Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd
Anatolian Science

ISSN,e-ISSN: 2548-1304
Volume:9, Issue: 2, pp:99-121,, 2024
https://doi.org/10.53070/bbd.1537792

Research Paper

Analysis of Artificial Intelligence Readiness Performances of G7 Countries: An Application with LOPCOW-based MARCOS Method

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Received:Aug.23, 2024 Accepted:Sep.09, 2024 Published: Dec.25, 2024

Abstract— The artificial intelligence (AI) readiness performance of major economies can significantly impact the global economy. Therefore, analyzing the AI readiness performance of these economies is of great importance. In this study, the AI readiness performances of G7 countries were assessed using the most recent Government Artificial Intelligence Readiness Index (GAIRI) data for 2023. The analysis revealed that the importance of GAIRI components varies by country, with Data and Infrastructure generally being the most significant components. A comparative analysis was conducted to assess the AI readiness levels of various nations. Employing the LOPCOW-MARCOS methodology, the study ranked the US, the UK, Canada, France, Japan, Germany, and Italy, respectively, based on their AI capabilities and preparedness. Notably, Italy's AI readiness performance was below the average, indicating the need for improvement to enhance its contribution to the global economy. The method applied proved to be sensitive in sensitivity analysis, credible and reliable in comparative analysis, and robust and stable in simulation analysis

Keywords: Artificial intelligence (AI), artificial intelligence readiness performance, G7, LOPCOW, LOPCOW based MARCOS.

1. Introduction

Artificial intelligence (AI) has become a strategic priority for many countries today (Salas-Pilco, 2021). The rapid development and proliferation of this technology have made it a significant factor determining countries' economic competitiveness. Therefore, the preparedness and infrastructure potential in AI emerge as a critical element that could shape a country's future success (Piton, 2023).

The preparedness and infrastructure potential of major economies in AI have become determinants of global competition. By enhancing their investments and innovation capabilities in the field of AI, these economies gain a competitive advantage (Cazzaniga, 2024). Given the wide range of potential applications of AI, from industrial processes to healthcare services, the preparedness of major economies in this area can influence the development of the global economy and other dimensions related to the economy (The International Telecommunication Union, 2018). Therefore, analyzing the performance of major economies in AI preparedness is deemed important (Saba and Monkam, 2024). In this context, the study calculated the performance score of G7 countries in AI preparedness pertaining to the most current year, 2023, based on the values of the components of the Government Artificial Intelligence Readiness Index (GAIRI). Therefore, in scope of motivation the study evaluated which GAIRI criteria G7 countries should prioritize in terms of the overall development of the global economy and its interdependent systems, and which countries need to improve their AI preparedness performances. Consequently, this study was considered to raise awareness about countries' AI preparedness capacity and to serve as a guide for countries to improve their AI preparedness performances. In this regard, the literature section of the research presented explanations regarding AI and relevant studies. The methodology part of the study explained the research's dataset and analysis, as well as the LOPCOW and MARCOS multi criteria decision making (MCDM) methods employed. Finally, the results and discussion part provided insights and discussions based on the research findings.

2. Literature Review

AI has transcended the realms of technology and industry, initiating a global transformative movement. This technology provides ground breaking advancements across a broad spectrum of industries, including healthcare, transportation, communication, and security, thereby enhancing overall efficiency (Pavaloiu, 2016; Ferreira et al., 2020). For nations, AI has become a critical tool for securing competitive advantages, supporting economic growth, and achieving strategic objectives (Aghion et al., 2019; Miklif et al., 2021). Furthermore, investing in AI research and development fosters the attraction of knowledge and talent, thereby positioning countries as hubs of excellence on the international stage. Consequently, AI has emerged as a significant determinant of nations' competitive edge in the contemporary era (Dampitakse et al., 2021; Yoganandham and Elanchezhian, 2023).

When reviewing the literature, one can encounter numerous definitions of AI. However, due to intelligence forming the foundation of AI, it is necessary to examine the definition of the concept of intelligence (Warwick, 2021). In accordance with this, intelligence can be elucidated as the cognitive capacity of an individual to gather knowledge from previous experiences, to engage in proficient reasoning, to retain substantial data, and to proficiently navigate the complexities of daily life (Jackson, 1985; Lucci & Kopec, 2016; Haugeland, 1995). When viewed through the lens of intelligence, AI can be defined as the discipline that explores the capacity of machines to acquire knowledge in a manner analogous to human learning, as well as their capacity to exhibit responsive behaviors (AlSedrah, 2017; Bates, 2023, Sheikh et al., 2023).

The first significant development in the realm of AI dates back to the 1950s when Alan Turing explored the feasibility of simulating human-like intelligence and rational thought. Turing devised the Turing test to ascertain whether computers could exhibit human-like thinking capabilities (Johns, 2021; Warwick, 2021). The second milestone in AI occurred in 1956, when McCarthy introduced the term "Artificial Intelligence" during the Dartmouth Conference, thereby introducing the concept of AI to the scientific community (Naveenkumar, 2021; Samuel, 2021; Sharma, 2021). Subsequently, McCarthy pioneered the development of the first programming language for AI, known as LISP (Ritanya, 2021; Tejaswi, 2021; Seal, 2021).

AI is causing significant transformations in many sectors today. Therefore, it is vital for countries to be prepared in the field of AI to gain a competitive advantage and support economic development. Formulating policies related to AI research and making investments in education and R&D enable countries to keep pace with technology and promote innovation. As countries are concerned with the advancement of their economies and related dimensions, they are constantly competing with each other (Rogerson et al., 2022). Consequently, countries prioritize their AI readiness performance and develop strategies and methods to achieve global resilience. Moreover, countries can establish collaborations with those proficient in AI by examining each other's readiness performances. In this regard, the measurement of countries' AI readiness performances becomes relevent, and countries today require metrics to assess their own preparedness (Hankins et al., 2023).

The sole scale that measures countries' readiness capacity for AI preparation potential is the Government Artificial Intelligence Readiness Index (GAIRI), developed by Oxford Insights. The index assesses countries' AI readiness performance values through three components (with 10 subcomponents dependent on the three components). Methodologically, countries' GAIRI (AI readiness performance) is measured by the arithmetic mean of components with the arithmetic mean of subcomponents (Hankins et al., 2023). The descriptions of these GAIRI components and subcomponents are presented in Table 1.

Table 1. Components and Subcomponents of the Data Set

Components	Sub-components	Descriptions
Government (GAIRI1)	Vision	Describes the state's implementation performance of AI.
	Governance and Ethics	An assessment of the existing regulatory landscape and ethical guidelines governing the implementation of AI, with a focus on their efficacy in fostering trust and credibility.
	Digital Capacity	Describes the state's current digital capacity.
	Adaptability	Describes the state's innovation effectiveness in AI.
Technology Sector (GAIRI2)	Maturity	Describes the scale of AI technology in states.
	Innovation Capacity	Describes the level of conditions that states have to support innovation in the technology sector.
	Human Capital	Describes the availability degree of the right skills to support the technology sector.
Data & Infrastructure (GAIRI3)	Infrastructure	Describes the potential of a country's technological infrastructure to support AI technologies.
	Data Availability	Describes the level to which existing data represents the population comprehensively.
	Representativeness	Describes the level to which existing data comprehensively represents the population.

Reference: Hankins et al. 2023

Countries prioritize AI activities to create decision support systems, forecasting, and systematization systems in order to establish global resilience. This is because AI is often associated with various technical, economic, and social dimensions, generally with a functionality that enhances these dimensions (Raj & Seamans, 2019; Hu & Yu, 2022). In terms of technology and innovation, Cockburn et al. (2018) have noted that AI promotes efficiency and innovation-oriented competition in almost every field. According to the authors, as countries expand their use of AI technologies, their innovation capacities could increase. Xue et al. (2021) have explained that AI is a significant factor in the establishment of research and development infrastructure in both military and civilian organizations, as well as in technological innovation. Luo et al. (2023) have emphasized that AI contributes to countries' economies by promoting innovation in organizations' operational production, product design, and customer services. In terms of sustainable development, Thamik and Wu (2022) have stated that AI is an important tool for promoting sustainable development incentives and ensuring the secure provision of sustainable development. Through a systematic literature review, Kulkov et al. (2023) have determined the contribution of countries' AI applications to sustainable development within the framework of the United Nations Sustainable Development Goals, identifying institutional, technical, and operational-focused areas. Researchers have observed that the effect of AI on the institutional field plays a significant role in ensuring the efficiency of relationships among companies, partners, and customers. Within this scope, the technical impact of AI is evaluated to contribute to societal development through the development of algorithms, while its operational impact is considered to be in the provision of internal transformations, business modeling, and strategies. Based on a literature review, Sulicha et al. (2023) have expressed that the main areas influenced by AI in terms of sustainable development include agriculture, computer science, economics, business management, and decision-making processes. In terms of healthcare, Kim and Huh (2020) have emphasized that errors, deficiencies, or inaccuracies can occur during the reading process of post-treatment medical data, and they have highlighted the use of AI programs to ensure accurate and appropriate treatments, aiming to mitigate such errors, inaccuracies, and deficiencies. Sauerbrei et al. (2023) have suggested that AI could have significant effects on patient-centered doctor-patient relationships in healthcare and facilitate the adaptation of AI to medical education, potentially enhancing the efficiency of healthcare systems in countries. From an educational perspective, Szoltysek and Stechly (2023) have stated that AI facilitates decision-making in educational matters and connects learning to logical sequences. Regarding art, Shen and Yu (2021) have noted that AI enriches art creation and activates natural responses based on the environmental context, as well as analyzing emotions. The researchers further emphasized that AI could provide integrated artistic expressions based on the study of natural human behaviors and integrated senses. In terms of security, Coole et al. (2021) have mentioned that AI is mainly used in security for identifying patterns and signals, detecting anomalies in behavior patterns, imaging, classification, and matching. From a legal perspective, Krausova (2017) has expressed that in the future, AI will not only make lawyers' work more efficient but will also significantly impact the law itself. In this context, the author stated that the usefulness of AI in law and its integration into the legal framework could be achieved through good and harmonious integration. In agriculture, Oliveira and Silva (2023) have examined the use of AI in agriculture, finding that more than 20 AI techniques are used in the field. The authors also observed that machine learning, convolutional neural networks, IoT, and big data techniques are predominantly used in agriculture within the scope of AI. Finally, in the field of sports, Meriçelli and İncetaş (2023) have emphasized that AI can be utilized for preparing training programs, score predictions, betting outcomes, sports health applications, tactics and strategies, player transfers, referee decision support systems, and sports journalism. Du (2024) discusses the potential changes brought about by AI in the workplace and shifts in employment structures by evaluating the existing literature. The research emphasizes the importance of proactive policies to address the challenges posed by AI and automation. It advocates for investing in education and training, fostering innovation and job creation, and implementing measures such as universal basic income to effectively manage these challenges. Zia et al. (2024) investigate the various roles of AI in project management and evaluate its impact on project success rates. Through a comprehensive literature review and data analysis, the study demonstrates that the integration of AI into project management has led to significant improvements in project success rates. Overall, the application of AI has been found to result in a meaningful increase in project success rates across various industries. This highlights AI's potential to streamline project workflows and mitigate risks by automating repetitive tasks, optimizing resource allocation, and enhancing decision-making processes. Garg et al. (2024) aimed to investigate the impact of AI on employee engagement and productivity in the workplace. The findings indicate that AI can positively influence both employee engagement and productivity. Additionally, the study examined the effects of AI on management, observing how AI automates data processing, decision-making, and repetitive tasks. Adigwe et al. (2024) investigate the impact of AI on the global economy. According to their findings, the integration of AI significantly enhances organizational competitiveness, which aligns with contemporary literature. Additionally, the study observes that higher levels of AI adoption in communities are associated with improved socioeconomic outcomes; however, there is a risk that this may exacerbate existing inequalities. Nahar (2024) examines the impact of AI-based innovation on sustainable development through a literature review. The study identifies a gap in the literature, noting that while there is reported correlation between AI and innovation, no prior research has forecasted the impact of AI-based innovation on sustainable development. The findings indicate that AI-based innovation has an effect on Sustainable Development Goals.

AI has been a pivotal catalyst for economic expansion in recent years. AI has the capacity to trigger economic growth by enhancing efficiency and optimizing business processes across various sectors (Atal, 2021; Ghosh, 2021; Prasad, 2021; Rajesh, 2021, Solos & Leonard, 2022). Additionally, AI facilitates the improvement of services economically, the development of data analytics and forecasting models, automation and streamlining processes, as well as enabling the emergence of new business models and industries. Consequently, the appeal of AI for countries continues to grow steadily (Barai, 2021; Gure, 2021; Johns, 2021). The advancements, strategic approaches, methodologies, and regulatory frameworks surrounding AI adoption within the G7 nations, representing the world's leading economies, hold the potential to significantly shape the global economic landscape and its interconnected facets. These facets encompass innovation, logistical efficiency, international trade volumes, talent competitiveness, foreign direct investment, and more. Moreover, the AI-related policies of these G7 countries can serve as influential models for other nations to emulate. In this regard, measuring the potential and potential development of AI readiness and performance of G7 countries is of great importance (OECD, 2023; Allen & Thadan, 2023). Finally, Hankins et al. (2023) have measured and ranked the values of AI readiness performance of these countries using GAIRI criteria. Accordingly, Hankins et al. (2023) have presented the artificial intelligence readiness performance values for G7 countries in Table 2.

Table 2. AI Readiness Performance Values of G7 Countries

Countries	Score	Rank
Canada	77,07	3
Germany	75,26	5
France	76,08	4
Italy	67,63	7
Japan	75,07	6
UK	78,57	2
USA	84,79	1
Mean	76,35	---

Reference: Hankins et al. (2023)

A comparative analysis of the AI readiness performance scores presented in Table 2 reveals that the US, the UK, and Canada have demonstrated superior levels of preparedness for AI adoption compared to their G7 counterparts. The average AI readiness performance score for the G7 group was exceeded by these three nations.

3. Material and Method

3.1 Analysis of the Study and Data Analysis

The study's dataset has replaced the GAIRI component values of G7 countries. This is because all G7 countries have a full score (100) for the "Vision" subcomponent. Therefore, in the LOPCOW method, the benefit-oriented normalization process of the "Vision" subcomponent value remains mathematically undefined. In addition, GAIRI components have a more comprehensive characteristic compared to subcomponents. In this context, the study evaluates the artificial intelligence readiness performances of G7 countries based on the most recent and up-to-date 2023 GAIRI criteria values. The AI readiness performances of these countries have been assessed using the LOPCOW-MARCOS method. The reason for using the LOPCOW method to determine the weight values of criteria and the MARCOS method to assess the AI readiness performances of countries is that these methods offer advantages and benefits compared to other MCDM approaches.

Upon reviewing the literature, no research has been found that explains the performance of G7 countries in AI preparedness using any MCDM method. Therefore, the study is considered to contribute to both the literature on artificial intelligence, the relationship between artificial intelligence and economic growth, enriching the relevant fields. Additionally, a review of the MCDM literature reveals that studies utilizing both LOPCOW and MARCOS methods are very limited. Therefore, this research is considered to contribute to the MCDM literature from a methodological perspective. As for the scope of the research constraint, only the current GAIRI 2023 year criteria for G7 countries have been considered. It is believed that including different years would increase the level of inclusivity of the research.

3.2 LOPCOW Method

LOPCOW (The Logarithmic Percentage Change-driven Objective Weighting) method represents a significant addition to the MCDM literature, pioneered by Ecer and Pamucar in 2022. This methodology is founded upon the principle of deriving optimal weights by amalgamating data of varying magnitudes. Moreover, it aims to minimize discrepancies between the significance levels of different criteria, thus ensuring a balanced consideration of diverse factors. Notably, LOPCOW incorporates the interrelationships between criteria, enhancing its efficacy in decision-making processes. Furthermore, LOPCOW incorporates the interdependencies between criteria and is unaffected by the presence of negative values in the raw data (Bektaş, 2022; Ecer & Pamucar, 2022). A thorough examination of previous research has highlighted the popularity of the LOPCOW method, with numerous studies dedicated to its application. These studies are tabulated in Table 3 for easy reference.

Table 3. LOPCOW Literature

Author(s)	Method(s)	Theme
Bektaş (2022)	MEREC, LOPCOW, COCOSO and EDAS	Assessing the capacity of the Turkish insurance sector
Biswas et al. (2022)	LOPCOW-EDAS	Conducting a comprehensive analysis of the effects of the Covid-19 pandemic on corporate profitability and sustainability.
Biswas & Joshi (2023)	LOPCOW	Assessing of performance of initial public offerings
Biswas et al. (2023)	LOPCOW	Comparison of energy efficiency and environmental sustainability between BRICS and G7 nations.
Das et al. (2023)	LOPCOW-CRADIS	Selecting the right portfolio optimization approach
Lukic (2023)	LOPCOW-EDAS	Analysis of the economic status of Western Balkan nations
Ulutaş et al. (2023)	PSI, MEREC, LOPCOW and MCRAT	Determining the optimal natural fiber for conventional commercial building insulation
Rong et al. (2023)	LOPCOW-ARAS	Risk evaluation of research and development endeavors within offline programming systems for industrial robots.
Dhruva et al. (2024)	Fermatean Fuzzy Set, LOPCOW-COCOSO	Choosing appropriate cloud service providers for healthcare facilities
Liu et al. (2024)	RCC-LOPCOW and OCRA	Assessing the capability of enterprise digital transformation
Ulutaş et al. (2024)	LOPCOW-PSI-MACONT	Analysis of third-party logistics service providers for car manufacturing firms
Sanyal et al. (2024)	LOPCOW-EDAS	Organic food selection
Rong et al. (2024)	LOPCOW-ARAS	Analysist of R&D projects
Putra et al. (2024)	LOPCOW-MARCOS	Analysis of best honorary teacher performance

The procedural steps for implementing this method, as delineated step by step as below (Ecer & Pamucar, 2022).

Step 1: Acquisition of the Decision Matrix(D)

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

j: $1, 2, 3, \dots m$, where n show the number of criteria

D: Decision matrix

C: Criterion

d_{ij}: Equation 1 provides the foundation for constructing the decision matrix, where "i_j" denotes the performance score of the $j-th$ criterion for the $i-th$ decision alternative.

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

Step 2: Normalization Process $\left(r_{ij}^{x}\right)$

The decision matrix values are determined based on Equations 2 and 3 for benefit and cost criteria, respectively.

Benefit-oriented criteria:

$$r_{ij}^{x} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Cost-oriented criteria:

$$r_{ij}^{x} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \tag{3}$$

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

Through the application of Equation 4, the mean squared error is scaled by dividing it by the product of the standard deviations for each criterion. This scaling process effectively removes the influence of different dataset sizes on the observed variance.

$$PV_{ij} = In \left| \frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^{2}}{m}}}{\boldsymbol{\sigma}} \right| \tag{4}$$

Step 4: Calculating Criterion Weights $\left(w_j\right)$

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

In measuring the weights of criteria, the LOPCOW method offers numerous benefits compared to other weighting methods. Firstly, the method imposes no restrictions on the number of criteria when determining their importance concerning decision alternatives. Therefore, the most significant distinction of the LOPCOW method from other objective weighting methods is that it eliminates the variance introduced by data size by calculating the mean squared value as a percentage of the standard deviations (Bektaş, 2022). Secondly, the LOPCOW method not only provides a consistent outcome but also takes into account the interrelations among risk criteria and addresses more problems where the weights of the criteria and experts are not predetermined (Ecer and Pamucar, 2022). Thirdly, the LOPCOW method effectively captures the experts' hesitation during the preference-sharing process. Accordingly, by using a logarithmic operator, it can significantly reduce the impact of extreme values (Cheng et al., 2024). Fourthly, LOPCOW offers an adaptive framework for adjusting the weights of criteria based on the relative changing dynamics of historical data (Hadad et al., 2024). Fifthly, the LOPCOW method provides a suitable solution for benefit- and cost-oriented criteria without any restrictions and can thus incorporate factors that do not affect it, such as negative raw data, i.e., negative values (Lukic, 2024). Lastly, LOPCOW is an objective weight determination method that requires no prior information. This approach not only understands the nature of criteria but also estimates hesitation during the preference articulation process using the variability distribution measure (Ecer et al., 2024).

3.3 MARCOS Method

The MARCOS method is a MCDM technique designed to evaluate the performance of various alternatives by establishing their relationship to reference points: the ideal and anti-ideal solutions. This method calculates utility functions for each alternative, facilitating a compromise ranking based on these reference points. The ideal and anti-ideal solutions vary depending on whether criteria are beneficial or cost-based. For beneficial criteria, the ideal solution maximizes utility, while for cost criteria, it minimizes utility. Conversely, the anti-ideal solution minimizes utility for beneficial criteria and maximizes it for cost criteria. In essence, the optimal decision is the one that aligns most closely with the ideal solution and is furthest from the anti-ideal solution (Ecer, 2020). The

MARCOS method has been widely employed by researchers in selection problems and performance evaluations, as evidenced by the extensive literature on the topic presented in Table 4.

Table 4. MARCOS Literature

Author(s)	Method(s)	Theme
Kumar et al. (2022)	BWM Fuzzy-MARCOS	Choosing coating materials for tooling sectors
Badi et al. (2023)	BWM-AHP-MARCOS	Selection of suitable locations for wind farm development
Singh et al. (2023)	CRITIC-MARCOS	Investigating the properties of automotive brake friction composites reinforced with agro-waste and natural fibers
Binh et al. (2024)	MARCOS	Identifying optimal process parameters for electrical discharge machining (EDM) with graphite electrodes
Ecer et al. (2024)	A fuzzy BWM and MARCOS integrated framework with Heronian function	Assessing cryptocurrency exchanges
El-Arby et al. (2024)	MARCOS	Location Selection
Erdoğan & Aydın (2024)	CRITIC-MARCOS	Evaluation of insurance firms listed on BIST
Dinh et al. (2024)	MARCOS	Optimization of a two-stage helical gearbox
Li et al. (2024)	ENTROPY-MARCOS	Assessment of service quality in mobile healthcare applications
Mastilo et al. (2024)	MEREC-MARCOS	Evaluating the banking sector
Dua (2024)	PSI-SAW and PSI-MARCOS	Hybrid approach model suggestion
Wang et al. (2024)	Fuzzy CRITIC-MARCOS	Evaluating of sustainable food suppliers
Zhao & Guo (2024)	Fuzzy-Delphi, AEW, BWM, and MARCOS	Selection of plans for constructing urban integrated energy systems

The implementation process of the method is explained in detail, following the steps outlined by Ecer (2020).

Step 1: Acquisition of the Decision Matrix (D)

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

j: $1, 2, 3, \dots m$, where n show the number of criteria

D: Decision matrix

C: Criterion

d_{ij}: Equation 1 provides the foundation for constructing the decision matrix, where "i_j" denotes the performance score of the $j-th$ criterion for the $i-th$ decision alternative.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{6}$$

Step 2: Acquisition of the Extended Decision Matrix (D^E)

To determine the values of AI and AII, Equation 7 is employed for benefit criteria and Equation 8 for cost criteria.

$$\begin{cases} AAI = \ If \ \min x_{ij} \ the \ criteria \ are \ benefit - based \ (j \in B) \\ AI = If \ \max x_{ij} \ the \ criteria \ are \ benefit - based \ (j \in B) \end{cases} \tag{7}$$

$$\begin{cases} AAI = \ If \ \max x_{ij} \ the \ criteria \ are \ cost - based \ (j \in B) \\ AI = If \ \min x_{ij} \ the \ criteria \ are \ cost - based \ (j \in B) \end{cases} \tag{8}$$

By incorporating the ideal (AI) and anti-ideal (AII) solutions, as specified in Equation 9, the initial decision matrix is extended to create the extended decision matrix.

$$D^E = \begin{array}{c} C \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AAI \\ AI \end{array} \begin{bmatrix} C_1 & C_2 & \cdots & C_N \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix} \tag{9}$$

Step 3: Standardization of the Extended Decision Matrix (N)

To standardize the extended decision matrix, Equation 10 is used for cost criteria and Equation 11 is used for benefit criteria. The standardized values are obtained through Equation 12.

$$n_{ij} = \frac{x_{ai}}{x_{ij}}, j \in C \tag{10}$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}}, j \in B \tag{11}$$

$$N = \begin{bmatrix} n_{11} & n_{12} & \cdots & n_{1n} \\ n_{21} & n_{22} & \cdots & n_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ n_{m1} & n_{m2} & \cdots & n_{mn} \\ n_{aa1} & n_{aa2} & \cdots & n_{aan} \\ n_{ai1} & n_{ai2} & \cdots & n_{ain} \end{bmatrix} \tag{12}$$

Step 4: Formation of the Weighted Matrix (V)

The V is computed as depicted in Equation 12, by multiplying the standardized matrix elements with the criterion weights, as shown in Equation 13. Subsequently, Equation 14 yields the weighted matrix.

$$v_{ij} = n_{ij}.w_j \tag{13}$$

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \\ v_{aa1} & v_{aa2} & \cdots & v_{aan} \\ v_{ai1} & v_{ai2} & \cdots & v_{ain} \end{bmatrix} \tag{14}$$

Step 5: Measurement of Alternative Utility Degrees (K_1^-, K_1^+)

First, the weighted scores for each alternative (S_i) are calculated using Equation 15. Then, the proximity of each alternative to both the anti-ideal (K_1^-) and ideal (K_1^+) solutions is measured using Equations 16 and 17 to determine their utility degrees.

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{15}$$

$$K_1^- = \frac{S_i}{S_{aai}} \tag{16}$$

$$K_1^+ = \frac{S_i}{S_{ai}} \tag{17}$$

Step 6: Computation of Alternative Utility Function Values ($f(K_i^-), f(K_i^+)$) and the approximate solution of decision alternatives $\left(f(K_i)\right)$

The utility function values for each decision alternative are computed to both the anti-ideal $\left(f(K_i^-)\right)$ and ideal $\left(f(K_i^+)\right)$ solutions using Equations 18 and 19. The approximate performance of these alternatives within the ideal-anti-ideal solution space is then measured using Equation 20.

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{18}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{19}$$

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{20}$$

In measuring the performance of decision alternatives or addressing selection problems, the MARCOS method offers several advantages over other MCDM methods. Firstly, the MARCOS method is noted for its robust and powerful nature in optimizing multiple objectives. It serves as a solid decision-making function due to its capabilities in determining reference points, defining relationships between alternatives and reference points, and assessing the benefit levels of alternatives based on these reference points. Additionally, it provides insights into preferences, contributing to the realistic and stable evaluation of method selection problems. Consequently, the MARCOS method enhances the accuracy and reliability of decision-making outcomes (Ecer, 2020). Secondly, the MARCOS method enables the assessment of the real situation and facilitates future improvements by taking relevant measures. It also allows for comparisons with the results of other multi-criteria decision-making methods (Lukic, 2022). Thirdly, the MARCOS method has the potential to handle complex multi-criteria and multi-alternative decision-making scenarios. It provides a structured framework that enables decision-makers to evaluate and rank alternatives based on a compromise solution, which is particularly useful in situations where conflicting criteria must be balanced (Jayakumar et al., 2024). Fourthly, the MARCOS method demonstrates flexibility and adaptability to various decision-making contexts (Wang et al., 2024). Fifthly, the method is robust in dealing with uncertainty and imprecision. The MARCOS method incorporates a systematic approach to handle uncertainty, which is crucial in real-world decision-making processes where data may be incomplete or imprecise. This feature is especially beneficial in dynamic environments where decision-makers must rely on uncertain information to make informed choices (Ding et al., 2024). Sixthly, the MARCOS method provides computational efficiency. It allows for the rapid processing of large datasets and complex decision matrices. This efficiency is critical in time-sensitive decision-making scenarios where quick analysis and decision-making are required (Abdulla et al., 2023). Seventhly, the method also promotes transparency and ease of understanding. The straightforward approach of the MARCOS method to ranking and evaluating alternatives makes it accessible to decision-makers who may not have extensive technical expertise in MCDM methods. This transparency facilitates better communication and understanding among stakeholders involved in the decision-making process (Demir et al., 2024). In conclusion, the MARCOS method offers a robust, flexible, and efficient framework for multi-criteria decision-making. Its ability to handle complex scenarios, adapt to various contexts, and process data efficiently makes it a valuable tool for decision-makers.

4. Results

4.1. Computational Analysis

In the analytical process, we initially constructed a decision matrix using Equation 1 to evaluate the GAIRI criteria for each decision alternative (country) based on the LOPCOW methodology. Given that all criterion values were utility-oriented, we subsequently applied Equation 2 to normalize the decision matrix values. The resulting decision and normalized decision matrix values are summarized in Table 5.

Proceeding with the analysis, we used Equation 4 to calculate the percentage values for each criterion associated with the decision alternatives based on the normalized values. Finally, Equation 5 was employed to determine the weights of the GAIRI criteria relative to the countries. The resulting percentage values, weights, and the corresponding weight rankings are summarized in Table 6.

Based on the weight rankings presented in Table 6, GAIRI3 is assigned the highest weight, followed by GAIRI1, and lastly, GAIRI2. A closer examination of Table 4 indicates that the difference in weights between GAIRI3 and GAIRI1 is not statistically significant.

In the subsequent analytical phase, we employed the LOPCOW-based MARCOS method to assess the artificial intelligence readiness of the G7 countries. Initially, Equation 6 was used to construct the decision matrix within the LOPCOW framework. Subsequently, Equation 9 was applied to extend this decision matrix. For criteria that were utility-oriented, Equation 7 was used, while Equation 8 was employed for cost-oriented criteria. The resulting extended decision matrix values are presented in Table 7.

Table 5. Decision (D) and Normalized Decision Matrixes $\left(r_{ij}^{x}\right)$

Decision Matrix (D)			
Countries	**GAIRI1**	**GAIRI2**	**GAIRI3**
	Max.	**Max.**	**Max.**
Canada	85,3	64,73	81,17
Germany	80,78	63,28	81,72
France	84,03	60,4	83,8
Italy	76,61	50,98	75,29
Japan	82,76	56,85	85,61
UK	82,5	68,8	84,42
USA	86,04	81,02	87,32
Max.	86,0	81,0	87,3
Min.	76,6	51,0	75,3
Normalized Decision Matrix $\left(r_{ij}^{x}\right)$			
Countries	**GAIRI1**	**GAIRI2**	**GAIRI3**
	Max.	**Max.**	**Max.**
Canada	0,922	0,458	0,489
Germany	0,442	0,409	0,534
France	0,787	0,314	0,707
Italy	0,000	0,000	0,000
Japan	0,652	0,195	0,858
UK	0,625	0,593	0,759
USA	1,000	1,000	1,000

Table 6. PV_{ij} and w Scores

Criteria	**GAIRI1**	**GAIRI2**	**GAIRI3**
$\boldsymbol{PV_{ij}}$	73,98	48,52	75,11
$\boldsymbol{w}$	0,374	0,246	0,380
Rank	2	3	1

Table 7. Extended Decision Matrix (D^{E})

Solutions	**GAIRI1**	**GAIRI2**	**GAIRI3**
	Max.	**Max.**	**Max.**
Ideal Solution (IS)	86,04	81,02	87,32
Anti-ideal Solution (AIS)	76,61	50,98	75,29

In the third step of the methodology, the extended decision matrix values were standardized using Equation 11 for benefit-oriented criteria and Equation 10 for cost-oriented criteria. The standardized extended decision matrix was then constructed using Equation 12. The resulting values are presented in Table 8.

Table 8. Standardized Scores (N)

Countries	**GAIRI1**	**GAIRI2**	**GAIRI3**
Canada	0,991	0,799	0,930
Germany	0,939	0,781	0,936
France	0,977	0,745	0,960
Italy	0,890	0,629	0,862
Japan	0,962	0,702	0,980
UK	0,959	0,849	0,967
USA	1,000	1,000	1,000
IS	1,000	1,000	1,000
AIS	0,890	0,629	0,862

In the fourth step, the standardized values are weighted using Equation 13, and a weighted matrix is formed using Equation 14. The weighted standardized values are described in Table 9 in relation to this.

Table 9. Weighted Standardized Values (V)

Criteria	GAIRI1	GAIRI2	GAIRI3
w	**0,374**	**0,246**	**0,380**
Canada	0,371	0,196	0,353
Germany	0,352	0,192	0,356
France	0,366	0,183	0,365
Italy	0,333	0,154	0,328
Japan	0,360	0,172	0,373
UK	0,359	0,208	0,367
USA	0,374	0,246	0,380
IS	0,374	0,246	0,380
AIS	0,333	0,154	0,328

In the fifth step of the process, we calculated the utility degrees of the decision alternatives. First, Equation 15 was used to aggregate the weighted standardized values for each alternative. Next, the ideal and anti-ideal levels of the alternatives were determined using Equations 17 and 16, respectively. The resulting utility values for the countries are presented in Table 10.

Tablo 10. Ideal (K_1^+) and Anti-ideal (K_1^-)Solution-based Utility Values

Countries	$\boldsymbol{S_i}$	$(\boldsymbol{K_1^+})$	$(\boldsymbol{K_1^-})$
Canada	0,921	0,921	1,129
Germany	0,899	0,899	1,102
France	0,913	0,913	1,120
Italy	0,816	0,816	1,000
Japan	0,905	0,905	1,110
UK	0,935	0,935	1,146
USA	1,000	1,000	1,226
IS	1,000	1,000	1,226
AIS	0,816	0,816	1,000

The sixth step involves the determination of both the ideal and anti-ideal utility function values for each decision alternative using Equations 19 and 18. Finally, Equation 20 is utilized to measure the approximate solution (performance) scores of decision alternatives. Accordingly, the ideal and anti-ideal utility function scores along with the approximate solution scores for countries are described in Table 11.

Table 11. Countries' Ideal $(f(K_i^+))$ and Anti-ideal $(f(K_i^-))$ Utility Function Values along with Approximate Solution $(f(K_i))$ Values

Countries	$(\boldsymbol{f(K_i^+})$	$(\boldsymbol{f(K_i^-})$	$\boldsymbol{f(K_i)}$	Rank
Canada	0,551	0,449	0,674	3
Germany	0,551	0,449	0,658	6
France	0,551	0,449	0,669	4
Italy	0,551	0,449	0,597	7
Japan	0,551	0,449	0,662	5
UK	0,551	0,449	0,684	2
USA	0,551	0,449	0,732	1
		Mean	0,657	

Upon examining Table 11, it is observed that the countries' AI readiness performances are realized as USA, UK, Canada, France, Japan, Germany, and Italy. Additionally, the average AI readiness performance values for countries have been calculated. It is determined that the countries surpassing the calculated average AI readiness performance value are USA, UK, Canada, France, Japan, and Germany.

4.2. Sensitivity Analysis

To assess the methodological robustness of the LOPCOW-MARCOS method, conducted a sensitivity analysis. This involved applying various weighting techniques to the dataset and comparing the resulting performance rankings of the decision alternatives. A significant divergence in these rankings would indicate that the chosen weight coefficient calculation method is sensitive (Gigovic et al., 2016). As shown in Table 12, we calculated the values obtained using different weighting methods for the GAIRI criteria of the countries to evaluate this sensitivity.

Table 12. Weight Score of Criteria According to Weighting Methods

Methods	Criteria	GAIRI1	GAIRI2	GAIRI3
ENTROPY	Score	0,058	0,854	0,088
	Rank	3	1	2
CRITIC	Score	0,316	0,360	0,324
	Rank	3	1	2
SD	Score	0,343	0,324	0,332
	Rank	1	3	2
SVP	Score	0,146	0,349	0,505
	Rank	3	2	1

In the continuation of sensitivity analysis, countries' AI readiness performances and performance rankings calculated using the ENTROPY, CRITIC, SD, and SVP-based MARCOS methods are presented in Table 13.

Table 13. Performance Values of Countries According to Different Methods

Countries	ENTROPY BASED MARCOS		CRITIC BASED MARCOS		SD BASED MARCOS		SVP BASED MARCOS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Canada	0,649	3	0,670	3	0,671	3	0,664	3
Germany	0,635	4	0,654	5	0,655	5	0,656	5
France	0,615	5	0,659	4	0,662	4	0,660	4
Italy	0,525	7	0,585	7	0,589	7	0,584	7
Japan	0,586	6	0,649	6	0,653	6	0,654	6
UK	0,684	2	0,685	2	0,684	2	0,687	2
USA	0,790	1	0,743	1	0,739	1	0,743	1

Upon examining Table 13, it is observed that the rankings of countries' AI readiness performances identified by the LOPCOW-based MARCOS method differ from those identified by the ENTROPY, CRITIC, SD, and SVP-based MARCOS methods. Therefore, based on this result, it is determined that the LOPCOW-based MARCOS method is sensitive in measuring countries' AI readiness performances with GAIRI criteria. A review of the literature on objective methods for determining criterion weights reveals that each criterion weighting method has distinct mathematical models (Ecer, 2020). Specifically, compared to other objective weighting methods, the LOPCOW method calculates the weights of criteria for countries by using the mean squared value as a percentage of the standard deviations and mitigates variance caused by data size through logarithmic calculations. This approach better reveals the true value of the data.

4.3. Comparative Analysis

The comparative analysis assess the associations and standings of the recommended approach in comparison to other methodologies for calculating MCDM methods. The proposed method must exhibit credibility, reliability, and consistency with other methodologies, while also showcasing a favorable and statistically significant relationship with various MCDM methodologies (Keshavarz-Ghorabaee et al., 2021). In this regard, the AI readiness performance scores of countries calculated by the LOPCOW-MARCOS method were compared with the performance values calculated by LOPCOW-based ARAS, EDAS, TOPSIS, WASPAS, SAW, GRA (Grey Relation Analysis), WPA, and ROV methods in the comparative analysis. Accordingly, the measured AI readiness performance scores and hierarchical order of countries compared to other LOPCOW-based MCDM technique are described in Table 14.

Table 14. Performance Scores Measured According to Other LOPCOW-MCDM Methods

Countries	ARAS		EDAS		TOPSIS		WASPAS	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Canada	0,915	3	0,545	3	0,528	3	0,919	3
Germany	0,894	6	0,434	6	0,444	5	0,898	6
France	0,906	4	0,497	4	0,478	4	0,911	4
Italy	0,808	7	0,000	7	0,000	7	0,811	7
Japan	0,896	5	0,447	5	0,439	6	0,901	5
UK	0,931	2	0,630	2	0,634	2	0,934	2
USA	1,000	1	1,000	1	1,000	1	1,000	1
Countries	**SAW**		**GRA**		**WPA**		**ROV**	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Canada	0,921	3	0,629	2	0,917	3	0,243	5
Germany	0,899	6	0,486	6	0,896	6	0,276	3
France	0,913	4	0,606	5	0,908	4	0,319	2
Italy	0,815	7	0,333	7	0,808	7	0,147	7
Japan	0,905	5	0,611	3	0,897	5	0,271	4
UK	0,935	2	0,606	4	0,934	2	0,351	1
USA	1	1	1,000	1	1	1	0,231	6

A comparative analysis of Tables 11 and 14 reveals a discrepancy in the rankings of countries' AI readiness performance values when assessed using the LOPCOW-MARCOS method versus the TOPSIS, GRA, and ROV techniques. To further illustrate the findings of this comparative analysis, please refer to Figures 1, 2, and 3 for the relevant visualizations.

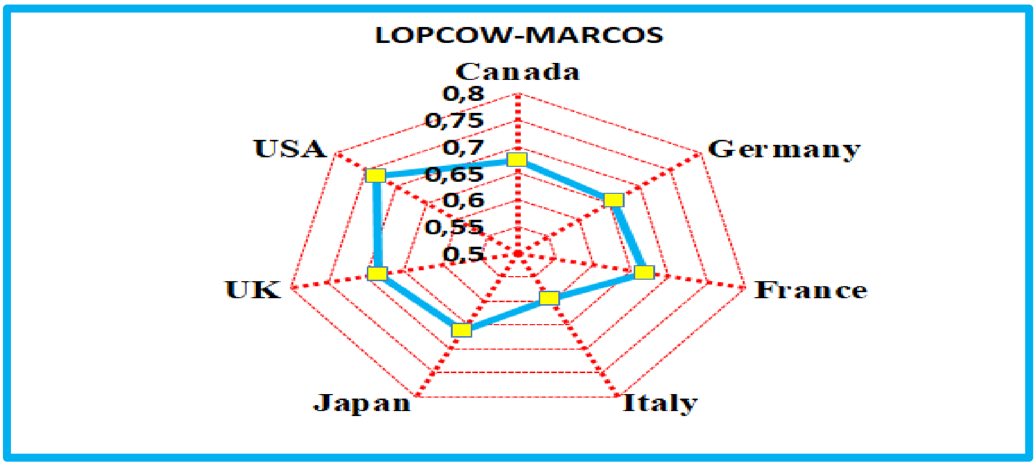

Figure 1. Positions of the Countries in Scope of LOPCOW-MARCOS

When Figure 1, Figure 2, and Figure 3 are considered together, it is observed that the performance fluctuations in countries relative to other methods are generally consistent with the LOPCOW-MARCOS method, except for the LOPCOW-ROV method. The results of this analysis indicate a strong correlation between the LOPCOW-MARCOS method and the other methods employed, with the exception of the LOPCOW-ROV method. The relationships of the LOPCOW-MARCOS method with other methods are described in Table 15 accordingly.

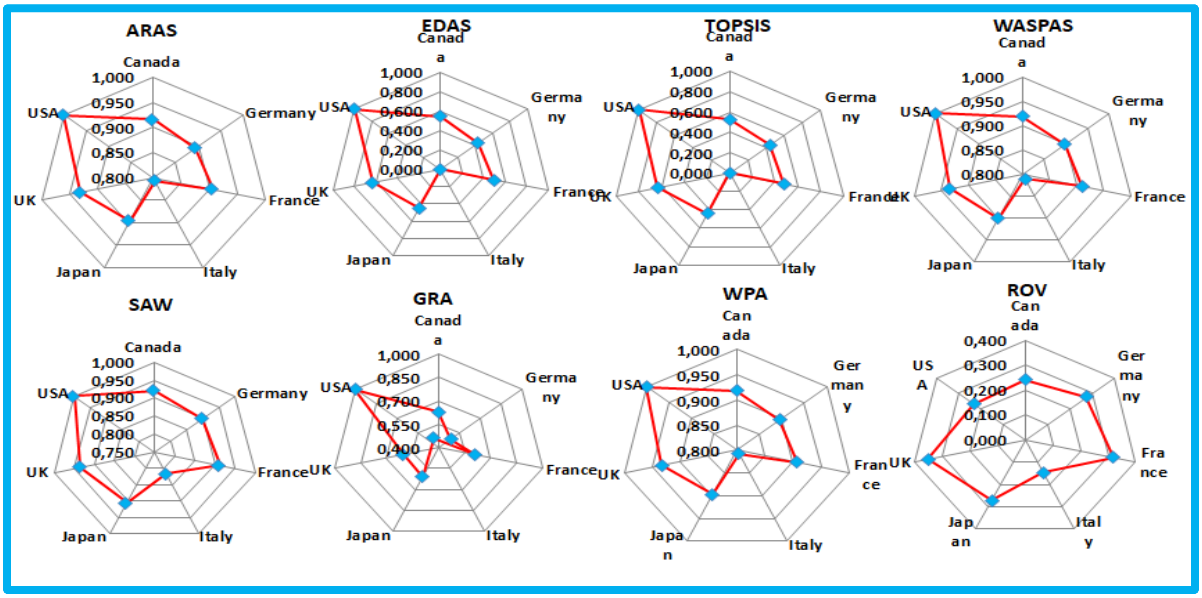

Figure 2. Positions of the Countiries in scope of MCDM Methods-1

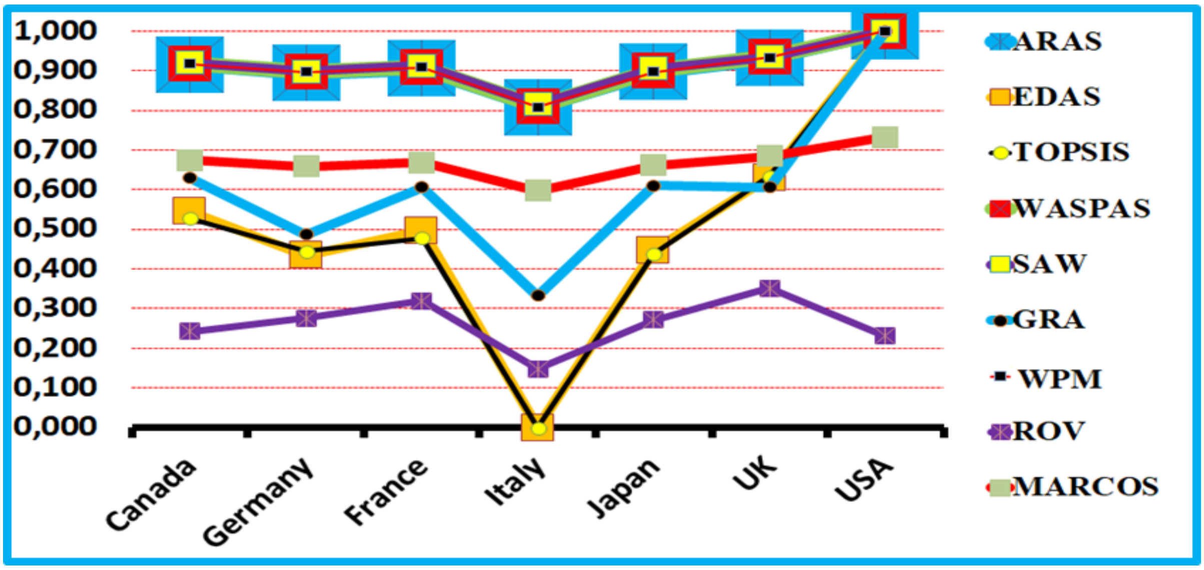

Figure 3. Positions of the Countiries in scope of MCDM Methods-2

Table 15. Correlation Scores of the LOPCOW-MARCOS Technique with Other LOPCOW-MCDM Technique

Methods	**ARAS**	**EDAS**	**TOPSIS**	**WASPAS**
MARCOS	0,998**	0,999**	0,997**	0,999**
Methods	**SAW**	**GRA**	**WPM**	**ROV**
MARCOS	0,999**	0,949**	0,999**	0,466*

p<.01, p*<.05**

Upon scrutinizing Table 15, it becomes evident that the LOPCOW-MARCOS method exhibits a strong, positive, and highly significant correlation with the remaining LOPCOW-MCDM methods. This finding serves as robust evidence to support the assertion that the LOPCOW-MARCOS method is both credible and reliable.

A review of the MCDM literature reveals that each MCDM method has distinct mathematical models and calculation techniques (Ecer, 2020). Particularly, when examining Figures 1, 2, and 3 together, the differences in performance values calculated using the MARCOS method are smaller compared to those obtained using other MCDM methods. This indicates that the MARCOS method is more precise in assessing the performance of countries. Additionally, this suggests that the MARCOS method, unlike other MCDM methods, accounts for the characteristic performance of all countries in its calculations. Consequently, the MARCOS method reveals the sharp characteristic structure of each country in performance measurement. As a result, the MARCOS method facilitates evaluating the real situation and making future improvements by implementing relevant measures.

4.4. Simulation Analysis

To assess the robustness and stability of the proposed method, a simulation analysis will be conducted. This analysis will involve generating various scenarios by modifying the values within the decision matrices. A stable method should exhibit increasing divergence in its results compared to other methods as the number of scenarios grows. Additionally, the average variance of the MCDM methods determined by the proposed method across these scenarios should be significantly greater than at least one other MCDM method, indicating its superior ability to discriminate between the relative importance of criteria. Finally, the analysis should demonstrate consistent variance among all MCDM methods within each individual scenario (Keshavarz-Ghorabaee et al., 2021). Table 16 presents the correlation values between the LOPCOW-MARCOS and other LOPCOW-MCDM methods, as calculated based on the initial 10 scenarios of the simulation analysis.

Table 16. Correlation Values of the LOPCOW-MARCOS Method with Other LOPCOW-MCDM Methods

Sce.	ARAS	EDAS	TOPSIS	WASPAS	SAW	GRA	WPM	ROV
1. Sce.	0,995**	0,994**	0,993**	0,996**	0,993**	0,951**	0,998**	0,471*
2. Sce.	0,999**	0,997**	0,994**	0,995**	0,997**	0,943**	0,993**	0,460*
3. Sce.	0,994**	0,996**	0,997**	0,994**	0,994**	0,939**	0,991**	0,456*
Sce.	ARAS	EDAS	TOPSIS	WASPAS	SAW	GRA	WPM	ROV
4. Sce.	0,997**	0,998**	0,998**	0,997**	0,989**	0,921**	0,99**	0,444*
5. Sce.	0,993**	0,993**	0,992**	0,992**	0,988**	0,907**	0,989**	0,439
6. Sce.	0,992**	0,99**	0,988**	0,987**	0,986**	0,883**	0,994**	0,435
7. Sce.	0,994**	0,987**	0,985**	0,988**	0,983**	0,876**	0,985**	0,431
8. Sce.	0,988**	0,986**	0,981**	0,981**	0,986**	0,875**	0,983**	0,425
9. Sce.	0,984**	0,981**	0,983**	0,979**	0,977**	0,871**	0,981**	0,419
10. Sce.	0,982**	0,985**	0,979**	0,983**	0,885**	0,865**	0,977**	0,413
Mean	0,992	0,991	0,989	0,989	0,978	0,903	0,988	0,439

p<.01, p*<.05**

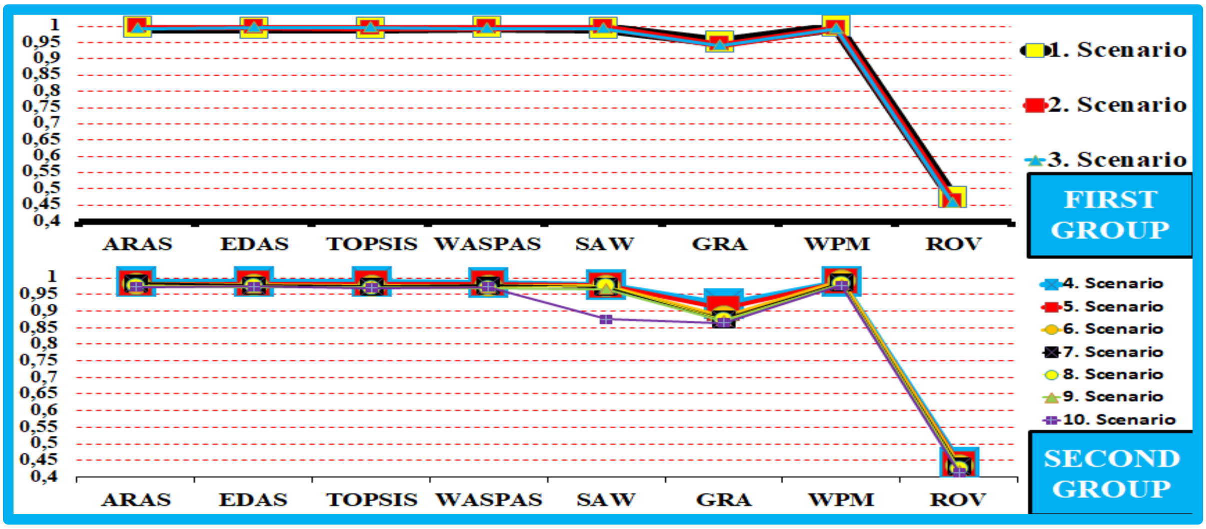

Figure 4. Correlation Position of the LOPCOW-MARCOS Technique with Other Technique within the Scenarios

Table 16 categorizes the 10 scenarios into two groups: the first three scenarios and the remaining seven. An analysis of Table 16 reveals that as the number of scenarios increases, the correlation values between the LOPCOW-MARCOS method and other methods decrease. This trend is visually represented in Figure 4.

Figure 4 illustrates that as the number of scenarios increases, the LOPCOW-MARCOS method exhibits increasing divergence from other LOPCOW-MCDM methods. This suggests that the distinctive characteristics of the LOPCOW-MARCOS method become more pronounced with a larger number of scenarios.

Table 17. Variance Score of Methods in scope of Scenarios

Scenarios	**ARAS**	**EDAS**	**TOPSIS**	**WASPAS**
1.Scenario	0,002785	0,075106	0,074777	0,025412
2.Scenario	0,00279	0,075526	0,074887	0,025717
3.Scenario	0,002795	0,075946	0,074997	0,026022
4.Scenario	0,0028	0,076366	0,075107	0,026327
5.Scenario	0,002805	0,076786	0,075217	0,026632
6.Scenario	0,00281	0,077206	0,075327	0,026937
7.Scenario	0,002812	0,07711	0,075437	0,027242
8.Scenario	0,002813	0,07669	0,075547	0,026937
9.Scenario	0,002814	0,07627	0,075657	0,027242
10.Scenario	0,002815	0,07585	0,075767	0,027547
Mean	0,0028039	0,0762856	0,075272	0,0266015

Scenarios	**SAW**	**GRA**	**WPM**	**ROV**	**MARCOS**
1.Scenario	0,02555	0,032579	0,0026564	0,0036248	0,001323
2.Scenario	0,025689	0,032884	0,0026878	0,0036615	0,001356
3.Scenario	0,025828	0,033189	0,0027192	0,0036982	0,001389
4.Scenario	0,025967	0,033494	0,0027506	0,0037349	0,001422
5.Scenario	0,026106	0,033799	0,002782	0,0037716	0,001455
6.Scenario	0,026245	0,034104	0,0028134	0,0038083	0,001488
7.Scenario	0,026384	0,034409	0,0028448	0,003845	0,001521
8.Scenario	0,026523	0,034714	0,0028762	0,0038817	0,001554
9.Scenario	0,026662	0,035019	0,0029076	0,0039184	0,001587
10.Scenario	0,026801	0,035324	0,002939	0,0039551	0,00162
Mean	0,0261755	0,0339515	0,0027977	0,00379	0,0014715

To evaluate the consistency of variances in the criterion weights of the LOPCOW-MARCOS method across different scenarios, a sensitivity analysis was conducted using the ADM (ANOM for variances with Levene) method. This statistical technique provides a visual representation to assess the equality of variances. The ADM plot consists of a central line representing the overall mean, accompanied by upper and lower decision limits. If the standard deviation of a cluster exceeds these limits, it indicates significant variance heterogeneity. Conversely, if all standard deviations fall within the limits, it suggests consistent variance. In this analysis, the variance values of the performance scores of countries measured by the LOPCOW-MARCOS method for each scenario were calculated. The resulting variance values for the methods within each scenario are presented in Table 17.

Upon examining Table 17, results indicated that the variance values of the performance scores calculated within the LOPCOW-MARCOS method are lower than those of other LOPCOW-MCDM methods, depending on the scenarios. In this regard, it is evaluated that in the LOPCOW-MARCOS method, the differences in performance values among decision alternatives are less pronounced or the values are closer to each other compared to other LOPCOW-MCDM methods. Furthermore, for the scenarios, the ADM analysis for the LOPCOW-MARCOS method is presented in the relevant plot in Figure 5.

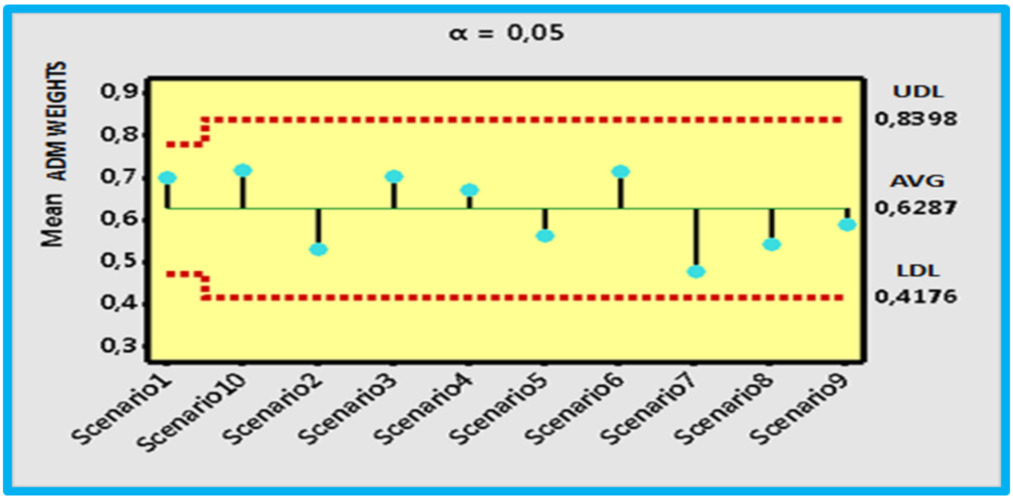

Figure 5. ADM Diagram

Figure 5 clearly shows that the calculated ADM values for all scenarios are consistently within the defined boundaries (UDL: Upper decision limit and LDL: Lower decision limit). This finding suggests that the variances in weights remain stable across different scenarios. This finding is further supported by the Levene's Test, the key statistics of which are presented in Table 18.

Table 18. Levene Test

Levene Score	df1	df2	*p*
0,239	2	10	0,127

p<.05**

Table 15 further corroborates the consistency of variances (homogeneity) in criterion weights across different scenarios. The p-value of 0,239 exceeds the significance threshold of 0.05, indicating a lack of statistical significance. This bolsters the conclusion that the LOPCOW-MARCOS method exhibits robustness and stability, as demonstrated by the simulation analysis results.

5. Conclusion and Discussion

Analysing the AI readiness of major economies is of growing importance in an era of intensifying global competition. This analysis serves as a critical tool for understanding the effect of AI technologies on economic growth and competitiveness. Furthermore, these performance assessments provide essential guidance for directing strategic investments and policymaking in the AI field. Ultimately, such analyses play a pivotal role in determining economies' positions in the AI landscape and gaining a competitive edge. This research evaluated the AI readiness capacity of the G7 countries, the world's leading economies, using the LOPCOW-MARCOS method. The analysis was based on the most recent GAIRI criteria values for 2023. Prior to the evaluation, the LOPCOW method was employed to determine the weights of the GAIRI criteria for each country.

The study revealed that the GAIRI criteria were ranked in order of importance as GAIRI3, GAIRI1, and GAIRI2. However, there was no significant difference in the weights assigned to GAIRI3 and GAIRI2. Subsequently, the LOPCOW-MARCOS method was used to assess the AI readiness capacity of the G7 countries. The results indicated that the US, the UK, Canada, France, Japan, and Germany outperformed the average AI readiness level. Italy ranked below the average.

In the third stage of the analysis, a sensitivity analysis was conducted to assess the robustness of the LOPCOW-MARCOS method. Various objective criterion weighting methods, including ENTROPY, CRITIC, SD, and SVP, were used to calculate the weights of the GAIRI criteria. The LOPCOW-MARCOS method was then applied to evaluate the performance of the countries using these different weightings. The results indicated that the rankings of countries' AI readiness performance differed when using the LOPCOW-MARCOS method compared to the ENTROPY, CRITIC, SD, and SVP-based MARCOS methods. This suggests that the LOPCOW-MARCOS method is sensitive to changes in the weighting of the GAIRI criteria.

The performance rankings of countries, as determined by the LOPCOW-MARCOS method, were subjected to a comparative analysis. The rankings were then juxtaposed with those obtained from various other LOPCOW-MCDM methods, namely ARAS, EDAS, TOPSIS, WASPAS, SAW, GRA, WPM, and ROV. The comparative analysis revealed discrepancies in the country rankings generated by the LOPCOW-MARCOS method when contrasted with the rankings produced by the LOPCOW-TOPSIS, GRA, and ROV methods. Moreover, a correlation analysis was conducted to examine the relationship between the LOPCOW-MARCOS method and other LOPCOW-MCDM methods. The results indicated a strong, positive correlation between the LOPCOW-MARCOS method and the other methods, with the exception of the LOPCOW-based ROV method. This suggests that the LOPCOW-MARCOS method is both credible and reliable.

A sensitivity analysis was conducted to assess the robustness of the LOPCOW-MARCOS method. Ten scenarios were created by varying the criterion values for the countries. The correlation between the LOPCOW-based MARCOS method and other LOPCOW-MCDM methods was calculated for each scenario. The results indicated a decreasing correlation between the LOPCOW-MARCOS method and other methods as the number of scenarios increased. To evaluate the consistency of variance in the AI readiness performance values measured by the LOPCOW-MARCOS method, an ADM test was performed. The results of the ADM test confirmed the homogeneity of variances across the scenarios.

Upon reviewing the literature, Hankins et al. (2023) identified the AI readiness performances of countries as USA, UK, Canada, France, Germany, Japan, and Italy. In the current study, the ranking was determined as USA, UK, Canada, France, Japan, Germany, and Italy. In terms of rankings, consistency was observed for the countries USA, UK, Canada, and France in both the current study and the research conducted by Hankins et al. (2023). Additionally, the average AI readiness performance values of these countries were measured according to the methods. According to the current study, the countries exceeding the average performance value were USA, UK, Canada, France, Japan, and Germany, while according to Hankins et al. (2023), the countries were USA, UK, and Canada. Therefore, considering the quantitative findings of both studies, it can be concluded that the USA, Germany, and Canada have a certain potential for AI readiness, while Italy has relatively less potential compared to other countries.

The level of readiness for AI among G7 countries can directly impact their economic growth potential. The adoption of AI technologies has the potential to enhance productivity and create new job opportunities. This can provide a competitive advantage, particularly for countries that prioritize AI investments. High AI readiness levels can also position these countries as leaders in technological innovation, which may lead to a prominent position in the global technology market. Conversely, this situation could increase the risk of technological lag and deepen economic inequalities for other countries.

Furthermore, the integration of AI into production processes can lead to profound changes in labor dynamics. Automation and AI applications may result in the disappearance of certain jobs while creating new job opportunities and areas of expertise. This transformation could cause significant shifts in the global labor market. Additionally, disparities in access to AI technologies and the ability to implement these technologies can exacerbate economic inequalities on an international scale. Countries that successfully adopt AI technologies may become economically stronger, while others might not fully benefit from this transformation. In terms of recommendations, based on the findings of the current study, it is deemed essential for G7 countries, especially considering their global potential, to prioritize the development of methods and strategies aimed at enhancing the GAIRI3 and GAIRI1 criteria to facilitate the practical application of AI worldwide. Specifically, it is suggested that Italy should implement policies and initiatives to increase its AI readiness performance, particularly for the development of the global economy and other economy-related dimensions. Therefore, by supporting AI policies of other countries and developing comprehensive strategies in this field, the global benefits of AI can be enhanced, leading to greater contributions to the global economy. Specifically, the AI and AI readiness policies of G7 countries should be designed to promote AI applications and ensure equitable technological access. Additionally, G7 countries need to invest in education and skills development programs to facilitate effective adoption of AI technologies globally. This investment can help the workforce adapt to the requirements of the AI era and contribute to the growth of international trade volumes. It can also improve countries' alignment with international economic and trade activities, enhancing efficiency and effectiveness in the global context.

Methodologically, countries' AI readiness performances can be measured using various MCDM methods such as COCOSO, MAUT, DNMA, MAIRCA, RAFSI, SECA, OPA, PIV, PSI, EAMR, CRADIS, OWA OPERATOR, WISP, WEDBA, etc., and the values and rankings obtained can be compared. Furthermore, not only the G7 countries but also other countries belonging to influential economic and trade organizations such as G20, BRICS, the European Union, OPEC, etc., can be assessed for their AI readiness performances to enable comparisons among nations. Lastly, to enhance the meaningfulness and comprehensiveness of the GAIRI methodology, It is proposed to enhance the granularity of the analysis by increasing the criteria and sub-criteria number, or alternatively, to develop a tailored GAIRI methodology for each individual country.

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