some political implications. Finally, the last section draws some brief conclusions.

2. Literature Survey

Once the history of the concept of innovation is examined, it is seen that Schumpeter first defined this concept as everything that brings profit to the entrepreneur and emerges as a result of technological developments (Schumpeter, 1965). Thompson, on the other

hand, defined innovation as "the development, acceptance, and implementation of new ideas, products, services and processes" (Thompson, 1965). Feeny and Rogers defined innovation as an implementation process that includes transformation of the new ideas to products and processes of businesses (Feeny and Rogers, 2003). In addition to these definitions, the innovation definition in the Oslo Manual published by OECD and Eurostat has begun to be taken as a basis in the international arena.

Innovation in the Oslo Manual has been categorized according to the four main patterns (OECD, 2005):

- Process innovation results in producing the same amount of goods and services while consuming fewer inputs.
- Product innovations are expected to improve existing products and services or even initiate new ones.
- Organizational innovation entails the creation of new management philosophies such as 5S and total quality management.
- Market innovation, on the other hand, is important for the promotion and pricing of products and services and other market-oriented strategies.

It is vital to measure the innovative performance of countries or businesses periodically to determine the effectiveness of their activities on innovation. To make these measurements, various models at macro and micro levels have been developed that measure the innovation performance of countries and businesses, taking different innovation indicators into account.

The first of these models is the European Innovation Scoreboard (EIS). EIS, which is created by European Union (EU), INSEAD, and the World Bank, measures the innovation performance of European countries and regions. The European innovation scoreboard analyses the innovation performances of 27 EU member countries and 11 non-EU countries comparatively. Innovation activities, investments, framework conditions, and impacts are determined in as four main indicators for measuring innovation performances (European Innovation Scoreboard, 2021).

The second of these models is the Regional Innovation Scoreboard (RIS), a widening version of the EIS. The RIS ensures a benchmarking of the performance of innovation systems across 240 regions of 22 EU countries (Regional Innovation Scoreboard, 2021). The third model is the Global Innovation Index (GII), which was put forward by INSEAD in France in 2007 to measure countries' innovation performance. The GII aims to ensure perceptive data on innovation, help countries in assessing their innovativeness performance and making scientific innovation policy considerations (Global Innovation Index, 2020). The analyses performed to rank the countries based on these indices help policymakers and governments worldwide, especially in industrialized countries, identify future development paths and design innovation policies.

2.1. *Innovation Studies*

Innovation is considerably acknowledged as a key factor of economic growth and a country's development. The recent dramatic increase in studies on innovation performance

indicates the importance of this issue. For instance, Hagedoorn and Cloodt (2003) statistically analysed 1200 international enterprises' innovation performance in four different high-tech sectors and compared these sectors. Among the performance indicators, R&D expenditures, number of patents, patent references, and new products were considered the main variables. In another study, applying a panel data approach, Jungmittag (2004) examined the impacts of innovations, technological specialization, and technology expansion on the economic growth and convergence of EU countries. Tokumasu and Watanabe (2008) analysed some members of EU countries based on their innovation capabilities using innovation capacity, innovation production, and institutional structure indicators. Zhuparova (2012) has suggested seven major variables for measuring the innovation, such as: quality of innovation strategy, level of innovation capacity, amount of investment, guidelines of innovative changes, the competitive situation of firms, speed of the development, and validity of the level of implementing an innovation strategy. Konings and Louw (2014) measured the innovation performances of the transportation sector in Europe with the Structural Equality Model. They analysed the data of 251 regions in Europe and determined that the regions' innovation performances in Germany and Sweden were better. Similarly, Roszko-Wójtowicz and Białek (2016) evaluated the innovation performance of EU member countries with cluster analysis, using the EIS data. Framework conditions, innovation activities, investments, and impacts are considered within the scope of the EIS. Recently, Paredes-Frigolett *et al.* (2021) suggested a multi-criteria framework to determine the strategy of innovation systems. They aimed to address shortcomings of mainstream empirical methodologies.

2.2. *MCDM in Innovation Field*

Measuring the innovation performance is a challenging MCDM problem, and the literature survey demonstrates that a scarce number of papers focused on the MCDM methods to the measurement of the innovation performance.

For instance, in their study, Lu *et al.* (2013) suggested strategies to improve the green innovation performance by considering a total of 15 criteria under 5 main dimensions using fuzzy DANP and fuzzy VIKOR methodologies. According to the findings of this study, the most important main criterion was entrepreneurial orientation, while the most important sub-criteria were described as innovation level, competitor analysis, and proactivity. The most important environmental strategy, on the other hand, has been identified as new product development performance. In another study, İnel and Türker (2016) examined the innovation performance of countries using the AHP&TOPSIS methodology. In the study, three basic criteria were examined: gross domestic product, R&D expenditures in the GDP, and the number of patents per capita. Eventually, the findings show that the most important criterion was the R&D expenditure in GDP. In their paper, do Carmo Silva *et al.* (2017) aimed to obtain the innovation ranking of Caribbean & Latin American countries using the TOPSIS method and the criteria in the GII. They proposed a methodology that supports the inclusion of global competitiveness models in decision-making. In another work, Kumar *et al.* (2019) evaluated companies using indicators of product, process, market, behaviuoral, and strategic innovation. They applied a heuristic fuzzy-based TOPSIS

procedure to rank firms' performance according to pre-defined criteria. Recently, Hájek *et al.* (2018) proposed a BSC and fuzzy integrated TOPSIS methodologies for evaluating the innovation performance of companies operating in Europe. Ayçin and Çakın (2019) evaluated the innovation performance of EU member countries with Entropy and MABAC methods, using the EIS data. According to the results, the most prominent criteria are intellectual assets, innovators, finance, and support variables. Switzerland, Sweden, and Denmark have the highest rankings in terms of innovation performance, respectively.

3. Research Methodology

GII is an important indicator that includes evaluating countries according to their capability and achievement in innovation and innovative issues (Dutta *et al.*, 2020). Whilst weighing of indicators, the MEREC method is suggested to avoid subjective evaluations in this work. Following the weight calculations, the countries are analysed with various MCDM techniques (CODAS, MABAC, MARCOS, MAIRCA, WASPAS, and CoCoSo) in terms of the innovation indicators. Finally, the Borda rule is handled to consolidate different ranking results of the MCDM techniques used. The subsections give information about the mentioned methods. Figure 1 exhibits the workflow of the introduced framework to measure the innovation level of countries.

3.1. *The MEREC Method*

MEREC focuses on the change in the total criteria weight by disabling that criterion when determining the weight of a criterion (Ecer and Pamucar, 2022). More clearly, the change in criteria weight gives the weight of a criterion (Kayapınar Kaya *et al.*, 2022). This feature distinguishes MEREC from other objective weighting methods (Shannon's entropy, CRITIC, CILOS, etc.). Some major advantages of MEREC over other objective weighting methods include ease of understanding, ease of computation, and a robust mathematical background (Ecer and Hashemkhani Zolfani, 2022). To date, as far as the authors' knowledge, there are solely a few research papers performed with MEREC. In this sense, this study also differs from other studies. MEREC has six steps which are highlighted as Appendix A.1 (Keshavarz-Ghorabaee *et al.*, 2021).

3.2. *CODAS (The Combinative Distance-Based Assessment)*

The CODAS technique was proposed by Keshavarz Ghorabaee *et al.* (2016) as a reliable approach to obtain the ranking of the alternatives in relation to the distances to the negative ideal solution. The distances of the alternatives to the negative ideal solution in the CODAS method are computed via two measures known as the Euclidean distance and the Taxicab distance. If two alternatives are incomparable (having equal or very close values) in terms of Euclidean distance, the Taxicab distance is used as a secondary measure. After the calculations, the alternative with a greater distance is determined as the most preferred choice (Keshavarz Ghorabaee *et al.*, 2016; Ecer *et al.*, 2021). CODAS has eight
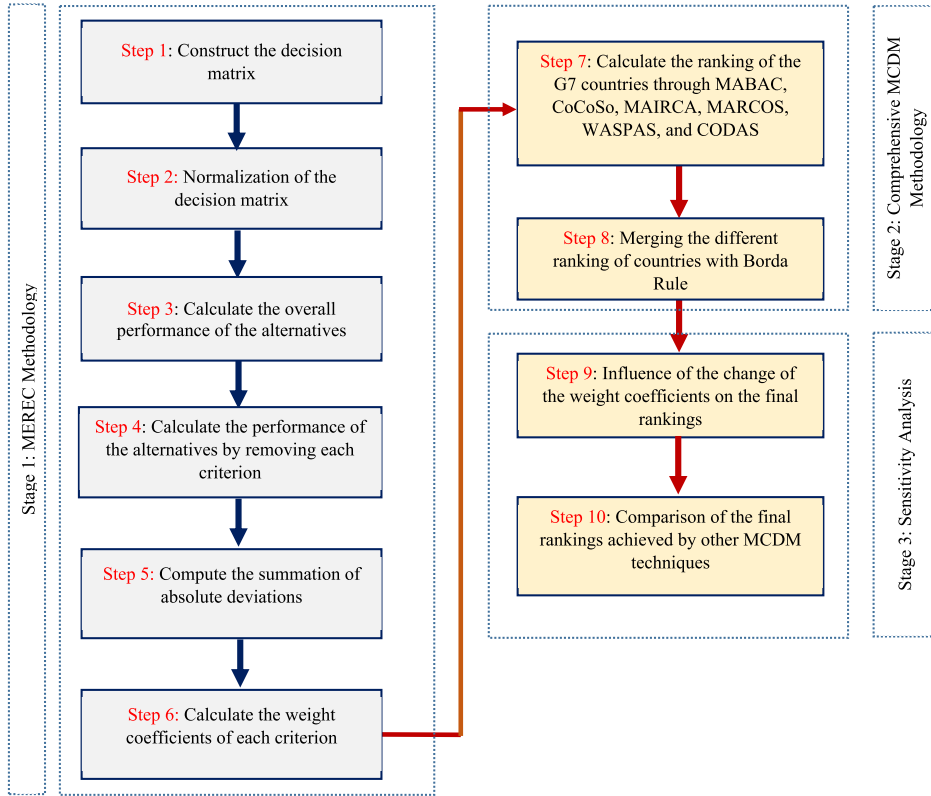
Fig. 1. The flowchart of the proposed framework.

steps which are highlighted as Appendix A.2 (Keshavarz Ghorabaee *et al.*, 2016; Mathew and Sahu, 2018; Badi *et al.*, 2018; Gül and Aydoğdu, 2021).

3.3. *MABAC (Multi-Attributive Border Approximation Area Comparison)*

The MABAC technique was introduced by Pamučar and Ćirović (2015) as an efficient ranking method based on the distance of the criterion function of each option from the border approximation area (BAA). The values of the criteria functions are determined for each option and the distances of these functions from the BAA are decided. The options are ranked according to the sum of the distances of options from the BAA. The alternative having the highest score is determined as the best choice. The superiorities of the MABAC method are not only the simple calculation and robustness in solution, but also potential values of benefits and losses, which are to be taken such a way into account that the outcome can be comprehensive (Dorfeshan and Mousavi, 2020). As mentioned in Appendix A.3, MABAC solves challenging problems through some steps (Pamučar and Ćirović, 2015; Gigović *et al.*, 2017; Wang *et al.*, 2019).

3.4. *MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution)*

The MARCOS technique was first presented by Stević *et al.* (2020) for determining the rankings of the alternatives which are based on defining the relationship between options and reference points. The utility functions of alternatives are determined based on the defined relations, whereas compromise ranking is calculated in terms of ideal and anti-ideal solutions. Further, utility functions display the ranking place of an option. The place of the best alternative is closest to the ideal, whilst farthest from the non-ideal point (Stević *et al.*, 2020). MARCOS is a flexible method that allows numerous attributes to be evaluated with a compromise solution. It is suitable for the solution of complicated real-life problems in spite of having an easy solution algorithm. In addition, MARCOS is a robust and confidential ranking method for the optimization of multiple objectives. These features can be sorted as its primary benefits compared with the other ranking methods (Pamucar *et al.*, 2021; Ecer and Pamucar, 2021). In Appendix A.4, detailed explanations of MARCOS's steps are depicted.

3.5. *MAIRCA (Multi Attributive Ideal-Real Comparative Analysis)*

The MAIRCA method introduced by Gigović *et al.* (2016) is an alternative ranking method based on the gap between ideal and real assessments. The total gaps for alternatives are obtained by summing the gap values for each criterion. At the end of the calculation process, the alternative with the lowest overall value gap is the most promising alternative (Gigović *et al.*, 2016; Pamučar *et al.*, 2017).

MAIRCA has a well-structured and simple decision tool for ranking alternatives and it is an available method for solving decision problems with plenty alternatives. It provides an objective ranking of alternatives depending on the predefined dominance threshold (Zolfani *et al.*, 2020; Ecer, 2022). Appendix A.5 presents the steps of MAIRCA (Pamučar *et al.*, 2017).

3.6. *CoCoSo (Combined Compromise Solution)*

The CoCoSo technique introduced by Yazdani *et al.* (2019) is an alternative ranking method based on the integration of simple additive weighting (SAW) and exponentially weighted product (EWP) models. CoCoSo has some advantages compared to the other multi attribute decision making methods. The optimal solution obtained by the CoCoSo method is not affected with ease by the changes of weight coefficient of the criterion or the deletion/addition of alternatives. It is a flexible method and decision makers can obtain a multi directional compromise solution whose results are consistent with the solutions obtained by other MCDM methods. These situation shows that the CoCoSo method is a robust method, which has advantages in reliability of the obtaining results (Peng *et al.*, 2019; Lai *et al.*, 2020; Torkayesh *et al.*, 2021). As explained in Appendix A.6, CoCoSo solves multi-criteria problems reliable and easily (Yazdani *et al.*, 2019; Ecer *et al.*, 2019; Kumar *et al.*, 2022).

3.7. *WASPAS (Weighted Aggregated Sum Product Assessment)*

Zavadskas *et al.* (2012) developed the WASPAS multi-criteria technique to rank alternatives. WASPAS is an effective MCDM method developed by combining weighted sum model (WSM) and weighted product model (WPM) approaches. Zavadskas *et al.* (2012) proved that the ranking accuracy obtained by the WASPAS method is much better than the results of the WPM or WSW approaches. The calculation steps of the method are short and easy. The method can focus on the benefit and cost-based criteria in the problem. The other primary superiority of the method can be stated that it allows the researcher to determine the parameter settings of WSM and WPM (Chakraborty *et al.*, 2015). Appendix A.8 depicts the steps of WASPAS (Zavadskas *et al.*, 2012; Chakraborty and Zavadskas, 2014).

3.8. *The Borda Rule*

The Borda rule was developed by De Borda (1781) to consolidate the ranking outcomes of different techniques. In a decision problem with n alternatives, each alternative is given $(n-1)$ points for the finest option, $(n-2)$ points for the second-best option, and so on. Further, the expected ranking is decided in descending order of Borda scores. In Appendix A.7, its procedure is demonstrated (Ecer, 2021).

4. Application and Sensitivity Analysis

This section of the study is dedicated to application and sensitivity checks. First, the application is explained in detail. Then, the effectiveness of the proposed method is tested. Seven main criteria based on GII reports are handled in this study as explained below (Global Innovation Index, 2020).

Institutions: Not only effective governance but also providing the necessary incentives and taking an institutional approach are crucial to innovation. This indicates the institutional framework of an economy.

Human Capital & Research: The level and quality of education and research services in an economy are among the main pillars of that country's innovation capability. This attempts to measure the human capital of economies.

Infrastructure: Efficient and environmentally friendly communication and transport and energy infrastructures facilitate the production and exchange of ideas, services and goods. It also feeds the innovation system via gained productivity and efficiency, optimal transaction costs, better reaching to markets, and sustainable development.

Market Sophistication: An environment that supports the availability of credit and investment, international market access, competition, and market scale, is crucial for the development of companies and the realization of innovation.

Business Sophistication: The fifth criterion, business sophistication, seeks to define the grade of business complexity to identify how well firms assist their innovative activities.

Table 1
Innovation indicators used for this paper.

Country	Indicator						
	Institutions	Human capital and research	Infrastructure	Market sophistication	Business sophistication	Knowledge and technology outputs	Creative outputs
Canada	90.2	51.8	53.3	78.5	50.5	39.1	40.2
France	83.7	56.2	57.7	59.4	50.2	45.1	46.7
Germany	84.6	61.1	58	56.1	53.7	51.7	49.1
Italy	74.6	43.7	56.6	50.5	36.7	42.3	35.9
Japan	89.3	47.3	60	64.3	57.1	46.4	37.2
The UK	86.1	58	60.3	74.4	51	54.4	52.7
The US	88.9	56.3	54.7	81.4	62.8	56.8	47.7

Source: Global Global Innovation Index (2020).

It will be possible for businesses to increase their productivity, competitiveness, and in-novation potential by employing highly qualified professionals and technicians.

Knowledge & Technology Outputs: It refers to the benefits of inventions and/or innovations to society, the environment, and social life.

Creative Outputs: The creativity's role in innovation is underestimated in innovation eval-uation and policy issues. Since the beginning of the GII, measuring creativity as a driver of the innovation outcomes has been taken into consideration.

Table 1 presents necessary data for countries according to the indicators considered. These data are used to calculate the criteria weights objectively and determine country performances with different MCDM methods considered in this work.

4.1. *Obtaining the Weight Values*

To extract the relative importance of criteria, as mentioned above, we tackle the MEREC method, which is an objective weighting method introduced very recently.

After obtaining the normalized decision matrix via Eq. (A.1), we find the overall per-formances of alternatives in Step 3 through Eq. (A.2). For example,

$$S_1 = \ln\left(1 + \left(\frac{1}{7}\left(\left|\ln(0.8271)\right| + \left|\ln(0.8436)\right| + \left|\ln(1)\right| + \cdots + \left|\ln(0.8930)\right|\right)\right)\right) = 0.1623.$$

Overall performances of the rest of the alternatives are 0.1736, 0.2086, 0.0196, 0.1665, 0.2491, and 0.2653, respectively. Using Eq. (A.3), we compute the overall performances of alternatives by removing each criterion. S'_{11} of the first alternative according to the first criterion:

$$S'_{11} = \ln\left(1 + \left(\frac{1}{7}\left(\left|\ln(0.8436)\right| + \left|\ln(1)\right| + \cdots + \left|\ln(0.8930)\right|\right)\right)\right) = 0.1390.$$

Table 2
The weight coefficients of innovation indicators.

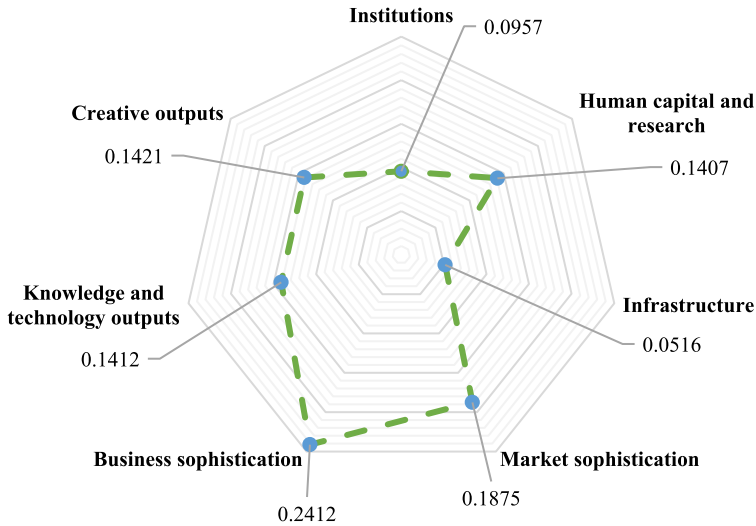|	Criteria						
	Institutions	Human capital and research	Infrastructure	Market sophistication	Business sophistication	Knowledge and technology outputs	Creative outputs
w	0.0957	0.1407	0.0516	0.1875	0.2412	0.1412	0.1421

Fig. 2. The radar chart of the indicators' weights.

All calculations are conducted in a similar way. Utilizing Eq. (A.4), we determine the removal effect of each criterion on the alternatives' overall performance.

$$E_1 = |0.1390 - 0.1623| + |0.1597 - 0.1736| + \cdots + |0.2459 - 0.2653| = 0.1094.$$

The removal effect of each criterion on the rest of the alternatives' overall performance is calculated as 0.1610, 0.0590, 0.2145, 0.2760, 0.1615, and 0.1625.

Applying Eq. (A.5), we find the weights of the criteria. For instance, the weight of the first criterion is:

$$w_1 = \frac{0.1094}{1.1439} = 0.0957.$$

As a result, the relative importance of criteria (indicators) is demonstrated in Table 2 and illustrated in Fig. 2.

Concerning the MEREC method's results, business sophistication is the most significant indicator for determining the innovative level of G7 countries, followed by market sophistication and creative outputs. These weights calculated are utilized in the calculations of the ranking methods in the next sub-section.

Table 3
Ranking outcomes of MCDM methods.

	MABAC		MAIRCA		MARCOS		CoCoSo		WASPAS		CODAS	
	S_i	Rank	Q_i	Rank	$f(K_i)$	Rank	K_i	Rank	Q_i	Rank	H_i	Rank
Canada	−0.0173	6	0.0721	6	0.6606	4	6.8112	6	0.8380	4	−0.0050	5
France	−0.0049	5	0.0704	5	0.6561	6	7.4074	4	0.8336	6	−0.0233	6
Germany	0.1277	3	0.0514	3	0.6885	3	8.4864	3	0.8733	3	−0.0002	3
Italy	−0.4624	7	0.1357	7	0.5400	7	2.0740	7	0.6843	7	−0.0586	7
Japan	−0.0021	4	0.0700	4	0.6583	5	7.3873	5	0.8356	5	−0.0043	4
The UK	0.2669	2	0.0316	2	0.7235	2	9.6263	2	0.9198	2	0.0166	2
The US	0.3574	1	0.0186	1	0.7614	1	10.3368	1	0.9689	1	0.0749	1

4.2. *Deciding the Ranking Order of Countries*

Undoubtedly, deciding the appropriate MCDM method is a key matter to solve challenging real-world problems. Because each method has its own characteristics, the results extracted may differ. Such an undesirable situation reduces confidence in the results. Accordingly, numerous researchers recommend merging the ranking results from various MCDM methods (Dortaj *et al.*, 2020; Varmazyar *et al.*, 2016).

4.2.1. *Obtaining Ranking Outcomes from Several MCDM Methods*
To derive the final alternative ranking, six powerful MCDM methods (MABAC, CoCoSo, MAIRCA, MARCOS, WASPAS, and CODAS) are first used in this section. By MS Excel, the methods are solved.

Thereby, the results of Table 3 are gathered. Clearly, the rankings obtained by the six methods are not the same, although the rankings for MABAC and MAIRCA, as well as MARCOS and WASPAS, are similar. Thus, these priority techniques produce dissimilar ranking results. Nevertheless, the results of all methods highlight that the top three innovative countries are the US, the UK, and Germany, respectively. Further, Italy is in the last place according to all methods. The ranking of the remaining countries varies as per the methods handled. Consequently, there is a need to achieve an agreeable ranking. Hence, the Borda rule is also applied in this sub-section.

4.2.2. *Achieving Overall Ranking for Alternatives*
Though robust and famous MCDM methods can be performed in a challenging problem, the ranking outcomes may not be the same. So, decision-makers are conflicted between unlike rankings when making the final decision. Fortunately, the Borda rule, as a useful and effective ranking strategy, offers aid in dealing with such situations. In other words, the Borda rule may be a beneficial vehicle to lead the decision problem to a single result by merging the different ranking results (Ecer, 2021). To make a more reliable decision, therefore, this work both determines the innovation levels of countries with the six MCDM methods and combines the ranking results obtained from these methods. Since each MCDM method has the potential to produce its own ranking result, the Borda rule offers a valuable response for innovation assessment. In a nutshell, it is performed to increase

Table 4
Results of the Borda rule.

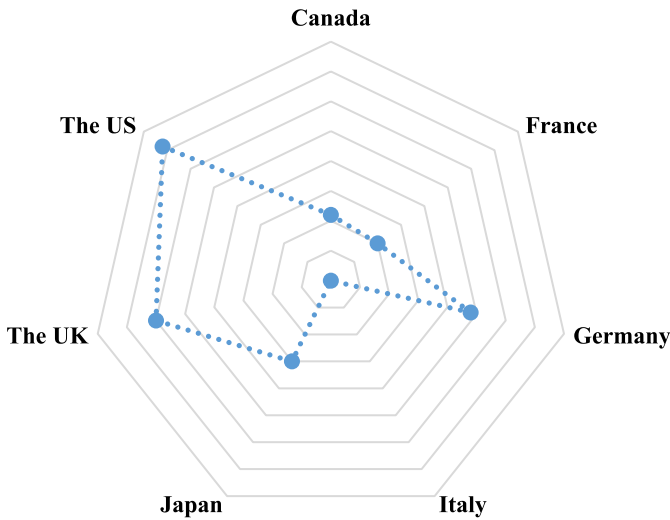|	Total	Final rank
Canada	11	5
France	10	6
Germany	24	3
Italy	0	7
Japan	15	4
The UK	30	2
The US	36	1

Fig. 3. Final ranking of G7 countries.

the reliability of both the evaluation process and the overall ranking. In this work, as a result, the rankings gathered by six methods of MABAC, CoCoSo, MAIRCA, MARCOS, WASPAS, and CODAS are merged with the Borda rule. Ultimately, the developed approach is prone to help authorities make reliable decisions in assessing the innovativeness of countries or cities.

Eventually, Table 4 presents the outcomes of the Borda rule. Taking both the ranking outcomes of Table 3 and the Borda rule into consideration, the overall ranking of countries may be obtained. As per the final results displayed in Fig. 3, G7 countries are ranked from the most innovative to the least innovative as the US, the UK, Germany, Japan, Canada, France, and Italy. The reason behind being the most innovative country of the US among the G7 countries could be that it is the country with the best position in three of seven indicators (business sophistication, market sophistication, and knowledge and technology outputs). More interestingly, these three indicators are the first, second, and fourth indicators of the most importance.

Table 5
Combination of weights for different scenarios.

Scenario	Weights	Ranking using the Borda rule
S_1	$w_1 = w_2 = \cdots = w_7 = 0.1428$	$A7 = A6 \succ A3 \succ A5 \succ A2 \succ A1 \succ A4$
S_2	$w_1 = 0.4$ The rest 0.1	$A7 \succ A6 \succ A5 \succ A3 \succ A1 \succ A2 \succ A4$
S_3	$w_2 = 0.4$ The rest 0.1	$A6 \succ A7 \succ A3 \succ A2 \succ A1 \succ A5 \succ A4$
S_4	$w_3 = 0.4$ The rest 0.1	$A6 \succ A3 \succ A7 \succ A5 \succ A2 \succ A1 \succ A4$
S_5	$w_4 = 0.4$ The rest 0.1	$A7 \succ A6 \succ A1 \succ A3 \succ A5 \succ A2 \succ A4$
S_6	$w_5 = 0.4$ The rest 0.1	$A7 \succ A6 \succ A3 \succ A5 \succ A2 \succ A1 \succ A4$
S_7	$w_6 = 0.4$ The rest 0.1	$A7 \succ A6 \succ A3 \succ A5 \succ A2 \succ A1 \succ A4$
S_8	$w_7 = 0.4$ The rest 0.1	$A6 \succ A7 \succ A3 \succ A2 \succ A1 = A5 \succ A4$

4.3. *Sensitivity Analysis*

A sensitivity analysis can ensure experts to validate the outcomes by some changes in the essential model and clarify the robustness of the proposed methodology (Böyükaslan and Ecer, 2021). For this purpose, a two-stage sensitivity analysis is realized in this paper: (i) the effect of changing criteria weights on the overall ranking, (ii) comparing ranking results obtained by a combination of well-known MCDM methods.

4.3.1. *Changing the Initial Criteria Weights*
This sub-section is performed to analyse the effect of the various criteria weight values on the rank of the alternatives. Consequently, several criteria weights are determined for eight different scenarios. Each scenario are highlighted by S_i ($i = 1, \ldots, 8$), respectively. Criteria weights assigned for each scenario are presented in Table 5. The first scenario (S_1) considers the equalized criteria weight values $w_1 = w_2 = \cdots = w_7 = 0.1428$. The remaining seven scenarios ($S_2, S_3, \ldots, S_8$) favour one of the criteria, $C_1, C_2, \ldots, C_7$, respectively. The favoured criterion has a weight $w = 0.4$, whereas the remaining have a value of 0.1. All scenarios are first evaluated with the six MCDM methods. Afterward, their results are merged with the Borda rule to achieve a final ranking. The discovered final rankings for each scenario are depicted in Table 5 and Fig. 4.

Results indicate that determining various weights to the evaluation criteria reveals dissimilar rankings, i.e. the proposed framework is sensitive to these weight values. When all the rankings in Table 5 are examined, the following can be decided: the alternative $A7$ maintained first in five out of eight scenarios. Further, in scenarios S_3 and S_8, the alternative $A7$ is in second place, while scenario S_4 is in third place. Nonetheless, the $A5$ ranks last in all scenarios. Further, minor differences are noticeable in the rankings of other alternatives. As a result, the alternative $A7$ dominates the others. Consequently, the ranking shown in Table 5 is approved.

4.3.2. *Comparison with Outcomes Achieved by Other MCDM Techniques*
The other stage of sensitivity control is the comparison of the ranking obtained with the proposed methodology with the ranking provided from robust MCDM techniques including COPRAS, TOPSIS, ARAS, EDAS, and MOORA. The results of these techniques are shown in Table 6. Although the rankings obtained by the five techniques are not the same
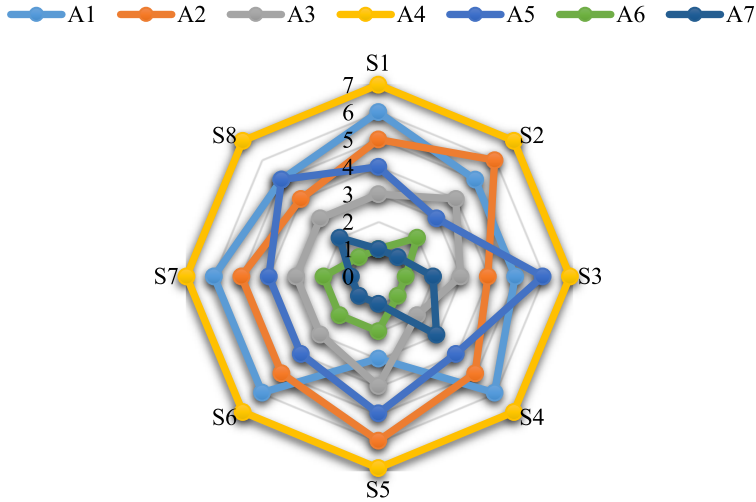
Fig. 4. Ranking of the alternatives for each scenario.

Table 6
Ranking outcomes of the other MCDM methods.

	COPRAS		TOPSIS		ARAS		EDAS		MOORA	
	P_i	Rank	C_i^*	Rank	K_i	Rank	ASi	Rank	Q_i	Rank
Canada	86.55	4	0.1058	5	0.8397	4	0.5340	5	0.3699	4
France	85.80	6	0.7642	4	0.8327	6	0.4197	6	0.3668	6
Germany	90.03	3	0.9308	2	0.8738	3	0.5679	3	0.3849	3
Italy	70.44	7	0.0000	7	0.6839	7	0.000	7	0.3012	7
Japan	86.17	5	0.0070	6	0.8362	5	0.5431	4	0.3683	5
The UK	94.79	2	1.0000	1	0.9197	2	0.7072	2	0.4052	2
The US	100.00	1	0.8478	3	0.9699	1	0.9933	1	0.4273	1

as the rankings of the introduced framework, the top three innovative countries are the US, the UK, and Germany, non-sequentially. Similarly, Italy is in the last place according to all the methods.

To aggregate the ranking results of these methods used in sensitivity analysis, the Borda rule is also applied once again. Finally, Table 7 presents the outcomes of the Borda rule in terms of the methods used in sensitivity analysis.

As per the final results of Borda rule, G7 countries are ranked from the most innovative to the least innovative as the US, the UK, Germany, Canada, Japan, France, and Italy. Finally, Spearman's correlation coefficient (SCC) is handled to decide the statistical correlation between the ranks provided by the results of the Borda rule, as shown in Table 8. The findings of the benchmarking of the Borda ranks by considering SCC show that there is a high and significant correlation between the Borda rule rankings. Finally, it is possible to conclude that the provided ranking is approved and dependable.

Table 7

Final rankings as per the sensitivity analysis.

	Total	Final rank
Canada	13	4
France	7	6
Germany	21	3
Italy	0	7
Japan	10	5
The UK	26	2
The US	28	1

Table 8

Results of the SCC.

		Borda rule (sensitivity analysis)
Borda rule (proposed model)	Spearman's correlation coefficient	0.927**
	n	7

** $p < 0.001$.

5. Discussion, Political Implications, and Recommendations

Now that innovation evaluations are a concept that includes many activities and can be examined from several perspectives, it has a highly complex nature. In the information age we live in, it is not difficult to access such data. Nonetheless, this vast amount of information can merely be meaningful provided that it is brought together in a scientific framework like MCDM. Suggesting paths to apply MCDM terminology to countries' innovation processes could be of considerable interest to policymakers, practitioners, and researchers. On the one hand, for economic development this has the potential to form better paths for countries to answer to their progressively competitive environment around the world. Thereby, assisting the innovation process with MCDM could produce valuable information for countries by increasing the reliability and validity of evaluation innovation activities. The viable potential of MCDM in the innovation field is further supported by the decision-making area where significant and rapid shifts are taking place. This notwithstanding, the number of innovation studies performed through MCDM is still quite low. Based on the above discussion, this work aims to fill the gap by offering a consolidated MCDM methodology to measure the innovation level of G7 countries.

Crises like the COVID-19 outbreak are frequently a source of innovation and sometimes industrial regeneration. For example, the French government has committed to a 25% increase in its R&D budget. German authorities have announced a massive 50 billion Euro stimulus package for promising technologies. Likewise, the US government plans to spend huge additional amounts of stimulus money to boost innovation (Dutta *et al.*, 2020). For years, as in this paper's findings, the US and Germany have had potent and stable innovation systems. The US is particularly prominent in terms of "market sophistication" and "business sophistication" pillars. Such strengths pave the way for it to take

the first place. Despite being positioned first in the ranking list, this country is not at the desired level regarding "infrastructure." Improvements to be made in the field of environmental sustainability can contribute to the strengthening of this aspect. "Human capital & research" is the most influential component in Germany's innovation performance. The undeniable support of enterprise resources to education in Germany plays a significant role in strengthening this aspect. It can be recommended that Germany, which is fragile in terms of "market sophistication," should increase technological investments and facilitate access to credit. In recent years, the UK has been developing the "infrastructure," "market sophistication," and "creative outputs" aspects. In this way, it has achieved to become the second most innovative country in the overall ranking. Nonetheless, "institutions" draw attention as the weak point of the country. This pillar can be strengthened if the business, regulatory, and political environment improves. As it is well-known, universities play a vital role in innovation systems. Canada's world-renowned universities are one of the key factors that boost the innovation level of this country. It would not be wrong to make a similar conclusion for the UK. Like the US, Canada is as well unsuccessful in terms of "infrastructure." In addition to environmental sustainability, arrangements in information and communication technologies can strengthen this aspect. Although it is successful in terms of R&D, Japan is not successful in terms of "human capital & research" compared to other innovative countries. Further, Japan could be a more innovative country if it also improves its "creative outputs" aspect. France gives incentives for companies to close the innovation finance gap. Moreover, it provided significant increases in its R&D budget. Yet, France's "business sophistication" aspect is the weakest among other innovation aspects. To overcome this, various strategies such as increasing university/industry collaborations, boosting knowledge-intensive employment, etc., can be suggested. Italy, which is relatively better in terms of "knowledge & technology outputs," is especially weak in "market sophistication." In this context, both the ease of obtaining loans and the protection of minority investors can be ensured.

6. Conclusion

In this paper, a collection of quantitative indicators from GII is handled to provide rankings of innovation levels for G7 countries. The proposed model is performed on a real case study and the innovation capability of these countries is assessed. In other words, this paper evaluates and ranks the countries from an innovation perspective via a novel MCDM-based assessment methodology. The introduced methodology covers seven innovation indicators. Further, the importance weights of these factors are gained by the MEREC method. Since different MCDM methods may produce varying results due to their characteristics, we examined the applicability of six MCDM techniques (CODAS, MABAC, MARCOS, CoCoSo, WASPAS, and MAIRCA), including various categories of MCDM techniques. Accordingly, the ranking values obtained from these techniques are then aggregated by the Borda rule to make a credible final ranking. To verify this methodology, G7 countries are evaluated utilizing available data gathered from GII. Afterward, a sensitivity check is achieved to prove the stability and reliability of this proposed

framework. Findings demonstrated that business sophistication is vital in determining the innovation level of countries. Further, the US is the most innovative country among G7 countries, as changing the MCDM methods considered does not affect the position of this country in the ranking. By the way, Italy showed a bad performance as per all techniques and the Borda rule.

The introduced methodology is an effort to ensure a reliable decision support system to evaluate the innovation capability of countries. The outcomes of such evaluation can give policymakers and authorities an idea of how to improve innovation level considering their weaknesses. To put it differently, innovation capacities can be increased by focusing on the weaknesses of the country.

Naturally, this work has some limitations. The number of evaluation criteria may be insufficient to determine the actual ranking of countries. Analyses can be made with the addition of new criteria in the future. In addition, this study used only the MEREC method in determining the criterion weights. Therefore, other objective methods can support the analysis to reach more reliable results. Lastly, the fact that only G7 countries are considered as case studies in this study can be seen as a limitation. Future studies may focus on different country associations such as OPEC, European Union, and MENA.

Availability of data and material Not applicable.

Code availability Not applicable.

Declarations conflict of interest The authors declare no conflicts of interest.

A. The preliminaries

A.1. *MEREC*

Step 1: Developing the decision matrix (X) with n alternatives and m criteria.

Step 2: Developing the normalized decision matrix by using Eq. (A.1):

$$n_{ij} = \begin{cases} \frac{\min_k x_{kj}}{x_{ij}}, & j \text{ is a benefit criterion,} \\ \frac{x_{ij}}{\max_k x_{kj}}, & j \text{ is a cost criterion.} \end{cases} \tag{A.1}$$

Step 3: Computing the overall performance of the alternatives by using Eq. (A.2):

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum_j \left|\ln(n_{ij})\right|\right)\right). \tag{A.2}$$

Step 4: Computing the performance of the alternatives by removing each criterion. By removing each criterion from the whole criteria set and by using Eq. (A.3), m sets of

performances are gained with respect to m criteria.

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m} \sum_{k, k \neq j} |\ln(n_{ij})|\right)\right). \tag{A.3}$$

Step 5: Calculating the summation of absolute deviations. Whereas E_j represents the effect of removing the jth criterion, the values of it can be calculated by using Eq. (A.4):

$$E_j = \sum_i |S'_{ij} - S_i|. \tag{A.4}$$

Step 6: Determining the weight values of the criteria by using Eq. (A.5):

$$w_j = \frac{E_j}{\sum_k E_k}. \tag{A.5}$$

A.2. *CODAS*

Step 1: Constructing the decision matrix (X) with m alternatives and n criteria as shown in Eq. (A.6):

$$X = [x_{ij}]_{n \times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \tag{A.6}$$

Step 2: Calculating the normalized decision matrix by using Eqs. (A.7)–(A.8) for benefit and cost type criteria, respectively.

$$n_{ij} = \frac{x_{ij}}{\max_i x_{ij}}, \quad \text{if } j \in B, \tag{A.7}$$

$$n_{ij} = \frac{\min_i x_{ij}}{x_{ij}}, \quad \text{if } j \in C. \tag{A.8}$$

Step 3: Calculating the weighted decision matrix by using Eq. (A.9):

$$r_{ij} = n_{ij} \cdot w_{ij}, \tag{A.9}$$

w_{ij} is the weight coefficient of the jth criterion.

Step 4: Determining the negative-ideal solution (NIS) point by using Eq. (A.10):

$$ns = [ns_j]_{1 \times m}, \quad ns_j = \min_i r_{ij}. \tag{A.10}$$

Step 5: Determining the distances of alternatives from the NIS.

The Euclidean and Taxicab distances of alternatives from the NIS are calculated by using Eqs. (A.11)–(A.12), respectively.

$$E_i = \sqrt{\sum_{j=1}^{m} (r_{ij} - ns_j)^2}, \tag{A.11}$$

$$T_i = \sum_{j=1}^{m} |r_{ij} - ns_j|. \tag{A.12}$$

Step 6: Determining the relative assessment matrix by using Eqs. (A.13)–(A.14):

$$R_a = [h_{ik}]_{n \times m}, \tag{A.13}$$

$$h_{ik} = (E_i - E_k) + \big(\psi(E_i - E_k) \times (T_i - T_k) \big), \tag{A.14}$$

where $k \in \{1, 2, \ldots, n\}$ and ψ denotes a threshold function to identify the equality of the Euclidean distances of two alternatives. This function is defined by using Eq. (A.15).

$$\psi(x) = \begin{cases} 1, & |x| \geqslant \tau, \\ 0, & |x| < \tau, \end{cases} \tag{A.15}$$

τ is the threshold parameter (a value between 0.01 and 0.05) which can be determined by the decision-maker.

Step 7: Calculating the assessment scores by using Eq. (A.16):

$$H_i = \sum_{k=1}^{n} h_{ik}. \tag{A.16}$$

Step 8. Ranking of the alternatives based on the value of the assessment scores (H_i). The alternative with the highest H_i value is determined as the best alternative.

A.3. *MABAC*

Step 1: Constructing the decision matrix (X) with m alternatives and n criteria as shown in Eq. (A.17):

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \\ \left[\begin{array}{cccc} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{array} \right] \end{array}. \tag{A.17}$$

Step 2: Calculating the normalized decision matrix by using Eqs. (A.18)–(A.19) for benefit and cost type criteria, respectively.

$$n_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-},$$
(A.18)

$$n_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+},$$
(A.19)

where $x_i^+ = \max(x_1, x_2, \ldots, x_m)$ is the maximum value; $x_i^- = \min(x_1, x_2, \ldots, x_m)$ is the minimum value of the observed criterion;

Step 3: Calculating the weighted decision matrix by using Eq. (A.20):

$$v_{ij} = w_i \cdot (n_{ij} + 1),$$
(A.20)

where w_i is the weight coefficients of the criteria.

Step 4: Calculating the elements of the border approximation area matrix (G) by using Eq. (A.21):

$$g_i = \left(\prod_{j=1}^{m} v_{ij} \right)^{\frac{1}{m}}.$$
(A.21)

After the calculations, matrix G is calculated as shown in Eq. (A.22):

$$G = \begin{matrix} C_1 & C_2 & \ldots & C_n \\ [\, g_1 & g_2 & \ldots & g_n \,] \end{matrix}.$$
(A.22)

Step 5: Calculating the distances from the BAA (Eq. (A.23)) by using Eq. (A.24):

$$Q = \begin{bmatrix} q_{11} & q_{12} & \ldots & q_{1n} \\ q_{21} & q_{22} & \ldots & q_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ q_{m1} & q_{m2} & \ldots & q_{mn} \end{bmatrix},$$
(A.23)

$$Q = V - G = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & \ldots & v_{1n} - g_n \\ v_{21} - g_1 & v_{22} - g_2 & \ldots & v_{2n} - g_n \\ \ldots & \ldots & \ldots & \ldots \\ v_{m1} - g_1 & v_{m2} - g_2 & \ldots & v_{mn} - g_n \end{bmatrix}.$$
(A.24)

Step 6: Determining the situation of alternatives to the BAA by using Eq. (A.25):

$$A_i \in \begin{cases} G^+, & \text{if } q_{ij} > 0, \\ G, & \text{if } q_{ij} = 0, \\ G^-, & \text{if } q_{ij} < 0. \end{cases}$$
(A.25)

As shown in Eq. (A.25), an alternative A_i can be located in the border approximation area (G), upper approximation area (G^+) or lower approximation area (G^-). In order for an alternative A_i to be the best alternative, most of the q_{ij} values should be in the upper approximation area. $q_{ij} > 0$ shows the closeness of the alternative A_i to the ideal alternative; whereas $q_{ij} < 0$ shows the closeness of the alternative A_i to the anti-ideal alternative.

Step 7: The final values of the criteria functions (S_i) for the alternatives are calculated by using Eq. (A.26):

$$S_i = \sum_{j=1}^{n} q_{ij}, \quad j = 1, 2, \ldots, n, \ i = 1, 2, \ldots, m. \tag{A.26}$$

The alternative with the highest S_i value is determined as the best alternative.

A.4. *MARCOS*

Step 1: Constructing the decision matrix (X) with m alternatives and n criteria.

Step 2: Creating the extended initial decision matrix by defining ideal (AI) and anti-ideal (AAI) solutions as shown in Eq. (A.27):

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ A_{AAI} \\ A_{AI} \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \left[\begin{array}{cccc} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \\ x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{array} \right]. \end{array} \tag{A.27}$$

AI and AAI solutions are calculated by using Eqs. (A.28)–(A.29) in terms of the nature of the criteria (B: benefit-based criteria, C: cost-based criteria).

$$AI = \max x_{ij}, \quad \text{if } j \in B \quad \text{and} \quad \min x_{ij}, \quad \text{if } j \in C, \tag{A.28}$$

$$AAI = \min x_{ij}, \quad \text{if } j \in B \quad \text{and} \quad \max x_{ij}, \quad \text{if } j \in C. \tag{A.29}$$

Step 3: Calculating the normalized extended initial decision matrix by using Eqs. (A.30)–(A.31):

$$n_{ij} = \frac{x_{ij}}{x_{ai}}, \quad \text{if } j \in B, \tag{A.30}$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}}, \quad \text{if } j \in C. \tag{A.31}$$

Step 4: Calculating the weighted decision matrix (V) by using Eq. (A.32):

$$v_{ij} = n_{ij} \times w_j. \tag{A.32}$$

Step 5: Calculating the utility degrees of alternatives (K_i) by using Eqs. (A.33)–(A.34):

$$K_i^+ = \frac{S_i}{S_{ai}}, \tag{A.33}$$

$$K_i^- = \frac{S_i}{S_{aai}}. \tag{A.34}$$

The sum of the elements of the V represents S_i value as shown in Eq. (A.35)

$$S_i = \sum_{i=1}^{n} v_{ij}. \tag{A.35}$$

Step 6: Calculating the utility function of alternatives $f(K_i)$ by using Eq. (A.36):

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}}. \tag{A.36}$$

Utility functions in relation to the ideal and anti-ideal solution are calculated by using Eqs. (A.37)–(A.38), respectively.

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-}, \tag{A.37}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}. \tag{A.38}$$

Step 7: Ranking the alternatives based on the final values of the utility function. The best alternative has the highest rank in terms of the value of the utility function.

A.5. *MAIRCA*

Step 1: Constructing the decision matrix (X) with m alternatives and n criteria as shown in Eq. (A.39):

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \\ \left[\begin{array}{cccc} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{array} \right] \end{array}. \tag{A.39}$$

Step 2: Preference determination of the choice of alternatives. During this process, the main assumption is that decision makers have no priority in the alternative selection process, as shown in Eqs. (A.40)–(A.41):

$$P_{Ai} = \frac{1}{m}; \quad \sum_{i=1}^{m} P_{Ai} = 1, \quad i = 1, 2, \ldots, m, \tag{A.40}$$

$$P_{A1} = P_{A2} = \cdots = P_{Am}. \tag{A.41}$$

Step 3: Determining the theoretical evaluation matrix (T_p) by using Eq. (A.42):

$$T_p = \begin{bmatrix} P_{A1} \cdot w_1 & P_{A1} \cdot w_2 & \cdots & P_{A1} \cdot w_n \\ P_{A2} \cdot w_1 & P_{A2} \cdot w_2 & \cdots & P_{A2} \cdot w_n \\ \vdots & \vdots & \ddots & \vdots \\ P_{Am} \cdot w_1 & P_{Am} \cdot w_2 & \cdots & P_{Am} \cdot w_n \end{bmatrix}. \tag{A.42}$$

Step 4: The elements of the real evaluation matrix (T_r) are calculated by using Eqs. (A.43)–(A.44) in terms of the nature of the criteria.

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_{ij}^-}{x_{ij}^+ - x_{ij}^-} \right), \tag{A.43}$$

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_{ij}^+}{x_{ij}^- - x_{ij}^+} \right). \tag{A.44}$$

After the calculations, the real evaluation matrix is obtained as shown in Eq. (A.45):

$$T_r = \begin{bmatrix} t_{r11} & t_{r12} & \cdots & t_{r1n} \\ t_{r21} & t_{r22} & \cdots & t_{r2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{rm1} & t_{rm2} & \cdots & t_{rmn} \end{bmatrix}. \tag{A.45}$$

Step 5: The elements of the total gap matrix (G) are calculated by using Eq. (A.46) and the total gap matrix is formed as shown in Eq. (A.47):

$$g_{ij} = t_{pij} - t_{rij}, \quad g_{ij} \in [0, \infty), \tag{A.46}$$

$$G = T_p - T_r = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix}. \tag{A.47}$$

Step 6: The final values of the criteria functions (Q_i) for the alternatives are calculated by using Eq. (A.48):

$$Q_i = \sum_{j=1}^{n} g_{ij}, \quad i = 1, 2, \ldots, m. \tag{A.48}$$

The alternative with the lowest Q_i value is determined as the best alternative.

A.6. *CoCoSo*

Step 1: Constructing the decision matrix (X) with m alternatives and n criteria as shown in Eq. (A.49):

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \tag{A.49}$$

Step 2: Calculating the normalized initial decision matrix by using Eqs. (A.50)–(A.51) for benefit and cost type criteria, respectively.

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \tag{A.50}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}. \tag{A.51}$$

Step 3: Calculating the S_i and P_i values for each alternative as shown in Eqs. (A.52)–(A.53), respectively

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}), \tag{A.52}$$

$$P_i = \sum_{i=1}^{n} r_{ij}^{(w_j)}. \tag{A.53}$$

Step 4: Calculating the relative weights of the alternatives using the following aggregation strategies as shown in Eqs. (A.54)–(A.56):

$$\xi_{ia} = \frac{S_i + P_i}{\sum_{i=1}^{m} (S_i + P_i)}, \tag{A.54}$$

$$\xi_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}, \tag{A.55}$$

$$\xi_{ic} = \frac{\lambda(S_i) + (1 - \lambda)(P_i)}{(\lambda \max_i S_i + (1 - \lambda) \max_i P_i)}. \tag{A.56}$$

In Eq. (A.56), λ (usually $\lambda = 0.5$) is chosen by the decision makers which shows that the flexibility and stability of the CoCoSo method can depend on other values.

Step 5: Ranking the alternatives based on the final values of the alternatives by using Eq. (A.57):

$$\xi_i = (\xi_{ia} \cdot \xi_{ib} \cdot \xi_{ic})^{\frac{1}{3}} + \frac{1}{3}(\xi_{ia} + \xi_{ib} + \xi_{ic}). \tag{A.57}$$

The alternative with the highest ξ_i value is determined as the best alternative.

A.7. *Borda Rule*

Step 1: Grade the alternatives.

First, the ranking strategy gives $(n - 1)$ points to the expert's most liked alternative and 0 points to the least liked. This process is repeated for each MCDM technique.

Step 2: Get the Borda score.

By summing up the scores obtained in Step 1, the Borda scores of alternatives are computed.

Step 3: Rank the alternatives.

To highlight the best alternative, the alternatives are ranked in descending order of their scores.

A.8. *WASPAS*

Step 1: Forming the decision matrix (X) with m alternatives and n criteria as demonstrated in Eq. (A.58):

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}. \tag{A.58}$$

Step 2: Constructing the normalized initial decision matrix by using Eqs. (A.59)–(A.60) for benefit and cost type criteria, respectively.

$$x_{ij}^* = \frac{x_{ij}}{\max_i x_{ij}}, \tag{A.59}$$

$$x_{ij}^* = \frac{\min_i x_{ij}}{x_{ij}}. \tag{A.60}$$

Step 3: Determining the relative importance of any alternative, based on WSM, by using Eq. (A.61):

$$Q_i^{(1)} = \sum_{j=1}^{n} x_{ij}^* w_j. \tag{A.61}$$

Step 4: Determining the relative importance of any alternative, based on WPM, by using Eq. (A.62):

$$Q_i^{(2)} = \prod_{j=1}^{n} (x_{ij}^*)^{w_j}. \tag{A.62}$$

Step 5: Calculating total relative importance of any alternative by using Eq. (A.63):

$$Q_i = 0.5 Q_i^{(1)} + 0.5 Q_i^{(2)}. \tag{A.63}$$

Also, a more generalized form of Eq. (A.63) is presented by using Eq. (A.64):

$$Q_i = \alpha Q_i^{(1)} + (1 - \alpha) Q_i^{(2)}. \tag{A.64}$$

The alternative with the highest Q_i value is identified as the best alternative.

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