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Research article

Multi-criteria decision making in evaluation of open government data indicators: An application in G20 countries

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Abstract: Open data has a large means of identifying commonly reachable information on different platforms. One of the open data sources is open government data. The goals of open governments are about building transparency, accountability and participation to strengthen governance and inform citizens. The aim of this study is twofold: (i) to propose a reliable decision-making tool for dealing with real-life problems and (ii) to demonstrate the practicality of the proposed model through a case study of its ranking with an open government data indicator for G20 countries. This study proposes a multi-criteria methodology that evaluates open data management systems used in e-government development. First, a set of evaluation criteria is established that cover the indicators used in the Global Open Data Index. Second, weights from the Logarithm Methodology of Additive Weights (LMAW) and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) methods were combined with the Bayesian approach to determine the weights of these criteria. Finally, the Weighted Aggregated Sum Product Assessment (WASPAS) method was used to obtain the ranking results. The novelties of the study lie in the combination of objective and subjective weighting methods, both in determining the ranking of G20 countries with open government data indicators and in deciding the importance levels of the criteria used. The "air quality" and "procurement" criteria are the top two criteria, with weights of 0,1378 and 0,1254 respectively. The findings also show that Australia is the best performer, while the United Kingdom is the second best performing. Comprehensive sensitivity analysis verifies the validity, robustness and effectiveness of the proposed framework. According to research findings and analysis, the methodology applied has the potential to assist policymakers and decision-makers in the process of modernization of existing public services in terms of open data and the opportunities it presents.

Keywords: open government data; LMAW; LOPCOW; Bayes approach; WASPAS
Mathematics Subject Classification: 62C86, 91B06, 90B50

1. Introduction

One of the most important actors of the digitalization era is the power of "open data". The fact that the data is open means that there are no restrictions that prevent it from being used in any way [1]. Open data for governments is the data (information) of the information (data) owned by public institutions and organizations, municipalities, universities and the private sector published under the appropriate license conditions and quickly accessed by users who need this information [2,3]. The open data movement is gaining momentum with efforts by governments to improve transparency, accountability and public participation. Open data and open government data are interrelated. The Venn diagram in Figure 1 shows the relationship between the terms government, data and open [4].

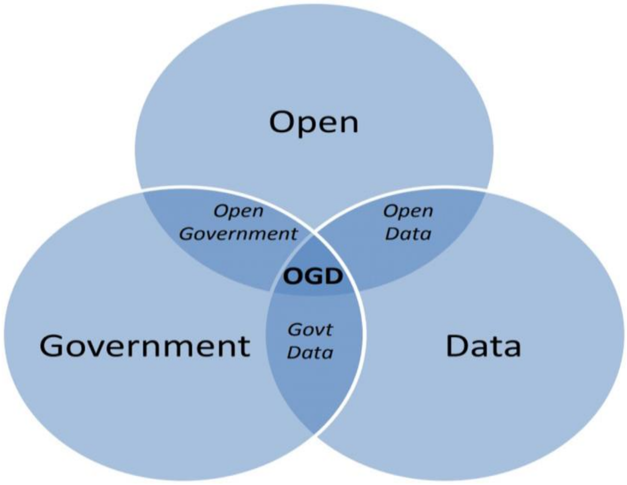

Figure 1. Open government data components.

Government data, on the one hand, means all government-related data that is available and easily accessible. On the other hand, open government refers to allowing access to government information disclosed earlier. A growing number of governments are collaborating within communities such as the International Open Data Convention [5], the Open Government Partnership [6], Open Definition [7] and Open Knowledge International [8]. Since there are studies of different institutions and organizations on the concept of open data, there are different opinions in the literature about what open data principles are and how their content will be detailed. Among these different views, the generally accepted principles are [9]; free and continuous accessibility, reusable and shareability, innovation orientation and inclusivity.

There are portals that play an important role in promoting open data applications in each country and region because they represent central points for publishing and accessing datasets. Open data portals are also an important part of the e-government infrastructure that provides access to public services. According to the 2021 report released by the European data portal, ten ways in which open data portals should improve for sustainability and added value have been proposed [10,11]. These ten suggested pathways are given in Figure 2 [12].

Figure 2. Ten ways to make the portal more sustainable.

(1) Organize open data for use: Create data that anyone can access, use, or share [13].
(2) Encourage Use: Impact stories and examples are often used in open data, but these are often intended to encourage aging data publishers rather than users.
(3) Be Discoverable Intuitively: It has been argued that portals can complicate data discovery.
(4) Publish Metadata: The requirement for enlightening, consistent, available metadata -data about data- is not new.
(5) Promote Standards: A standard is an agreed way of doing something. Well-defined common standards ensure that the parties have a common understanding of the issue under discussion.
(6) Match documents frequently: Even if supporting documents are available, their length and technicality can make them the most useless, especially if presented in PDF format.
(7) Connection Data: Previous research by the European data portal has revealed that datasets are often used with each other, with the most popular combination being population statistics, environmental datasets and data from regions and cities [14].
(8) Be Measurable: Data portals require at least two types of measurement (for publishers) and quality (for users).
(9) Co-Locator Tools: Numerous tools are available for data manipulation, but while some tools are household names for the Open Data Herald, others, including basic mapping and visualization tools, are unknown to most potential users.
(10) Be Accessible: A survey conducted on the 260 Open Data portal found that about a quarter of datasets are published in a portable document format (PDF), which is not machine-readable [15].

The ten recommendations are not presented as an abstract list. It should be considered as a tool that can be used to critically assess the current state of portals and to make an honest inventory.

Scientists are currently focusing on MCDM and fuzzy MCDM methods to tackle complex real-life problems [16–21]. The main motivations for the study using some of these methods are threefold: (i) to develop a sound and effective decision-making tool to efficiently solve real-world problems, (ii) to ensure the combined use of objective and subjective weighting methods, (iii) to rank the G20 countries with the principle of transparency in the open data policies of states. We aim to achieve a robust and powerful decision-making tool called the LMAW-LOPCOW-WASPAS framework. This information proposes a model that will allow the G20 countries to rank with open government data with the introduced approach. To avoid unanswered questions about the ranking of countries, this study aims to answer the following research questions:

- ✓ Which criteria are more important to determine the most suitable country in the ranking of their country?
- ✓ Which country is better in the ranking of countries?
- ✓ Which approach is more appropriate for a detailed assessment of alternative countries?

This article is arranged as follows: The methods applied in the existing literature on the subject are presented in the second part. The LMAW-LOPCOW-WASPAS methods for ranking countries are described in Chapter 3. In the following section, the ranking of the countries is applied and then the validity of the results is tested by sensitivity analysis.

1.1. Literature review

In this study, the literature was examined by dividing it into three subsections. In the first subsection, studies with open data, in the second subsection, studies using MCDM methods and open data, and in the third and last subsection, some of the studies using LMAW, LOPCOW weighting methods and WASPAS sequencing methods are included.

1.1.1. Open data studies

Some of the studies on open data: In order to deliver effective local and global comparative studies based on open data, Giles-Corti et al. [10] proposed an open-source urban indicator computing system. Twenty-five cities in 19 countries were analyzed using the framework to determine geographical indicators of urban design and transport features that support health and sustainability. Amara-Ouali et al. [11] first gave an overview of open datasets ready for use in the field and then examined the strengths and weaknesses of electric vehicle charging load models. Finally, recommendations were made to match the models examined with six datasets found in the study that had not been previously investigated in the literature. The open data search studied more than 860 repositories and nearly 60 datasets related to modeling electric vehicle charging load. Huston et al. [13] provided a brief history of open data, as well as an exploration of the feasible advantages and challenges of open data, as well as a review of the current state of open data in public health in Canada, with an emphasis on infectious illnesses. Arderne et al. [14] used cutting-edge geospatial data analysis methods to generate the first composite map of the open-licensed global energy system, demonstrating the significance of the data acquired with accuracy by the verification group of 14 nations at both national and regional levels. Yochum et al. [15] presented a systematic review and map of location-based linked open data in the field of tourism, as well as an overview of the current state of research in the region. Ayre and Craner [22] talked about the history and benefits of open data.

1.1.2. MCDM and studies using open data

Some of the studies that solve the problems related to open data with MCDM methods: Luthfi et al. [23] assessed the risks and benefits of deciding to open a dataset using the Fuzzy AHP method. Máchová and Lněnička [24] used fuzzy AHP for the selection of open data management systems. Boulbazine and Kebiche [25] Entropy, TOPSIS and SAW methods and the public transportation-oriented development of light rail lines in Algeria were measured using open data sources. Kubler et al. [26] compared quality with the AHP method in the open data portal. Grace and Gil-Garcia [27] A cross-sectional investigation of web analytics activity data from New York State's open health data site was carried out to evaluate users' interaction with open datasets. Towse et al. [28] There have recommendations for enhancing the quality of open data.

1.1.3. Studies using LMAW, LOPCOW and WASPAS methods

Since LMAW and LOPCOW methods are new to the literature, the number of studies is limited for now. Some of the studies on the WASPAS method are included.

Studies using LMAW method; Pamucar et al. [29] is the study in which the method for evaluating the operational efficiency of the logistics service provider is included in the literature. The suggested framework was used to execute a case study of a comparative analysis of six prominent Logistics service providers in India. The LMAW approach was modified in the study of Bozanic et al. [30] by using triangular fuzzy numbers. In the study of Görçün and Küçükönder [31], a case study was conducted on the identification of priority sectors. In their efforts to enhance green agricultural production through uncertain decision-making, Puška et al. [32] employed a smart combination of Z-numbers, fuzzy LMAW method and fuzzy CRADIS method to pinpoint the optimal green supplier that can assist agricultural producers. Tešić et al. [33] assessed the effectiveness of the MARCOS model, which utilizes fuzzy logic and multiple attribute decision-making to aid army engineering units in selecting suitable dump trucks. The model considers factors such as construction features, as well as costs associated with purchasing and maintenance. In a study assessing the quality of health and wellness products in online customer reviews, Sıcakyüz [34] introduced a hybrid approach that blends the use of fuzzy WASPAS for ranking with triangular fuzzy LMAW for determining weights. As examined by Asadi et al. [35], the adoption of blockchain technology in the supply chains of small and medium-sized enterprises was investigated using the fuzzy LMAW method. The study conducted by Subotić et al. [36] aimed to assess the roadway network by utilizing eight geometric parameters relevant to road use and considering the data pertaining to light commercial vehicles. Specifically, six measurement sections of the road network were evaluated as part of the investigation. Deveci et al. [37] introduced a novel hybrid approach for fuzzy multi-criteria decision-making that integrates the LMAW and RAFSI methodology and utilizes it to determine the most effective locations to park e-scooters.

In studies using the LOPCOW method; Ecer and Pamucar [38] participated in the literature on the method to evaluate the bank's sustainability performance. An objective method for weighting called LOPCOW was developed and a new sorting method called DOBI was introduced. Ecer et al. [39] presented the q-rung fuzzy LOPCOW-VIKOR model for determining the optimal agricultural UAVs. Ecer et al. [40] the present study developed a decision-making model, namely the IVFNN-Delphi-LOPCOW-CoCoSo framework that provides practical and robust solutions, capable of mitigating intricate uncertainties. The purpose of this model is to assess the sustainability performance of micro-mobility solutions. Niu et al. [41], introduced a well-founded decision support framework aimed at enhancing the proficiency of a railway management department within the framework of a vague Fermatean collection. Biswas et al. [42] made an assessment of the comparative performance of the IPO listing. The dividend payment abilities of firms operating within the durable consumer goods industry were analyzed by Biswas et al. [43]. Biswas et al. [44] conducted an examination of the Mumbai Stock Exchange in India to compare the stock performance of companies operating in the FMCG and consumer durables sectors.

Studies using the WASPAS method; Thanh and Lan [45] were used to locate the solar power plant in South Vietnam by proposing a fuzzy multi-criteria decision-making model that included strengths-weaknesses-opportunities-challenges (SWOC) analysis, fuzzy AHP model and a weighted aggregated sum product assessment (WASPAS). Eghbali-Zarch et al. [46] proposed a decision model with the integrated determination of target criterion weights (IDOCRIW) and weighted aggregate total product assessment (WASPAS) in fuzzy information, listing potential strategic alternatives for performance evaluation at the strategic level according to the sustainable development criteria. In the study Vaid et al. [47], MCDM methodologies VIKOR (Vlsekriterijumsko kompromisno Rongiranje) and WASPAS were used to select the different quietest generators available on the market. Liu et al. [48] devised a methodology called BCF-CRITIC-WASPAS to address MCDM issues involving bipolar complex fuzzy data. Salimian et al. [49] introduced a novel approach encompassing the IVIF-RPR-MABAC and IVIF-WASPAS models. The primary objective of this approach is to determine the ratings and corresponding weights of specific criteria based on the preferences of decision-makers. The integration of prioritized averaging and the Maclaurin symmetric averaging operator in a probabilistic language environment was proposed by Darko and Liang [50]. Dede and Zorlu [51] conducted a geographic heritage evaluation utilizing MCDM techniques, as well as the ENTROPY and WASPAS methodologies. Görçün et al. [52] introduced an enhanced iteration of the WASPAS method utilizing the T2NN algorithm and incorporating the Bonferroni function, referred to as T2NN WASPAS'B. The aim was to assist in the selection of an appropriate Ro-Ro vessel from the secondary market. According to Kar et al. [53], after determining the weights of the features using CRITIC in nonlinear space for cloud vendor selection, the cloud vendors were ranked using the algorithm comprising the WASPAS procedure and sequencing fusion schemes

2. Materials and methods

In this section, the flowchart of the suggested integrated decision-making framework is given in Figure 3. Initially, the information was structured once the criteria and alternatives had been established. Subsequently, once the mathematical expressions for the LMAW and LOPCOW techniques are presented, the Bayesian approach is employed to merge the LMAW and LOPCOW weights and derive the overall weights for the criteria. The WASPAS technique is classified as a categorization mechanism afterward. The proposed model undergoes scrutiny through several sensitivity analyses in order to determine its validity and applicability in the final stage.

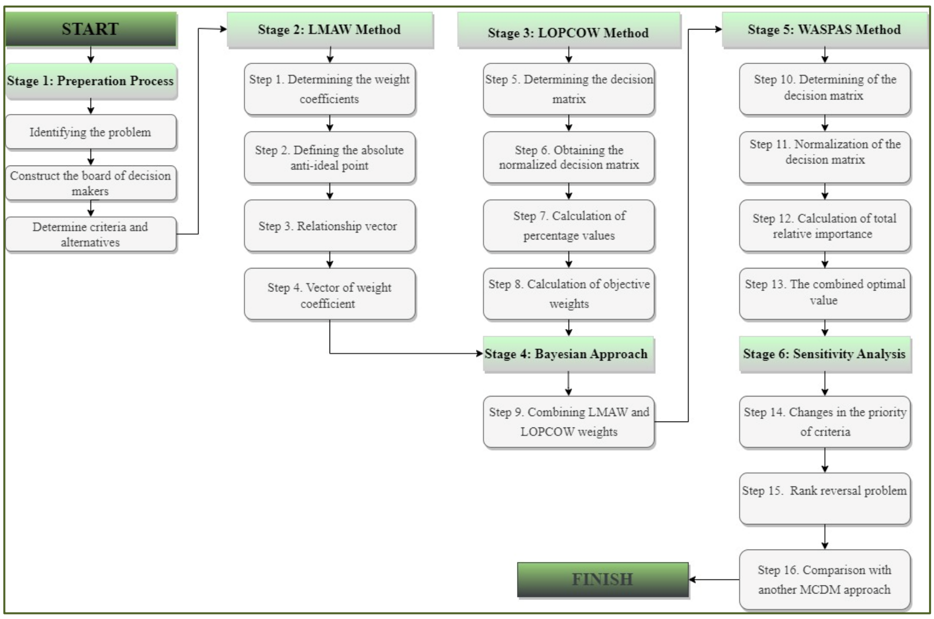

Figure 3. Flowchart of the proposed integrated decision-making framework.

2.1. Calculation procedure of the LMAW method

Pamučar et al. [54] LMAW method, which was brought to the literature in 2021, is one of the newest methods used in the sequence of alternatives in criterion weighting. Here, the criterion is given to the presence of weight coefficients. When selecting the LMAW approach, it is imperative to consider several key factors. First, it is crucial to prioritize resistance to order reversal issues. Second, the method must be evaluated for its ability to generate stable and reliable outcomes in a dynamic setting. Third, it is worth noting that the LMAW technique has demonstrated stability even when handling substantial amounts of data across multitudes of simulations. Fourth, it is noteworthy that the mathematical framework underpinning this approach facilitates comprehension of potential alternative methodologies and resultant conclusions in a digital context. Finally, additionally, the method facilitated the simultaneous evaluation of alternatives that were expressed in qualitative or quantitative criteria types. The application steps of this subjective criterion weighting method are as follows [54]:

m alternative $A = \{A_1, A_2, \ldots, A_m\}$ n criterion $C = \{C_1, C_2, \ldots, C_n\}$ according to k number of experts $E = \{E_1, E_2, \ldots, E_k\}$ are evaluated by a predetermined linguistic scale.

Step 1. Determining the weight coefficients of criteria

Experts in the set $E = \{E_1, E_2, \ldots, E_k\}$ prioritize the criteria $C = \{C_1, C_2, \ldots, C_n\}$ based on values on a predefined linguistic scale. Prioritization increases the value of the criteria with the highest significance on the linguistic scale while decreasing the value of the criterion with the lowest importance on the linguistic scale. In this way, the priority vector is obtained from, $P^e = \left(\gamma_{C_1}^e, \gamma_{C_2}^e, \ldots, \gamma_{C_n}^e\right)$.

$\gamma_{C_n}^e$: C_t $(1 \le t \le n)$ value on a linguistic scale assigned by expert e $(1 \le e \le k)$ according to the criterion.

Step 1.1. Defining the absolute anti-ideal point (γ_{AIP})

It is defined, in the priority vector, the minimum values from the priority vector must be lower than the lowest value. For the architects of the method γ_{AIP};

$$\gamma_{AIP} = \frac{\gamma_{min}^e}{S}$$

where $\gamma_{min}^e = min\left\{\gamma_{C_1}^e, \gamma_{C_2}^e, \ldots, \gamma_{C_n}^e\right\}$ and $s = 3$.

Step 1.2. Computing the relationship between absolute anti-ideal point and the elements of the priority vector.

It is determined using Eq (1).

$$\eta_{C_n}^e = \frac{\gamma_{C_n}^e}{\gamma_{AIP}}. \tag{1}$$

Thus, the relationship vector $R^e = \left(\eta_{C_1}^e, \eta_{C_2}^e, \ldots, \eta_{C_n}^e\right)$ is obtained. Where $\eta_{C_n}^e$ is the value of the relation vector obtained by using the expression Eq (3), and R^e is the relation vector of expert e $(1 \le e \le k)$.

Step 1.3. Determination of the vector of weight coefficients $w_j = (w_1, w_2, \ldots, w_n)^T$

By applying Eq (2), the values of the weight coefficients of the criteria for the specialist e $(1 \le e \le k)$ are obtained.

$$w_j^e = \frac{\log_A\left(\eta_{C_n}^e\right)}{\log_A(b^e)}, A > 1. \tag{2}$$

where, the relationship vector $\eta_{C_n}^e$ are elements of R, and $b^e = \prod_{j=1}^{n} \eta_{C_n}^e$. These obtained values must meet the condition of $\sum_{j=1}^{n} w_j^e = 1$ of the weight coefficients. Then the $w_j = (w_1, w_2, \dots, w_n)^T$ of the weight coefficients is obtained by the Bonferroni collector Eq (3).

$$w_j = \left(\frac{1}{k(k-1)} \sum_{x=1}^{k} \left(w_j^{(x)}\right)^p \sum_{\substack{y=1 \\ y \neq x}}^{k} \left(w_j^{(y)}\right)^q\right)^{\frac{1}{p+q}}. \tag{3}$$

$p, q \geq 0$ are the stabilization parameters of the Bonferroni collector. The weight coefficients must satisfy $\sum_{j=1}^{n} w_j = 1$.

2.2. Calculation procedure of the LOPCOW method

The objective criterion introduced by Ecer and Pamučar to the literature in 2022 is one of the newest methods used for weighting. In choosing the LOPCOW method, (1) it provides suitable solutions for benefit and cost-oriented criteria without any criterion limitation, (2) expressing the mean square values of the series as a percentage of their standard deviations, eliminating the difference (gap) caused by the size of the data, (3) There are factors such as not being affected by negative raw data, in other words, negative values. The implementation steps of this method are as follows [55].

Step 1. Creation of the initial decision matrix m alternative, for the decision problem consisting of n criteria, the initial decision matrix (X) is created as in Eq (4).

$$\mathrm{X} = \begin{bmatrix} \mathrm{x}_{11} & \cdots & \mathrm{x}_{1j} & \cdots & \mathrm{x}_{1n} \\ \vdots & \vdots & \vdots & \ddots & \ddots \\ \mathrm{x}_{m1} & \cdots & \mathrm{x}_{mj} & \cdots & \mathrm{x}_{mn} \end{bmatrix}. \tag{4}$$

Step 2. Obtaining the normalized decision matrix (R)

The linear max-min normalization technique is employed for the elements of the normalized decision matrix. Eq (5) is applied for cost-specific criteria and Eq (6) is applied for benefit-specific criteria.

$$r_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \tag{5}$$

$$r_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}}. \tag{6}$$

Step 3. Calculation of percentage values (PV) of criteria Eq (7) is used for the percentage value of each criterion.

$$PV_{ij} = \left| ln \left[\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^2}{m}}}{\sigma} \right] \right| .100. \tag{7}$$

where σ standard deviation represents the number m alternative.

Step 4. Calculation of objective weights

The heavy coefficients of each criterion are obtained by Eq (8).

$$w_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}}. \tag{8}$$

The condition of the sum of weights in Eq (8) must be met ($\sum_{i=1}^{n} w_j = 1$).

2.3. Bayesian approach for combining LMAW and LOPCOW weights

The weight values obtained from both subjective weighting methods are combined with the help of Eq (9). In this way, the optimal weight values of the criteria are determined based on the Bayesian approach [56]. In the equation below, the criterion weights of LMAW and LOPCOW are represented as w_j^{LMAW} and w_j^{LOPCOW}, respectively.

$$w_j = \frac{w_j^{LMAW} . w_j^{LOPCOW}}{\sum_{j=1}^{m} w_j^{LMAW} . w_j^{LOPCOW}}. \tag{9}$$

2.4. Calculation procedure of the WASPAS method

The WASPAS method, which is a combination of WSM (Weighted Sum Model) and WPM (Weighted Product Model) methods, was introduced to the literature by E. K. Zavadskas, Z. Turskis, J. Antucheviciene, A. Zakarevicius in 2012. The WASPAS approach was favored due to its uncomplicated procedures and the ability to conduct sensitivity analysis based on different λ coefficients. The solution stages of the method are as follows [57]:

Step 1. Determining of the decision matrix

First, the decision matrix for the problem is created.

$$X = \left[x_{ij}\right]_{mxn} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \; i = 1,2,\ldots,m \quad j = 1,2,\ldots,n.$$

x_{ij}: performance of the $i.$ alternative in criterion $j.$

Step 2. Normalization of the decision matrix

Using Eq (10), the decision matrix is normalized by taking into account the cost and benefit aspects of the criteria.

For benefit criterion: $x_{ij}^{*} = \frac{x_{ij}}{maksx_{ij}}$ For cost criterion: $x_{ij}^{*} = \frac{minx_{ij}}{x_{ij}}$. (10)

Step 3. Calculation of total relative importance

Calculation of total relative importance using a normalized matrix. It is calculated using Eqs (11) and (12) for total relative significance relative to WSM and WPM.

$$WSM: \left(Q_i^{(1)}\right) = \sum_{j=1}^{n} x_{ij}^{*} w_j \tag{11}$$

$$WPM: \left(Q_i^{(2)}\right) = \prod_{j=1}^{n} x_{ij}^{*w_j}. \tag{12}$$

Step 4. The combined optimal value meaning (Q_i) is calculated and the alternatives are ranked according to these values.

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)}. \tag{13}$$

The combined optimality coefficient λ is usually 0,5 and ve $0 \leq \lambda \leq 1$. The alternative with the largest Q_i values as a result value is considered the best alternative.

3. Application of the proposed methodology

The indicators used in the Global Open Data Index were used as the criteria of the study. State Budget (OD1): A high level of national government budget, i.e., not actual spending, but government expenditure planned for the next year. National Statistics (OD2): They are basic national statistics on Gross Domestic Product (GDP) or demographic and economic indicators such as unemployment and population statistics. Procurement (OD3): The office is in charge of collecting all national and federal government tenders and awards. Procurement planning and other phases are not included in this analysis. Open data on procurement can help companies compete more fairly, detect fraud more easily, and provide governments and citizens with better services. Increased government compliance can be achieved by monitoring tenders, which allows new groups to participate in tenders. National Laws (OD4): This type of data requires all national laws and legislation to be published online, but it does not need information concerning legislative conduct, such as voting records, to be available. Administrative Boundaries (OD5): Information on administrative units or areas specified for administrative purposes by a (local) authority. Draft Legislation (OD6): Information on legislation currently being debated in the national parliament as well as votes on bills (not to be confused with past national laws). Invoice data for the current regulatory period should be accessible. Air quality (OD7): Information on average daily concentrations of air contaminants, notably those that may be hazardous to human health. National Maps (OD8): A geographical map of the United States that contains national highways, waterways and elevation marks. The map should be at least 1:250,000 scale (1 cm 2.5km). Many applications benefit from geographic information, such charting unemployment data or demography, as well as trip planning. Temperature, precipitation and wind predictions for the next three days (OD9). Estimates for each area of the nation should be supplied. Short-term weather forecasts are useful for organizing public events and are also dependable. Company registration (OD10) is a list of businesses that have been registered. This data category includes balance sheets and other financial documents. It is not required to include extensive financial information such as. Open data from corporate records may be utilized for a variety of reasons. Results of the Election (OD11) This data category requires the results of all major national election competitions organized by election zone / district. Provides information on the voting procedure, vote outcomes and selection statistics. What are the majorities and minorities in the election? How many votes are valid, invalid, or tainted? The index analyses polling center data to achieve maximum openness. Locations (OD12) A database of related geographical places based on postal codes/postal codes as well as latitude and longitude (or similar coordinates in an explicitly published coordinate system). Data must be accessible for the entire country. Water quality (OD13) Data on water quality, measured at the water source, is essential for both the provision of services and the prevention of disease.

The information on the G20 countries and their abbreviations used in the analysis and the criteria of open data are given in Table 1. Since it was desired that the number of explanations of the criteria should be high, all criteria were accepted as benefit characteristics (max). Some of the Global Open Data Index data of China, South Korea and Saudi Arabia, which are G20 countries, were not included in the analysis because they were zero.

Table 1. Global open data index [8].

	OD1	OD2	OD3	OD4	OD5	OD6	OD7	OD8	OD9	OD10	OD11	OD12	OD13
	max	max	max	max	max	max	max	max	max	max	max	max	max
Germany (G1)	100	100	100	80	80	65	65	65	50	45	15	0	0
USA (G2)	100	100	100	100	100	85	85	85	80	65	65	15	0
Argentina (G3)	100	100	100	85	85	80	80	80	65	65	65	0	0
Australia (G4)	100	100	100	100	100	100	100	100	85	85	80	80	50
Brazil (G5)	100	100	100	100	100	83	85	85	70	65	65	35	30
Indonesia (G6)	85	80	65	60	45	45	0	0	0	0	0	0	0
France (G7)	100	100	100	100	100	85	85	80	70	70	65	50	45
South Africa (G8)	80	80	80	65	65	65	60	60	45	0	0	0	0
India (G9)	100	100	85	80	70	65	65	45	45	45	0	0	0
United Kingdom (G10)	100	100	100	100	100	100	85	85	85	85	85	70	50
Italy (G11)	100	100	100	100	85	85	65	50	15	0	0	0	0
Japan (G12)	100	100	100	100	85	85	85	85	85	50	45	0	0
Canada (G13)	100	100	100	100	100	100	80	80	80	50	50	50	45
Mexico (G14)	100	100	100	100	85	85	86	80	80	65	45	45	0
Russia (G15)	100	100	100	85	85	45	45	45	45	0	0	0	0
Turkey (G16)	85	80	80	80	65	45	45	45	15	15	0	0	0

Table 1 is arranged to express the percentages of countries to disclose their data. According to the Table 1, while the USA's explanation of the OD6 criterion is 85%, the explanation of the OD12 criterion is 15%.

3.1. Determining the subjective weights with LMAW method

To calculate the values of the weight coefficients of the criteria, four experts prioritized the criteria according to the scale in Table 2.

Table 2. Prioritization scale [48].

Linguistic Variables	Prioritization Score
Absolutely low	1
Very low	1,5
Low	2
Medium	2,5
Equal	3
Medium high	3,5
High	4
Very high	4,5
Absolutely high	5

Given that the evaluation was done by four experts, four priority vectors are identified and given in Table 3.

Table 3. Expert priority vectors.

	OD1	OD2	OD3	OD4	OD5	OD6	OD7	OD8	OD9	OD10	OD11	OD12	OD13
E1	4	3,5	4	2,5	3	1,5	5	4,5	2,5	2	3	2,5	2
E2	4,5	2,5	4,5	3,5	3,5	2	4,5	4	3	3	2	2	1,5
E3	4	3	4,5	3	3,5	2,5	5	4	3,5	2,5	2,5	1,5	1
E4	3,5	3,5	4,5	3,5	3,5	3,5	5	4	3,5	3,5	3	2	1

Then the absolute anti-ideal point value $\gamma_{AIP} = 0{,}5$ is arbitrarily defined. Using data from expert priority vectors and $\gamma_{AIP} = 0{,}5$ applying Eq (1), the relationship between the elements of the priority vector and the absolute anti-ideal point (γ_{AIP}) is determined. The elements of the R^1 vector are obtained by using the expression Eq (1) as follows.

$$\eta^1_{OD_1} = \frac{4}{0{,}5} = 8, \eta^1_{OD_2} = \frac{3{,}5}{0{,}5} = 7, \eta^1_{OD_3} = \frac{4}{0{,}5} = 8, \eta^1_{OD_4} = \frac{2{,}5}{0{,}5} = 5, \ldots, \eta^1_{OD_{13}} = \frac{2}{0{,}5} = 4$$

$$R^1 = (8, 7, 8, 5, 6, 3, 10, 9, 5, 4, 6, 5, 4).$$

The elements of the vector w^1_j belonging to the first specialist for calculating the vector of weight coefficients are obtained by applying the expression Eq (2) as follows.

$$b^1 = 8.7.8.5.6.3.10.9.5.4.6.5.4 = 8709120000$$

$$w^1_1 = \frac{\ln(8)}{\ln(8709120000)} = 0{,}0909, \ldots, \quad w^1_{13} = \frac{\ln(4)}{\ln(8709120000)} = 0{,}0606.$$

$w^1_j =$

$(0{,}0909; 0{,}0850; 0{,}0909; 0{,}0703; 0{,}0783; 0{,}0480; 0{,}1006; 0{,}0960; 0{,}0703; 0{,}0606; 0{,}0783; 0{,}0703; 0{,}0606)$.

The obtained values of the weight coefficients meet the condition $\sum_{j=1}^{13} w^1_j = 1$. The elements of the remaining vectors w^2_j, w^3_j and w^4_j are obtained in a similar way. By applying Eq (3), the collective vector of the weight coefficients is obtained.
$w_1 = 0{,}0896$ Value of the weight coefficient, w^e_j ($1 \le e \le 4$) for each expert, respectively $w^1_1 = 0{,}0909$, $w^2_1 = 0{,}0955$, $w^3_1 = 0{,}0914$ and $w^4_1 = 0{,}0808$. It is obtained with average values.

$w_1 = \{0{,}0909 \;\; 0{,}0955 \;\; 0{,}0914 \;\; 0{,}0808\}^{p,q=1}$

$w_1 =$

$$\sqrt{\frac{0{,}0909^1.0{,}0955^1 + 0{,}0909^1.0{,}0914^1 + 0{,}0909^1.0{,}0808^1 + \cdots + 0{,}0606^1.0{,}0477^1 + 0{,}0606^1.0{,}0303^1 + 0{,}0606^1.0{,}0288^1}{4(4-1)}} = 0{,}0896.$$

The remaining values of the vectors of the weight coefficients are obtained in a similar way and the weights are calculated.

$w_j =$

$(0{,}0896; 0{,}0786; 0{,}0935; 0{,}0786; 0{,}0823; 0{,}0646; 0{,}0982; 0{,}0910; 0{,}0786; 0{,}0724; 0{,}0708; 0{,}0589; 0{,}0412)^T$.

According to the LMAW method, air quality (OD7) with a weight of 0,0982 was the most frequently announced criterion, while water quality with a weight of 0,0412 (OD13) was the least disclosed criterion.

3.2. Determining the objective weights with LOPCOW method

Using Eq (6), the decision matrix in Table 1 is normalized and given in Table 4.

Table 4. Normalized decision matrix.

	OD1	**OD2**	**OD3**	**OD4**	**OD5**	**OD6**	**OD7**	**OD8**	**OD9**	**OD10**	**OD11**	**OD12**	**OD13**
	max	max	max	max	max	max	max	max	max	max	max	max	max
G1	1,0000	1,0000	1,0000	0,5000	0,6364	0,3636	0,6500	0,6500	0,5882	0,5294	0,1765	0,0000	0,0000
G2	1,0000	1,0000	1,0000	1,0000	1,0000	0,7273	0,8500	0,8500	0,9412	0,7647	0,7647	0,1875	0,0000
G3	1,0000	1,0000	1,0000	0,6250	0,7273	0,6364	0,8000	0,8000	0,7647	0,7647	0,7647	0,0000	0,0000
G4	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,9412	1,0000	1,0000
G5	1,0000	1,0000	1,0000	1,0000	1,0000	0,6909	0,8500	0,8500	0,8235	0,7647	0,7647	0,4375	0,6000
G6	0,2500	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
G7	1,0000	1,0000	1,0000	1,0000	1,0000	0,7273	0,8500	0,8000	0,8235	0,8235	0,7647	0,6250	0,9000
G8	0,0000	0,0000	0,4286	0,1250	0,3636	0,3636	0,6000	0,6000	0,5294	0,0000	0,0000	0,0000	0,0000
G9	1,0000	1,0000	0,5714	0,5000	0,4545	0,3636	0,6500	0,4500	0,5294	0,5294	0,0000	0,0000	0,0000
G10	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	1,0000	1,0000	1,0000	0,8750	1,0000
G11	1,0000	1,0000	1,0000	1,0000	0,7273	0,7273	0,6500	0,5000	0,1765	0,0000	0,0000	0,0000	0,0000
G12	1,0000	1,0000	1,0000	1,0000	0,7273	0,7273	0,8500	0,8500	1,0000	0,5882	0,5294	0,0000	0,0000
G13	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,8000	0,8000	0,9412	0,5882	0,5882	0,6250	0,9000
G14	1,0000	1,0000	1,0000	1,0000	0,7273	0,7273	0,8600	0,8000	0,9412	0,7647	0,5294	0,5625	0,0000
G15	1,0000	1,0000	1,0000	0,6250	0,7273	0,0000	0,4500	0,4500	0,5294	0,0000	0,0000	0,0000	0,0000
G16	0,2500	0,0000	0,4286	0,5000	0,3636	0,0000	0,4500	0,4500	0,1765	0,1765	0,0000	0,0000	0,0000
Standard deviation	0,3400	0,4031	0,3081	0,3399	0,2967	0,3464	0,2423	0,2496	0,3271	0,3653	0,3875	0,3585	0,4297
Mean square	0,9057	0,9014	0,8907	0,8119	0,7714	0,6578	0,7359	0,7111	0,7436	0,6275	0,5680	0,4394	0,4987
PV	97,9667	80,4719	106,1742	87,0604	95,5553	64,1423	111,0986	104,6984	82,1151	54,1136	38,2412	20,3682	14,8948

This created Table 4 with normalized data. Since standard deviation and mean square values are needed to calculate PV values, these values are given separately in the last two rows of Table 4. Then, the PV values for each criterion were calculated using Eq (7) and given in Table 4. For example, for criterion (OD1), this value is calculated as follows.

$$PV = \left| ln\left(\frac{0,9057}{0,3400}\right).100 \right| = 97,9667.$$

Finally, the final weights of the criteria were found with Eq (8). As an example, the significance weight of (OD1) is found as follows.

$$w_1 = \frac{97,9667}{97,9667+80,4719+106,1742+\cdots+38,2412+20,3682+14,8948} = 0,1024.$$

The final weights were similarly obtained for the remaining criteria.

$w_j =$

$(0{,}1024; 0{,}0841; 0{,}1110; 0{,}0910; 0{,}0999; 0{,}0670; 0{,}1161; 0{,}1094; 0{,}0858; 0{,}0566; 0{,}0400; 0{,}0213; 0{,}0156)^T$.

According to the LOPCOW method, air quality (OD7) with a weight of 0,1161 was the most frequently announced criterion, while water quality with a weight of 0,0156 (OD13) was the least disclosed criterion.

3.3. The optimal weights from Bayesian approach

Weight coefficients obtained by both subjective and objective weighting methods are given in Table 5 by obtaining Bayes weights using Eq (9). As an example, the combined significance weight of (OD1) is found as follows.

$$BAYES\ w = \frac{(0{,}1024.0{,}0896)}{0{,}0828} = 0{,}1108.$$

Table 5. Combined Weights achieved by Bayes approach.

	OD1	OD2	OD3	OD4	OD5	OD6	OD7	OD8	OD9	OD10	OD11	OD12	OD13
LOPCOW w	0,1024	0,0841	0,1110	0,0910	0,0999	0,0670	0,1161	0,1094	0,0858	0,0566	0,0400	0,0213	0,0156
LMAW w	0,0896	0,0786	0,0935	0,0786	0,0823	0,0646	0,0982	0,0910	0,0786	0,0724	0,0708	0,0589	0,0412
LOPCOW w. LMAWw	0,0092	0,0066	0,0104	0,0071	0,0082	0,0043	0,0114	0,0100	0,0067	0,0041	0,0028	0,0013	0,0006
BAYES w	0,1108	0,0798	0,1254	0,0863	0,0993	0,0523	0,1378	0,1203	0,0815	0,0494	0,0342	0,0152	0,0077

The weights of the study were combined and used in the WASPAS method.

$w_j =$

$(0{,}1108; 0{,}0798; 0{,}1254; 0{,}0863; 0{,}0993; 0{,}0523; 0{,}1378; 0{,}1203; 0{,}0815; 0{,}0494; 0{,}0342; 0{,}0152; 0{,}0077)^T$.

According to the Bayes approach, air quality (OD7) with a weight of 0,1378 was the most frequently announced criterion, while water quality with a weight of 0,0077 (OD13) was the least announced criterion.

3.4. Performance assessment of countries employing WASPAS

Using Eq (10), the decision matrix in Table 1 is normalized and given in Table 6.

Then the values of Eq (11) for $Q^{(1)}$ and Eq (12) for $Q^{(2)}$ were calculated. Calculations for G1 are shown. $Q_{11}^{(1)} = 1.0{,}1108 = 0{,}1108, \dots, Q_{113}^{(1)} = 0.0{,}0077 = 0$ and $Q_1^{(1)} = 0{,}1108 + 0{,}0798 + \cdots + 0 + 0 = 0{,}7464$. $Q_{11}^{(2)} = 1^{0{,}1108} = 1, \dots, Q_{113}^{(2)} = 0^{0{,}0077}$ and $Q_1^{(2)} = 1.1 \dots 0.0 = 0$. The calculation of the Q value for G1 using Eq (13) is shown:

$$Q_1 = 0{,}5(0{,}7464 + 0) = 0{,}3732.$$

The results obtained by performing similar procedures for all alternatives are given in Table 7.

Table 6. Normalized decision matrix.

	OD1	OD2	OD3	OD4	OD5	OD6	OD7	OD8	OD9	OD10	OD11	OD12	OD13
	max	max	max	max	max	max	max	max	max	max	max	max	max
G1	1,0000	1,0000	1,0000	0,8000	0,8000	0,6500	0,6500	0,6500	0,5882	0,5294	0,1765	0,0000	0,0000
G2	1,0000	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	0,8500	0,9412	0,7647	0,7647	0,1875	0,0000
G3	1,0000	1,0000	1,0000	0,8500	0,8500	0,8000	0,8000	0,8000	0,7647	0,7647	0,7647	0,0000	0,0000
G4	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,9412	1,0000	1,0000
G5	1,0000	1,0000	1,0000	1,0000	1,0000	0,8300	0,8500	0,8500	0,8235	0,7647	0,7647	0,4375	0,6000
G6	0,8500	0,8000	0,6500	0,6000	0,4500	0,4500	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
G7	1,0000	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	0,8000	0,8235	0,8235	0,7647	0,6250	0,9000
G8	0,8000	0,8000	0,8000	0,6500	0,6500	0,6500	0,6000	0,6000	0,5294	0,0000	0,0000	0,0000	0,0000
G9	1,0000	1,0000	0,8500	0,8000	0,7000	0,6500	0,6500	0,4500	0,5294	0,5294	0,0000	0,0000	0,0000
G10	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	1,0000	1,0000	1,0000	0,8750	1,0000
G11	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	0,6500	0,5000	0,1765	0,0000	0,0000	0,0000	0,0000
G12	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	0,8500	0,8500	1,0000	0,5882	0,5294	0,0000	0,0000
G13	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,8000	0,8000	0,9412	0,5882	0,5882	0,6250	0,9000
G14	1,0000	1,0000	1,0000	1,0000	0,8500	0,8500	0,8600	0,8000	0,9412	0,7647	0,5294	0,5625	0,0000
G15	1,0000	1,0000	1,0000	0,8500	0,8500	0,4500	0,4500	0,4500	0,5294	0,0000	0,0000	0,0000	0,0000
G16	0,8500	0,8000	0,8000	0,8000	0,6500	0,4500	0,4500	0,4500	0,1765	0,1765	0,0000	0,0000	0,0000

Table 7. Q Values and ranking of alternatives.

	$\boldsymbol{Q^{(1)}}$	$\boldsymbol{Q^{(2)}}$	$\boldsymbol{Q}$	**Rank**
Germany	0,7464	0,0000	0,3732	10
USA	0,9089	0,0000	0,4545	6
Argentina	0,8483	0,0000	0,4242	9
Australia	0,9980	0,9979	0,9980	1
Brazil	0,9067	0,8990	0,9029	4
Indonesia	0,3596	0,0000	0,1798	16
France	0,9098	0,9046	0,9072	3
South Africa	0,6054	0,0000	0,3027	14
India	0,6828	0,0000	0,3414	12
United Kingdom	0,9594	0,9570	0,9582	2
Italy	0,6953	0,0000	0,3476	11
Japan	0,8792	0,0000	0,4396	8
Canada	0,9027	0,8915	0,8971	5
Mexico	0,8870	0,0000	0,4435	7
Russia	0,6566	0,0000	0,3283	13
Turkey	0,5547	0,0000	0,2774	15

Australia ranked first in terms of disclosing its data, while Indonesia ranked last.

4. Sensitivity analysis

This section performs three different sensitivity analyses to verify the reliability and robustness of the sequencing results from the proposed approach. In the first sensitivity analysis, the effect of changes in the criteria's weighting coefficients on the alternatives' ranking results is tested. In the second, the resistance of the proposed model to the rank reversal problem was investigated. In the third, the ranking results of the proposed approach are compared with other powerful MCDM approaches (i.e., SAW, MooraRate and TOPSIS).

4.1. Variation of criteria weight

A weight sensitivity study was performed using the criteria weighting approach to determine how the suggested model influenced ranking performance by adjusting the weight of the most significant criterion. Steps for the process are provided based on the change in weight [58,59] and applications to multi-criteria decsion making [60–66].

Step 1. Determination of the weight elasticity coefficient.

The number that expresses the relative balance of other weights in relation to certain changes in the weight of the most important criterion during sensitivity analysis is called the weight elasticity coefficient (α_c). This value is always defined as "1" for the most important criterion. For other criteria, Eq (14) is used.

$$\alpha_c = w_c^0/(1 - w_s). \tag{14}$$

w_c^0: the original value of the changed weight

w_s: weight of the most important criterion

Step 2. Determination of the Δx parameter.

The Δx parameter represents the amount of change applied to the weight set according to the associated elasticity coefficients. The change in the weight of the most important criterion should be limited. Otherwise, weights may take negative values and violate the weight proportionality constraint. When the Δx parameter is positive, it may show an increase in relative severity, or it may show a decrease when it is negative.

The limits for Δx are defined as the amount of the highest weight change in the most critical criterion in the negative and positive directions. The limit of the variable Δx is calculated using Eq (15).

$$-w_s \leq \Delta x \leq min\{w_c^o/\alpha_c\}. \tag{15}$$

Step 3. Calculation of new criterion weights the following Eq (16) is used to determine the new weights of the other criteria Eq (17) for the weights of the most important criterion.

$$w_s = w_s^o + \alpha_s \Delta x, \tag{16}$$

$$w_c = w_c^o - \alpha_c \Delta x. \tag{17}$$

w_s^o: the original weight of the criterion subjected to sensitivity analysis

w_c^o: the original value of the changing weights

This new criterion weight set must always meet the universal condition of weight proportion, i.e., $\sum w_s + \sum w_c = 1$. Any change in the criteria weights combined with the Bayes approach can significantly change the order of alternatives in some cases. Sensitivity analysis is performed to check if there is such a situation and to ensure the determination and strength of the application. First, it is assumed that the weight coefficient (α_s) of the most important criterion (OD7) is the same for the other criteria (α_c). It is estimated using Eq (14) as given in Table 8.

Table 8. Coefficient of weight flexibility for changing weights.

Criteria	Calculated Weights	α_c	Δx
OD7	0,1378	1,000	
OD1	0,1108	0,1108/(1-0,1378)=0,1285	0,1108/0,1285=0,8626
OD2	0,0798	0,0798/(1-0,1378)= 0,0926	0,0798/0,0926=0,8618
OD3	0,1254	0,1254/(1-0,1378)= 0,1454	0,1254/0,1454=0,8624
OD4	0,0863	0,0863/(1-0,1378)= 0,1001	0,0863/0,1001=0,8621
OD5	0,0993	0,0993/(1-0,1378)= 0,1151	0,0993/0,1151=0,8627
OD6	0,0523	0,0523/(1-0,1378)=0,0606	0,0523/0,0606=0,8630
OD8	0,1203	0,1203/(1-0,1378)=0,1395	0,1203/0,1395=0,8626
OD9	0,0815	0,0815/(1-0,1378)=0,0945	0,0815/0,0945=0,8624
OD10	0,0494	0,0494/(1-0,1378)=0,0573	0,0494/0,0573=0,8621
OD11	0,0342	0,0342/(1-0,1378)=0,0397	0,0342/0,0397=0,8617
OD12	0,0152	0,0152/(1-0,1378)=0,0176	0,0152/0,0176=0,8636
OD13	0,0077	0,0077/(1-0,1378)=0,0090	0,0077/0,0090=0,8556

Then the limiting limits of the weight change (Δx) for the criterion (OD7) are calculated. It is located between -0,1378≤Δx ≤0,8622. Beyond these limits, the weights of the criterion (OD7) will take negative values. Once these limits were defined, 21 sets of new weights were calculated using the Eqs (16) and (17) as shown in Table 9. The calculation of new criteria using Eqs (16) and (17) with Δx=-0,1 is exemplified.

Table 9. New criterion weights.

Δx	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12	w13
-0,1378	0,1285	0,0926	0,1454	0,1001	0,1151	0,0606	0,0000	0,1395	0,0945	0,0573	0,0397	0,0176	0,0090
-0,1	0,1237	0,0891	0,1399	0,0964	0,1108	0,0584	0,0378	0,1343	0,0909	0,0552	0,0382	0,0169	0,0086
-0,05	0,1172	0,0845	0,1327	0,0914	0,1050	0,0553	0,0878	0,1273	0,0862	0,0523	0,0362	0,0160	0,0082
0	0,1108	0,0798	0,1254	0,0863	0,0993	0,0523	0,1378	0,1203	0,0815	0,0494	0,0342	0,0152	0,0077
0,05	0,1044	0,0752	0,1181	0,0813	0,0935	0,0493	0,1878	0,1133	0,0767	0,0466	0,0322	0,0143	0,0073
0,1	0,0980	0,0706	0,1108	0,0763	0,0878	0,0462	0,2378	0,1064	0,0720	0,0437	0,0302	0,0134	0,0069
0,15	0,0915	0,0659	0,1036	0,0713	0,0820	0,0432	0,2878	0,0994	0,0673	0,0408	0,0282	0,0125	0,0064
0,2	0,0851	0,0613	0,0963	0,0663	0,0762	0,0402	0,3378	0,0924	0,0626	0,0380	0,0263	0,0116	0,0060
0,25	0,0787	0,0567	0,0890	0,0613	0,0705	0,0371	0,3878	0,0854	0,0578	0,0351	0,0243	0,0108	0,0055
0,3	0,0723	0,0521	0,0818	0,0563	0,0647	0,0341	0,4378	0,0784	0,0531	0,0322	0,0223	0,0099	0,0051
0,35	0,0658	0,0474	0,0745	0,0513	0,0590	0,0311	0,4878	0,0715	0,0484	0,0294	0,0203	0,0090	0,0046
0,4	0,0594	0,0428	0,0672	0,0463	0,0532	0,0280	0,5378	0,0645	0,0437	0,0265	0,0183	0,0081	0,0042
0,45	0,0530	0,0382	0,0599	0,0413	0,0475	0,0250	0,5878	0,0575	0,0389	0,0236	0,0163	0,0072	0,0037
0,5	0,0466	0,0335	0,0527	0,0363	0,0417	0,0220	0,6378	0,0505	0,0342	0,0208	0,0144	0,0064	0,0033
0,55	0,0401	0,0289	0,0454	0,0313	0,0359	0,0189	0,6878	0,0436	0,0295	0,0179	0,0124	0,0055	0,0028
0,6	0,0337	0,0243	0,0381	0,0263	0,0302	0,0159	0,7378	0,0366	0,0248	0,0150	0,0104	0,0046	0,0024
0,65	0,0273	0,0196	0,0309	0,0213	0,0244	0,0129	0,7878	0,0296	0,0200	0,0122	0,0084	0,0037	0,0019
0,7	0,0208	0,0150	0,0236	0,0162	0,0187	0,0098	0,8378	0,0226	0,0153	0,0093	0,0064	0,0029	0,0015
0,75	0,0144	0,0104	0,0163	0,0112	0,0129	0,0068	0,8878	0,0157	0,0106	0,0064	0,0045	0,0020	0,0010
0,8	0,0080	0,0058	0,0090	0,0062	0,0072	0,0038	0,9378	0,0087	0,0059	0,0036	0,0025	0,0011	0,0006
0,85	0,0016	0,0011	0,0018	0,0012	0,0014	0,0007	0,9878	0,0017	0,0012	0,0007	0,0005	0,0002	0,0001
0,8622	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	1,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

As a result, the new weight values of the derived criteria according to 21 scenarios are given in Table 9 and shown in Figure 4.

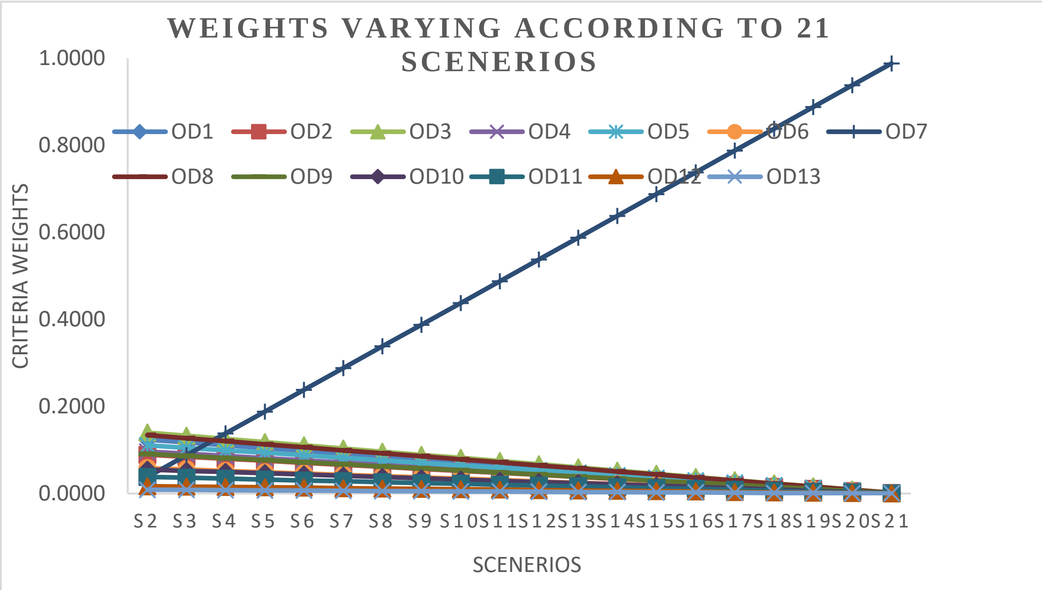

Figure 4. Weights that change according to the change in the most important criterion.

The 21 weight sets in Table 9 and the performance of the G20 countries in disclosing open data are recalculated and the rankings obtained are given in Figure 5.

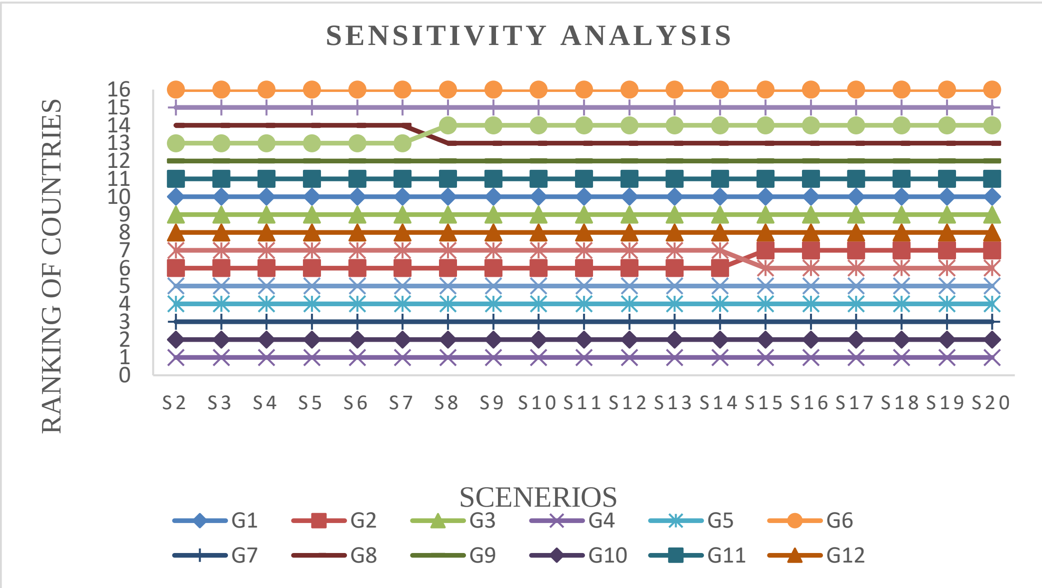

Figure 5. Changes to the rankings of alternatives.

The results show that assigning different weights to the criteria over 20 sets confirms that the model is sensitive to changes in some weight coefficients, leading to changes in the ranking of some countries (USA, Mexico, South Africa, Russia). While the weight of the criteria varied over the sets, there was no change in the order of the other alternatives.

4.2. Rank reversal problem

MCDM methods can be tested for stability by adding or removing weak alternatives from the original cluster. The MCDM method is not expected to show a significant change in the ranking of alternatives in such cases. The "popular rank reversal problem" refers to this phenomenon, which has received a great deal of attention in the literature [58,59]. It is possible to test a model's validity for decision-making by creating dynamic matrices and then analyzing the model's solutions under the new conditions.

15 scenarios were constructed in the model to mimic the change in the constituents of the choice matrix. 15 situations should be prepared as a rule (one less than the total number of alternatives). Following the application of the WASPAS approach to the first experiment, the G20 nations are ordered based on the findings provided in the S0 scenario (original order). The country with the fewest rankings is eliminated in the following scenario (S1). Following that, the remaining 15 countries are reranked. Thus, a total of 15 scenarios (S1–S15) are created, whereby the worst-ranked country from the set is eliminated in each subsequent scenario, and the rankings are given in Figure 6.

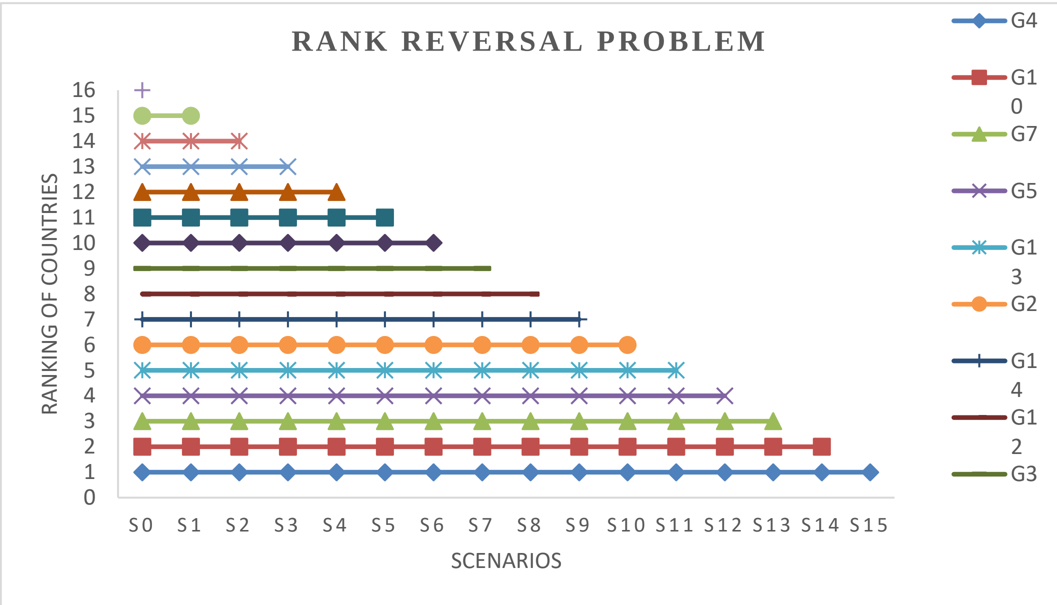

Figure 6. Results of rank reversal analysis.

It can be clearly noted from Figure 6 that the WASPAS model provides valid results in a dynamic environment and that the model has a strong resistance to the problem of row reversal. In all scenarios, the superiorities in the first ranking are maintained.

4.3. Comparison with other MCDM procedures

Multi-criteria decision-making methods based on different ranking methodologies are used to calculate the stability of the ranking performed in the comparative analysis. The robustness and reliability of ranking scores of alternatives is examined in many complex decision environments by comparing the results of one model to other available and established methods. SAW [67], MooraRate [68] and TOPSIS [69] were compared to the LBWA-LOPCOW-WASPAS model in order to select the best insurance company and demonstrate the mode's reliability. These techniques were selected due to their wide range of benefits, versatility and ability to sort out alternatives in a multi-criteria selection environment efficiently. The comparison results from different MCDM procedures are shown in Figure 7 and given in Table A1 in the Appendix.

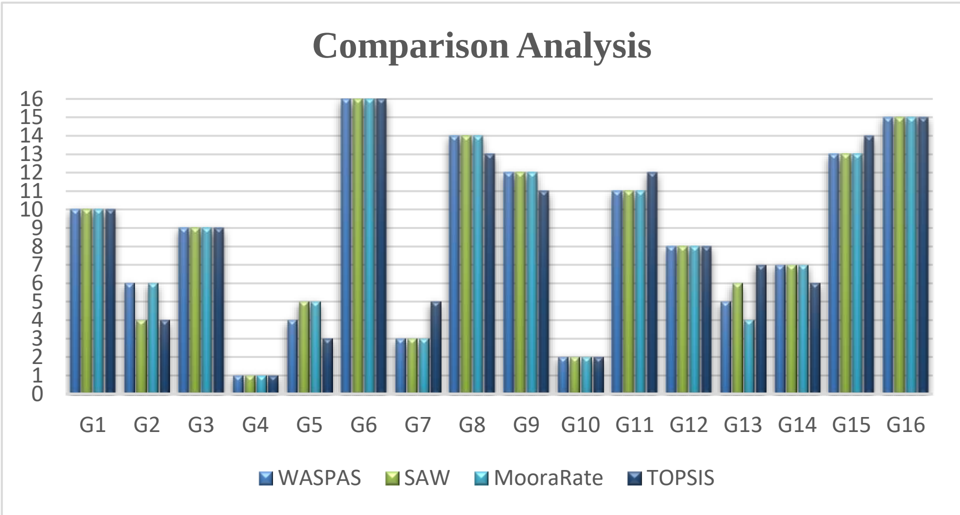

Figure 7. Ranking of G20 countries with different MCDM methods.

According to Figure 7, the rankings of the G20 countries Germany, Argentina, Australia, Indonesia, United Kingdom, Japon and Turkey are the same in all methods. The ranking of other G20 countries differed according to methods. Spearman Rank Correlation (SRC) was used to determine the relationship between the results obtained by different methods. A comparison of the rankings by applying the SRC is given in Table 10.

Table 10. SRC values of the tested methods.

SRC	WASPAS	SAW	MOORARATE	TOPSIS
WASPAS	1	0,991	0,997	0,974

The proposed model was found to be confirmed and reliable with an average correlation value of 0.987 between the other three MCDM techniques and the WASPAS approach used.

5. Discussion

In this study, both subjective (LMAW) and objective (LOPCOW) approaches were used to prioritize the published values of open government data. The Global Open Data Index was used to prioritize the criteria affecting the ranking of countries. As an alternative, the G20 countries were preferred. The G4 (Australia) has the highest performance in the disclosure of government data, followed by the G10 (United Kingdom), G7 (France) and G5 (Brazil). When the findings are evaluated with LMAW-LOPCOW, it is seen that the most important criterion is air quality with a weight of 0,0982-0,1161 (OD7). Next is (OD3) procurement with a weight of 0,0935-0,1110, national maps with a weight of 0,0910-0,1094 and (OD1) state budget with a weight of 0,0896-0,1024. The weights obtained from both methods were combined with the Bayesian approach to obtain a single weight value. Figure 8 shows combined weight values.

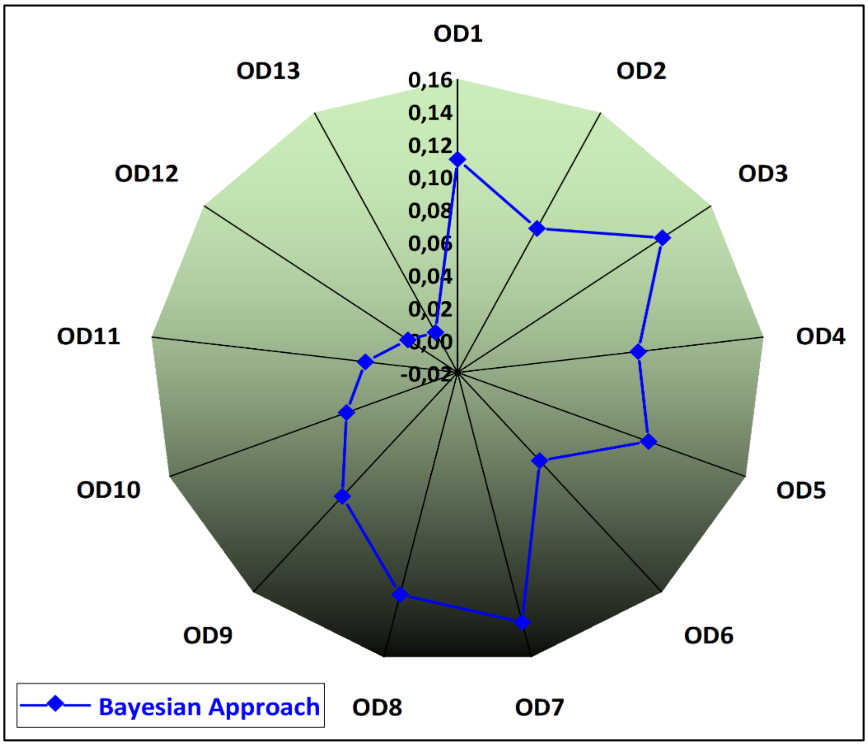

Figure 8. Combined weight coefficient values with Bayesian approach.

Air quality with a weight of 0,1378 is the top priority with a Bayesian approximate, followed by Procurement with a weight of 0,1254, National Maps with a weight of 0,1203 and State Budget with a weight of 0,1108. According to this finding, states prioritize the explanation of air quality, procurement, national maps and state budget data, respectively.

Managerial implications

The accessibility of information and data generated by states makes states more transparent and accountable to their citizens. For this reason, measuring the performance of the countries disclosing their data was evaluated as a decision problem. A model has been created that can be solved with a simple, transparent and reliable MCDM that facilitates the decision-making process regarding the prioritization of publicly disclosed open data sets. A thirteen-criteria procedure is presented, which is formed from the factors in the Global Open Data Index.

According to the findings, it is seen that states prioritize disclosing their data on air quality. The results also show that among the G20 countries, Australia ranks first with its performance in disclosing its data, followed by the United Kingdom. The ranking of countries is also consistent with the sensitivity analysis.

6. Conclusions

In this study, for the first time in the literature, the LMAW-LOPCOW-WASPAS integrated approach was proposed for the evaluation of G20 countries with government open data. First, the factors in the Global Open Data Index were defined as criteria for the study, and then both LMAW and LOPCOW methods were used to determine the weights of these criteria. Then, with the Bayesian approach, these two weight values were combined. Then the WASPAS method was applied to obtain the ranking of countries. In addition, a detailed sensitivity analysis was performed to confirm the results obtained.

Empirical findings reveal that air quality is the most important data in ranking countries according to open data performance, followed by procurement and national maps. The findings also suggest that Australia performed best, followed by the United Kingdom. Comprehensive sensitivity analysis confirms the validity, robustness and effectiveness of the proposed framework.

In the context of the G20 countries, a model has been proposed to solve a real-life problem, such as measuring countries' performance in disclosing their data. The study has three advantages: first, to determine which of the criteria used in the ranking of countries is more important, second, to show which country performs better in the ranking of countries, and the other is to determine which approach is more appropriate for the detailed evaluation of alternative countries. One of the limitations of the proposed multi-criteria model is the consideration of metrics included in the Global Open Data Index. Another limitation is the use of G20 countries in the ranking.

There is still room for improvement in future studies as there may be different evaluation criteria or different MCDM methods (CRADIS, MARA, COBRA, etc.) and their various extensions (spherical fuzzy clusters, intuitive fuzzy sets, etc.) that may be a potential research topic in the future. The robustness of this proposed model can be checked by considering a large number of alternatives and criteria. This easy-to-use model can be used to solve a variety of complex engineering, medical, basic science and management-related problems.

Appendix

Table A1. Ranking of G20 countries according to different MCDM procedures.

	WASPAW		SAW		MooraRate		TOPSIS	
	Q_i	Rank	V_i	Rank	Y_i	Rank	C_i	Rank
G1	0,3732	10	0,7464	10	177,4914	10	0,0688	10
G2	0,4545	6	0,9089	4	276,2659	6	0,2419	4
G3	0,4242	9	0,8483	9	241,9920	9	0,1630	9
G4	0,9980	1	0,9980	1	401,8659	1	0,8718	1
G5	0,9029	4	0,9067	5	285,3945	5	0,2435	3
G6	0,1798	16	0,3596	16	68,5846	16	0,0000	16
G7	0,9072	3	0,9098	3	307,0749	3	0,2375	5
G8	0,3027	14	0,6054	14	120,2359	14	0,0388	13
G9	0,3414	12	0,6828	12	155,0379	12	0,0436	11
G10	0,9582	2	0,9594	2	376,2871	2	0,3407	2
G11	0,3476	11	0,6953	11	173,6791	11	0,0401	12
G12	0,4396	8	0,8792	8	250,3712	8	0,1929	8
G13	0,8971	5	0,9027	6	298,8819	4	0,1969	7
G14	0,4435	7	0,8870	7	267,2734	7	0,2120	6
G15	0,3283	13	0,6566	13	147,4044	13	0,0284	14
G16	0,2774	15	0,5547	15	104,3839	15	0,0179	15

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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