ANALYSIS OF ARTIFICIAL INTELLIGENCE READINESS PERFORMANCE OF EUROPEAN UNION COUNTRIES: AN APPLICATION USING THE LOPCOW-BASED GRA METHOD

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Abstract

The activities and strategies of the European Union (EU), one of the world's most significant economic actors, in the field of ArtificiaI Intelligence (AI) have the potential to influence the global economy and the AI policies of other countries. Therefore, analyzing the AI readiness performance of EU countries is considered crucial. In this study, the AI readiness performance of EU countries for the most recent year, 2023, was measured using the LOPCOW-based Grey Relational Analysis (GRA) Multi-Criteria Decision Making (MCDM) method, based on the Government AI Readiness Index (GAIRI) criteria values. According to the findings, the most critical GAIRI criterion for countries was identified as the government. Secondly, the top three countries with the highest AI readiness performance were found to be Finland, France, and Germany, while the bottom three were Croatia, Romania, and Greece, respectively. Additionally, the average AI readiness performance value for countries was measured, and it was assessed that EU countries with below-average performance need to improve their AI readiness to contribute to the global economy. Finally, sensitivity, comparison, and simulation analyses indicated that the AI readiness performance of EU countries under the GAIRI framework can be measured using the LOPCOW-based GRA method.

Keywords: *Artificial Intelligence (AI), AI readiness performance, European Union (EU) countries, LOPCOW, LOPCOW-based GRA*

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AVRUPA BIRLIĞI ÜLKELERININ YAPAY ZEKÂ HAZIRLIK PERFORMANSLARININ ANALIZI: LOPCOW TABANLI GRA YÖNTEMI İLE BIR UYGULAMA

Öz

Dünyanın en önemli ekonomik aktölerinen olan Avrupa Birliği (AB)'nin yapay zekâ (YZ) konusundaki faaliyetleri ve stratejileri küresel akonomiyi ve diğer ülkelerin YZ konusundaki politikalarını etkileyebilemktedir. Dolayısıyla AB ülkelerinin YZ hazırlık performanslarının analizinin önemli olduğu düşünülebilir. Bu kapsamda araştırmada, en son ve güncel olan 2023 yılı için AB ülkelerinin Hükümet Yapay Zeka Hazırlık Performansı (HYZHP) kriter değerleri üzerinden ülkelerin yapay zeka hazırlık performansları LOPCOW tabanlı Gri İlişkisel Analiz (GİA) Çok Kriterli Karar Verme (ÇKKV) yöntemi ile ölçülmüştür. Bulgular kapsaminda ilk olarak ülkelere göre en önemli HYZHP kriterinin Hükümet olduğu tespit edilmişit. İkinci olarak en fazla YZ hazırlık perforsına sahip ilk üç ülkenin Finlandiya, Fransa ve Almanya, buna karşın en az performansa sahip olan ilk üç ülkenin ise sırasıyla Hırvatistan, Romanya ve Yunanistan olduğu belirlenmiştir. Ayrıca ülkelere göre ortalama YZ hazırlık performans değeri ölçülmüş ve ortalama değerden az performansa sahip olan AB ülkelerinin küresel ekonomiye katkılarının olması için YZ hazırlık performanslarını artırmaları gerektiği değerlendirilmiştir. Son olarak duyarlılık, karşılaştırma ve simülasyon analizlerine göre AB ülkelerinin HYZHP kapsamında YZ hazırlık performanslarının LOPCOW tabanlı GİA yöntemi ile ölçülebileceği sonucuna ulaşılmıştır.

Anahtar Kelimeler: *Yapay zekâ (YZ), yapay zekâ hazırlık performansı, Avrupa Birliği (AB) ülkeleri, LOPCOW, LOPCOW tabanlı GRA.*

Introduction

Artificial Intelligence (AI) holds strategic importance for countries today (Mannuru et al., 2023). This technology has significant potential to accelerate economic growth, improve public services, and drive innovations across various sectors such as healthcare, education, and security (Demaidi, 2023). Efficient utilization of AI can help countries gain a competitive edge globally, enhance citizens' quality of life, and address social and environmental issues more cost-effectively (Yin and Sieng, 2024). Therefore, measuring countries' AI readiness performance is of great importance. Such measurement will raise awareness among countries regarding their AI readiness performance (Rogerson et al., 2024). This awareness will enable countries to monitor their progress in the AI field, identify their strengths and weaknesses, make strategic decisions, allocate resources effectively, and engage in international competition and cooperation (Shearer et al., 2020).

The European Union (EU) is one of the largest economic integrations in the world (Basılgan, 2012). According to the literature explaining the relationship between AI and economic growth, high AI performance significantly contributes to countries' economic growth and improvement (Qin et al., 2023; Trabelsi, 2024). As a major global actor, the EU's activities and strategies in AI can influence the global economy and other countries' AI policies. Therefore, analyzing the AI readiness performance of EU countries is considered important (Hankins et al., 2023). In this study, the AI readiness performance of EU countries for the most recent year, 2023, was measured using the Government AI Readiness Index (GAIRI) criteria data and the LOPCOW-based Grey Relational Analysis (GRA) multi-criteria decision making (MCDM) method.

In this context, the first motivation of the research is to identify which GAIRI criteria EU countries should prioritize to contribute to the global economy. The second motivation is to determine which EU countries need to improve their AI readiness performance to enhance their contributions to the global economy. The third motivation of this research is to assess whether the AI readiness performance of countries within the GAIRI framework can be measured using the LOPCOW-based GRA method. The theoretical framework of the study first explains the significance of AI and its importance for countries. The second part of the theoretical framework examines the relationship between the EU and AI. The methodology section outlines the analysis and data set of the research, explaining the LOPCOW and GRA methods. In the conclusion, inferences and discussions are provided based on the quantitative values identified in the findings.

The Theoretical Framework

AI and Its Importance for Countries

AI is a branch of computer science that focuses on developing computer programs capable of performing tasks that typically require human intelligence. AI algorithms exhibit capabilities such as learning, perception, problem-solving, language comprehension, and/or logical reasoning (Mohammed, 2019).

When examining the AI literature, numerous definitions of AI can be found (Sheikh et al., 2023). According to Bansla and Bansla (2012), AI is described as a system that perceives its environment and takes actions to maximize its chances of success. Garg (2021) defines AI as the branch of science and engineering that involves developing intelligent machines and smart programs. Another definition describes AI as a field of computer science that creates real-time problem-solving and optimal decision-making systems related to human intelligence, particularly in pattern recognition (Saketh, 2021). Sharma (2021) describes AI as the modelling of human intelligence and learning capabilities by machines. In summary, AI can be explained as the science and engineering of creating machine learning systems, intelligent machines, and computer programs (Wilks, 2019; Chishti et al., 2020; Poole and Mackworth, 2023).

Nowadays, countries emphasize AI readiness activities to develop decision support systems, forecasting, and systematization systems, and thereby achieve global competitiveness (Ulnicane, 2022; Maslej et al., 2023; Özkaya and Demirhan, 2023). This is because AI is intertwined with various technical, economic, and social dimensions and often enhances these aspects (Boden, 2018; Davenport, 2019; Russell and Norvig, 2022). Therefore, countries continuously analyze their AI performance due to its functionality. Consequently, countries focus on the development of their economies and other related dimensions, consistently competing with one another. In this context, countries prioritize their AI performance and, to achieve global competitiveness, they establish AI infrastructure and develop strategies and methods for AI readiness. Additionally, by examining each other's AI readiness performance, countries can form collaborations with those that excel in AI. Thus, measuring the AI readiness performance of countries becomes increasingly important, and there is a growing need for metrics that assess their AI performance (Nettel et al., 2022).

Accordingly, there are two metrics that measure countries' AI readiness performance today. The first is The Global AI Index (GAI) created by Tortois, which consists of three primary criteria: implementation, innovation, and investment. The index measured the AI performances of 62 countries as of 2023 (Cesareo and White, 2023). The second is the Government AI Readiness Index (GAIRI) by Oxford Insights. This index measured the AI performance values of 193 countries for the latest year, 2023, across three criteria. Countries' GAIRI criteria range from 1 to 100. The countries' AI readiness performances are determined based on the arithmetic average of their GAIRI criterion values (Hankins et al., 2023).

AI and EU Countries

EU is the largest integrated economy and trade bloc worldwide, playing significant roles in international investments (Ministry of Foreign Affairs Directorate for European Union Affairs of the Republic of Turkey, 2020). Additionally, in 2023, the share of the EU in global gross domestic product based on purchasing power parity is estimated to be approximately 14.46% (O'Neill, 2024).

Economically, when examining the relationship between AI and dimensions of economic growth, various literature reveals that AI significantly and positively contributes to economic growth (Gries and Naudé, 2020; Wang et al., 2021; Kuzior et al., 2023; Yoganandhamand and Elanchezhian, 2023). Moreover, countries' AI readiness performances contribute significantly to the development of crucial dimensions such as education, healthcare, innovation, and sustainable development (Fadziso, 2018; d'Elia, 2022; Chervona et al., 2023; Sulich et al., 2023). According to Hankins et al., (2023), within the scope of the 2023 GAIRI report, the average AI readiness performance of 193 countries is 44.97, whereas the average AI readiness performance of EU countries is determined to be 65.98. Thus, the average AI readiness performance of EU countries exceeds the global average by 46.7%. Consequently, the AI readiness performance of EU countries can influence global economy and other economy-related dimensions (such as education, healthcare, innovation, sustainable development, etc.) and the strategies of other countries regarding AI readiness, underscoring the importance of analyzing the AI readiness performance of EU countries (Hankins et al., 2023). Therefore, with this awareness, EU countries are developing strategies and programs to steer the development of AI (Craglia, 2018; Güner, 2019).

Studies on the relationship between the EU and AI can be categorized into two main areas: measuring AI readiness performances among EU countries and general AI-related studies within the EU. In the first category, Hankins et al., (2023) assessed the AI readiness of EU countries for 2023 based on GAIRI criteria, finding that Finland, France, and Germany had the highest performances, while Croatia, Romania, and Greece had the lowest. They also identified that Finland, France, Germany, Netherlands, Denmark, Sweden, Austria, Estonia, Ireland, Luxembourg, Portugal, Italy, Spain, and Belgium exceeded the average AI readiness performance. Özkaya and Demirhan (2023) used the PROMETHEE II MCDM method to measure the AI readiness of 22 EU countries for 2021. They ranked Netherlands, Germany, and France as the top three, with Hungary, Greece, and Slovakia at the bottom. When examining general studies on the relationship between EU countries and AI, Carriço (2018) argued that the EU should lead in AI development to advance socially and economically, using technology to address societal issues. Mancheva (2021) explored AI's impact on SMEs in EU countries, concluding that AI can streamline management, service, and trade processes, enhance human capital, foster new products and business models, and increase productivity. Ulnicane (2022) analyzed the EU's ethical stance on AI through its policies, highlighting the EU's global collaboration on ethical AI and its leadership in this area. The study indicated that the EU has established principles for ethical AI use and a robust infrastructure for systematic AI utilization. Woszczyna and Mania (2023) discussed AI governance strategies by national regulators in the EU, noting differences among member states' strategic projects. They concluded that EU countries have distinct AI strategies. Wilk–Ilewicz (2021) examined EU regulatory activities in AI, assessing the need for robust regulatory oversight capabilities. Glauner (2022) reviewed the EU's official AI regulation published in April 2021, emphasizing the importance of further developing health and safety issues.

Method and Material

Data Set and Analysis of the Research

The dataset for this study comprises the most recent and up-to-date 2023 GAIRI component values for EU countries. In this regard, the GAIRI component values (decision matrix) for the countries are presented in Table 1.

Table 1: Data Set (Decision Matrix)

Countries	Government (GAIRI1)	Technology Sector (GAIRI 2)	Data Infrastructure (GAIRI3)
Austria	77,69	56,43	82,98
Belgium	73,09	56,02	72,74
Bulgaria	66,04	38,17	71,73
Croatia	42,25	39,35	66,42
Cyprus	69,39	42,04	71,09
Czechia	72,25	47,72	75,55
Denmark	84,11	59,98	77,65
Estonia	80,54	52,52	79,54
Finland	88,34	60,36	83,39
France	84,03	60,4	83,8
Germany	80,78	63,28	81,72
Greece	55,92	48,37	69,56
Hungary	69,96	42,2	69,82
Ireland	71,51	56,96	81
Italy	76,61	50,98	75,29
Latvia	72,07	38,57	70,27
Lithuania	75,31	43,7	70,99
Luxembourg	83,11	46,51	78,6
Malta	80,74	40,89	69,31
Netherlands	78,9	61,96	82,55
Poland	69,79	46,84	72,66
Portugal	80,48	50,95	73,42
Romania	51,42	39,23	66,3
Slovakia	67,7	40,6	73,9
Slovenia	71,75	41,86	74,29
Spain	72,86	50,96	78,6
Sweden	74,7	62,71	80,26

Reference: Hankins et al., 2023

In the research, GAIRI's AI readiness performance data were preferred because GAI provides measurement values for 15 EU countries, whereas GAIRI provides them for all EU countries.

The LOPCOW method for weighting criteria in MCDM boasts its flexibility in handling any number of criteria. Unlike other objective weighting approaches, LOPCOW reduces the impact of data size on weight variability. It achieves this by expressing the mean squared value as a percentage of the standard deviations (Bektaş, 2022). The GRA method is one of the techniques used to analyze uncertainties in MCDM problems, providing simpler solutions compared to mathematical analysis methods in situations involving uncertainty (Peker and Baki, 2011). Additionally, it is an analytical method that can be employed in decision problems involving large datasets (Kurt Gümüş and Balcı, 2020). Therefore, due to the described advantages of these methods, the weights of the GAIRI criteria for EU countries were measured using the LOPCOW method, and the AI readiness performances of the countries were assessed using the LOPCOW-based GRA method.

LOPCOW Method

This innovative approach emphasizes the importance of combining data with varying scales to achieve optimal weight allocation for decision criteria. By doing so, LOPCOW strives to minimize discrepancies in the perceived significance of different criteria, fostering a more balanced evaluation process. Notably, the method incorporates the interrelationships between criteria, leading to more robust decision-making (Ecer and Pamucar, 2022) Additionally, LOPCOW is not affected by the presence of negative values within the raw data, further enhancing its versatility (Bektaş, 2022). Upon reviewing the literature, it is evident that many researchers have utilized the LOPCOW method for calculating criteria weights concerning decision alternatives. Studies related to LOPCOW are presented in Table 2.

Table 2: LOPCOW Literature

Author(s)	Method(s)	Theme
Chatterjee and Chakraborty, 2024	LOPCOW-TOPSIS	Optimization of non-traditional machining processes
Yımaz Özekenci, 2024	LOPCOW-COCOSO	Financial Performance evaluation of BIST Energy Sectors
Öztaş and Öztaş, 2024	LOPCOW-MAIRCA	Assessing of innovation performance of G20 countries
Putra et al., 2024	LOPCOW-MARCOS	Determining of teacher performance
Rong et al., 2024	The FMEA model based on LOPCOW-ARAS	Risk analysis of research and development of industrial robot
Trung Do, 2024	LOPCOW	Analysis the effect of criterion weights on the ranking of the top ten universities in Vietnam
Vandua et al., 2024	LOPCOW, MEREC, CRITIC based MARA, RAM and PIV	Material selection

The procedural steps for implementing this method are outlined below in a detailed step-by-step manner (Ecer and Pamucar, 2022).

Step 1: Obtaining the Decision Matrix (DM)

i: $1, 2, 3 \ldots n$, where m represents the number of decision alternatives

j: $1, 2, 3, \ldots m$, where n represents the number of criteria

DM: Decision matrix

C: Criterion

The decision matrix is constructed based on Equation 1, where "i_j" represents the performance of the $i-th$ decision alternative on the $j-th$ criterion. In this context, the decision matrix is formulated as per Equation 1.

$$DM = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: Normalization Procedure for the Decision Matrix $\left(k_{ij}^{x}\right)$

Within this step, the decision matrix values for benefit-oriented criteria are determined using Equation 2, while those for cost-oriented criteria are calculated using Equation 3.

For benefit-oriented criteria:

$$p_{ij}^{x} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \quad (2)$$

For cost-oriented criteria:

$$p_{ij}^{x} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \quad (3)$$

Step 3: Quantifying the Percentage Value of Each Criterion $\left(PV_{ij}\right)$

Equation 4 is employed to normalize the mean squared value by expressing it as a proportion of the standard deviations for each criterion. This normalization process effectively eliminates the influence of data size on the variation, ensuring that all criteria are evaluated on an equal footing. In Equation 4, the symbol $'\sigma'$ represents the standard deviation, and $'ln'$ denotes the natural logarithm.

$$PV_{ij} = In \left| \frac{\sqrt{\frac{\sum_{i=1}^{m}\left(p_{ij}^{x}\right)^2}{m}}}{\boldsymbol{\sigma}} .100 \right| \tag{4}$$

Step 4: Determining the Weights of Criteria (w)

$$w_j = \frac{PV_{ij}}{\sum_{\boldsymbol{k}} PV_{ij}} \tag{5}$$

GRA Method

GRA (Grey Relations Analysis) is particularly versatile for addressing decision-making problems with complex interrelationships among variables. It can be used independently or with hybrid models to enhance problem-solving capabilities (Dinçer, 2019). GRA offers advantages over traditional multivariable statistical methods, especially in scenarios where assumptions may lead to deviations and distortions. These advantages include effective results with uncertain data, no distributional requirements for data, straightforward computation of grey relational coefficients, and reduced computational burden compared to other statistical techniques. According to the literature, numerous studies have employed the GRA method for measuring the performance of decision alternatives or solving selection and decision problems (Atan and Altan, 2020). Recent studies related to GRA are detailed in Table 3.

Table 3: GRA Literature

Author(s)	Method(s)	Theme
Setiawansyah et al., 2023	GRA-PIPRECIA/S	Assessing best staff
Bhanutej and Rao, 2024	GRA and COCOSO	Assessing Healthcare Efficacy
Esangbedo et al., 2024	RROCW-Improved GRA	Subcontractor Selection
Kannan and Sivaram, 2024	GRA	Determining Aluminum Alloy in Dry Conditions
Karumuri et al., 2024	TAGUCHI-GRA	Analysis of friction stir welding for dissimilar aluminium alloy
Li et al., 2024	GRA	Analysis of oily sludge treatment technology
Xuerui and Yuguang, 2024	GRA	Evaluation of the medical data

In this context, the application steps of the GRA method are explained below (Özarı and Eren, 2019; Köse and Canbulut, 2020; Uludağ and Doğan, 2021).

Step 1: Construction of the Decision Matrix (X)

First, the factor series is defined as specified in Equation 6.

$$x_i = \big(x_i(j), \dots x_i(n)\big), i = 1,2, \dots, n \tag{6}$$

In Equation 6, x_i represents the decision alternatives. The performance values that the decision alternatives have received for each criterion are denoted as x_i. Accordingly, the decision matrix is constructed using Equation 7.

$$X = \begin{bmatrix} x_1(1) & x_2(1) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_m(1) & x_m(2) & \dots & x_m(n) \end{bmatrix} \tag{7}$$

Step 2: Provision of the Reference Series and the Comparison Matrix (x_0)

The reference series created for the comparison of factors is specified in Equation 8.

$$x_0 = \big(x_0(j)\big), j = 1,2, \dots, n \tag{8}$$

In Equation 8, $x_0(j)$ denotes the most suitable value for criterion j within the normalized values. This reference series is created by considering the best value of each criterion found in the decision matrix as shown in Equation 7. Within this scope, the reference series is incorporated as the first row in the decision matrix depicted in Equation 7, thereby transforming it into a comparison matrix.

Step 3: Normalization of the Decision Matrix

In case the criteria are benefit-oriented (maximization), Equation 9 is utilized.

$$x_i^* = \frac{x_i(j) - min_j\, x_j\,(j)}{max_j\, x_j\,(j) - min_j\, x_j\,(j)} \tag{9}$$

In case the criteria are cost-oriented (minimization), Equation 10 is utilized.

$$x_i^* = \frac{max\, x_j\,(j) - x_i(j)}{max_j\, x_j\,(j) - min_j\, x_j\,(j)} \tag{10}$$

In the optimal scenario, it is appropriate to select an average value from the series values. In this case, normalization is achieved using Equation 11.

$$x_i^* = \frac{|x_i(j) - x_{0b}(j)|}{max_j\, x_j(j) - x_{0b}(j)} \tag{11}$$

In Equation 11, $x_{0b}(j)$ represents the determined optimal value and is the target value for criterion j, where $max_j\, x_j(j) > x_{0b}(j) > min_j\, x_j(j)$. Following these procedures, the decision matrix shown in Equation 7 is transformed into the normalized decision matrix shown in Equation 12.

$$X_i^* = \begin{bmatrix} x_1{}^*(1) & x_1{}^*(2) & \cdots & x_1{}^*(n) \\ x_2{}^*(1) & x_2{}^*(2) & \cdots & x_2{}^*(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_m{}^*(1) & x_m{}^*(2) & \dots & x_m{}^*(n) \end{bmatrix} \tag{12}$$

Step 4: Construction of the Absolute Value Table

The absolute difference between x_0^* and x_1^* denoted as $\Delta_{01}(j)$, is determined using Equation 13

$$\Delta_{01}(j) = |x_0^* - x_1^*(j)|, i = 1,2,\dots,m;\ j = 1,2,\dots,n \tag{13}$$

Considering Equation 12, the absolute value matrix shown in Equation 14 is constructed.

$$\Delta_{0i}(j) = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \cdots & \Delta_{01}(n) \\ \Delta_{02}(1) & \Delta_{02}(2) & \cdots & \Delta_{02}(n) \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{0m}(1) & \Delta_{0m}(2) & \dots & \Delta_{0m}(n) \end{bmatrix} \tag{14}$$

Step 5: Construction of the Grey Relational Coefficient Matrix

$$\gamma_{0i} = \frac{\Delta_{min} + \zeta\Delta max}{\Delta_{0i}(j) + \zeta\Delta max} \tag{15}$$

$$\Delta max = max_i max_j \zeta(j); \Delta min = min_i min_j \Delta_{0i}(j) \tag{16}$$

In Equation 15, the parameter ζ is defined as the distinguishing coefficient and ranges between 0 and 1. The use of the ζ parameter is necessitated by the need to adjust the difference between Δ_{0i} and Δ_{max}. Within this scope, the ζ parameter eliminates the possibility of Δ_{max} being an outlier in the data series. In the literature, the ζ parameter is generally observed to take a value of 0.5.

Step 6: Determination of Grey Relational Grades

When the importance levels of the criteria are equal, the grey relational grade is measured using Equation 17. When the importance levels differ, it is measured using Equation 18.

$$\Gamma_{0i} = \frac{1}{n}\sum_{j=1}^{n} \gamma_{0i}(j), i: 1,2,3, \ldots., m. \tag{17}$$

$$\Gamma_{0i} = \sum_{j=1}^{n}[w_i\ (j)\ \gamma_{0i}(j)], i: 1,2,3, \ldots., m. \tag{18}$$

In Equations 17 and 18, Γ_{0i} represents the grey relational grade, and w_i denotes the importance level of the $i-th$ criterion

Results

Computational Analysis

In the research, initially under the LOPCOW method, the weighting coefficients (significance values) of GAIRI criteria for EU countries were calculated considering Equality 1, Equality 2, Equality 3, Equality 4, and Equality 5 and the calculated values are shown in Table 4.

Table 4: Weights of GAIRI Criteria

Weights	GAIRI1	GAIRI2	GAIRI3	Mean
Score	0,494	0,220	0,286	0,333
Rank	1	3	2	-----

Upon examining Table 4, the weighting values of GAIRI criteria are ranked as GAIRI1, GAIRI3, and GAIRI2. Furthermore, according to Table 4, it is observed that GAIRI1 has a higher weighting value compared to other GAIRI criteria, indicating disparities among them. Additionally, the average weighting value of GAIRI criteria was measured, and GAIRI1 was identified as having a higher average value than the measured average.

Secondly, in the research, the AI readiness performances of EU countries were calculated using GRA based on LOPCOW, considering from Equality 6 to Equality 18 Accordingly, the AI readiness performance values of EU countries are presented in Table 5.

Table 5: AI Readiness Performance of EU Countries

Countries	Score	Rank	Countries	Score	Rank
Austria	0,742	6	Ireland	0,648	10
Belgium	0,563	14	Italy	0,584	13
Bulgaria	0,445	24	Latvia	0,476	20
Croatia	0,336	27	Lithuania	0,518	17
Cyprus	0,469	22	Luxembourg	0,676	9
Czechia	0,536	16	Malta	0,558	15
Denmark	0,760	5	Netherlands	0,800	4
Estonia	0,680	8	Poland	0,495	19
Finland	0,946	1	Portugal	0,610	11
France	0,881	2	Romania	0,361	26
Germany	0,823	3	Slovakia	0,473	21
Greece	0,415	25	Slovenia	0,506	18
Hungary	0,467	23	Spain	0,586	12
			Sweden	0,724	7
Mean=0,595					

Upon examining Table 5, it has been determined that the top three countries with the highest AI readiness performance are Finland, France, and Germany, while the bottom three countries with the least performance are Croatia, Romania, and Greece. Additionally, the average AI readiness performance value of EU countries was calculated, and it was found that the countries with performance above the average value are Finland, France, Germany, Netherlands, Denmark, Austria, Sweden, Estonia, Luxembourg, Ireland, and Portugal, respectively.

Sensitivity Analysis

In this study, It is performed a sensitivity analysis to assess the methodological robustness of the LOPCOW-based GRA method. Sensitivity analysis, within the context of MCDM, entails using different weighting techniques on a single dataset. This method enables a comparative evaluation of the resulting values and rankings of decision alternatives' performance. It is expected variations in the performance rankings of the identified decision alternatives, highlighting the sensitivity of the chosen weight coefficient calculation method. Such variations are anticipated when comparing the performance rankings of decision alternatives derived from the application of different methods (Gigovič et al., 2016). In this context, firstly, the weighting values of GAIRI criteria for EU countries were calculated using the ENTROPY, CRITIC, SD, SVP, and MEREC methods, and the calculated values are presented in Table 6.

Table 6: Criterion Weight Values According to Various Weighting Methods

Criteria	CCPI1	CCPI2	CCPI3
ENTROPY	0,383	0,525	0,092
Rank	2	1	3
CRITIC	0,321	0,397	0,282
Rank	2	1	3
SD	0,256	0,390	0,354
Rank	3	1	2
SVP	0,510	0,350	0,140
Rank	1	2	3
MEREC	0,647	0,140	0,213
Rank	1	3	2

As part of sensitivity analysis, secondly, the AI readiness performance values of EU countries were measured using the ENTROPY, CRITIC, SD, SVP, and MEREC-based GRA methods, and the measured values were ranked. The relevant values are presented in Table 7.

Table 7: AI Readiness Performance Values of EU Countries According to ENTROPY, CRITIC, SD, SVP, and MEREC-based GRA Methods

Countries	ENTROPY GRA		CRITIC GRA		SD GRA		SVP GRA		MEREC GRA	
	S.	R.	S.	R.	S.	R.	S.	R.	S.	R.
Austria	0,686	7	0,734	7	0,751	6	0,703	7	0,728	6
Belgium	0,604	10	0,569	11	0,557	12	0,590	12	0,572	15
Bulgaria	0,408	25	0,414	25	0,409	25	0,435	24	0,465	24
Croatia	0,339	27	0,338	27	0,338	27	0,337	27	0,335	27
Cyprus	0,443	21	0,439	21	0,430	21	0,467	22	0,494	22
Czechia	0,507	16	0,511	15	0,507	15	0,529	16	0,553	17
Denmark	0,793	6	0,751	6	0,733	7	0,790	5	0,783	4
Estonia	0,631	9	0,643	9	0,639	9	0,664	8	0,702	8
Finland	0,897	1	0,912	1	0,911	1	0,928	1	0,964	1
France	0,842	3	0,875	2	0,887	2	0,854	2	0,872	2
Germany	0,888	2	0,867	3	0,869	3	0,847	3	0,799	3
Greece	0,434	23	0,422	24	0,419	24	0,425	25	0,414	25
Hungary	0,444	20	0,435	22	0,424	22	0,468	21	0,494	21
Ireland	0,640	8	0,663	8	0,676	8	0,634	10	0,628	11
Italy	0,566	13	0,556	14	0,546	14	0,586	13	0,607	13
Latvia	0,438	22	0,433	23	0,421	23	0,472	20	0,510	20
Lithuania	0,487	17	0,475	17	0,460	19	0,519	17	0,554	16
Luxembourg	0,595	11	0,609	10	0,598	10	0,653	9	0,721	7
Malta	0,511	15	0,490	16	0,466	17	0,562	15	0,617	12
Netherlands	0,827	4	0,834	4	0,844	4	0,801	4	0,772	5
Poland	0,480	18	0,474	18	0,466	16	0,496	18	0,513	19
Portugal	0,593	12	0,569	13	0,550	13	0,621	11	0,650	10

Countries	ENTROPY GRA		CRITIC GRA		SD GRA		SVP GRA		MEREC GRA	
	S.	R.	S.	R.	S.	R.	S.	R.	S.	R.
Romania	0,358	26	0,354	26	0,350	26	0,363	26	0,368	26
Slovakia	0,432	24	0,443	20	0,440	20	0,459	23	0,491	23
Slovenia	0,461	19	0,469	19	0,463	18	0,493	19	0,530	18
Spain	0,552	14	0,569	12	0,572	11	0,570	14	0,591	14
Sweden	0,808	5	0,782	5	0,786	5	0,755	6	0,692	9

When Table 5 and Table 7 are evaluated together, it is observed that the rankings of EU countries' AI readiness performance identified by the LOPCOW-based GRA method differ not so much from the rankings of these countries' AI readiness performance values measured by the ENTROPY, CRITIC, SD, SVP, and MEREC-based GRA methods. Based on this finding, it is concluded that the measurement of EU countries' AI readiness performance under GAIRI using the LOPCOW-based GRA method is ideal sensitive.

Comparative Analysis

The comparative analysis examines the relationships and standings of the proposed method in relation to other techniques employed for calculating MCDM methods. The proposed approach should exhibit credibility and reliability with other methodologies, while also demonstrating a favorable and statistically significant correlation with various weight coefficient methods (Keshavarz-Ghorabaee, et al., 2021). In the scope of comparative analysis, firstly, the ARAS, SAW, TOPSIS, MARCOS, and PIV methods, which are frequently utilized in decision alternatives' performance measurement or selection problems according to the MCDM literature, were used to measure the AI readiness performance values of EU countries. The measured values were ranked and presented in Table 8.

Table 8: AI readiness performance values and rankings of EU countries according to LOPCOW-based ARAS, SAW, TOPSIS, MARCOS, and WASPAS methods

Countries	LOPCOW ARAS		LOPCOW SAW		LOPCOW TOPSIS		LOPCOW MARCOS		LOPCOW WASPAS	
	S.	R.	S.	R.	S.	R.	S.	R.	S.	R.
Austria	0,912	6	0,914	6	0,772	9	0,744	7	0,913	6
Belgium	0,852	13	0,852	14	0,656	15	0,692	14	0,852	14
Bulgaria	0,743	24	0,747	24	0,481	24	0,603	24	0,744	24
Croatia	0,596	27	0,600	27	0,011	27	0,507	27	0,592	27
Cyprus	0,774	20	0,777	21	0,549	22	0,626	20	0,775	20
Czechia	0,825	16	0,828	16	0,629	17	0,670	15	0,827	15
Denmark	0,944	4	0,944	4	0,884	3	0,760	5	0,944	4
Estonia	0,903	8	0,904	8	0,807	6	0,729	8	0,904	8

Countries	LOPCOW ARAS		LOPCOW SAW		LOPCOW TOPSIS		LOPCOW MARCOS		LOPCOW WASPAS	
	S.	R.	S.	R.	S.	R.	S.	R.	S.	R.
Finland	0,988	1	0,988	1	0,973	1	0,796	1	0,988	1
France	0,965	2	0,966	2	0,907	2	0,782	2	0,966	2
Germany	0,951	3	0,951	3	0,843	4	0,774	3	0,950	3
Greece	0,716	25	0,718	25	0,299	25	0,596	25	0,716	25
Hungary	0,774	21	0,776	22	0,557	21	0,624	22	0,775	21
Ireland	0,873	11	0,874	11	0,648	16	0,718	9	0,873	11
Italy	0,861	12	0,863	12	0,718	12	0,695	12	0,862	12
Latvia	0,774	22	0,777	20	0,586	19	0,620	23	0,774	22
Lithuania	0,813	17	0,815	17	0,657	13	0,651	17	0,814	17
Luxembourg	0,892	9	0,895	9	0,813	5	0,714	10	0,892	9
Malta	0,828	15	0,830	15	0,719	10	0,654	16	0,827	16
Netherlands	0,938	5	0,938	5	0,806	7	0,766	4	0,938	5
Poland	0,799	18	0,801	18	0,572	20	0,649	18	0,800	18
Portugal	0,877	10	0,878	10	0,775	8	0,702	11	0,877	10
Romania	0,647	26	0,650	26	0,188	26	0,538	26	0,647	26
Slovakia	0,768	23	0,772	23	0,522	23	0,625	21	0,769	23
Slovenia	0,797	19	0,800	19	0,600	18	0,644	19	0,798	19
Spain	0,850	14	0,853	13	0,657	14	0,694	13	0,852	13
Sweden	0,910	7	0,910	7	0,718	11	0,746	6	0,909	7

When Table 5 and Table 8 are evaluated together, it is observed that the rankings of countries' AI readiness performance identified under the LOPCOW-based GRA method differ not from the performance rankings under other LOPCOW-based MCDM methods. Accordingly, the visual positions of EU countries under the LOPCOW-based GRA and other LOPCOW-based MCDM methods are shown in Figure 1, Figure 2, and Figure 3.

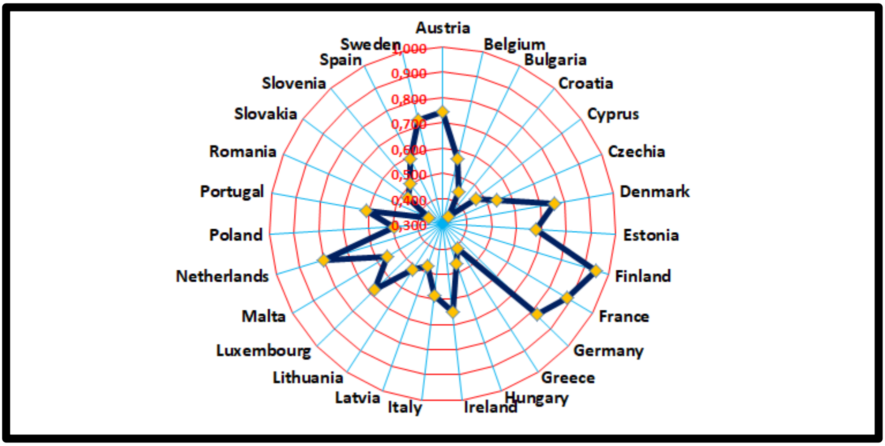

Figure 1: Position of LOPCOW based GRA

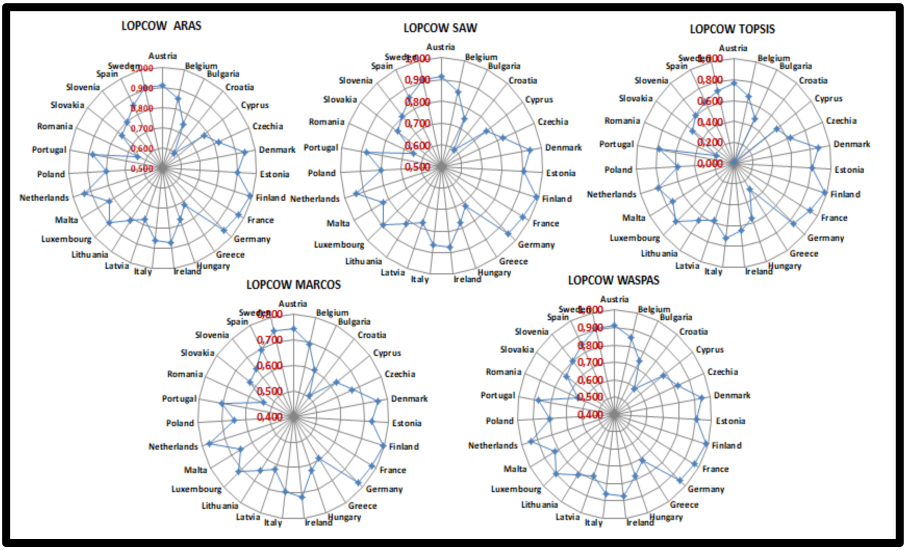

Figure 2: Position of LOPCOW based MCDM Methods-1

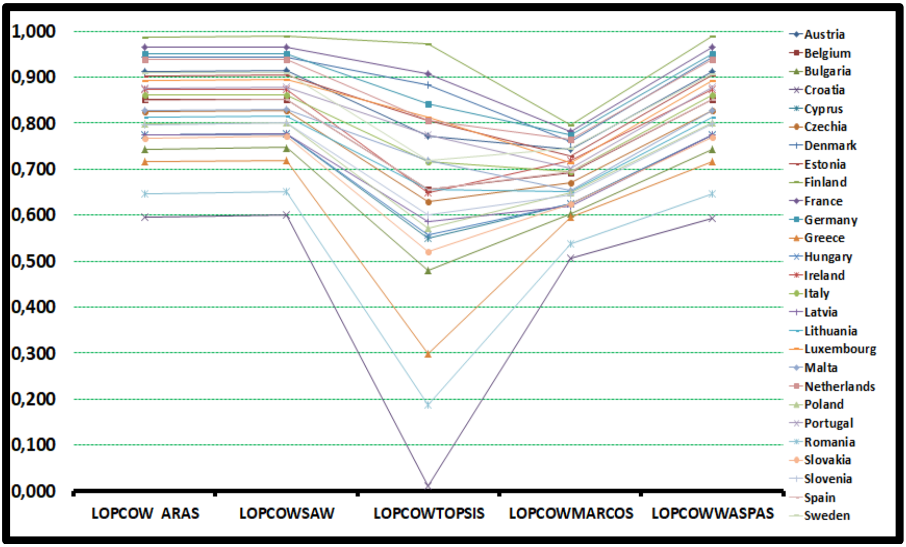

Figure 3: Position of LOPCOW based MCDM Methods-2

When evaluating Figures 1, 2, and 3 together, it is observed that the fluctuations in AI readiness performance values of EU countries calculated under the LOPCOW-based GRA method generally align with those from other LOPCOW-based MCDM methods. This indicates a positive and strong correlation between the AI readiness performance values calculated by the

LOPCOW-based GRA method and those calculated by other LOPCOW-based MCDM methods. The Pearson correlation coefficients between the performance values for methods with normal distribution are presented in Table 9.

Table 9: Correlations Among the MCDM Methods

Method(s)	LOPCOW ARAS	LOPCOW SAW	LOPCOW TOPSIS	LOPCOW MARCOS	LOPCOW WASPAS
LOPCOW GRA	0,951**	0,951**	0,878**	0,964**	0,950**

p**<.01

According to Table 9, it has been determined that the AI readiness performance values of EU countries calculated under the LOPCOW-based GRA method have a significant, positive, and high correlation with the performance values of EU countries measured under other LOPCOW-based MCDM methods. Therefore, based on all quantitative results identified within the scope of comparative analysis, it is concluded that the measurement of EU countries' AI readiness performance under GAIRI using the LOPCOW-based GRA method is credible and reliable.

Simulation Analysis

To evaluate the robustness and stability of the proposed method, a simulation analysis will be conducted by applying different values to the decision matrices, creating various scenarios. A reliable method should show increasing divergence from other methods as the number of scenarios increases. The proposed method's average variance of criterion weights across scenarios should be significantly higher than at least one other objective weighting method, demonstrating its superior ability to distinguish criteria importance. The analysis should also confirm consistency in criterion weight variance across all methods within each scenario (Keshavarz-Ghorabaee, et al., 2021). In the simulation analysis, 10 scenarios were created, with the first three classified as the first group and the remaining seven as the second group. The Pearson correlation coefficients between the AI readiness performance values of EU countries under the LOPCOW-based GRA method and those calculated by other LOPCOW-based MCDM methods are presented in Table 10.

Table 10: Correlation Scores between LOPCOW-based GRA and Other MCDM Methods

MCDM Methods	LOPCOW ARAS	LOPCOW SAW	LOPCOW TOPSIS	LOPCOW MARCOS	LOPCOW WASPAS
1. Scenario	0,975**	0,978**	0,878**	0,975**	0,972**
2. Scenario	0,943**	0,941**	0,889**	0,956**	0,941**
3. Scenario	0,967**	0,963**	0,854**	0,941	0,961**

MCDM Methods	LOPCOW ARAS	LOPCOW SAW	LOPCOW TOPSIS	LOPCOW MARCOS	LOPCOW WASPAS
4. Scenario	0,934**	0,932**	0,843**	0,938**	0,929**
5. Scenario	0,924**	0,921**	0,832**	0,912**	0,921**
6. Scenario	0,912**	0,906**	0,821**	0,92**	0,909**
7. Scenario	0,902**	0,901**	0,805**	0,9**	0,888**
8. Scenario	0,889**	0,887**	0,789**	0,887**	0,879**
9. Scenario	0,876**	0,869**	0,777**	0,879**	0,865**
10. Scenario	0,858**	0,855**	0,754**	0,839**	0,842**
Mean	0,918	0,915	0,824	0,915	0,911

**p<.01

Upon examining Table 10, it is observed that there are positive and significant correlation values between the AI readiness performance values of EU countries calculated under the LOPCOW-based GRA method and the performance values of countries measured under other LOPCOW-based MCDM methods across 10 scenarios. Additionally, according to Table 9, as the scenarios increase, it is found that the correlations between the AI readiness performance values of countries calculated under the LOPCOW-based GRA method and the performance values measured under other LOPCOW-based MCDM methods decrease. A visual representation explaining these relationships between the LOPCOW-based GRA method and other LOPCOW-based MCDM methods is presented in Figure 4.

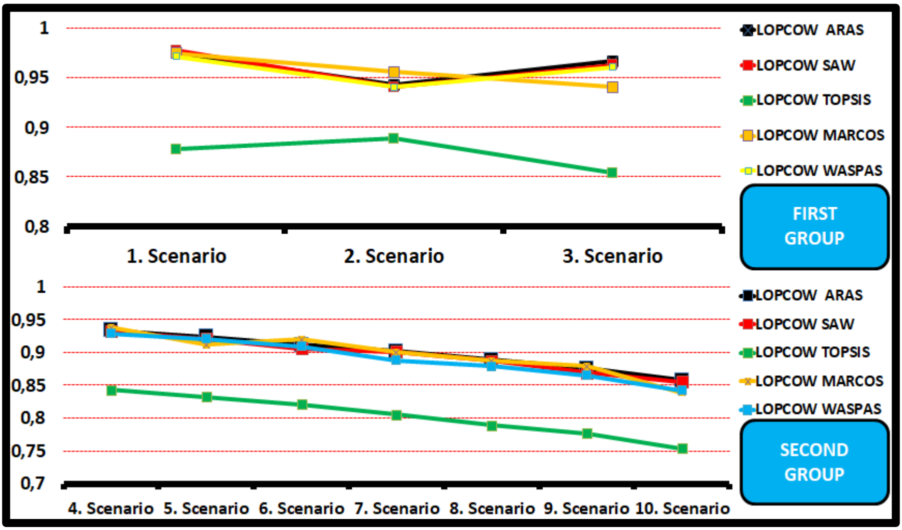

Figure 4: Correlation Analysis of LOPCOW-based GRA with Other MCDM Techniques

According to Figure 4, it is observed that as the scenarios increase, the correlation values between the LOPCOW-based GRA method and other LOPCOW-based MCDM methods decrease. Based on this finding, it is evaluated that as the scenarios increase, the characteristic feature of the LOPCOW-based GRA method becomes more pronounced.

ADM analysis was employed to assess the consistency of variances in LOPCOW-GRA's criterion weights across scenarios. A visual representation (refer to Figure 5 for details) confirms homogeneity if all groups' standard deviations fall within the upper and lower decision limits (UDL and LDL). Additionally, a variance analysis was conducted for each scenario (data in Table 11) to evaluate the variability of performance scores across countries using the LOPCOW-GRA method compared to other MCDM techniques.

Table 11. Variance Score of LOPCOW based-MCDM Methods Under Scenarios

Scenario	Gra	Aras	Saw	Topsis	Marcos	Waspas
1. Sce.	0,0270	0,0086	0,0101	0,0453	0,0062	0,0083
2. Sce.	0,0248	0,0089	0,0103	0,0458	0,0065	0,0088
3. Sce.	0,0266	0,0092	0,0105	0,0463	0,0068	0,0093
4. Sce.	0,0264	0,0097	0,0106	0,0468	0,0071	0,0088
5. Sce.	0,0302	0,0092	0,0109	0,0473	0,0074	0,0103
6. Sce.	0,0261	0,0097	0,0112	0,0478	0,0077	0,0108
7. Sce.	0,0278	0,0106	0,0115	0,0483	0,008	0,0113
8. Sce.	0,0296	0,0107	0,0116	0,0488	0,0083	0,0128
9. Sce.	0,0264	0,0115	0,0117	0,0493	0,0086	0,0133
10. Sce.	0,0292	0,0119	0,0116	0,0498	0,0089	0,0145
Mean	0,0274	0,0100	0,0110	0,0476	0,0076	0,0108

The simulation analysis further strengthens the case for LOPCOW-GRA. Compared to LOPCOW-based ARAS, SAW, MARCOS, and WASPAS methods, LOPCOW-GRA exhibited a higher average variance across 10 scenarios (refer to Table 11). This indicates a stronger ability of LOPCOW-GRA to differentiate between GAIRI criteria when evaluating EU countries. Finally, ADM analysis, visually represented in Figure 5, confirms the homogeneity of variances in the LOPCOW-GRA method, supporting its stability in assessing EU countries' AI readiness.

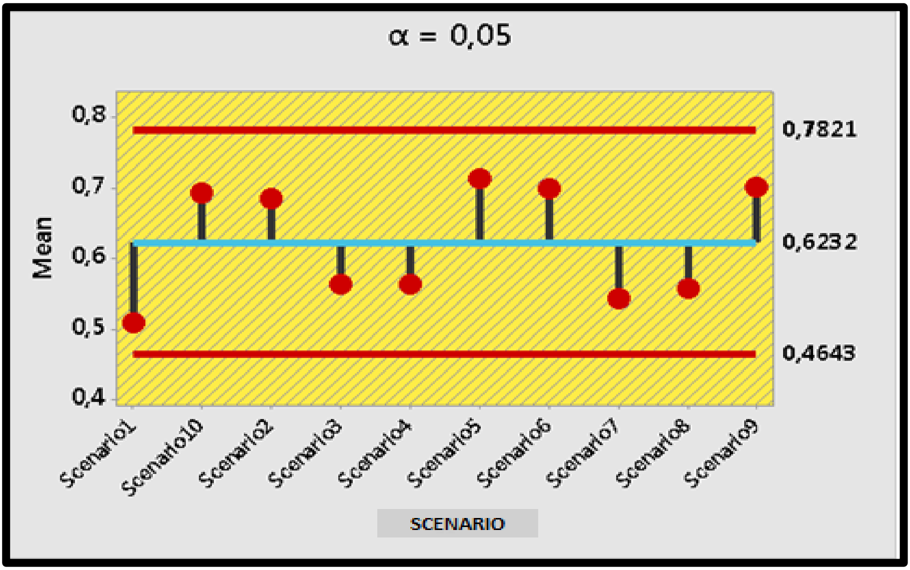

Figure 5: ADM Visual

Figure 5 illustrates a uniform distribution (homogenous) of the calculated ADM values across all scenarios. Importantly, all values remain within the established Upper Decision Limit (UDL) and Lower Decision Limit (LDL). This consistency indicates uniform weight variances across the scenarios. Levene's Test results, summarized in Table 12, further support this conclusion.

Table 12: Variance Values of MCDM Methods in scope of Scenarios

Levene Statistic	df1	df2	Sig.
0,232	2	10	0,159

*p<.05

Upon reviewing Table 12, it is noted that the Levene Statistic value is 0.232, with a significance value greater than 0.05, indicating that the variances are homogeneous. Therefore, when the results of the simulation analysis are considered collectively, it is concluded that the LOPCOW-based GRA method is robust and stable for assessing countries' climate change performance within the framework of the GAIRI.

Conclusion

AI readiness is crucial for countries as it determines their ability to effectively implement and benefit from AI technologies, driving economic growth, innovation, and competitiveness in the global landscape. Given that the AI readiness of EU countries can influence global economic strategies and the AI policies of other nations, analyzing the AI readiness performance of EU countries is crucial. In this study, the AI readiness performance of EU countries was examined using the most recent and updated GAIRI components through the LOPCOW-based GRA method.

The findings indicate that, according to the LOPCOW method, the weights (significance levels) of the GAIRI (Government) criteria for EU countries are ranked as GAIRI1, GAIRI3 (Data Infrastructure), and GAIRI2 (Technology Sector). Notably, the weight of the GAIRI1 criterion significantly differs from GAIRI2 and GAIRI3 due to its higher value. Additionally, the average GAIRI weight values for EU countries were calculated, and it was observed that GAIRI1 is the only component with a value higher than the average.

In the second part of the study, the AI readiness performances of EU countries were measured using the LOPCOW-based GRA method. It was found that the top three countries with the highest AI readiness performance are Finland, France, and Germany, while the bottom three are Croatia, Romania, and Greece. Furthermore, the average AI readiness performance of EU countries was calculated, identifying that the countries exceeding the average performance are Finland, France, Germany, the Netherlands, Denmark, Austria, Sweden, Estonia, Luxembourg, Ireland, and Portugal.

In the study, various analyses were conducted to evaluate countries' AI readiness performances based on the GAIRI criteria using the LOPCOW-based GRA method. Sensitivity analysis revealed that the rankings determined by this method differed from those determined by ENTROPY, CRITIC, SD, SVP, and MEREC-based GRA methods, indicating the LOPCOW-based GRA method's sensitivity within the GAIRI context. Comparative analysis showed that the rankings from the LOPCOW-based GRA method also differed from those identified by the LOPCOW-based ARAS, SAW, TOPSIS, MARCOS, and WASPAS methods. However, the AI readiness performance values measured by the LOPCOW-based GRA method were significantly, positively, and highly correlated with those measured by all other LOPCOW-based MCDM methods, establishing the method's credibility and reliability. In the simulation analysis, 10 different decision matrices (scenarios) were used. It was observed that as the number of scenarios increased, the correlation coefficient between the AI readiness performance values measured by the LOPCOW-based GRA method and those calculated by other LOPCOW-based MCDM methods decreased. The average variance values of the LOPCOW-based GRA method were compared with those of other LOPCOW-based MCDM methods, revealing that the LOPCOW-based GRA method had a higher average variance value. ADM analysis confirmed that the variances were homogeneous, indicating that the LOPCOW-based GRA method is stable and robust in measuring countries' AI readiness performance within the GAIRI context.

Upon reviewing the literature, it is evident that the findings of Hankins et al., (2023) align with those of the current study in identifying Finland, France, and Germany as the top three EU countries with the highest AI readiness performance, and Croatia, Romania, and Greece as the lowest. Both studies also find that Finland, France, Germany, Netherlands, Denmark, Sweden, Austria, Estonia, Ireland, Luxembourg, and Portugal have above-average AI performance values. However, Hankins et al. also rank Italy, Spain, and Belgium above average, which differs from the current study's findings. Thus, holistically, both studies conclude that Finland, France, Germany, Netherlands, Denmark, Sweden, Austria, Estonia, Ireland, Luxembourg, and Portugal have superior AI readiness performance compared to other EU countries. Özkaya and Demirhan (2023), using the PROMETREE II MCDM method with The Global AI Index component data for 2021, ranked the AI readiness of 22 EU countries. They identified the Netherlands, Germany, and France as the top three performers, and Hungary, Greece, and Slovakia as the lowest. Despite the year difference, consistency is observed in both studies with France and Germany in the top positions and Greece among the lowest. Therefore, when evaluating all three studies together, it is concluded that France and Germany demonstrate stable AI readiness performance.

To strengthen the EU contribution to the global AI landscape and economy, a two-pronged approach is recommended. First, strategies, policies, and methods should be developed to improve the Government AI Readiness Index (GAIRI), a key metric for AI preparedness within the EU. Second, EU member states with below-average AI readiness scores (including Spain, Italy, and others) should prioritize efforts to enhance their capabilities. Looking forward, research should expand its scope beyond the EU to encompass countries within international economic organizations like G20, G7, and BRICS, as well as major carbon emitters. MCDM methods, such as EDAS, CODAS, and others, can be employed to evaluate and compare AI readiness performance across these diverse nations. This comparative analysis will provide valuable insights into the relative AI preparedness of individual countries.

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