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Uncovering the Hidden Insights of the Government AI Readiness Index: Application of Fuzzy LMAW and Schweizer-Sklar Weighted Framework

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ABSTRACT

There is considerable promising in artificial intelligence (AI) and algorithms, with governments worldwide increasingly investing in this transformative technology. The potential benefits include improved performance, cost reduction, efficient management, and crime prediction and prevention, among others. The AI era holds the promise of revolutionizing various aspects of society. However, as countries prepare to leverage the power of artificial intelligence, questions arise about the validity of rankings published on the readiness of the governments for the application of AI. In this article, the weighting criteria that are analysed in the Oxford Insights AI Readiness Index are scrutinized, aiming to provide a more accurate assessment. Instead of conventional averaging, arithmetic and geometric non-linear functions are employed to analyse and assess the rank of the countries. Through clustering analysis, countries are categorized into three distinct groups based on observed criteria, offering a nuanced perspective on government AI readiness. This clustering approach not only facilitates a more effective categorization of countries based on their AI preparedness, but also accentuates the variations and similarities within each cluster, which enables deeper insights into regional trends and pinpoint targeted strategies for enhancement within each cluster.

1. Introduction

Artificial Intelligence (AI) revolutionizes government decision-making processes by offering transformative capabilities. Recognizing its potential, governments are increasingly adopting AI to enhance efficiency and effectiveness in policymaking. Leveraging AI enables governments to analyze vast datasets, identify patterns, and uncover insights that inform evidence-based policies. AI

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streamlines government operations by automating labor-intensive tasks, such as data analysis and document processing, freeing up resources for strategic initiatives. Furthermore, AI-driven insights empower policymakers to address complex societal challenges more effectively. With AI, governments can optimize resource allocation, improve service delivery, and foster innovation, leading to a more efficient and responsive public sector.

Benefits brought by the implementation of AI from the perspective of each government is only one aspect, but it is also necessary to look at the extent to which each country is prepared to truly apply AI in its sectors and to use the advantages of AI in practice. The governments should prepare the ground for efficient implementation of the AI to use all the advantages it offers. What does it mean when we emphasize "ground" as a condition? It means that analysis should be performed regarding laws, regulations, infrastructure, availability of human resources in the country where the AI will be implemented. Oxford researchers have noticed the importance of these conditions and have annually published a report that indicates the state of AI in governments from the chosen countries. This report called the Government AI Readiness Index rank governments according to their level of preparedness in artificial intelligence since 2017 [1].

Oxford's database, the AI Readiness Index [2], stands as a pivotal information source regarding countries' readiness to adopt and apply artificial intelligence across diverse sectors. This database offers comprehensive analyses and rankings, enabling a deeper comprehension of infrastructure, regulatory frameworks, education, and other critical factors pivotal for AI technology.

Oxford research gives an insight into the problem of government readiness for adopting AI and the question that arises is whether it is possible to use other methods to rank the given countries according to the selected criteria. In this way, results that are obtained differ from the Oxford results. The aim of this paper is to obtain, based on the data in Oxford Insights: Government AI Readiness Index research [2], the efficiency, and rankings of countries by applying the proposed methodology and to compare the obtained results with the results in the mentioned research. Using the results from this study, countries can create a strategy for the future application of AI.

The main goal of the paper is the development and application of a new methodology for ranking countries according to their readiness for AI acceptance and spotting if there is a difference in the ranks compared to the existing Oxford ranking. This goal was accomplished through the following key contributions:

i. The research methodology suggested in this paper provides a new tool for analyzing governments' AI Readiness Index and it enables more accurate ranking of the countries;
ii. Fuzzy sine trigonometry LMAW model (fuzzy ST-LMAW) used to process expert assessments and define fuzzy weight coefficients of criteria;
iii. Defined arithmetic and geometric non-linear functions which are employed to analyze AI Readiness index;
iv. Performed clustering analysis where countries are categorized into distinct groups based on observed criteria;
v. Comparison between the results in this paper and results from Oxford's database which allows meaningful conclusions for future research and gives validation to the research carried out and presented in this paper.

The paper is organized as follows: Section 2 section presents a brief overview of the motivation for the proposed research and the gap recognized in this field, as well as a literature review. Section 3 describes the proposed multi-criteria framework for assessment of governments' AI readiness index and the research method in the paper. Section 4 presents the case study results. Finally, the main conclusions are summarized in the section 5.

2. Background

The motivation for this research arises from Oxford's database, the AI Readiness Index, which stands as a pivotal information source regarding countries' readiness to adopt and apply artificial intelligence across diverse sectors. Delving into the Government AI Readiness Index uncovers crucial insights spanning governmental policy frameworks, regulations, and strategies concerning AI adoption, along with technological advancements, data utilization, and infrastructure. As AI becomes increasingly recognized as a pivotal driver of economic advancement and competitiveness, nations with robust AI readiness may enjoy a distinct edge in attracting investments, nurturing innovation, and cultivating high-value employment opportunities within AI-related sectors. The advent of AI technologies holds transformative potential, and promising advancements in various industries.

Scrutinizing government AI readiness provides invaluable insights into a country's capacity to harness AI for societal betterment, tackling prevalent challenges, and improving citizens' well-being. Evaluating government AI readiness offers a glimpse into nations' capabilities to address ethical and regulatory dilemmas associated with AI, including privacy safeguards, bias mitigation, and mechanisms for ensuring accountability.

Examining the Government AI Readiness Index fosters international collaboration and knowledge exchange among governments, policymakers, researchers, and industry stakeholders. By benchmarking AI readiness across nations, stakeholders can glean valuable insights from one another's experiences and best practices, catalyzing the formulation of more effective AI policies and strategies on a global scale.

Invaluable perspectives into the prevailing landscape of AI adoption and governance at the national level are provided based on assessment of the Government AI Readiness Index. Moreover, it serves as a cornerstone for shaping discussions and decisions regarding AI policy, innovation, and societal impact, propelling societies toward a more informed and prosperous AI-enabled future. Also, policymakers can pinpoint areas necessitating enhancement and craft more efficacious policies conducive to fostering AI development and integration.

After conducting more comprehensive research, we have observed that certain parameters exhibit varying significance levels within this analysis. This observation suggests that some factors exert a greater influence on outcomes or results compared to others. When considering the broader context, this variability in parameter significance may indicate the complexity of the system or process under study. Therefore, it is imperative to comprehend and consider this variability when interpreting results and drawing conclusions. Furthermore, identifying key parameters with a high significance level can offer valuable guidance for allocating resources and implementing more effective strategies to achieve desired objectives or enhance system and process performance. For instance, although infrastructure plays a critical role in supporting various processes and systems, its full potential may remain unrealized without an adequate presence of skilled personnel. Quality personnel can optimize infrastructure utilization and contribute to the achievement of goals and initiatives.

1.1 Literature review

Artificial Intelligence can have a significant impact on public policies and services - it is expected that the potential will exist to free up nearly one-third of public servants’ time. Governments can also use AI to design better policies and make better decisions, improve communication and engagement with citizens and residents, and improve the speed and quality of public services [3]. Also, governments from the countries around the world are increasingly integrating artificial intelligence systems into both production and delivery of public services, where some of the AI promises include efficiency gains and a more effective public administration [4]. Authors in the mentioned paper present a review of the literature covering the extent of AI applied to the public sector.

In the past years not many papers were published regarding the implications and succession of the AI application led by governments. To explore more on this topic, we used bibliographic database - Scopus. By filtering the published papers by keywords “government” and “artificial intelligence” in the period 2022-2024, 318 results were obtained, which were downloaded in the form of a .csv file. Additional analysis of papers in the database resulted in 48 papers published. VOSviewer (Visualizing Scientific Landscapes) is a free software designed for the visualization and analysis of bibliometric and scientific data.

By choosing a country as the unit of analysis and a minimum of 4 documents by authors from one country, out of a total of 29 countries from the available file, 4 countries meet the criteria. We can conclude from the analysis that the authors from different countries do not cooperate in this research field.

By choosing the Co-occurrence/All keywords analysis, we get an insight into the occurrence of all keywords. For the calculation method, we choose Full counting and a minimum of 5 occurrences of one keyword. Out of a total of 455 keywords, 8 meet the requirements. A co-occurrence network of all keywords was obtained and presented (Figure 1). Most occurring keywords are Ethics and Human. Authors in [5] conducted a survey and showed that belief in the governance responsibility of the government was associated with ethical concerns about AI, and authors in [6] state that AI turned into a field of knowledge that has been consistently displacing technologies for a change in human life.

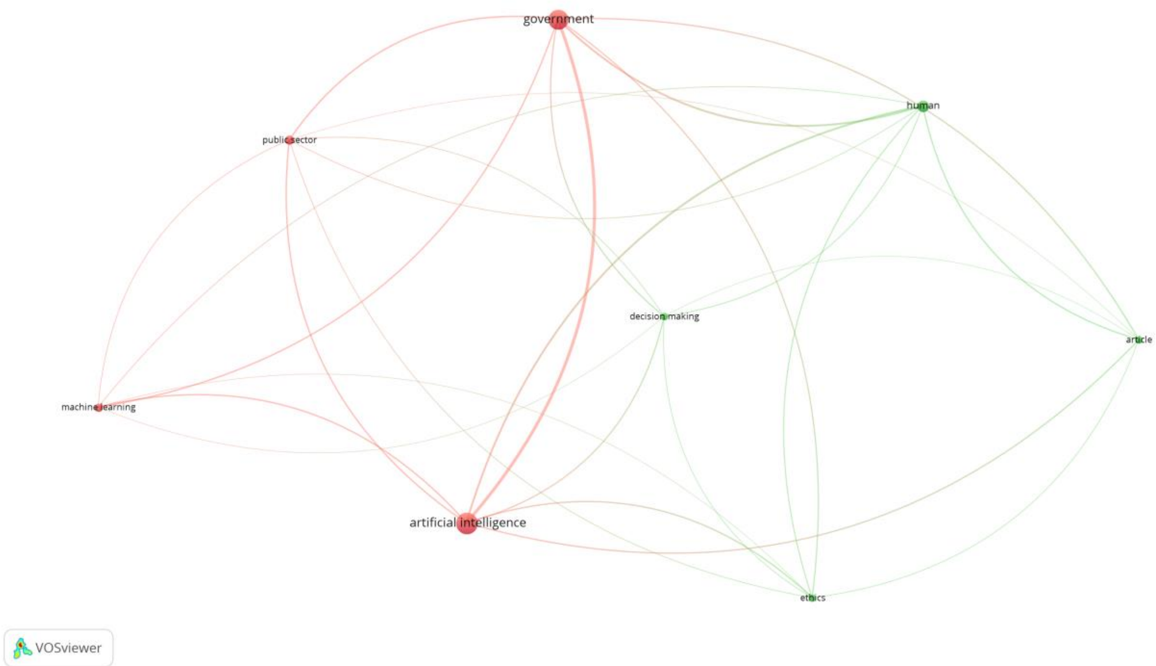

Fig. 1. Network of occurrences of all keywords

The potential benefits of AI are easy to comprehend, but implementation in the public sector in countries can be difficult. It is important to ensure effective AI adoption in the public sector and this challenge is addressed in the report [7], where the author posts very interesting and current research question: how ready is a given government to implement AI in the delivery of public services to their citizens? The scope of the report is 193 countries, using indicators that are available for most of the selected countries and are used for their ranking based on readiness to implement AI in the public services.

Authors Alhosani and Alhashmi in [8] recommend a strategic approach to AI adoption in the public sector, answering critical questions about organizational theory's role in improving government AI adoption, the challenges governments have in adopting AI, and the potential benefits AI might offer public service delivery.

Since research on AI and the public sector is still in an early stage, there are various research opportunities available that scholars need to address, to extend theoretical and empirical knowledge in this field and to apply and implement AI technology in the public sector with great potential to increase its efficiency [9].

It must be emphasized that many of the published papers deal with efficiency of AI in different areas of the public sector. Authors *Zheng et al*. [10] investigate AI service provision by the government, highlighting the bilateral relationship between the needs of the public sector and the solutions provided by AI applications. In doing so, the authors show that supporting e-government tools with AI technology increases efficiency and improves government service provision. Moreover, the articles of Chun and Wai [11-12] address service-oriented applications in public administration that focus on optimizing immigration forms with the aid of AI technologies. These AI-based services support e-government and help to reduce processing times, minimize the workload, and improve the workflow, thus increasing efficiency and driving economic growth.

It can be noticed that only a few of the published papers are analyzing the efficiency of the government readiness to implement the AI. In the paper [1], authors state that, although some of the world's top AI innovators are ready but are not prioritizing and promoting responsible AI.

It would be very useful to highlight which countries and to what extent these countries apply AI in the public sector and how successful they are. The answer can be found in the Oxford research [2]. The authors in the mentioned research determined the efficiency and ranking of each country based on the data obtained. This research is used as motivation for the research proposed in this paper and enabled an insight into the analyzed problem. The question that arises is whether it is possible to use some other methods to rank the given countries according to the selected criteria. In accordance with the above, the aim of this paper is to obtain, based on the data in Oxford Insights research, the efficiency and rankings of countries by applying the proposed methodology and to compare the obtained results from both researches. Using the results from this research, countries can create a strategy for the future application of AI.

3. The multi-criteria framework for assessment of governments' AI readiness index

To provide a more accurate assessment of the government AI Readiness Index, a multicriteria framework based on two modules is proposed in this research (Figure 2). Multicriteria decision making framework was developed having in mind its advantages that have been proven in literature [13-15] In the first module, the extension of the logarithmic method of additive weights (LMAW) presented by *Pamucar et al*. in [16] using fuzzy sets and fuzzy sine trigonometry functions. Fuzzy sine trigonometry LMAW model (fuzzy ST-LMAW) was used to process expert assessments and define fuzzy weight coefficients of criteria.

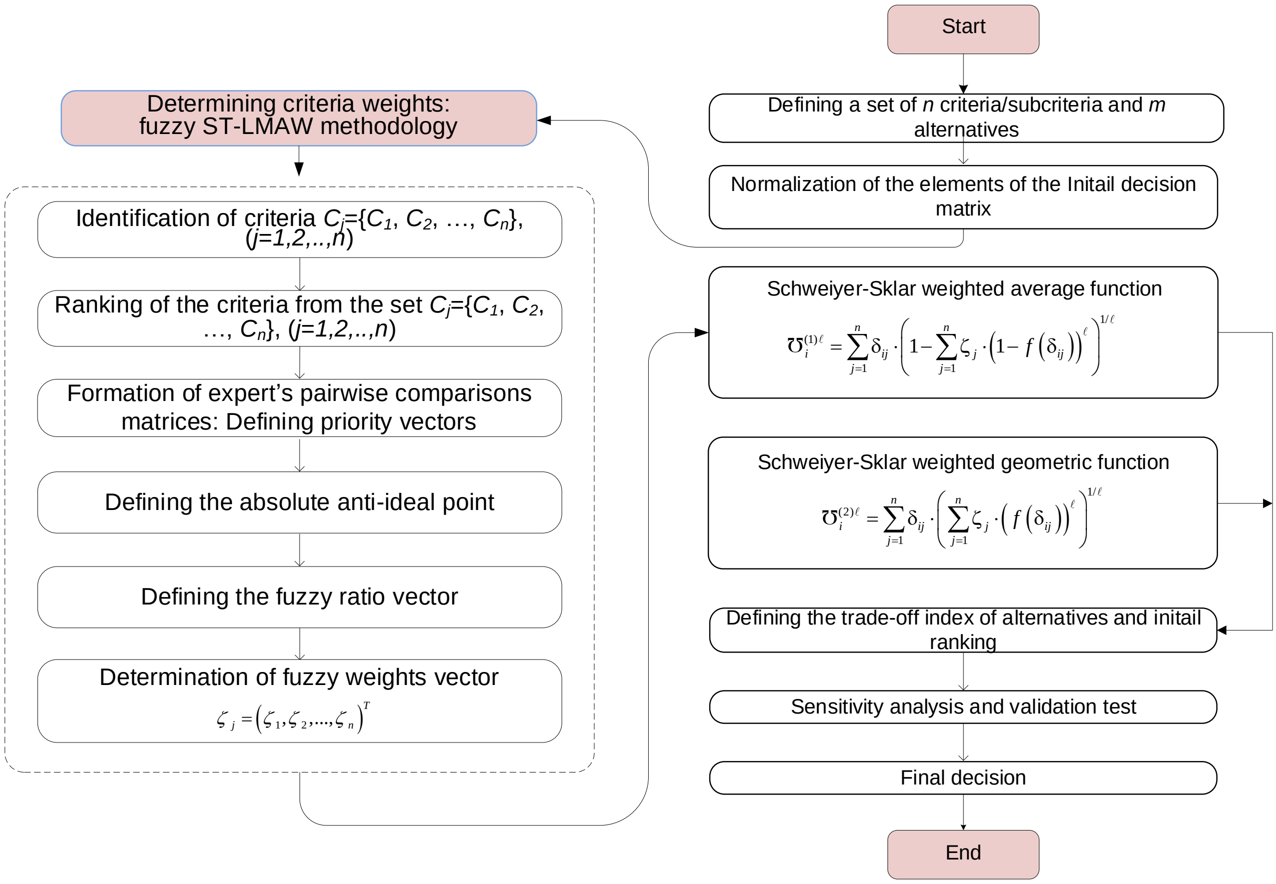

Fig. 2. Fuzzy sine trigonometry LMAW and Schweizer-Sklar weighted evaluation model

Within the second module, the Schweizer-Sklar weighted evaluation (SSWE) model for the evaluation of alternatives was implemented. Two Schweizer-Sklar weighted functions for the evaluation of alternatives are defined and a nonlinear aggregation function is proposed for the final evaluation of the alternatives. The basic assumptions of the proposed methodology are further presented.

3.1. Preliminaries on fuzzy Schweizer-Sklar norms

Definition 1. The real numbers x_1 and x_2 are given, and $\ell \in (-\infty,0)\cup(0,+\infty)$, then the Schweizer-Sklar (SS) norms [17] can be defined using expressions (1) and (2):

a) SS *T*-norm $\Delta^{\ell}_{(x_1,x_2)}$:

$$\Delta^{\ell}_{(x_1,x_2)} = \left(x_1{}^{\ell} + x_2{}^{\ell} - 1\right)^{1/\ell} \tag{1}$$

b) SS *T*-norm $\nabla^{\ell}_{(x_1,x_2)}$:

$$\nabla^{\ell}_{(x_1,x_2)} = 1 - \left((1-x_1)^{\ell} + (1-x_2)^{\ell} - 1\right)^{1/\ell} \tag{2}$$

where $(x_1,x_2) \in [0,1]$.

Based on expressions (1) and (2), arithmetic operations with SS norms can be performed.

Definition 2. Let's suppose that x_1 and x_2 are numbers $(x_1, x_2) \in [0,1]$, also, let $0 < \theta < +\infty$ and $\ell \in (-\infty, 0) \cup (0, +\infty)$. If the following additive function $f(x_i) = x_i \big/ \sum_{i=1}^{n} x_i$ is formulated, then arithmetic rules with SS norms by applying expressions (3)-(6) can be defined:

(1) Addition "$\oplus$":

$$x_1 \oplus x_2 = 1 - \left((1-x_1)^{\ell} + (1-x_2)^{\ell} - 1\right)^{1/\ell} \tag{3}$$

(2) Multiplication "$\otimes$":

$$x_1 \otimes x_2 = \left(x_1^{\ell} + x_2^{\ell} - 1\right)^{1/\ell} \tag{4}$$

(3) Multiplying by a constant, where $0 < \theta < +\infty$:

$$\theta x_1 = 1 - \left(\theta(1-x_1)^{\ell} - (\theta - 1)\right)^{1/\ell} \tag{5}$$

(4) Exponentiation, where is it $0 < \theta < +\infty$:

$$x_1^{\theta} = \left(\theta x_1^{\ell} - (\theta - 1)\right)^{1/\ell} \tag{6}$$

3.2. Fuzzy sine trigonometry LMAW method

In the next section, the fuzzy sine trigonometry LMAW model (fuzzy ST-LMAW) is presented. This methodology was used to define the weighting coefficients of the criteria and is based on the concept of fuzzy logarithmic additive function. Fuzzy logarithmic additive function was used to establish mutual dependence between criteria, while fuzzy sets [18-21] were used to exploit uncertainty in expert assessments. Non-linear functions of sine trigonometry were used to aggregate expert assessments and define the final values of the weighting coefficients. In the following part, the steps of the fuzzy ST-LMAW model are presented:

Step 1. Suppose that h experts participate in the research and that n criteria are defined $\psi_j = (\psi_1, \psi_2, ..., \psi_n)$. Then, by applying a predefined fuzzy scale [22], expert assessments of the importance of criteria within the priority vector $\Im^e = (\overset{e}{\wp}_{(\psi_1)}, \overset{e}{\wp}_{(\psi_2)}, .., \overset{e}{\wp}_{(\psi_n)}), (1 \le e \le h)$ can be presented, where $\overset{e}{\wp}_{(\psi_n)} = \left(\overset{e(l)}{\wp}_{(\psi_n)}, \overset{e(m)}{\wp}_{(\psi_n)}, \overset{e(u)}{\wp}_{(\psi_n)}\right)$ represents the fuzzy assessment assigned by the e-th expert to the n-th criterion.

Step 2. To define the ratio vector, it is necessary to average the value of the absolute anti-ideal point (χ_{AIP}). The value χ_{AIP} is defined based on the condition $0 < \chi_{AIP} < \min_{1 \le y \le k}\left(\wp_k\right)$, where k represents the total number of fuzzy linguistic values from the predefined fuzzy scale.

Step 3. The relationship vector is defined as the relationship between the priority vectors $\Im^e = (\overset{e}{\wp}_{(\psi_1)}, \overset{e}{\wp}_{(\psi_2)}, .., \overset{e}{\wp}_{(\psi_n)})$ and the absolute anti-ideal point (χ_{AIP}). The fuzzy relation vector can be represented as $\mathbb{Q}^e = \left(\overset{e}{\mu}_{\psi_1}, \overset{e}{\mu}_{\psi_2}, .., \overset{e}{\mu}_{\psi_n}\right)$, where $1 \le e \le h$. The elements of the fuzzy relationship vector are defined using the expression (7):

$$\overset{e}{\mu}_{\psi_j} = \frac{\overset{e}{\wp}_{(\psi_j)}}{\chi_{AIP}} \tag{7}$$

where $\overset{e}{\wp}_{(\psi_n)} \in \Im^e$ and $\overset{e}{\wp}_{(\psi_n)} = \left(\overset{e(l)}{\wp}_{(\psi_n)}, \overset{e(m)}{\wp}_{(\psi_n)}, \overset{e(u)}{\wp}_{(\psi_n)}\right)$.

Step 4. The final values of the weight coefficients for each expert are calculated by applying expression (8):

$$\zeta_j^e = \frac{\ln\left(\mu_{\psi_j}^e\right)}{\ln\left(\partial_j^e\right)} \tag{8}$$

where the value ∂_j^e is obtained by applying expression (9).

$$\partial_j^e = \left(\sum_{j=1}^{n} \zeta_j^e \frac{2}{\pi} \arcsin\left(\prod_{j=1}^{n} \left(\sin\left(\frac{\pi f\left(\zeta_j^e\right)}{2} \right)^{1/n} \right) \right) \right)^n \tag{9}$$

where $\zeta_j^e \in \mathbb{Q}^e$, $f\left(\zeta_j^e\right) = \zeta_j^e / \sum_{j=1}^{n} \zeta_j^e$, $1 \le e \le h$ and n represents the number of criteria.

By applying expressions (8) and (9) h fuzzy vectors of weighting coefficients are obtained, and it is necessary to perform a fusion of the defined fuzzy weighting factors. Using expression (10), the aggregated vector of weight coefficients is defined.

$$\zeta_j = \left(\zeta_j^{(l)}, \zeta_j^{(m)}, \zeta_j^{(u)}\right) = \begin{pmatrix} \sum_{d=1}^{h} \zeta_j^{(l)e} \frac{2}{\pi} \arcsin\left(\prod_{d=1}^{h} \left(\sin\left(\pi f\left(\zeta_j^{(l)e}\right) / 2 \right)^{\xi_e} \right) \right), \\ \sum_{d=1}^{h} \zeta_j^{(m)e} \frac{2}{\pi} \arcsin\left(\prod_{d=1}^{h} \left(\sin\left(\pi f\left(\zeta_j^{(m)e}\right) / 2 \right)^{\xi_e} \right) \right), \\ \sum_{d=1}^{h} \zeta_j^{(u)e} \frac{2}{\pi} \arcsin\left(\prod_{d=1}^{h} \left(\sin\left(\pi f\left(\zeta_j^{(u)e}\right) / 2 \right)^{\xi_e} \right) \right) \end{pmatrix} \tag{10}$$

where ξ_e represents the expert's weighting coefficient *e*, *h* represents the number of experts, while $\zeta_j = \left(\zeta_1, \zeta_2, ..., \zeta_n\right)^T$ represents the aggregated vector of criteria's weighting coefficients.

3.3. Schweizer-Sklar weighted evaluation method

The weight coefficients defined after applying the fuzzy ST-LMAW model represent the input parameters of the Schweizer-Sklar weighted evaluation (SSWE) model. Suppose that a multi-criteria framework is defined, which contains *m* alternatives (A_i, *i*=1,2,...,*n*) and *n* criteria (C_j, *j*=1,2,...,*m*). Then, based on Definitions 1 and 2, the SSWE model can be defined as follows:

Step 1: Based on the collected information about the alternatives A_i (*i*=1,2,...,*n*) within the criterion C_j (*j*=1,2,...,*m*), an initial decision matrix $\Omega = \left[\varphi_{ij}\right]_{m \times n}$ was generated, where φ_{ij} represents the assessment *i*-th alternative in relation to the *j*-th criterion.

Step 2: If the elements of the matrix $\Omega = \left[\varphi_{ij}\right]_{m \times n}$ are represented by different measurement units, it is necessary to standardize the values. By standardization, all elements of the matrix $\Omega = \left[\varphi_{ij}\right]_{m \times n}$ are recalculated into the same criterion interval. Standardization is carried out using expression (11).

$$\delta_{ij}=\begin{cases}\delta_{ij}=\dfrac{\varphi_{ij}}{\max\limits_{1\le i\le m}(\delta_{ij})} & if \quad j\in \text{Benefit},\\[2ex] \delta_{ij}=-\dfrac{\varphi_{ij}}{\max\limits_{1\le i\le m}(\varphi_{ij})}+\max\limits_{1\le i\le m}\left(\dfrac{\varphi_{ij}}{\max\limits_{1\le i\le m}(\varphi_{ij})}\right)+\min\limits_{1\le i\le m}\left(\dfrac{\varphi_{ij}}{\max\limits_{1\le i\le m}(\varphi_{ij})}\right) & if \quad j\in \text{Cost}.\end{cases} \tag{11}$$

where i=1,2,...,n and j=1,2,...,m.

Applying expression (11), a standardized matrix $\Omega^S=\left[\delta_{ij}\right]_{m\times n}$ is obtained.

Step 3: Non-linear weighted Schweizer-Sklar functions were defined by applying weighted arithmetic averaging, weighted geometric averaging and expressions (1)-(6):

a) Weighted average Schweizer-Sklar function ($\mho_i^{(1)\ell}$) is presented in the following expression (12).

$$\mho_i^{(1)\ell}=\sum_{j=1}^{n}\delta_{ij}\cdot\left(1-\sum_{j=1}^{n}\zeta_j\cdot\left(1-f\left(\delta_{ij}\right)\right)^{\ell}\right)^{1/\ell} \tag{12}$$

where $f\left(\delta_{ij}\right)=\delta_{ij}\Big/\sum_{j=1}^{n}\delta_{ij}$ and $\ell\in(-\infty,0)\cup(0,+\infty)$.

b) Weighted geometric Schweizer-Sklar function ($\mho_i^{(2)\ell}$) is presented in the following expression (13).

$$\mho_i^{(2)\ell}=\sum_{j=1}^{n}\delta_{ij}\cdot\left(\sum_{j=1}^{n}\zeta_j\cdot\left(f\left(\delta_{ij}\right)\right)^{\ell}\right)^{1/\ell} \tag{13}$$

where $f\left(\delta_{ij}\right)=\delta_{ij}\Big/\sum_{j=1}^{n}\delta_{ij}$ and $\ell\in(-\infty,0)\cup(0,+\infty)$.

Step 4. Defining final evaluations of alternatives. By applying the expression (14), the final evaluations of the alternatives are defined:

$$\mathbb{R}_i=\frac{\mho_i^{(1)\ell}+\mho_i^{(2)\ell}}{1+\left\{\rho\left(\dfrac{1-f(\mho_i^{(1)\ell})}{f(\mho_i^{(1)\ell}}\right)+(1-\rho)\left(\dfrac{1-f(\mho_i^{(2)\ell}}{f(\mho_i^{(2)\ell}}\right)\right\}} \tag{14}$$

where $\rho\in[0,1]$.

The ranking of the alternatives is defined based on the value $\mathbb{R}_i$, where the alternative with a higher value $\mathbb{R}_i$ has a higher ranking.

4. Application of fuzzy sine trigonometry LMAW method and SSWE method for assessment of governments' AI readiness index

Oxford's AI Readiness Index serves as the cornerstone of this research, offering indispensable insights into nations' readiness to embrace artificial intelligence (AI) across sectors. This case study zeroes in on Government AI Readiness, shedding light on the varying significance levels among parameters such as policies, regulations, and technological advancements, which significantly influence AI adoption. Through this analysis, countries are ranked based on their AI readiness, offering a nuanced understanding of their preparedness.

Since the proposed multi-criteria framework consists of two phases, in the following part, within the first phase, the application of the fuzzy sine trigonometry LMAW method for defining the weighting coefficients of the criteria is presented. In the second phase, the application is presented. The ten criteria presented in Table 1 were used to evaluate the countries.

Table 1
The criteria list of evaluation - Oxford Insights: Government AI Readiness Index [2]

Pillar	Dimension	Indicator
Government	Vision (C1)	AI strategy
	Governance & Ethics (C2)	Data protection and privacy laws Cybersecurity Regulatory quality Ethical principles Accountability
	Digital Capacity (C3)	Online services Foundational IT infrastructure Government Promotion of Investment in Emerging Technologies
	Adaptability (C4)	Government Effectiveness
		Government responsiveness to change Procurement Data
Technology Sector	Maturity (C5)	Number of AI Unicorns log transformation Number of non-AI Unicorns log transformation Value of trade in ICT services (per capita) log transformation Value of trade in ICT goods (per capita) log transformation Computer software spending
	Innovation Capacity (C6)	Time spent dealing with government regulations VC availability R&D Spending log transformation Company investment in emerging technology AI research papers log transformation
	Human Capital (C7)	Graduates in STEM or computer science Github Activity log transformation Female STEM Graduates Quality of Engineering and Technology Higher Ed ICT skills
Data & Infrastructure	Infrastructure (C8)	Telecommunications Infrastructure Supercomputers log transformation Broadband Quality 5G Infrastructure Adoption of Emerging Technologies
	Data Availability (C9)	Open Data Data governance Mobile-cellular telephone subscriptions Households with internet access Statistical Capacity
	Data Representativeness (C10)	Cost of cheapest internet-enabled device (% of monthly GDP per capita) Gender gap in internet access

The evaluation of the countries was carried out based on Dimensions (given in Table 1) which were assigned code marks from C1 to C10. It is interesting that dimension C1 is a categorical variable, the values for the vision can be determined only as: exists, not exist or vision defining the vision in progress. A detailed explanation of all criteria values can be found in [2].

In the following part of the paper, the application of the fuzzy ST-LMAW model for defining the weighting coefficients of Dimensions are presented.

a) Application of the fuzzy ST-LMAW model for determining weight coefficients of dimensions

Step 1: Nine experts participated in the research and evaluated the significance of the dimensions. The fuzzy linguistic scale shown in Table 2 was used to represent the expert assessments of the dimensions.

Table 2
Fuzzy linguistic scale

Linguistic terms	Linguistic values of TrFNs
Absolutely low (AL)	(1, 1.5, 2.5)
Very low (VL)	(1.5, 2.5, 3.5)
Low (L)	(2.5, 3.5, 4.5)
Medium low (ML)	(3.5, 4.5, 5.5)
Equal (E)	(4.5, 5.5, 6.5)
Medium high (MH)	(5.5, 6.5, 7.5)
High (H)	(6.5, 7.5, 8.5)
Extremely high (EH)	(7.5, 8.5, 9.5)
Absolutely high (AH)	(8.5, 9, 10)

Assessments of the importance of the dimensions are presented within the priority vectors as shown in Table 3.

Table 3
Experts' priority vectors

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9
C1	H	E	E	H	VH	E	VH	H	VH
C2	MH	E	H	H	AH	VH	H	H	E
C3	AH	VH	VH	E	VH	H	H	E	AH
C4	H	E	E	ML	E	VL	E	E	VL
C5	VL	VL	E	ML	L	L	E	L	L
C6	H	MH	H	VH	E	MH	MH	E	H
C7	H	MH	VH	H	MH	E	MH	VH	H
C8	AH	H	AH	VH	AH	AH	VH	VH	H
C9	VH	VH	H	VH	H	AH	VH	AH	VH
C10	H	H	E	MH	MH	H	MH	E	MH

Steps 2 and 3: Based on the condition $0 < \chi_{AIP} < \min_{1 \le y \le k}\left(\wp_k\right)$, the value of the absolute anti-ideal point $\chi_{AIP} = 0.5$ is defined. The value of the absolute anti-ideal point can take values within the interval $\left]0,1\right[$, therefore the value $\chi_{AIP} = 0.5$ was accepted because it is in the middle of this interval. Based on the value χ_{AIP} and priority vector (Table 3), the elements of the relationship vector (Table 4) are defined.

Table 4
Ratio vectors

Crit.	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	...	Expert 8	Expert 9
C1	(12,14,16)	(8,10,12)	(8,10,12)	(12,14,16)	(14,16,18)	...	(12,14,16)	(14,16,18)
C2	(10,12,14)	(8,10,12)	(12,14,16)	(12,14,16)	(16,18,18)	...	(12,14,16)	(8,10,12)
C3	(16,18,18)	(14,16,18)	(14,16,18)	(8,10,12)	(14,16,18)	...	(8,10,12)	(16,18,18)
C4	(12,14,16)	(8,10,12)	(8,10,12)	(6,8,10)	(8,10,12)	...	(8,10,12)	(2,4,6)
C5	(2,4,6)	(2,4,6)	(8,10,12)	(6,8,10)	(4,6,8)	...	(4,6,8)	(4,6,8)
C6	(12,14,16)	(10,12,14)	(12,14,16)	(14,16,18)	(8,10,12)	...	(8,10,12)	(12,14,16)
C7	(12,14,16)	(10,12,14)	(14,16,18)	(12,14,16)	(10,12,14)	...	(14,16,18)	(12,14,16)
C8	(16,18,18)	(12,14,16)	(16,18,18)	(14,16,18)	(16,18,18)	...	(14,16,18)	(12,14,16)
C9	(14,16,18)	(14,16,18)	(12,14,16)	(14,16,18)	(12,14,16)	...	(16,18,18)	(14,16,18)
C10	(12,14,16)	(12,14,16)	(8,10,12)	(10,12,14)	(10,12,14)	...	(8,10,12)	(10,12,14)

Step 4: Based on vectors and expressions (8) and (9), weight coefficients of dimensions for each expert were calculated. In this way, a total of nine fuzzy vectors of the weighting coefficients of the dimensions were obtained. The weighting coefficient of the first dimension (C1) for the first expert is defined using expression (8):

$$\zeta_{C_1}^{1} = \frac{\ln\left(12,14,16\right)}{\ln\left(176\cdot 10^{8},1327\cdot 10^{8},5111\cdot 10^{8}\right)} = \left(0.092,0.103,0.118\right)$$

where $\ln\left(176\cdot 10^{8},1327\cdot 10^{8},5111\cdot 10^{8}\right)$ is obtained by applying the expression (9). In the following part, the calculation of the modal fuzzy value of $\ln\left(\partial_j^e\right)$ is given:

$$\ln\left(\partial_{C1}^{(m)1}\right) = \left(138\frac{2}{\pi}\arcsin\left(\begin{array}{l}\sin\left(\frac{\pi\cdot 0.10}{2}\right)^{1/10}\cdot\sin\left(\frac{\pi\cdot 0.09}{2}\right)^{1/10}\cdot\sin\left(\frac{\pi\cdot 0.13}{2}\right)^{1/10}\cdot\ldots\cdot\\ \sin\left(\frac{\pi\cdot 0.13}{2}\right)^{1/10}\cdot\sin\left(\frac{\pi\cdot 0.12}{2}\right)^{1/10}\cdot\sin\left(\frac{\pi\cdot 0.10}{2}\right)^{1/10}\end{array}\right)\right)^{10} = 1327\cdot 10^{8}$$

Calculation of left and upper values of $\partial_{C1}^{1} = \left(\partial_{C1}{}^{(l)1},\partial_{C1}{}^{(m)1},\partial_{C1}{}^{(u)1}\right)$ are calculated in a similar way.

By applying the expression (10), obtained vectors were merged and the final fuzzy vector of dimension weights was obtained. These final values are presented in Table 5.

Table 5
Final fuzzy vector of dimension weights

Criteria	Fuzzy value	Crips values
C1	(0.090,0.103,0.118)	0.118
C2	(0.091,0.104,0.119)	0.119
C3	(0.094,0.106,0.121)	0.121
C4	(0.062,0.083,0.101)	0.101
C5	(0.051,0.073,0.092)	0.092
C6	(0.089,0.101,0.117)	0.117
C7	(0.091,0.103,0.119)	0.119
C8	(0.101,0.112,0.125)	0.125
C9	(0.100,0.111,0.125)	0.125
C10	(0.087,0.100,0.116)	0.116

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Fuzzy values of weight coefficients of dimensions are shown in Figure 3.

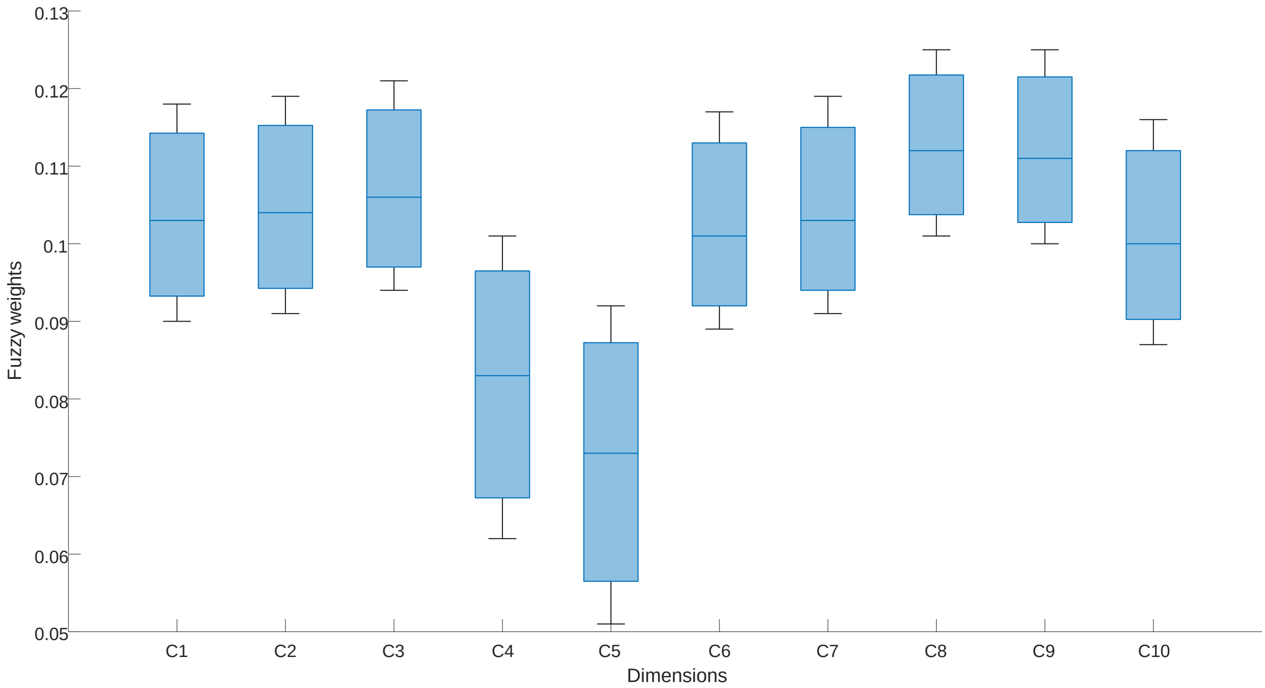

Fig. 3. Fuzzy values of weight coefficients of dimensions

Based on the fuzzy values presented in Figure 3, the conclusion that dimensions C8, C9 and C3 have the greatest significance in the ranking can be drawn, while dimensions C4 and C5 have the least significance. For the evaluation of the states (alternatives), defuzzified values from Table 5 were used. For defuzzification, the expression for mathematical expectation within the β distribution was used.

b) Application of the Schweizer-Sklar weighted evaluation model for ranking countries

Steps 1 and 2: Data for this research is used from OXFORD database. Data was found for 193 countries where the assigned country codes are A1 to A185. The data for the evaluated countries in relation to the defined dimensions are shown in Table A1 (Appendix) together with the initial decision matrix of dimensions 185x10. Standardization of matrix elements $\Omega = \left[\varphi_{ij}\right]_{193\times10}$ was not performed since all data in the decision matrix are in the same criterion interval and all criterion values belong to the group of *max* criteria.

Step 3: Two Schweizer-Sklar (SS) nonlinear functions (12) and (13) are defined for each alternative. The input parameters for the calculation of SS non-linear functions of alternatives are weighting coefficients of dimensions (Table 5) and criteria values from Table A1. By applying the expressions (12) and (13), the Schweizer-Sklar functions of alternatives are defined, which are shown in Figure 4.

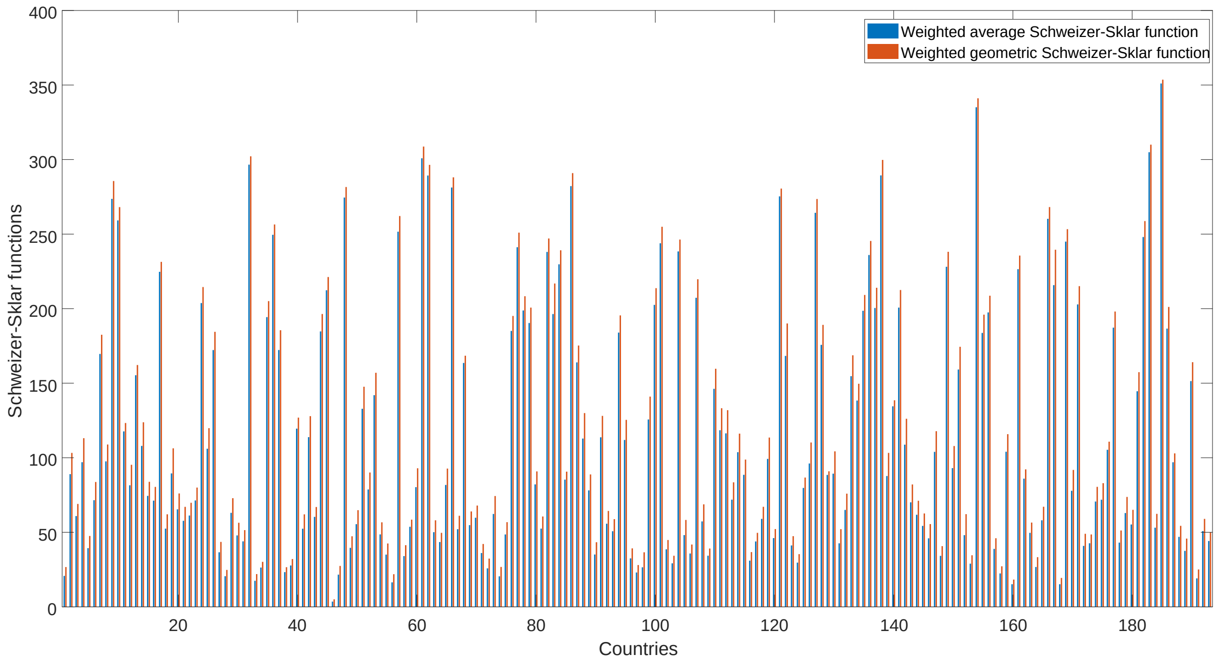

Fig. 4. Schweizer-Sklar functions of alternatives

For the calculation of the values shown in Figure 4, the stabilization parameter of the SS functions $\ell = 2$ was used. The results from Figure 4 show a high correlation between the results of the SS functions $\mho_i^{(1)\ell}$ and $\mho_i^{(2)\ell}$, which confirms statistical correlation SC=0.998 obtained by the application of the Spearman coefficient (SC).

Step 4: Final assessments of alternatives and their ranking are defined using expression (14) and presented in Figure 5.

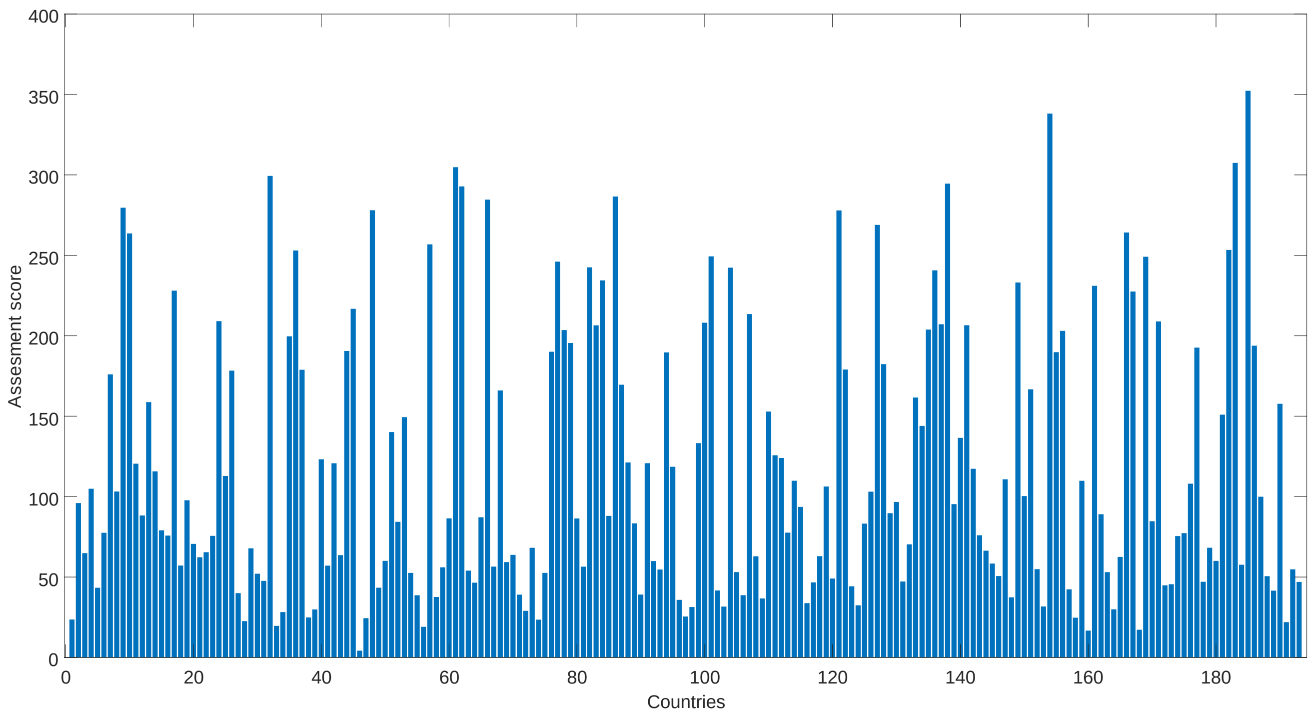

Fig. 5. Final evaluations of alternatives

Final estimates of alternatives (Figure 5) are defined for parameter values $\ell = 2$ and ρ=0.5. Adopted value of the parameter ρ is ½, and in this way the equal influence of SS functions $\mho_i^{(1)\ell}$ and $\mho_i^{(2)\ell}$ in the final rank is simulated. Based on the defined estimates from Figure 5, the ranking of the considered countries was carried out. Countries with a higher assessment score are assigned a better rank and these results are shown in Table A2 (Appendix). The ranks from Table A2 were compared with the ranks presented on the Oxford database and these comparisons are shown in Figure 6.

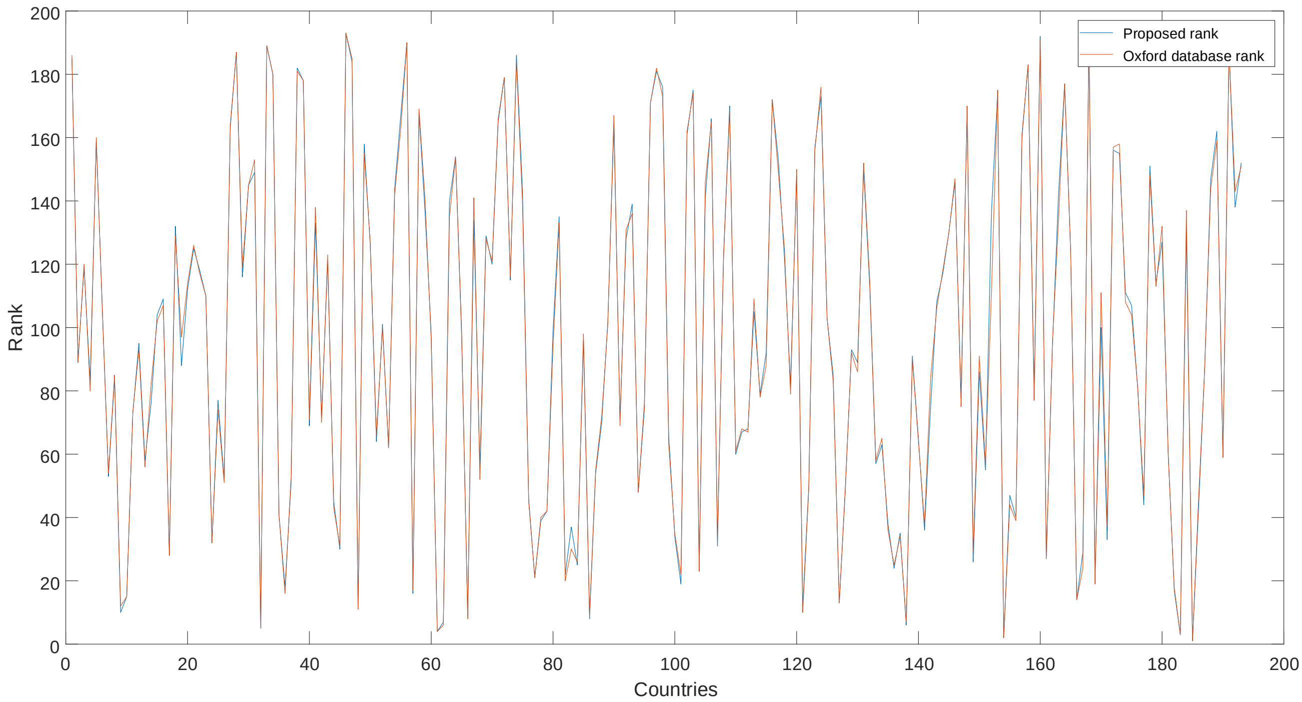

Fig. 6. Comparison of proposed country rankings and rankings presented in the Oxford database

The statistical correlation shows a high correlation between the two groups of ranks, which is also confirmed by the graphic representation in Figure 6.

The nonlinear aggregation functions utilized in this paper can better capture subtle nuances and interdependencies among the data outperforming the conventional averaging method used in the Oxford database. While the average function provides a simplistic overview, nonlinear functions offer a more nuanced understanding by accounting for variations and dependencies within the data. This research enables a more accurate assessment of government AI readiness, considering the multidimensional nature of the criteria involved.

In the following part, a sensitivity analysis of the model was performed to further verify the presented results. Since the initial results (Figure 5) are defined for parameter values $\ell = 2$ and ρ=0.5, the question arises whether the results are going to differ if other values ℓ and ρ from the interval $\ell \in (-\infty, 0) \cup (0, +\infty)$ and $\rho \in [0,1]$ are applied. Sensitivity analysis is presented through two experiments. In the first experiment, changing of the parameter ℓ value was performed in the interval $1 \le \ell \le 50$. A total of 50 scenarios were generated and within each scenario a new set of assessment score alternatives was generated. Figure 7 shows the changes of the assessment score ($\mathbb{R}_i$) alternative for the parameter change $1 \le \ell \le 50$.

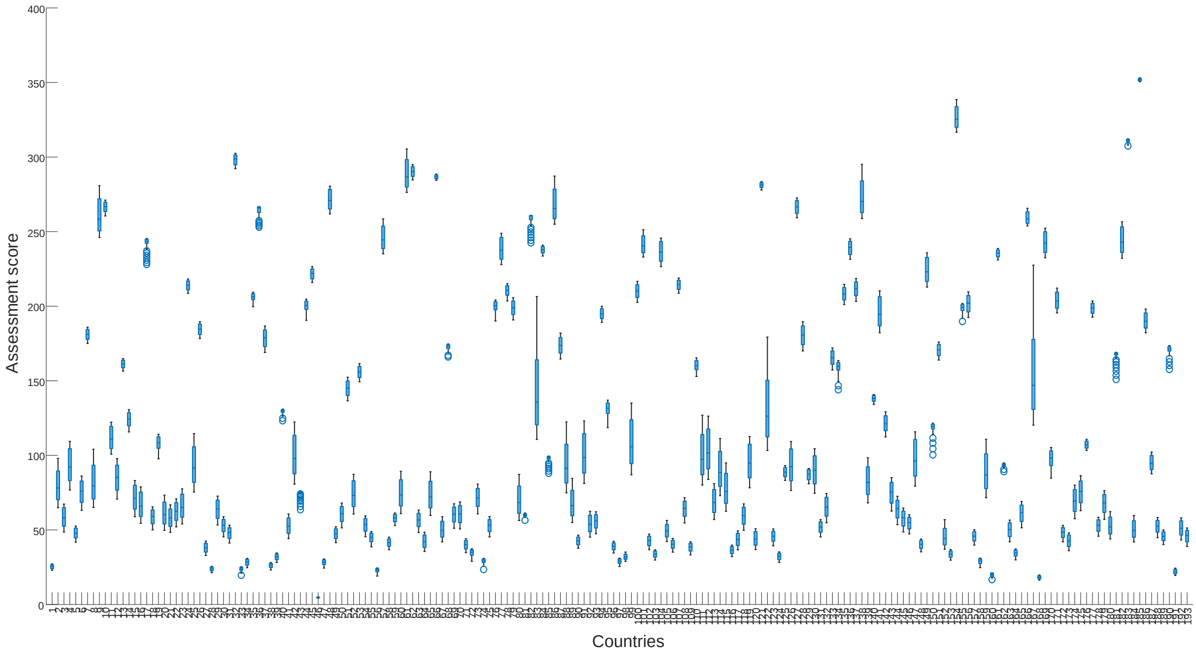

Fig. 7. Changes in assessment score alternatives ($\mathbb{R}_i$) for parameter $1 \le \ell \le 50$

The results from Figure 7 show that the SSWE model is sensitive to the change of the parameter ℓ. However, these changes are not significant for most of the alternatives. The first-ranked countries (alternatives) showed especially stability. The stability of the results is confirmed by the correlation coefficient, which ranges between 0.98 and 1.00 (Figure 8).

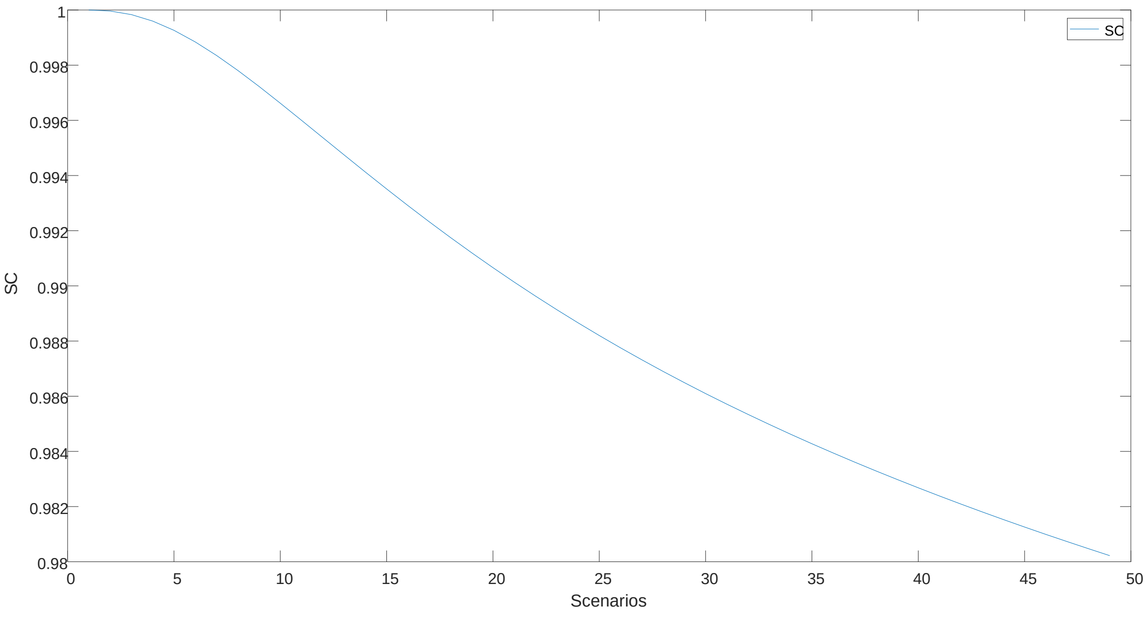

Fig. 8. Statistical correlation for different values of parameter $1 \le \ell \le 50$

For the second experiment, the value of the parameter ℓ remained constant, and the value of the parameter ρ changed in the interval $0 \le \rho \le 1$ and a total of 50 scenarios were generated. In the first scenario, the value ρ=0.0 was assigned, while in each subsequent scenario, the value was increased by 0.02. The influence of the parameter ρ on the assessment score of the alternatives for the 50 scenarios is shown in Figure 9.

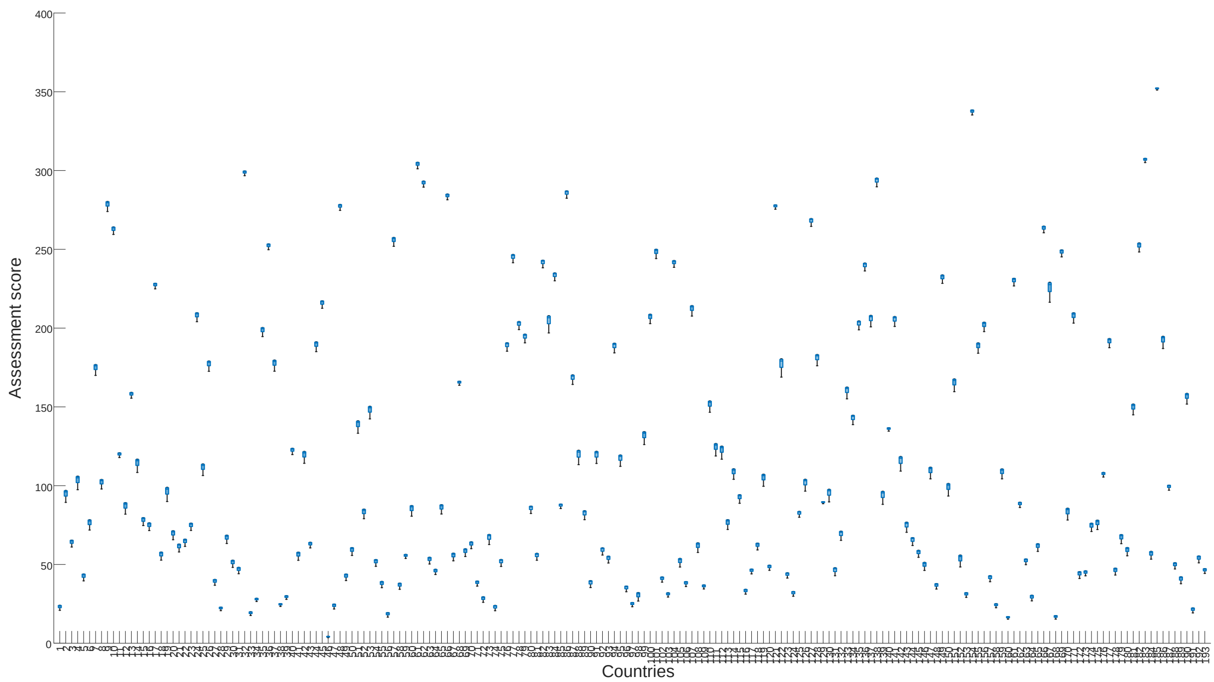

Fig. 9. Assessment score of the alternatives ($\mathbb{R}_i$) depending on the parameter ρ, $0 \le \rho \le 1$

The results from Figure 9 show that the parameter ρ affects minimal changes $\mathbb{R}_i$. Such results are expected since there is a high correlation between the values of $\mho_i^{(1)\ell}$ and $\mho_i^{(1)\ell}$, which is shown in Figure 4. The presented analysis in both experiments confirms that the initial values of $\mathbb{R}_i$ (Figure 5) are not subject to influence of changes in the stabilization parameters of the multi-criteria framework. Based on this, the conclusion can be made that the presented ranking from Table A2 is credible.

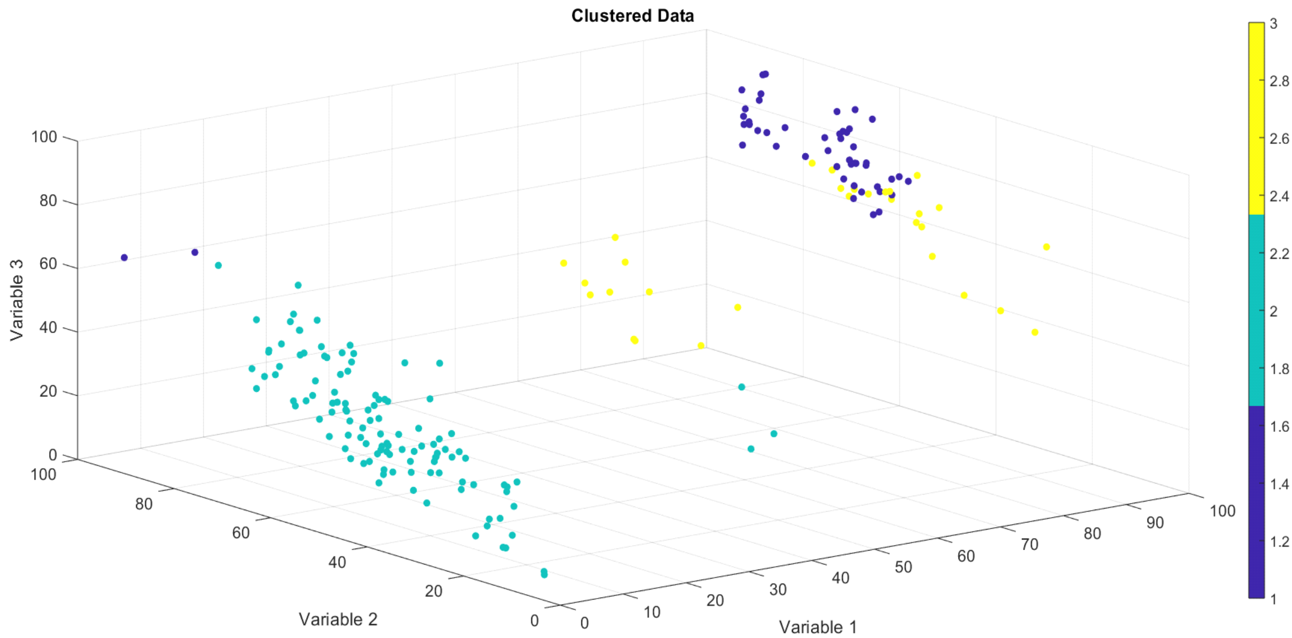

Fig. 10. Countries grouped into three clusters

Clustering approach can help categorization of the countries based on their AI readiness more effectively, so the countries analyzed in this research are clustered into three distinct groups (Figure 10). One can notice that the countries with the higher ranks are clustered into one cluster, and the countries with the lowest ranks are clustered together. Countries with the ranks in between are grouped together in one cluster. This analysis can, in a way, validate the results obtained in this research using the proposed methodology.

4. Conclusion

In this article, we have studied Oxford's AI Readiness Index, a key information source that evaluates countries' preparedness to adopt and implement artificial intelligence across various sectors [23]. This analysis reveals that the parameters exhibit the same level of significance throughout the report, which we consider to be the main shortcoming.

The second limitation arises from the first, where the AI Index is calculated as the arithmetic mean of the criterion values. This method of averaging assumes that all criteria have equal importance and influence on the overall score, which may not accurately reflect the complex nature of AI readiness. By treating all parameters as equally significant, the index may overlook the varying impacts that different criteria can have on a country's ability to adopt and implement artificial intelligence. This approach could lead to an oversimplified assessment and potentially obscure critical areas that require more attention or resources.

We have proposed a methodological framework designed to overcome these shortcomings. By weighting the criteria based on their actual impact, our approach ensures that the index better reflects the complexities and diverse factors influencing AI readiness. Instead of arithmetic averaging, we utilized a non-linear model incorporating both geometric and arithmetic functions. The proposed methodology not only overcomes the stated disadvantages of the analysis performed in the Oxford study but enables to notice and capture the differences and the interdependencies among the data that are not obvious. Using the nonlinear aggregation functions for the analysis enables a more accurate assessment of government AI readiness, and this was the goal of the research done and presented in this paper. This approach allows for a more accurate representation of the varying significance of different parameters and provides a more nuanced and comprehensive assessment of a country's AI readiness.

Finally, the countries were clustered into three distinct groups. This clustering approach helps to categorize countries based on their AI readiness more effectively, highlighting the variations and similarities within each cluster. By grouping countries with similar levels of AI preparedness, we can better understand regional trends and identify targeted strategies for improvement in each group.

Another future direction of research would be the application of the Data Envelopment Analysis (DEA) method to evaluate the efficiency of countries. DEA can provide a more detailed and objective assessment of how effectively countries utilize their resources in the adoption and implementation of artificial intelligence, offering insights into best practices and areas needing improvement.

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Appendix

Table A1
Initial decision matrix

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Afghanistan (A1)	0.00	8.96	34.60	12.40	6.67	51.61	6.84	39.56	25.52	19.26
Albania (A2)	0.00	54.06	61.65	54.40	17.95	35.84	42.13	24.89	67.44	73.53
Algeria (A3)	0.00	38.55	45.10	36.74	11.29	42.41	37.99	27.82	49.59	64.51
Andorra (A4)	0.00	55.28	38.85	61.14	37.88	47.76	19.49	41.33	65.51	87.87
Angola (A5)	0.00	36.96	33.03	20.21	10.43	23.16	21.93	33.97	33.27	71.86
Antigua and Barbuda (A6)	0.00	47.16	41.91	44.24	25.66	27.00	30.03	31.90	56.99	83.13
Argentina (A7)	100.00	69.38	63.78	48.08	25.46	36.81	43.54	55.06	75.75	71.96
Armenia (A8)	0.00	50.37	66.48	57.13	23.72	36.75	40.27	52.37	54.46	68.88
Australia (A9)	100.00	92.33	76.20	64.84	35.46	57.81	64.44	71.33	87.91	98.02
Austria (A10)	100.00	69.54	77.05	64.19	45.57	63.19	60.52	65.37	85.06	98.50
Azerbaijan (A11)	50.00	51.70	66.55	55.20	14.27	42.82	35.23	55.04	49.37	69.05
Bahamas (A12)	0.00	45.55	51.65	40.77	26.08	27.00	41.20	35.89	56.09	89.53
Bahrain (A13)	50.00	53.77	73.38	54.71	30.03	42.64	45.06	57.41	73.49	82.66
Bangladesh (A14)	100.00	29.53	63.92	38.38	11.35	41.81	25.05	41.63	58.03	62.66
Barbados (A15)	0.00	39.82	43.10	51.20	26.86	29.06	42.69	34.58	54.76	72.67
Belarus (A16)	0.00	38.27	48.45	37.08	21.88	35.11	39.84	33.73	62.31	67.12
Belgium (A17)	100.00	69.41	64.87	58.10	46.03	64.59	57.44	61.92	70.67	85.64
Belize (A18)	0.00	22.42	36.26	35.10	21.75	28.27	37.25	23.68	52.77	74.13
Benin (A19)	100.00	53.21	50.10	42.21	8.86	34.06	30.46	18.03	31.69	65.10
Bhutan (A20)	0.00	42.79	59.47	44.98	15.33	28.41	29.18	25.78	61.51	61.28
Bolivia (A21)	0.00	37.59	41.46	34.82	16.34	29.51	34.12	24.11	61.83	65.95
Bosnia and Herzegovina (A22)	0.00	43.93	33.30	34.46	19.13	33.74	42.17	28.35	50.78	70.47
Botswana (A23)	0.00	54.89	37.47	46.92	17.19	37.95	32.46	45.59	45.59	66.32
Brazil (A24)	100.00	69.28	72.03	48.47	34.01	49.71	51.52	62.37	71.01	87.33
Brunei Darussalam (A25)	0.00	32.21	61.41	64.64	30.31	41.44	53.82	46.08	61.95	80.59
Bulgaria (A26)	100.00	55.92	62.25	46.01	26.54	47.17	40.79	61.19	75.99	78.00
Burkina Faso (A27)	0.00	43.60	37.93	26.62	7.56	30.28	16.75	14.33	43.88	53.56
Burundi (A28)	0.00	10.99	32.12	30.67	4.66	30.09	13.89	13.33	25.91	44.64
Cabo Verde (A29)	0.00	48.35	55.67	42.71	20.45	30.44	30.81	23.53	40.43	70.99
Cambodia (A30)	0.00	35.74	47.68	28.30	12.95	32.54	22.10	24.96	41.13	69.41
Cameroon (A31)	0.00	40.93	36.96	45.75	10.57	32.62	23.02	20.93	28.74	63.84
Canada (A32)	100.00	91.97	78.70	70.54	52.78	74.14	67.27	72.79	78.36	92.37
Central African Republic (A33)	0.00	9.93	17.43	26.69	5.83	28.73	18.37	12.73	19.10	52.34
Chad (A34)	0.00	37.57	21.23	25.62	6.80	26.49	16.66	30.13	22.91	44.64
Chile (A35)	100.00	71.57	66.02	60.66	34.72	38.56	49.44	58.97	74.71	77.46
China (A36)	100.00	70.39	82.29	56.60	57.25	70.08	54.95	76.89	60.24	87.13
Colombia (A37)	100.00	73.98	67.73	58.20	21.29	38.27	46.27	49.83	62.65	77.42
Comoros (A38)	0.00	12.46	21.58	29.43	12.37	30.02	19.58	18.97	31.46	43.57
Congo (A39)	0.00	30.88	27.61	31.50	12.29	31.32	15.44	16.71	23.38	51.10
Costa Rica (A40)	50.00	60.05	56.17	47.42	27.94	37.28	34.39	33.77	70.21	78.30
Côte D'Ivoire (A41)	0.00	61.28	43.80	32.25	10.88	29.32	20.66	24.43	45.05	61.70
Croatia (A42)	0.00	62.95	60.88	45.18	26.43	43.57	48.04	55.80	57.89	85.59

Table A1
Initial decision matrix (continued)

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Cuba (A43)	50.00	20.87	26.74	43.69	21.54	35.67	24.05	20.79	40.12	71.54
Cyprus (A44)	100.00	64.24	59.01	54.32	32.47	51.42	42.22	57.72	64.58	90.98
Czechia (A45)	100.00	64.59	66.76	57.63	35.54	53.42	54.20	66.05	79.84	80.74
Democratic People's Republic of Korea (A46)	0.00	3.29	8.05	20.80	0.00	19.52	23.29	1.69	8.88	0.00
Congo (A47)	0.00	30.42	22.16	20.87	2.47	31.31	15.39	9.33	21.44	58.20
Denmark (A48)	100.00	92.24	73.69	70.49	43.16	69.18	67.59	69.35	75.72	87.89
Djibouti (A49)	0.00	11.59	32.47	33.65	21.41	34.40	32.69	21.28	32.12	69.35
Dominica (A50)	0.00	35.36	31.15	45.36	21.36	28.27	23.91	31.13	50.99	73.81
Dominican Republic (A51)	100.00	56.53	59.23	56.52	14.79	28.88	32.35	47.71	56.72	71.75
Ecuador (A52)	0.00	43.54	61.74	39.24	19.77	34.89	28.79	45.40	56.83	73.48
Egypt (A53)	100.00	70.46	61.12	41.20	19.21	49.87	51.25	29.24	43.80	76.28
El Salvador (A54)	0.00	29.34	42.13	23.33	18.76	31.20	28.96	25.34	49.28	68.55
Equatorial Guinea (A55)	0.00	27.65	19.44	32.68	17.97	34.12	26.48	18.39	25.21	70.37
Eritrea (A56)	0.00	3.35	9.03	26.56	7.44	30.03	21.01	12.74	20.94	55.26
Estonia (A57)	100.00	70.94	80.95	70.26	35.38	70.79	51.40	61.94	86.20	90.47
Eswatini (A58)	0.00	25.85	34.60	34.75	13.30	30.49	10.85	18.22	33.69	65.53
Ethiopia (A59)	50.00	27.55	38.37	33.25	6.06	35.40	19.60	34.86	26.29	59.19
Fiji (A60)	0.00	24.98	64.60	61.54	23.29	48.72	33.37	31.83	51.83	71.75
Finland (A61)	100.00	92.68	84.34	76.36	44.04	73.43	63.61	73.50	81.79	94.89
France (A62)	100.00	88.72	84.92	62.46	51.04	65.88	64.28	78.37	79.00	94.04
Gabon (A63)	0.00	35.96	31.79	32.74	17.68	36.72	28.61	27.94	38.56	72.92
Gambia (A64)	0.00	43.42	26.14	30.97	5.05	29.93	27.43	43.20	37.30	53.94
Georgia (A65)	0.00	60.37	52.48	55.00	20.15	33.93	36.92	31.69	53.69	69.14
Germany (A66)	100.00	91.20	74.99	56.94	53.96	72.97	62.92	78.60	75.04	91.50
Ghana (A67)	0.00	58.18	48.36	32.09	8.32	42.41	18.95	25.30	37.40	56.91
Greece (A68)	50.00	64.44	60.41	48.83	36.42	46.93	61.75	52.55	72.95	83.18
Grenada (A69)	0.00	26.24	38.53	46.29	21.70	29.57	25.16	30.61	47.53	73.81
Guatemala (A70)	0.00	39.39	40.02	38.79	16.22	31.01	27.60	44.42	44.73	69.18
Guinea (A71)	0.00	35.63	33.87	37.11	7.29	33.45	19.21	20.67	28.06	58.36
Guinea Bissau (A72)	0.00	15.13	17.97	28.16	9.09	28.73	18.61	18.01	31.99	64.66
Guyana (A73)	0.00	44.26	40.70	37.50	17.74	29.06	34.76	29.23	41.17	87.33
Haiti (A74)	0.00	11.28	12.82	11.60	11.21	30.78	26.68	14.06	25.99	62.25
Honduras (A75)	0.00	36.52	25.83	40.65	17.86	40.97	31.59	15.77	42.50	67.75
Hungary (A76)	100.00	61.58	65.59	52.67	32.44	46.87	47.29	58.69	70.89	79.89
Iceland (A77)	100.00	66.88	73.20	64.75	34.34	71.25	52.75	65.55	83.71	90.13
India (A78)	100.00	79.50	69.45	51.76	33.35	62.92	51.90	51.72	61.75	76.04
Indonesia (A79)	100.00	70.38	72.50	62.09	27.87	52.02	50.56	51.95	59.43	78.77
Iran (A80)	0.00	44.01	53.40	28.85	23.65	47.05	45.62	49.37	54.38	63.89
Iraq (A81)	50.00	25.62	19.80	20.00	17.02	55.60	14.58	17.34	47.41	62.04
Ireland (A82)	100.00	69.53	60.81	55.71	53.13	56.56	61.18	65.85	77.64	99.50
Israel (A83)	0.00	75.71	76.21	62.79	49.70	89.81	59.37	67.76	73.02	88.50
Italy (A84)	100.00	85.55	69.89	50.99	40.34	52.84	59.74	67.30	74.58	84.01
Jamaica (A85)	50.00	49.63	42.81	49.59	22.46	31.75	31.03	27.46	42.34	72.78
Japan (A86)	100.00	89.40	73.06	68.59	38.40	68.33	63.83	79.91	90.99	85.93

Table A1
Initial decision matrix (continued)

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Jordan (A87)	100.00	61.67	64.17	44.41	21.40	51.57	48.89	48.15	63.42	75.51
Kazakhstan (A88)	0.00	54.31	75.68	64.26	16.73	37.80	38.39	50.80	74.95	72.65
Kenya (A89)	0.00	53.98	61.65	44.47	13.20	48.80	24.84	46.64	44.44	63.67
Kiribati (A90)	0.00	26.09	33.19	43.68	10.28	30.60	9.05	21.19	31.16	67.15
Kuwait (A91)	0.00	53.09	54.92	44.57	33.59	38.14	50.00	55.30	71.12	86.13
Kyrgyzstan (A92)	0.00	44.53	43.00	46.60	12.94	26.87	28.78	23.33	53.29	61.09
Lao People's Democratic Republic (A93)	0.00	33.47	38.34	41.76	18.02	34.61	24.79	22.52	42.22	70.14
Latvia (A94)	100.00	67.86	63.62	56.80	28.92	42.42	44.36	59.43	69.24	82.13
Lebanon (A95)	100.00	39.05	39.50	23.68	15.90	44.93	50.16	45.09	53.94	66.90
Lesotho (A96)	0.00	39.54	27.04	35.08	10.26	32.17	18.95	14.24	22.41	61.61
Liberia (A97)	0.00	17.94	29.65	29.53	7.44	32.21	20.06	13.17	15.61	53.87
Libya (A98)	0.00	11.84	12.75	15.50	18.16	53.00	13.14	5.34	49.98	58.11
Liechtenstein (A99)	0.00	59.03	45.40	61.07	40.63	51.89	50.83	43.70	74.66	87.87
Lithuania (A100)	100.00	69.03	72.09	60.11	30.88	55.48	44.75	61.47	61.73	89.77
Luxembourg (A101)	100.00	72.96	86.57	72.91	36.15	56.67	46.70	72.08	74.79	88.94
Madagascar (A102)	0.00	40.23	32.34	27.46	7.51	28.84	21.48	34.97	27.65	60.80
Malawi (A103)	0.00	34.69	25.94	27.37	9.31	32.77	19.39	13.46	28.69	54.18
Malaysia (A104)	100.00	72.17	78.46	69.31	34.32	61.53	66.55	59.03	74.22	82.77
Maldives (A105)	0.00	26.99	52.47	47.40	24.39	16.82	21.17	52.82	61.47	13.59
Mali (A106)	0.00	35.91	34.44	28.48	10.39	27.95	19.00	19.32	37.13	59.11
Malta (A107)	100.00	83.73	76.58	62.64	32.89	46.24	43.54	61.35	63.60	82.97
Marshall Islands (A108)	0.00	23.82	38.04	59.14	28.35	45.69	22.74	22.43	33.84	77.53
Mauritania (A109)	0.00	36.63	24.30	27.92	13.21	29.03	24.57	21.67	33.04	55.70
Mauritius (A110)	100.00	66.46	63.64	49.19	22.92	42.93	26.05	49.79	59.95	68.32
Mexico (A111)	0.00	55.26	66.15	50.92	27.19	41.08	50.38	51.25	72.22	81.99
Monaco (A112)	0.00	62.95	39.23	64.81	38.33	47.76	33.80	61.29	60.23	87.87
Mongolia (A113)	0.00	45.20	58.61	39.50	18.67	31.31	33.15	26.91	62.06	71.31
Montenegro (A114)	0.00	53.89	53.96	52.98	26.49	36.96	43.15	53.65	64.80	78.67
Morocco (A115)	0.00	63.88	45.06	41.22	20.65	43.71	42.70	50.95	49.05	70.37
Mozambique (A116)	0.00	31.05	30.97	25.59	7.09	30.11	16.26	33.21	19.52	58.72
Myanmar (A117)	0.00	25.08	30.08	31.34	11.46	36.40	36.06	27.31	48.17	53.93
Namibia (A118)	0.00	44.45	41.02	42.60	16.72	39.22	28.96	25.89	43.97	67.55
Nauru (A119)	0.00	52.67	40.11	59.99	35.76	44.47	35.39	38.87	62.41	89.23
Nepal (A120)	0.00	46.20	42.62	35.33	9.33	34.36	28.93	22.66	35.97	52.55
Netherlands (A121)	100.00	72.41	79.80	63.37	51.41	69.25	65.22	80.29	83.29	84.09
New Zealand (A122)	0.00	70.85	74.34	62.21	29.61	52.04	59.49	64.49	88.85	91.64
Nicaragua (A123)	0.00	32.76	33.93	31.44	15.00	32.46	31.52	17.34	35.50	62.52
Niger (A124)	0.00	37.87	30.21	33.82	5.13	30.41	12.09	13.87	33.53	50.93
Nigeria (A125)	50.00	49.91	43.13	36.71	11.20	39.48	22.79	42.67	32.05	75.92
North Macedonia (A126)	0.00	60.42	51.88	45.88	22.75	35.07	43.86	48.32	50.64	89.37
Norway (A127)	100.00	92.54	67.06	67.48	44.21	61.48	59.21	68.95	84.47	90.78
Oman (A128)	100.00	56.33	74.11	46.96	21.20	41.25	50.67	56.48	71.39	81.40
Pakistan (A129)	50.00	35.98	47.51	38.52	16.77	45.29	40.15	42.12	48.91	57.56
Panama (A130)	0.00	49.50	58.56	45.24	25.14	33.39	41.25	31.05	59.03	90.38

Table A1
Initial decision matrix (continued)

Country	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Papua New Guinea (A131)	0.00	22.51	43.61	37.14	13.10	32.03	22.55	18.99	34.61	74.92
Paraguay (A132)	0.00	50.74	47.24	51.82	13.94	28.56	30.47	25.12	48.75	72.51
Peru (A133)	100.00	72.17	62.79	45.65	19.87	36.05	40.94	47.94	64.38	74.21
Philippines (A134)	100.00	55.40	58.38	47.95	24.72	46.99	31.42	49.52	67.14	51.71
Poland (A135)	100.00	64.05	65.47	49.65	31.32	49.31	59.89	61.95	66.10	89.92
Portugal (A136)	100.00	87.50	73.30	61.10	37.36	54.03	61.46	60.72	77.89	81.65
Qatar (A137)	100.00	58.18	71.42	48.95	30.99	48.92	53.02	61.18	69.60	99.65
Republic of Korea (A138)	100.00	87.78	91.57	70.85	38.46	59.04	65.60	79.35	95.65	80.06
Republic of Moldova (A139)	0.00	55.92	63.49	51.34	19.33	29.16	36.14	27.98	66.17	79.91
Romania (A140)	50.00	58.94	52.94	43.82	29.76	39.32	48.62	58.57	67.55	72.79
Russian Federation (A141)	100.00	70.01	71.38	55.13	21.51	50.81	57.81	56.59	73.75	83.45
Rwanda (A142)	100.00	62.91	65.91	42.45	8.75	48.31	26.54	21.27	42.05	58.11
Saint Kitts and Nevis (A143)	0.00	47.85	31.10	47.90	27.26	27.00	30.02	36.53	54.03	83.13
Saint Lucia (A144)	0.00	47.31	39.00	35.17	21.60	28.27	33.98	27.28	53.11	72.83
Saint Vincent and the Grenadines (A145)	0.00	37.24	36.73	48.16	21.01	28.27	23.91	26.89	46.57	68.95
Samoa (A146)	0.00	28.71	36.84	44.54	20.77	30.60	17.19	19.24	39.70	74.88
San Marino (A147)	0.00	49.89	35.60	62.94	38.33	47.76	46.53	39.92	61.02	87.87
Sao Tome and Principe (A148)	0.00	40.73	25.87	35.03	8.75	30.02	21.10	18.81	25.22	61.63
Saudi Arabia (A149)	100.00	65.63	87.52	61.68	30.16	49.95	68.65	71.17	75.28	72.06
Senegal (A150)	100.00	46.61	40.88	51.11	17.50	43.25	22.26	25.54	33.52	62.23
Serbia (A151)	100.00	78.12	67.99	51.03	22.02	42.83	46.55	32.78	56.04	77.09
Seychelles (A152)	0.00	36.37	48.02	61.39	28.94	5.21	24.36	60.66	56.08	0.00
Sierra Leone (A153)	0.00	20.26	29.43	37.73	4.40	30.13	19.77	16.34	31.29	55.92
Singapore (A154)	100.00	88.34	91.08	82.17	54.77	75.61	68.20	77.73	91.08	99.15
Slovakia (A155)	100.00	65.43	57.61	47.78	32.80	45.50	43.51	58.96	77.78	84.95
Slovenia (A156)	100.00	61.63	70.51	54.85	27.20	52.33	46.07	65.17	75.34	82.37
Solomon Islands (A157)	0.00	19.62	37.19	38.08	15.34	31.82	23.06	20.10	34.31	66.00
Somalia (A158)	0.00	20.51	26.97	24.56	7.44	30.03	20.57	13.21	17.26	55.26
South Africa (A159)	0.00	57.77	55.64	37.88	25.51	48.18	46.97	54.42	60.19	76.78
South Sudan (A160)	0.00	17.53	13.75	22.16	7.84	27.08	18.47	11.07	15.13	44.64
Spain (A161)	100.00	66.94	72.46	52.02	39.84	52.75	60.30	68.46	80.08	87.28
Sri Lanka (A162)	50.00	28.37	63.02	26.80	25.83	39.25	33.98	28.77	56.86	66.17
State of Palestine (A163)	0.00	25.72	34.88	24.00	17.52	49.75	28.44	44.67	34.35	60.08
Sudan (A164)	0.00	14.69	20.32	26.69	5.27	36.19	28.61	15.88	25.69	62.70
Suriname (A165)	0.00	44.56	28.77	39.76	19.21	29.71	31.63	30.10	52.45	71.75
Sweden (A166)	100.00	71.72	80.91	46.17	44.70	75.73	67.69	77.93	75.49	87.35
Switzerland (A167)	0.00	90.35	67.86	71.09	47.61	78.47	62.80	76.19	84.66	95.41
Syrian Arab Republic (A168)	0.00	9.59	26.67	18.44	6.95	42.09	35.37	11.94	24.35	1.37
Taiwan (A169)	100.00	60.07	71.99	69.27	35.76	62.17	65.81	74.48	78.85	89.20
Tajikistan (A170)	100.00	31.94	36.00	44.76	5.72	32.59	22.91	40.78	42.52	45.00
Thailand (A171)	100.00	75.50	77.20	56.16	27.67	59.16	37.18	62.04	77.30	72.31
Timor-Leste (A172)	0.00	20.93	38.64	37.41	10.82	30.22	22.91	23.41	38.26	69.57
Togo (A173)	0.00	41.36	33.75	43.86	8.80	29.94	21.13	36.76	27.32	53.99
Tonga (A174)	0.00	37.58	47.41	56.47	26.72	45.69	28.14	26.95	45.03	72.44

Table A1
Initial decision matrix (continued)

Trinidad and Tobago (A175)	0.00	46.76	45.51	38.52	22.96	29.34	44.45	32.82	44.53	82.79
Tunisia (A176)	50.00	54.89	55.67	32.70	22.40	47.04	45.97	26.25	60.05	68.03
Türkiye (A177)	100.00	74.82	73.43	52.05	29.87	47.49	49.59	51.15	67.23	74.02
Turkmenistan (A178)	0.00	26.86	29.34	24.01	22.29	34.63	34.62	23.98	29.74	75.09
Tuvalu (A179)	0.00	25.48	36.08	55.54	28.19	45.69	28.14	25.17	44.54	77.53
Uganda (A180)	0.00	48.84	55.89	47.50	5.51	36.79	20.58	25.62	37.15	61.13
Ukraine (A181)	100.00	51.79	66.07	57.88	31.77	40.03	36.73	31.62	67.03	65.59
United Arab Emirates (A182)	100.00	69.21	88.89	55.18	34.76	62.86	72.38	67.50	65.93	95.41
United Kingdom (A183)	100.00	91.11	74.18	64.72	59.99	76.44	69.95	75.04	84.26	93.95
Tanzania (A184)	0.00	43.24	56.62	42.00	4.47	39.91	17.75	39.11	28.77	59.37
United States of America (A185)	100.00	89.08	82.74	72.36	84.77	89.10	69.20	88.34	80.76	92.86
Uruguay (A186)	100.00	72.99	69.25	55.36	24.82	33.61	47.53	56.65	77.59	81.74
Uzbekistan (A187)	50.00	46.70	59.49	40.10	14.36	34.30	25.75	47.83	59.65	64.99
Vanuatu (A188)	0.00	25.06	40.76	38.94	20.34	30.60	24.73	25.58	39.17	68.22
Venezuela (A189)	0.00	11.09	30.59	26.99	14.55	32.79	31.09	22.15	40.85	69.87
Viet Nam (A190)	100.00	62.03	66.46	47.67	28.38	46.38	38.70	33.72	67.49	68.53
Yemen (A191)	0.00	30.27	34.47	13.64	6.95	47.23	38.63	5.57	20.45	1.37
Zambia (A192)	0.00	51.30	42.41	35.59	8.04	32.21	20.74	39.05	31.38	62.84
Zimbabwe (A193)	0.00	37.18	31.74	27.42	12.03	32.50	25.68	38.91	35.97	59.02

Table A2
Rank and assessment score

Alternative	Assessment score	Rank	Alternative	Assessment score	Rank	Alternative	Assessment score	Rank
A1	23.641	185	A66	284.665	9	A130	96.682	89
A2	96.002	90	A67	56.508	134	A131	47.237	150
A3	64.887	119	A68	166.019	56	A132	70.368	113
A4	104.919	83	A69	59.308	129	A133	161.646	57
A5	43.371	159	A70	63.804	120	A134	143.977	63
A6	77.534	106	A71	39.076	165	A135	203.872	38
A7	176.031	53	A72	29.005	179	A136	240.691	24
A8	103.177	84	A73	68.191	115	A137	207.175	35
A9	279.614	10	A74	23.523	186	A138	294.565	6
A10	263.636	15	A75	52.592	143	A139	95.346	91
A11	120.502	73	A76	190.070	46	A140	136.532	65
A12	88.286	95	A77	246.094	21	A141	206.581	36
A13	158.760	58	A78	203.559	39	A142	117.315	75
A14	115.741	76	A79	195.515	42	A143	75.995	108
A15	79.084	104	A80	86.447	99	A144	66.392	117
A16	75.783	109	A81	56.480	135	A145	58.412	130
A17	228.059	28	A82	242.539	22	A146	50.626	146
A18	57.190	132	A83	206.514	37	A147	110.796	78
A19	97.755	88	A84	234.443	25	A148	37.405	169
A20	70.642	112	A85	88.010	96	A149	233.121	26
A21	62.297	125	A86	286.560	8	A150	100.348	86

Table A2
Rank and assessment score (continued)

Alternative	Assessment score	Rank	Alternative	Assessment score	Rank	Alternative	Assessment score	Rank
A22	65.464	118	A87	169.575	54	A151	166.735	55
A23	75.632	110	A88	121.280	70	A152	54.913	137
A24	209.090	32	A89	83.385	102	A153	31.725	174
A25	112.851	77	A90	39.130	164	A154	338.122	2
A26	178.315	52	A91	120.801	71	A155	189.827	47
A27	40.014	163	A92	59.960	128	A156	203.043	40
A28	22.629	187	A93	54.710	139	A157	42.379	160
A29	67.890	116	A94	189.688	48	A158	24.753	183
A30	52.078	145	A95	118.581	74	A159	109.852	80
A31	47.623	149	A96	35.810	171	A160	16.703	192
A32	299.400	5	A97	25.491	181	A161	231.052	27
A33	19.662	189	A98	31.376	176	A162	89.078	94
A34	28.241	180	A99	133.250	66	A163	53.047	142
A35	199.682	41	A100	208.113	34	A164	29.953	177
A36	253.024	18	A101	249.373	19	A165	62.521	124
A37	178.856	51	A102	41.657	161	A166	264.214	14
A38	24.930	182	A103	31.681	175	A167	227.507	29
A39	29.875	178	A104	242.362	23	A168	17.248	191
A40	123.222	69	A105	53.089	141	A169	249.143	20
A41	57.119	133	A106	38.745	166	A170	84.699	100
A42	120.770	72	A107	213.478	31	A171	208.944	33
A43	63.621	121	A108	62.908	123	A172	44.869	156
A44	190.545	45	A109	36.695	170	A173	45.555	155
A45	216.777	30	A110	152.898	60	A174	75.501	111
A46	4.254	193	A111	125.736	67	A175	77.327	107
A47	24.440	184	A112	124.030	68	A176	108.047	81
A48	278.048	11	A113	77.611	105	A177	192.647	44
A49	43.375	158	A114	109.879	79	A178	47.078	151
A50	60.065	126	A115	93.612	92	A179	68.208	114
A51	140.164	64	A116	33.808	172	A180	60.060	127
A52	84.333	101	A117	46.710	153	A181	150.952	61
A53	149.396	62	A118	62.992	122	A182	253.371	17
A54	52.567	144	A119	106.288	82	A183	307.471	3
A55	38.698	167	A120	49.103	148	A184	57.645	131
A56	19.068	190	A121	277.929	12	A185	352.321	1
A57	256.853	16	A122	179.048	50	A186	193.839	43
A58	37.622	168	A123	44.263	157	A187	99.936	87
A59	56.063	136	A124	32.464	173	A188	50.573	147
A60	86.510	98	A125	83.220	103	A189	41.576	162
A61	304.802	4	A126	103.084	85	A190	157.722	59
A62	292.868	7	A127	268.920	13	A191	21.992	188
A63	54.001	140	A128	182.369	49	A192	54.830	138
A64	46.500	154	A129	89.705	93	A193	46.985	152
A65	87.172	97						

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Data Availability Statement
The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Conflicts of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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