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Analysis of Innovation Performance of South- Eastern European Countries in Transition Economies: An Application of the Entropy-Based ARTASI Method

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ABSTRACT

Innovation performance has emerged as a crucial policy concern for nations undergoing institutional change and economic restructuring. Using a novel hybrid multi-criteria decision-making (MCDM) framework, this study assesses the innovation capacities of five transition economies in South-Eastern Europe: Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia. Although the Global Innovation Index (GII) is widely regarded as a comprehensive benchmarking tool, its aggregated scoring system often obscures contextual subtleties, particularly in smaller or less-studied economies. To address these limitations, this study combines the ARTASI ranking model with objective weighting methods—Entropy and CRITIC—providing a transparent, flexible, and reproducible evaluation framework. The results indicate that output-oriented indicators—such as Knowledge and Technology Outputs, Market Sophistication, and Creative Outputs—are the most significant factors in differentiating national innovation performance. Among the analyzed countries, Serbia leads the regional ranking, followed by North Macedonia and Montenegro, while Albania and Bosnia and Herzegovina exhibit notable output-related deficiencies. Robustness checks—including sensitivity analysis and cross-validation with alternative MCDM techniques—confirm the model's stability and reliability. Beyond addressing a geographic gap in innovation literature, this study offers a methodologically refined approach to innovation evaluation. The proposed framework can serve as a foundation for comparative research in similar socioeconomic contexts and guide evidence-based policy-making in transition economies.

1. Introduction

In the domain of global economic development, innovation is regarded as a key driver of national competitiveness, technological progress, and long-term growth [1]. To systematize and contextualize the assessment of innovation across countries, the Global Innovation Index (GII) has emerged as the

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preeminent worldwide framework. Developed by the World Intellectual Property Organization (WIPO) in collaboration with Cornell University and INSEAD, the GII employs a multidimensional evaluation that captures innovation inputs—including institutions, human capital and research, infrastructure, and market and business sophistication—as well as outputs, such as knowledge and technology creation and creative production [2].

While the GII has become a cornerstone of innovation policy and international comparisons, its focus remains heavily skewed toward developed economies and large-scale emerging markets, often overlooking smaller transition economies undergoing structural innovation changes. This is particularly evident in South-Eastern Europe, where countries such as Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia have received limited empirical attention despite their strategic geographic importance and unique socioeconomic challenges [3]. As these nations align with EU innovation models and implement institutional reforms, analyzing their GII performance presents a valuable research opportunity with implications for regional development and policy-making.

However, methodologies for analyzing GII data remain largely homogeneous. Although the GII provides a robust composite index, recent advancements in Multi-Criteria Decision Making (MCDM) have introduced transparent, flexible, and reproducible evaluation tools. Among these, Entropy and CRITIC have gained prominence as objective weighting methods: Entropy measures information dispersion across criteria, while CRITIC accounts for both contrast intensity and inter-criteria conflict. Despite their growing adoption in performance assessment research [4,5], these methods have yet to be systematically integrated into GII-based analyses.

Furthermore, a disconnect persists between objective weighting techniques and modern MCDM ranking models, which address limitations of traditional tools like TOPSIS or AHP. In this context, the ARTASI (Alternative Ranking Technique based on Adaptive Standardized Intervals) method, proposed by Pamučar et al. [6], represents a significant advancement. ARTASI effectively mitigates issues such as rank reversal, scale sensitivity, and information loss during normalization—challenges particularly relevant to high-dimensional policy performance analysis.

This study bridges two critical gaps: first, by examining innovation trends in South-Eastern European transition economies, and second, by pioneering the application of hybrid MCDM tools (combining ARTASI with Entropy/CRITIC) to GII-based innovation performance. The proposed framework not only refines country rankings but also yields actionable policy insights for regional innovation development.

2. Review of Literature

Innovation is a primary driver of sustainable growth, competitiveness, and resilience in both developed and developing economies [1,7]. In transition economies undergoing the shift from central planning to market-based systems, innovation plays a particularly strategic role. It serves as both a marker of progress toward EU integration and international standards, and a pathway to overcoming legacy inefficiencies, technological dependency, and brain drain [8,9].

In this context, we adopt a broad definition of innovation encompassing product, process, marketing, and organizational domains, as outlined in the Oslo Manual. South-Eastern European countries - including Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia - face structural weaknesses such as low R&D investment, policy discontinuity, and poor institutional quality. These factors collectively hinder innovation performance, making these countries an important yet underexplored area in innovation research [3].

2.1 The Global Innovation Index: Range and Application

The World Intellectual Property Organization, in association with INSEAD and Cornell University, has developed the Global Innovation Index (GII), which has become a widely used global benchmark for innovation performance [2]. Since its introduction in 2007, the GII has provided a multidimensional assessment of innovation through seven foundational pillars, divided into input dimensions (institutions, human capital, research, infrastructure, market sophistication, and business sophistication) and output dimensions (knowledge and technology outputs, and creative outputs).

Numerous studies have utilized the GII for cross-country comparisons, performance tracking, and policy benchmarking [10,11]. For instance, Huarng and Yu [12] employed fsQCA to analyze which combinations of GII elements contribute to innovation success. Similarly, Queirós and Yáñez-Orozco [11] conducted a transnational study that identified human capital and business sophistication as the most critical pillars for innovation output.

Despite its widespread use, scholars have noted that the aggregated nature of GII rankings may obscure country-specific characteristics, masking both particular strengths and weaknesses [10]. Additionally, concerns have been raised about the GII's methodological transparency regarding weighting procedures, prompting the development of alternative models based on objective, data-driven approaches [3].

2.2 Objective Weighting in Innovation Assessment: Entropy and CRITIC

To enhance the reporting of results and strengthen the robustness of analysis, researchers are increasingly employing Multi-Criteria Decision Making (MCDM) techniques to disaggregate and re-prioritize GII data. Within MCDM, objective weighting methods - particularly Entropy and CRITIC - have gained prominence due to their ability to eliminate subjectivity and generate reproducible weightings.

Rooted in Information Theory, the Entropy method determines criterion importance by measuring variation across data points. Indicators demonstrating greater dispersion receive higher weights, reflecting their discriminative power [4]. This approach, successfully applied in research by Ecer and Aycin [13] and Özmerdivanlı [14,15], has revealed innovation and financial performance patterns not evident in aggregate scores.

The CRITIC method (Criteria Importance Through Intercriteria Correlation) incorporates both variation intensity and criteria interdependence through standard deviation and correlation matrix analysis. This method has demonstrated particular utility in producing stable, context-sensitive results, especially when analyzing highly interrelated indicators [16]. In a regional study, Stojanović et al. [3] applied CRITIC to assess innovation performance in South-Eastern European countries, finding it more effective than composite GII rankings in highlighting inter-pillar differences.

Despite these methodological advances, current research remains limited by the singular application of either Entropy or CRITIC, with few studies conducting comparative analyses or combining both approaches. Furthermore, the application of these methods to transition economies remains exceptionally rare, creating both methodological and contextual gaps in the literature.

2.3 Ranking Innovation Performance: From Classical to Adaptive Models

After determining weights, MCDM requires a ranking method to order alternatives based on weighted scores. Traditional ranking methods like TOPSIS, VIKOR, and PROMETHEE have been widely used in innovation studies [5,10,17]. However, these techniques present well-documented limitations, including rank reversal, normalization challenges, and difficulties in handling nonlinear interdependencies [18].

Recent studies have addressed these challenges through hybrid models and novel methodologies. Ecer and Aycin [13] developed a hybrid approach combining Entropy, MEREC, MARCOS, and CODAS, demonstrating improved rank consistency. Nevertheless, these models still fail to fully resolve scaling bias and information distortion issues.

To overcome these limitations, Pamucar et al. [6] proposed the ARTASI method (Alternative Ranking Technique based on Adaptive Standardized Intervals). ARTASI employs variable data intervals that better preserve original information structures while eliminating rank reversal. The method effectively handles variable scales and supports complex decision-making scenarios.

Although theoretically sound for innovation evaluation, ARTASI has seen limited practical application with GII data. Notably, no existing study has combined ARTASI with both Entropy and CRITIC for innovation performance assessment - a potentially powerful combination that could yield highly accurate and unbiased results.

A review of relevant studies (Table 1) reveals two significant gaps: (1) most GII research overlooks smaller transition economies in the Western Balkans, and (2) studies predominantly use traditional MCDM models without incorporating ARTASI or integrating Entropy with CRITIC in unified frameworks.

Table 1
The Summary of Literature on the Global Innovation Index

Study	Method	Region/Focus	Key Findings
Crespo and Crespo [19]	GII cluster analysis	EU	Innovation output often lags input performance, especially in moderate innovators.
Karimi et al. [5]	AHP, Hybrid MCDA	Innovation metrics	MCDM revealed structural inefficiencies in innovation output scoring.
Silva et al. [10]	TOPSIS, PROMETHEE	EU countries	Ranking shifted compared to official GII; subjective weight use criticized.
Omer et al. [20]	Machine Learning	Africa	Innovation influenced by informal economy and entrepreneurial resilience.
Stojanović et al. [3]	CRITIC, CRADIS	Western Balkans	Montenegro top-ranked; CRITIC highlighted inter-pillar discrepancies.
Huarng and Yu [12]	fsQCA	Global (64 countries)	Multiple configurations of GII dimensions yield innovation success.
Ecer and Aycin [13]	Entropy, MARCOS, MEREC	G7 countries	Business sophistication & infrastructure most influential; hybrid model improves ranking consistency.
Bate et al. [21]	Panel data analysis	Global, income-level focus	High-income countries benefit more from infrastructure; market sophistication helps low-income countries.
Pamucar et al. [6]	ARTASI	Theoretical application	Avoids rank reversal, scale sensitivity, and normalization errors.
Queirós and Yáñez-Orozco [11]	Regression Analysis	64-country analysis	Human capital and business sophistication identified as innovation drivers.

The studies summarized in Table 1 demonstrate growing academic interest in evaluating innovation performance through structured, data-driven methods. Three key trends emerge from this analysis:

First, Global Innovation Index (GII) research has primarily focused on high-income, institutionally mature regions. The extant literature frequently examines G7 countries [13] and EU member states [10], while some studies analyze large but highly diverse country groups, introducing additional complexity into comparative assessments [12]. This research predominantly employs traditional MCDM tools like TOPSIS and PROMETHEE, along with regression-based models. While valuable, these approaches often overlook contextual factors, particularly in transition economies with unique developmental trajectories [3].

Second, there is a growing trend toward using Entropy and CRITIC methods to enhance transparency and reduce subjectivity. Özmerdivanlı [14] demonstrates how Entropy identifies the most impactful sectors, while CRITIC and its D-CRITIC variant better account for inter-criteria trade-offs, yielding more reliable results. However, current research typically applies these methods separately, with few studies combining them within a unified analytical framework that would enable comprehensive result comparisons.

Third, research on transition economies remains limited, with only a small subset of studies (e.g., Stojanović et al. [3]) conducting in-depth, pillar-level analyses using GII data. This gap significantly diminishes the GII's diagnostic value for developing regional innovation strategies.

In conclusion, while the ARTASI method offers distinct methodological advantages—particularly in addressing normalization and rank reversal issues (Pamucar et al. [6])—it has yet to be applied in GII-based innovation research. This oversight is particularly notable given ARTASI's design for policy-oriented, multi-criteria assessment.

2.4 Research Gap and Motivation of the Study

Innovation has emerged as a critical driver of sustainable development, national competitiveness, and long-term economic growth [1,7]. This recognition has created demand for reliable, comprehensive tools to assess national innovation performance. The Global Innovation Index (GII), developed by WIPO in collaboration with Cornell University and INSEAD, represents one of the most comprehensive international frameworks for such evaluation. Its dual structure, examining both innovation inputs and outputs, provides a holistic view of national innovation ecosystems. While methodologically robust and widely adopted, the GII's ranking system often obscures contextual factors, particularly affecting the assessment of countries undergoing economic and institutional transitions [3].

Extensive research has addressed these limitations through Multi-Criteria Decision Making (MCDM) techniques that deconstruct GII data to yield more nuanced insights [10,13]. Objective weighting methods like Entropy and CRITIC have proven particularly valuable, deriving weights from data variation and interrelationships to reduce subjectivity and enhance transparency [4,15,16]. However, these methods are rarely employed together in existing studies, with most research using either Entropy (e.g., Ecer and Aycin [13]) or CRITIC (e.g., Stojanović et al. [3]) separately, limiting opportunities for comparative validation and combined benefits.

Furthermore, conventional GII-based MCDM analyses employing TOPSIS, PROMETHEE, or ARAS ranking methods face well-documented limitations, including rank reversal, normalization sensitivity, and performance challenges with high-dimensional data [18]. Pamucar et al. [6] proposed the ARTASI method (Alternative Ranking Technique Based on Adaptive Standardized Intervals), which demonstrates superior stability and information preservation in complex decision matrices. Despite its promise, ARTASI remains underutilized in innovation assessment, and no study has yet integrated it with both Entropy and CRITIC methods for GII indicator analysis.

The existing GII research landscape shows significant geographical bias, focusing predominantly on developed economies (e.g., EU, G7 nations) and rapidly emerging markets [10,11]. South-Eastern European transition economies—including Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia—remain notably underrepresented, despite their ongoing institutional reforms and alignment with EU innovation policies [3]. These countries present unique challenges, including weak innovation infrastructure, policy instability, and limited R&D funding, making them particularly compelling cases for region-specific innovation studies [8,9].

Our study makes two key contributions to the field:

i. It provides an in-depth analysis of innovation performance in South-Eastern European transition economies, a significantly under-researched area.
ii. We introduce a novel evaluation framework combining Entropy and CRITIC weighting techniques with the ARTASI ranking method, offering a more reliable and adaptive approach for innovation performance assessment.

By addressing both the regional research gap and the need for more integrative methodologies in GII-based studies, our work aims to deliver academically rigorous and policy-relevant findings.

3. The Suggested Model

This section presents a structured, analytically grounded multi-criteria decision-making (MCDM) framework designed to evaluate national innovation performance in South-Eastern European transition economies. The proposed model integrates the Entropy objective weighting method with the ARTASI ranking technique (Alternative Ranking Technique based on Adaptive Standardized Intervals) to assess country performance across seven Global Innovation Index (GII) criteria.

The decision problem focuses on five countries (Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia) evaluated against seven innovation criteria from GII 2023. We first construct a decision matrix, then apply the Entropy method to determine criterion weights based on their information content and discriminative power. The weighted data undergoes analysis through ARTASI, which employs adaptive normalization and computes relative utility scores to establish final country rankings.

Following weight determination, we normalize criterion values to a [1-100] scale. The ARTASI methodology then proceeds through six systematic stages:

i. Identification of ideal and anti-ideal solutions;
ii. Utility calculation;
iii. Score aggregation into final composite values (Ωi);
iv. Ranking determination;
v. Comparative analysis with alternative MCDM methods (WASPAS, EDAS, MABAC, and CoCoSo);
vi. Robustness validation.

The subsequent sections detail the mathematical foundations and procedural implementation of these weighting and ranking techniques, as illustrated in Figure 1.

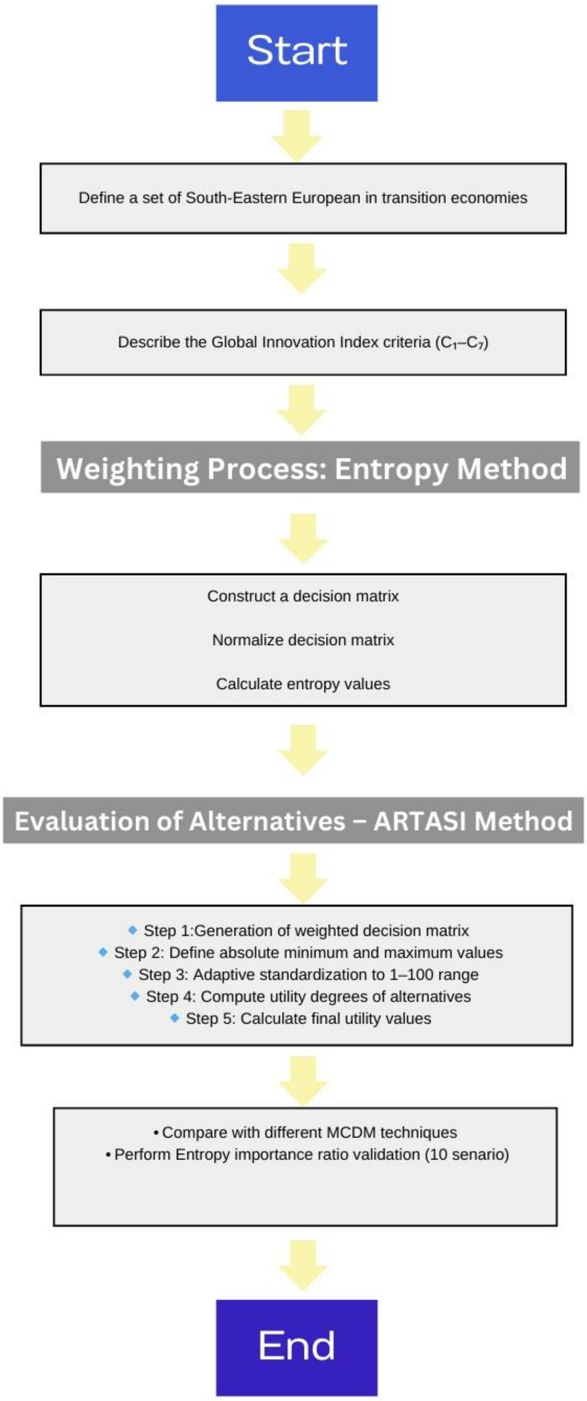

Fig. 1. Entropy-ARTASI methodology

3.1 Entropy Method

Determining the weight of criteria in MCDM models is a critical component of the decision-making process [22]. Criteria weights can be established either subjectively—based on expert judgment—or objectively using mathematical and statistical approaches. In this study, the Entropy method is adopted as an objective technique for determining the weight of each criterion. Originally introduced by Clausius in 1865 as a concept in thermodynamics and later adapted by Shannon [23] and Clausius [24] in information theory, entropy has evolved into a powerful tool for quantifying uncertainty. In the context of MCDM, entropy is widely used to assess the degree of divergence or contrast a criterion exhibits across decision alternatives [25]. A criterion with greater variability conveys more information and therefore deserves greater weight.

The ARTASI method, which integrates interval standardization and adaptability into the decision-making framework, was employed in this study to enhance the robustness and flexibility of the evaluation process [26]. This method enables a more nuanced ranking of alternatives by incorporating both ideal and anti-ideal utility values across adaptively scaled criteria. In parallel, the entropy method was used to objectively determine the weights of the evaluation criteria. As a variability-based objective weighting technique, entropy quantifies the discriminating power of each criterion by measuring its inherent information content. This study adopts a structured five-step procedure for entropy-based weighting, following the methodological framework proposed by Özmerdivanlı [15].

Step 1: Construction o the Decision Matrix

Let $X = \left[x_{\{ij\}}\right]$ denote the decision matrix, where i = 1,3, ……,m represents the alternatives and j= 1,3, …...,n denotes the evaluation criteria. Each element reflects the performance value of

$$\Delta= \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: Normalization of the Decision Matrix

To eliminate the influence of differing measurement units, the matrix is normalized using:

$$\mathrm{Pij} \ = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

This step ensures comparability across criteria.

Step 3: Entropy Value Calculation

The entropy for each criterion is computed as:

$$E_{ij} = -k \sum_{j=1}^{n} e_{ij} \, ln e_{ij} k = \frac{1}{\ln(m)} \tag{3}$$

Where e_{ij} denotes the normalized value of the i-th alternative under the j-th criterion; k is a constant normalization factor defined as k=$\frac{1}{\ln(m)}$, where mmm represents the number of alternatives; and E_{ij} represents the entropy value of criterion j, which quantifies the degree of uncertainty or disorder associated with that criterion.

Step 4: Degree of Diversification

The contrast intensity of each criterion is calculated as:

$$d_j = 1 - E_j \tag{4}$$

A higher dj indicates greater importance due to more dispersed values.

Step 5: Calculation of Criteria Weights

The normalized objective weight of each criterion is obtained as:

$$w_j = \frac{\mathrm{dj}}{\sum_{j=1}^{n} \mathrm{dj}} \tag{5}$$

These weights are then utilized in the ARTASI model to compute final rankings.

In conclusion, the Entropy method offers a statistically robust and data-oriented approach to determining the significance of each criterion. By quantifying the relative contrast intensity and eliminating subjectivity, this method enhances the transparency, reliability, and consistency of the overall evaluation model.

3.2 Evaluation Model: ARTASI Method

In this study, the evaluation of innovation performance is conducted using the ARTASI (Alternative Ranking Technique based on Adaptive Standardized Intervals) method. This method provides a flexible framework to rank multiple alternatives by combining standardized criteria values with utility functions derived from decision-maker preferences and data structures.

The ARTASI model is employed after determining objective criterion weights through the Entropy method. Its strength lies in eliminating the rank reversal problem and allowing nonlinear standardization within a defined interval. This section outlines the step-by-step implementation of the ARTASI methodology in evaluating the innovation capacities of South-Eastern European countries.

Step 1: Construction of the Initial Decision Matrix

In this step, the raw performance values of five South-Eastern European countries across seven Global Innovation Index (GII) criteria are collected and organized. These values serve as the foundational data input for the ARTASI method and reflect national innovation capabilities across multiple dimensions.

Let us assume that the set of alternatives is defined as A = {A_1, A_2, ..., A_m} and the set of evaluation criteria is C={C1, C2,..., Cn}. The initial decision matrix, denoted by $\Delta = \left[x_{\{ij\}}\right]_{\{m\,x\,n1\}}$, is constructed using secondary data extracted from the Global Innovation Index (GII) 2023. Each element $x_{\{ij\}}$ represents the performance of the i th alternative under the j th criterion. This study treats all criteria as benefit-type, where higher values indicate superior performance. The structure of the decision matrix can be formalized as follows:

$$\Delta = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{6}$$

Where $x_{\{ij\}} \in$ R represents the observed data for the *i* th country with respect to the *j* th innovation performance indicator. These values serve as the primary input for the ARTASI algorithm and will be normalized and transformed in the subsequent steps.

Step 2: Determination of Absolute Maximum and Minimum Values

To ensure accurate standardization, the upper and lower bounds for each criterion are calculated. This step enhances sensitivity by adjusting normalization based on data distribution across the selected countries.

Based on the initial decision matrix X = c, the absolute maximum and minimum values are determined for each criterion C_J. These boundary values are essential to conduct adaptive normalization in the ARTASI framework. The absolute maximum value for the j^{th} criterion is computed as:

$$x_J{}^{max} = max_{1\leq\ i\ \leq\ m}\ (x_{\{ij\}}) + (max_{1\leq\ i\ \leq\ m}\ (x_{\{ij\}}))^{\frac{1}{m}} \tag{7}$$

The absolute minimum value for the j^{th} criterion is computed as:

$$x_J{}^{min} = min_{1\leq\ i\ \leq\ m}\ (x_{\{ij\}}) - (min_{1\leq\ i\ \leq\ m}\ (x_{\{ij\}}))^{\frac{1}{m}} \tag{8}$$

Here, *m* represents the total number of alternatives, while $x_J{}^{max}$ and $x_J{}^{min}$ indicate the upper and lower bounds used for the standardization of values across each criterion. These transformed bounds preserve the variation and ensure a comparable scale for subsequent evaluation steps.

Step 3: Standardization of the Initial Decision Matrix

The decision matrix is transformed into a common scale [1–100], eliminating unit differences between criteria. This enables cross-country comparison and ensures consistency in further utility-based calculations.

In this step, the matrix values are mapped into a standardized interval $[\psi^{(l)} + \psi^{(u)}]$, where $\psi^{(l)} = 1$ and $\psi^{(u)} = 100$. These thresholds represent the left and right limits of the standardized interval and are used to convert the raw decision matrix into a comparable scale across all criteria.

The standardization of each element x_{ij} of the decision matrix is performed using the following equation:

$$\phi_{ij} = \frac{\psi^{(u)} - \psi^{(l)}}{x_J{}^{max} - c x_J{}^{min}}\ x_{ij} + \frac{x_J{}^{max}\ .\ \psi^{(l)} - x_J{}^{min}\ .\psi^{(u)}}{x_J{}^{max} - x_J{}^{min}} \tag{9}$$

where ϕ_{ij} is the is the standardized value for the *i* th alternative with respect to the *j* th criterion.

If the criterion is of the cost (min) type, the standardized value ζ_{ij} is calculated by applying the reverse sorting procedure as:

$$\zeta_{ij} = -\phi_{ij} + \max_{1 \le i \le m} \phi_{ij} + \min_{1 \le i \le m} \phi_{ij} \tag{10}$$

In this study, since all criteria are benefit-type, reverse standardization is not applied, and the final standardized matrix is defined as:

$$\nabla = [\zeta_{ij}]_{m\ x\ n} = [\phi_{ij}]_{m\ x\ n} \tag{11}$$

Step 4: Defining the Degree of Usefulness of Alternatives

At this stage, each country's proximity to the ideal and anti-ideal values is computed based on their normalized scores and criterion weights. These values determine how advantageous each alternative is in the innovation landscape.

a) The degree of usefulness with respect to the ideal value is calculated using:

$$\vartheta_{ij}{}^{+} = \frac{\zeta_{ij}}{\max_{1 \le i \le \zeta_{ij}}}\ .\ \mathrm{w}_j\ .\ \psi^{(u)} \tag{12}$$

b) The level of utility is determined with respect to the optimal value. By utilizing the expression (13), the values of the matrix $\nabla = [\zeta_{ij}]_{mxn}$ is converted:

$$\vartheta_{ij} = \frac{\min\limits_{1 \le i \le m} (\zeta_{ij})}{\zeta_{ij}} \cdot w_j \cdot \psi^{(u)} \tag{13}$$

The degree of usefulness with respect to the anti-ideal value is calculated using:

$$\vartheta_{ij}{}^{-} = -\vartheta_{ij}{}^{+} + \max_{1 \le i \le m} \vartheta_{ij}{}^{+} + \min_{1 \le i \le m} \vartheta_{ij}{}^{+} \tag{14}$$

These expressions reflect how close each alternative is to the ideal and anti-ideal solutions for each criterion and form the basis for calculating the final aggregated utility score in the subsequent step.

Step 5: Aggregation of Usefulness Values

In this step, the partial usefulness values calculated in the previous stage are aggregated to determine an overall degree of utility for each country. These aggregate scores reflect each country's overall innovation potential under the weighted criteria.

a) Aggregated usefulness in relation to the ideal value:

$$\Im_i{}^{+} = \sum_{j=1}^{n} \Im_{ij}{}^{+} \tag{15}$$

b) Aggregated usefulness in relation to the anti-ideal value:

$$\Im_i{}^{-} = \sum_{j=1}^{n} \Im_{ij}{}^{-} \tag{16}$$

Step 6: Calculation of Final Utility Function and Ranking

The final utility score Ω_i for each alternative is computed based on a nonlinear aggregation of both ideal and anti-ideal utilities. Two parameters —a and b — are used to adjust the balance and sensitivity of aggregation. In line with Pamucar *et al.,* [6], this study adopts *a* = 0.5 and *b* = 1 to equally weight the contributions of both components.

The utility function is defined as:

$$\Omega_i = (\Im_i^{+} + \Im_i^{-})^a \mathrm{f}\,(\Im_i^{+}) + (1 - a)\,\mathrm{f}\,(\Im_i^{-}) \tag{17}$$

Where:

$$f(\Im_i^{+}) = \frac{\Im_i^{+}}{\Im_i^{+} + \Im_i^{-}}\,,\mathrm{f}\,(\Im_i^{-}) = \frac{\Im_i^{-}}{\Im_i^{+} + \Im_i^{-}} \tag{18}$$

Under the selected parameter values, this simplifies to:

$$\Omega_i = 0.5 \cdot f(\Im_i^{+}) + 0.5 \cdot f(\Im_i^{-}) \tag{19}$$

Higher values of Ω_i indicate better innovation performance. The final ranking of alternatives is determined based on the descending order of Ω_i scores.

4. Results

In this study, the global innovation performances of the South-Eastern European countries in transition economies, namely Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia, were comprehensively analyzed in line with a multi-criteria assessment framework. The global innovation performance of 5 countries has been examined within the scope of the Global Innovation Index (GII) published annually since 2007 under the leadership of WIPO (World Intellectual Property Organization) and in cooperation with Cornell University and INSEAD (European Institute of Business Administration). The sub-indices used in GII measurements consist of 2 basic indicators: input and output. Input sub-indicators consist of C1-Institutions, C2-Human capital and research, C3-Infrastructure, C4-Market sophistication, and C5-Business sophistication, while output sub-indicators consist of C6-Knowledge and technology outputs and C7-Creative outputs. The main criteria used in the study are shown in Table 2.

Table 2
List of criteria for the assessment of innovation performance of South-Eastern European countries in transition economies

Codes	Main criteria	Type
	Input	
C1	Institutions	Max
C2	Human capital and research	Max
C3	Infrastructure	Max
C4	Market sophistication	Max
C5	Business sophistication	Max
	Output	
C6	Knowledge and technology outputs	Max
C7	Creative outputs	Max

4.1 Entropy-Based Determination of Criteria Weights

The entropy method for obtaining the weighting coefficients of the criterion was executed in five steps, detailed in the following section:

Step 1. First, a decision matrix is created to determine the criteria weights for the South-Eastern European countries in transition economies. Data from the 2024 global innovation index is used for the entropy technique, and Table 3 shows the 2024 decision matrix.

Table 3
Decision matrix for seven GII

Alternatives	C1	C2	C3	C4	C5	C6	C7
Albania	50.3	21.6	52.3	24.2	26.8	14.4	13.6
Bosnia and Herzegovina	30	30.4	40.6	46.5	19.7	20.3	14.7
Montenegro	39.8	32.6	44.5	36.9	27.9	19.8	23
North Macedonia	44.4	27.9	49.1	32.2	29.9	23.7	22.5
Serbia	46.5	35.4	52.3	42.2	27.2	29.6	17.9

Step 2. The decision matrix is normalized using expression (2), Table 4. The value of the *i*th alternative for the *j*th criterion is shown by x_{ij}. As an example, the normalization of the decision matrix for the C1 criterion of the Albania alternative is shown below:

$$p_{Albania,C1} = \frac{50.3}{50.3 + 30 + 39.8 + 44.4 + 46.5} = 0.238$$

Table 4
Normalized decision matrix

Alternatives	C1	C2	C3	C4	C5	C6	C7
Albania	0,238	0,146	0,219	0,133	0,204	0,134	0,148
Bosnia and Herzegovina	0,142	0,206	0,170	0,255	0,150	0,188	0,160
Montenegro	0,189	0,220	0,186	0,203	0,212	0,184	0,251
North Macedonia	0,210	0,189	0,206	0,177	0,227	0,220	0,245
Serbia	0,220	0,239	0,219	0,232	0,207	0,275	0,195

Step 3. The Entropy value for each criterion is calculated using expression (3) and is shown in Table 5. Calculation for criteria C1 is shown below as an example:

$$E_{C1} = -1/\ln(5) \sum_{C11}^{5} \left[(-0.342) + (-0.277) + (-0315) + (-0.333) \right) = -\frac{-1.595}{\ln(5)} = 0.991$$

Step 4. The differentiation degree for each criteria is defined as presented in expression (4) and shown in Table 5. The computation for criteria C1 is shown in the following example:
$d_{C1} = 1 - 0.991 = 0.009$

Step 5. The weight for each criterion is computed using expression (5) and is shown in Table 5. For instance, the calculation of criteria C1 is shown here:
$w_{C1} = 0.009/(0.009 + 0.008 + 0.003 + 0.015 + 0.006 + 0.017 + 0.014) = 0.126$

Table 5
The Entropy weights calculations of the given criteria

Alternatives	C1	C2	C3	C4	C5	C6	C7
Albania	-0.342	-0.281	-0.333	-0.268	-0.324	-0.269	-0.283
Bosnia and Herzegovina	-0.277	-0.325	-0.301	-0.349	-0.284	-0.314	-0.293
Montenegro	-0.315	-0.333	-0.313	-0.324	-0.329	-0.311	-0.347
North Macedonia	-0.328	-0.315	-0.325	-0.306	-0.337	-0.333	-0.345
Serbia	-0.333	-0.342	-0.333	-0.339	-0.326	-0.355	-0.319
Sum	-1.595	-1.596	-1.605	-1.586	-1.600	-1.583	-1.587
E_j	0.991	0.992	0.997	0.985	0.994	0.983	0.986
d_j	0.009	0.008	0.003	0.015	0.006	0.017	0.014
w_j	0.126	0.115	0.041	0.207	0.081	0.236	0.196
Weight (%)	12.6	11.5	0.41	20.7	0.81	23.6	19.6
Rank	4	5	7	2	6	1	3

The final values of the weighting coefficients determined according to the entropy method are shown in Figure 2. When the criteria weights in Figure 2 are examined, it is seen that the C6, C4, and C7 criteria have higher weight values compared to the others. This shows that criteria such as Knowledge and technology outputs (C6), Market sophistication (C4), and Creative outputs (C7) have one of the most dominant effects in the decision-making process. It is seen that the output set is more dominant in innovation performance. In contrast, the weights of the C3 and C5 criteria in the input set are quite low; therefore, their effects on the model are minimal. In general, Figure 2 clearly reflects the relative importance of the innovation performance criteria and provides guidance on the priority development areas.

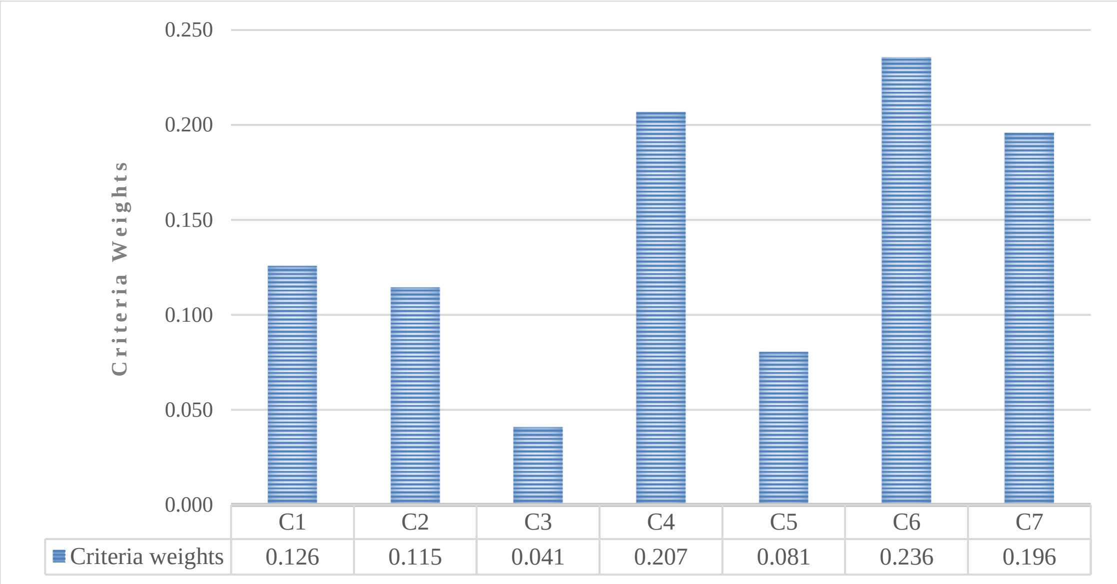

Fig. 2. Final values of the weight coefficients of the criteria (Entropy)

4.2 Model Assessment with the ARTASI Model

The evaluation of alternatives was carried out using the Entropy method as follows:

Step 1. The initial decision matrix is presented in Table 3.

Step 2. By applying expressions (7) and (8), the absolute minimum and maximum values within each criterion are defined in Table 6.

An example of defining the absolute minimum and maximum values for criterion C1 is shown in the next part:

a) Absolute maximum values (7) for C1:

$$\psi_{C1}^{max} = \max_{1\le i\le 5}(50.3, 30, 39.8, \ldots, 46.5) + \left\{\max_{1\le i\le m}(50.3, 30, 39.8, \ldots, 46.5)\right\}^{1/5} = 50.3 + 50.3^{1/5} = 52.49$$

b) Absolute maximum values (8) for C1:

$$\psi_{C1}^{min} = \min_{1\le i\le 5}(50.3, 30, 39.8, \ldots, 46.5) + \left\{\min_{1\le i\le m}(50.3, 30, 39.8, \ldots, 46.5)\right\}^{1/5} = 30 + 30^{1/5} = 31.97$$

The residual values from Table 6 are derived in a similar manner. The absolute minimum and maximum values that were acquired in this section were used in order to achieve the goal of standardizing the criterion values that were included within the matrix.

Table 6
Absolute minimum and maximum values

Criteria	ψ_j^{max}	ψ_j^{min}
C1	52.49	31.97
C2	37.44	23.45
C3	54.51	42.70
C4	48.66	26.09
C5	31.87	21.52
C6	31.57	16.10
C7	27.87	15.29

Step 3. Expressions (9) through (11) were used for the standardization of matrix elements. The mapping of criterion values from Table 7 was changed to the range [1, 100]. The limit values $\psi^{(1)} = 1$ and $\psi^{(u)} = 1$ were used. The idea that the range [1, 100] is big enough for the distribution of utility y functions of 5 alternatives led to the setting of the limit values of the criterion intervals ($\psi^{(1)} = 1$ and $\psi^{(u)} = 1$). Since all the criteria are of maximum type, it is assumed that $\zeta_{ij} = \phi_{ij}$ and expression 9 is omitted. The resulting standardized initial decision matrix is displayed in Table 7.

The transformation into the criterion interval [1,100] was done by using the expression (9):

$$\phi_{Albania,C1} = \frac{100-1}{52.49-31.97}50.3 + \frac{52.49.1-31.97.100}{52.49-31.97} = 89.4$$

Table 7
Standardized initial decision matrix

Alternatives	C1	C2	C3	C4	C5	C6	C7
Albania	89.43	-12.08	81.50	-7.30	51.51	-9.91	-16.40
Bosnia and Herzegovina	-8.53	50.18	-16.58	90.54	-16.35	27.86	-5.05
Montenegro	38.76	65.75	16.11	48.42	62.03	24.66	80.67
North Macedonia	60.96	32.49	54.67	27.80	81.14	49.62	75.50
Serbia	71.10	85.56	81.50	71.68	55.34	87.39	28.00

Step 4. Expressions (12) and (14) determine the usefulness of alternatives in relation to ideal and anti-ideal values in Tables 8 and 9, respectively. The technique for determining the utility of Tables 8 and 9 at places *Albania-C1* is outlined below:

a) Using expression (12) to describe the level of benefit of alternative Albania for criterion C11 about the ideal value:

$$\vartheta^{+}_{Albania,C1} = \frac{89.43}{\max\limits_{1\le i\le 5}(89.43; -8.53; 38.76; \dots; 71.10)} = 0.126.100 = 12.57$$

b) To determine the usefulness of alternative Albania for criterion C1, consider its anti-ideal value, expression (12) and (13). By using expression (13), we get:

$$\vartheta_{Albania,C1} = \frac{\min\limits_{1\le i\le 5}(89.43; -8.53; 38.76; \dots; 71.10)}{89.43} 0.126.100 = -1.20$$

Next, employing expression (14), we establish the degree of utility of alternative Albania for criteria C1 in relation to the anti-ideal value:

$$\vartheta^{-}_{Albania,C1} = -12.57 + \max\limits_{1\le i\le 5}(-1.20; 12.57; -2.77; \dots; -1.57) + \min\limits_{1\le i\le 5}(-1.20; 12.57; -2.77; \dots; -1.57) = 11.01$$

The residual values in Tables 8 and 9 are calculated similarly.

Table 8
Alternatives' levels of utility in relation to the ideal value

Alternatives	C1	C2	C3	C4	C5	C6	C7
Albania	-1.20	12.57	-2.56	12.57	-3.99	12.57	12.57
Bosnia and Herzegovina	-1.20	7.37	-2.56	12.57	-2.53	4.01	-0.79
Montenegro	5.45	9.66	2.49	6.72	9.61	3.55	12.57
North Macedonia	8.57	4.78	8.43	3.86	12.57	7.14	11.77
Serbia	10.00	12.57	12.57	9.95	8.57	12.57	4.36

Table 9
Alternatives' levels of utility in relation to the anti-ideal value

Alternatives	C1	C2	C3	C4	C5	C6	C7
Albania	11.01	-4.67	2.19	-3.30	12.57	-5.06	20.94
Bosnia and Herzegovina	-2.77	10.93	-12.94	10.29	-3.71	-2.01	-7.37
Montenegro	12.57	10.21	12.57	11.17	-2.93	-1.43	-7.37
North Macedonia	11.57	12.57	3.44	12.57	11.39	-3.97	16.31
Serbia	11.32	9.67	2.19	10.55	12.57	-5.06	20.94

Step 5. In Table 10, expressions (15) and (16), which show the combined usefulness ratings of the alternatives are shown. The level of usefulness of each alternative can be found by adding up the criteria values for each option in Tables 8 and 9. In the case of the first alternative (Albania). for example:

$$\Im_i^+ = \{(12.57) + (-1.78) + (12.57) + (-1.01) + (7.98) + (-1.43) + (-2.56)\} = 26.36$$

$$\Im_i^- = \{(11.01) + (-4.67) + (2.19) + (-3.30) + (12.57) + (-5.06) + (20.94)\} = 33.68$$

Table 10
Aggregated utility degrees of alternatives

Alternatives	$\Im_i^+$	$\Im_i^-$
Albania	26,36	33,68
Bosnia and Herzegovina	16,88	-7,59
Montenegro	50,05	34,80
North Macedonia	57,12	63,89
Serbia	70,61	62,19

Step 6. Table 11 displays the final utility function values for each alternative (expressions (12) and (14)). The final utility functions were calculated using the parameters $\varphi = 1$ and $\alpha = 0.5$. The final utility function value for the initial alternative (Albania) is computed as follows:

$$\Omega_{Albania} = (26.36 + 33.68)\{0.5 \cdot 0.44^1 + 0.5 \cdot 0.56^1\}^{1/1} = 30.02$$

Where

$$f\left(\left(\frac{26.36}{(26.36+33.68)}\right)\right) = 0.44 \text{ and } f\left(\left(\frac{33.68}{(26.36+33.68)}\right)\right) = 0.56.$$

Table 11
Utility functions and ranking alternatives

Alternatives	$\boldsymbol{f(\Im_i^+)}$	$\boldsymbol{f(\Im_i^-)}$	$\boldsymbol{\Omega_i}$	Rank
Albania	0.44	0.56	30.02	4
Bosnia and Herzegovina	1.82	-0.82	4.65	5
Montenegro	0.59	0.41	42.43	3
North Macedonia	0.47	0.53	60.51	2
Serbia	0.53	0.47	66.40	1

The utility functions corresponding to the remaining alternatives are presented in a manner consistent with the structure outlined earlier. Figure 3 clearly illustrates the utility functions associated with these alternatives. As depicted in Figure 3, Serbia is first among the options with the highest utility score($\Omega_i = 66.40$) shown in the table, therefore showing the close approach to the positive ideal solution. North Macedonia and Montenegro follow it and show good utility qualities. In contrast, Bosnia and Herzegovina ranks lowest, primarily due to a significantly high value of $f(\Im_i^+)$ and a negative $f(\Im_i^-)$, reflecting its greater distance from the ideal solution. These findings form the basis for more sensitivity and robustness studies shown in the next sections. The utility functions, detailed in Table 11 and visually represented in Figure 3, reflect the initial solution and necessitate a comprehensive evaluation in terms of stability and robustness. Accordingly, the following section presents a sensitivity analysis and robustness assessment conducted through comparisons with well-established conventional Multiple Criteria Decision Making (MCDM) methods reported in the literature.

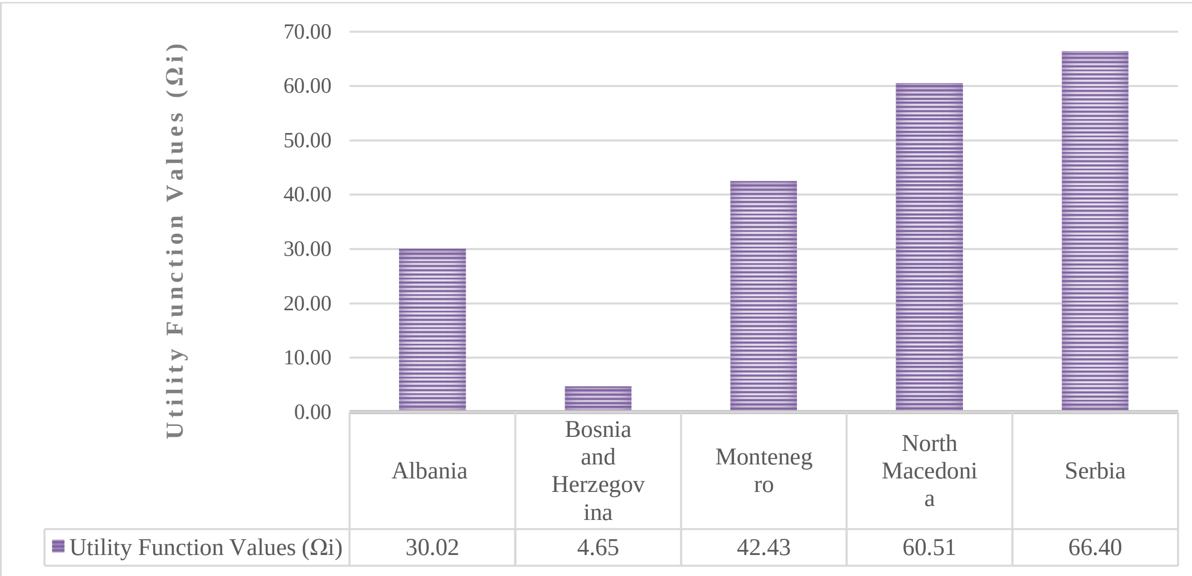

Fig. 3. Utility functions of alternatives

5. Sensitivity analysis and validation of results

In MCDM models, the reliability of the final rankings largely depends on the accuracy and stability of the criteria weights [27]. However, these weights can change due to differences in expert opinion, data uncertainty, or policy changes. Therefore, a sensitivity analysis is required to evaluate how changes in the criteria weights affect the overall results. Sensitivity analysis provides insights into the robustness and stability of the model, which will be very helpful in determining whether small fluctuations in the inputs will lead to significant changes in the decision outputs [28]. Based on this, sensitivity analysis is performed to test the reliability of the final rankings of this study. To assess the robustness of the model results, a sensitivity analysis was conducted by altering the weights of criteria under different hypothetical scenarios:

vii. Scenario 1: The weight of Knowledge and Technology Outputs (C6) was reduced by 10%.
viii. Scenario 2: The weights of Infrastructure (C3) and Business Sophistication (C5) were doubled.
ix. Scenario 3: The weights of Market Sophistication (C4), Knowledge & Technology Outputs (C6), and Creative Outputs (C7) increased by 20%. These indicators, reflecting the final innovation outcomes, were tested for dominance in determining country performance.

x. Scenario 4: The weights of input criteria (Institutions (C1), Human Capital (C2), Infrastructure (C3), Market Sophistication (C4), and Business Sophistication (C5)) were each increased by 20%.
xi. Scenario 5: The weights of output criteria (Knowledge & Technology Outputs (C6), and Creative Outputs (C7)) were each increased by 20%.
xii. Scenario 6: The weight of C3 (Infrastructure), originally the least impactful criterion (4.1%), was increased by 400% to test whether infrastructure alone could affect the overall rankings.
xiii. Scenario 7: All criteria were given equal weights
xiv. Scenario 8: Input and output criteria were given 50% weight.
xv. Scenario 9: 70% weight was given to input criteria and 30% to output criteria.
xvi. Scenario 10: 30% weight was given to input criteria and 70% to output criteria.

The results are summarized in Table 12. As seen in Table 12, the ranking of the alternatives remained the same in all scenarios. Serbia consistently maintained the highest benefit score indicating a solid innovation performance, while Bosnia and Herzegovina remained in the lowest position in all weight changes. Obtaining the same ranking in all scenarios demonstrates the robustness of the proposed model.

Furthermore, to ensure methodological consistency, alternative rankings derived from the Entropy-ARTASI technique are compared with those obtained from WASPAS, EDAS, CoCoSo and MABAC (Figure 4). WASPAS, EDAS, CoCoSo and MABAC models showed high correlation with the findings of the ARTASI model. A correlation of 90% was achieved between ARTASI and all other models, indicating significant consistency (Figure 5). It is important to highlight that the statistical differences between the studied models are minimal, as shown by the Spearman correlation coefficient (SCC) [26].

$$SCC = \begin{bmatrix} ARTASI & 1 & 0.90 & 0.90 & 0.90 & 0.90 \\ WASPAS & 0.90 & 1 & 1 & 1 & 1 \\ EDAS & 0.90 & 1 & 1 & 1 & 1 \\ CoCoSo & 0.90 & 1 & 1 & 1 & 1 \\ MABAC & 0.90 & 1 & 1 & 1 & 1 \end{bmatrix}$$

These high Spearman correlation coefficients highlight the robustness and validity of the ARTASI rankings, with minimal statistical deviations from the other models.

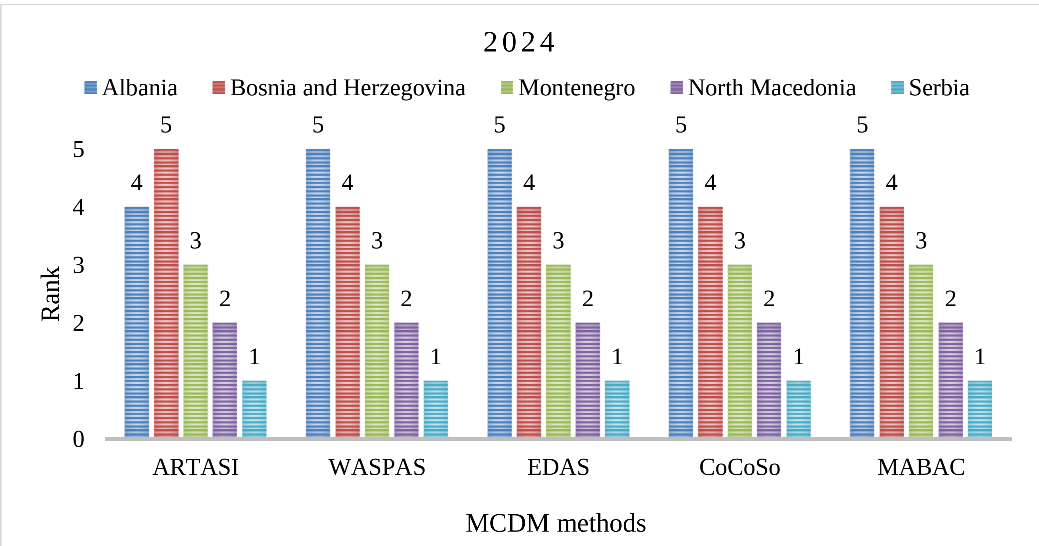

Fig. 4. Comparison of Entropy-ARTASI results to different MCDM techniques

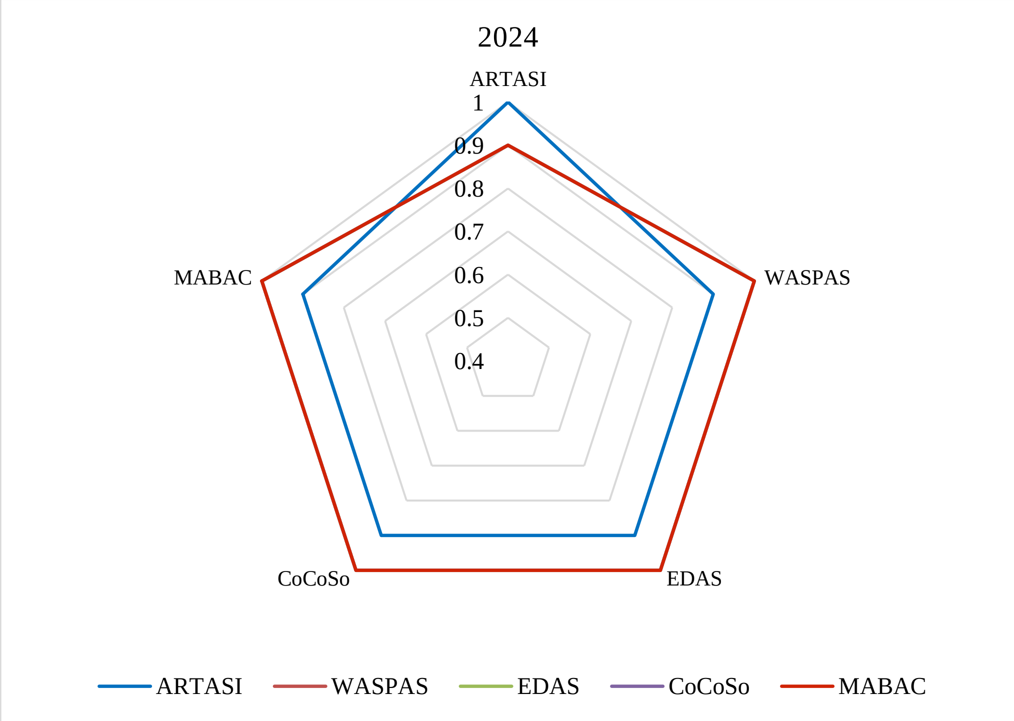

Fig. 5. Spearman Correlation Between ARTASI and different MCDM techniques

Table 12
Utility functions and ranking of alternatives after defined scenarios application

Scenarios	A	B&H	M	NM	S	Rank
Proposed model Ω_i	30	4.65	42.4	60.5	66.4	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 1 (C6 ↓ %10) Ω_i	30.7	4.76	43.5	62	68	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 2 (C3 & C5 ↑ 100%) Ω_i	26.8	4.14	37.8	54	59.21	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 3 (C4, C6 & C7 ↑ 20%) Ω_i	26.6	4.12	37.6	53.7	58.88	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 4 (Input criteria ↑ %20) Ω_i	32.3	5.01	45.7	65.2	71.55	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 5 (Output criteria ↑ 20%) Ω_i	27.6	4.28	39.1	55.7	61.13	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 6 (C3 ↑ 40%) Ω_i	25.8	3.99	36.5	52	57.06	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 7 (Equal weight)	34.1	5.28	48.2	68.7	75.44	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 8 (50% input & 50% output) Ω_i	23.9	3.7	33.7	48.1	52.81	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 9 (70% input & 30% output) Ω_i	33.4	5.17	47.2	67.4	73.93	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina
Scenario 10 (30% input & 70% output) Ω_i	14.3	2.22	20.3	28.9	31.69	Serbia> North Macedonia> Montenegro> Albania> Bosnia and Herzegovina

* A-Albania, B&H - Bosnia and Herzegovina, M – Montenegro, NM - North Macedonia, S – Serbia.

6. Discussion

This study contributes to the existing literature by presenting a novel application of the Entropy-ARTASI model to assess innovation performance in South-Eastern European transition economies. While the Global Innovation Index (GII) is widely used to measure national innovation capabilities, previous studies have primarily focused on high-income or institutionally mature countries such as the G7 and EU member states [10,13]. In contrast, empirical studies focusing on countries such as Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia are rare. This study addresses a critical regional gap in the innovation literature by targeting these underrepresented transition economies.

Previous studies have widely used the Global Innovation Index (GII) to assess national innovation capacity. However, most of these studies have focused on high-income or institutionally mature countries such as the G7 or EU member states [10,13]. As noted in the literature, smaller transition economies have been largely neglected, especially those struggling with structural barriers and limited resources [3]. This study addresses this gap by focusing on only five transition economies (Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia) and provides a detailed and region-specific assessment. On the other hand, in terms of methodology, most of the existing studies have used traditional MCDM techniques such as TOPSIS, VIKOR, and PROMETHEE. Despite their basic nature, these methods have been criticized for their sensitivity to normalization and rank reversal issues [18]. Based on this, in this study, combining the Entropy weighting technique with the ARTASI ranking model provides a framework that is clear and powerful and capable of handling complex, high-dimensional decision settings.

The findings show that output-oriented indicators (i.e., Knowledge and Technology Outputs (C6), Market Sophistication (C4), and Creative Outputs (C7)) exert the most significant influence on national innovation performance in the selected countries. These results are consistent with previous studies that identify output factors and market dynamics as central drivers of innovation outcomes [11,12]. In contrast, input criteria such as Infrastructure (C3) and Business Sophistication (C5) were found to have minimal impact, indicating that output performance is a more effective discriminator for assessing innovation capabilities in transition economies. The results reveal that Serbia outperforms all other countries in terms of innovation capacity, followed by North Macedonia and Montenegro. Albania and Bosnia and Herzegovina, on the other hand, are ranked lower, reflecting significant performance differences, especially in the output dimensions. These findings substantiate the findings of Stojanović *et al.,* [3], who identified Serbia as a regional leader.

On the other hand, a key strength of the model lies in its robustness, which is confirmed by a comprehensive sensitivity analysis involving ten hypothetical weight adjustment scenarios. In all scenarios, country rankings remain unchanged, indicating that the model results are stable and robust to changes in criterion weights. This robustness is particularly important in a policy-making context where reliable assessments of targeted innovation strategies are essential. Furthermore, comparative analysis with alternative MCDM methods (WASPAS, EDAS, MABAC, CoCoSo) showed high Spearman correlation coefficients (above 0.9). This confirmed that the Entropy-ARTASI model produces stable and consistent results with established techniques. This methodological validation adds credibility to the practical applicability of the proposed model.

In summary, the study provides a rigorous, transparent, and repeatable assessment model that enhances the diagnostic value of GII data for transition economies. The combined use of the entropy weighting method and the ARTASI ranking technique provides an effective framework for capturing the relative innovative performance of countries undergoing institutional and structural reforms. This methodological approach can be extended to similar contexts and adapted for broader policy evaluation purposes.

7. Conclusion, Limitations, and Future Research

This study utilized a novel multi-criteria decision-making (MCDM) framework that combines the ARTASI ranking method and the Entropy weighting technique to assess the innovation performance of five transition economies in South-Eastern Europe: Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia. The study adds a regionally focused contribution to the literature on innovation performance as well as a methodological advancement by using this integrative model to analyze the Global Innovation Index (GII) indicators.

The empirical results demonstrate that the most important factors in explaining national innovation performance across the chosen transition economies are output-related indicators, specifically Knowledge and Technology Outputs (C6), Market Sophistication (C4), and Creative Outputs (C7). On the other hand, input indicators with less discriminatory power included Business Sophistication (C5) and Infrastructure (C3). These findings point to a structural imbalance in the innovation ecosystems of the countries under study, where gains in inputs have not yet resulted in improved output performance.

Serbia performed the best among the nations examined, followed by North Macedonia and Montenegro, while Albania, Bosnia, and Herzegovina trailed behind. Extensive sensitivity analyses and cross-validation with other MCDM techniques validated the model's robustness, showing high methodological reliability and result stability.

This study addresses common flaws in conventional ranking methods by introducing a replicable hybrid model for evaluating national innovation from a theoretical standpoint. In practice, it offers a strong, data-driven instrument that can help decision-makers create focused innovation policies for transitioning economies.

Although this study offers insightful information about the innovation performance of South-Eastern European transition economies using a novel methodological framework, several limitations must be considered. First, the analysis is limited in observing temporal trends or policy impacts over time because it is based on cross-sectional data from a single year. A longitudinal approach would provide more dynamic insights into how innovation capabilities change in response to institutional or economic shifts. Second, the study only uses the Global Innovation Index's (GII) indicators, which may miss crucial context-specific factors like informal entrepreneurship, the ability to transform digitally, or the effectiveness of governance, even though the GII is complete. Third, the ranking process may not fully capture strategic national priorities due to the lack of expert judgment or stakeholder input, even though the combination of Entropy and CRITIC guarantees objectivity in weighting. Lastly, while useful, concentrating only on five nations in a single geographic area limits the generalizability of the findings to broader global contexts.

Future research could pursue several directions based on this study's results. Researchers would be able to investigate the temporal evolution of innovation capacity through a longitudinal extension employing multi-year GII data, revealing how reforms or crises impact national innovation performance over time. Furthermore, adding region-specific indicators—like metrics for innovation culture, R&D absorption capacity, or digital readiness indices—could improve the contextual accuracy of performance reviews, especially in economies going through structural change. In order to reflect both data-driven rigor and policy relevance, future research could test hybrid weighting models that incorporate stakeholder input with objective techniques. The Entropy-ARTASI framework's resilience and adaptability would be further confirmed by applying it to other regions, including Central Asia, Latin America, and Sub-Saharan Africa, to enable comparative assessments. Lastly, attempts to convert intricate evaluation models into interactive dashboards or easily navigable visual tools may encourage policymakers to adopt them, closing the gap between theoretical understanding and practical application.

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Conflicts of Interest

The authors declare no conflicts of interest.

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