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INNOVATION PERFORMANCE ASSESSMENT OF SELECTED BALKAN COUNTRIES BASED ON THE GLOBAL INNOVATION INDEX USING AN ENTROPY-BASED TOPSIS FRAMEWORK

KÜRESEL İNOVASYON ENDEKSİ TEMELİNDE SEÇİLMİŞ BALKAN ÜLKELERİNİN İNOVASYON PERFORMANSININ ENTROPİ TABANLI TOPSIS ÇERÇEVESİYLE DEĞERLENDİRİLMESİ

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Abstract: Innovation constitutes a fundamental driver of sustainable economic growth, productivity improvement, and structural convergence with the European Union, particularly for Balkan and Western Balkan economies. However, the considerable heterogeneity observed in innovation performance across the region necessitates a multidimensional and comparative evaluation framework. Accordingly, this study examines the innovation performance of ten Balkan countries by employing an Entropy-based TOPSIS multi-criteria decision-making (MCDM) approach based on seven criteria derived from the Global Innovation Index (GII). The Entropy results reveal substantial variation in the informational contribution of the criteria, indicating that Creative Outputs and Knowledge and Technology Outputs represent the most discriminative dimensions of innovation performance. The Entropy-based TOPSIS rankings show that Bulgaria, Greece, Croatia, Slovenia and Romania form the high-performance group, whereas Montenegro, Serbia, North Macedonia, Albania and Bosnia and Herzegovina remain below the regional average. Sensitivity analysis confirms the robustness of the rankings against structural changes in the criteria set, while comparative and correlation analyses demonstrate strong consistency between the Entropy-based TOPSIS outcomes and those obtained from other widely used MCDM methods. The findings highlight the importance of strengthening knowledge-based, technological, and creative outputs to enhance regional competitiveness and long-term economic development.

Keywords: Balkan Countries, Innovation, MCDM

JEL: O31, O32, O33, O57, C44

Öz: İnovasyon, özellikle Balkan ve Batı Balkan ekonomileri açısından sürdürülebilir ekonomik büyümenin, verimlilik artışının ve Avrupa Birliği ile yapısal yakınsamanın temel belirleyicilerinden biridir. Bununla birlikte, bölge ülkelerinin inovasyon performansları arasında gözlenen belirgin farklılıklar, çok boyutlu ve karşılaştırmalı bir değerlendirme yaklaşımını gerekli kılmaktadır. Bu doğrultuda, çalışmada Küresel İnovasyon Endeksi (Global Innovation Index-GII) kapsamında yer alan yedi kriter esas alınarak on Balkan ülkesinin inovasyon performansı, Entropi tabanlı TOPSIS çok kriterli karar verme (ÇKKV) yöntemi kullanılarak değerlendirilmiştir. Entropi sonuçları, kriterlerin bilgi katkılarının önemli ölçüde farklılaştığını ortaya koymakta; özellikle Yaratıcı Çıktılar (Creative Outputs) ile Bilgi ve Teknoloji Çıktıları (Knowledge and Technology Outputs) kriterlerinin

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inovasyon performansını ayırt etmede en yüksek açıklayıcılığa sahip boyutlar olduğunu göstermektedir. Entropi tabanlı TOPSIS sıralamasına göre Bulgaristan, Yunanistan, Hırvatistan, Slovenya ve Romanya yüksek performans grubunda yer alırken; Karadağ, Sırbistan, Kuzey Makedonya, Arnavutluk ve Bosna-Hersek bölgesel ortalamasının altında kalmaktadır. Duyarlılık analizi, elde edilen sıralamaların kriter yapısındaki değişimlere karşı yüksek düzeyde sağlamlık sergilediğini doğrularken, karşılaştırmalı ve korelasyon analizleri Entropi tabanlı TOPSIS sonuçlarının yaygın olarak kullanılan diğer ÇKKV yöntemleriyle güçlü bir tutarlılık gösterdiğini ortaya koymaktadır. Elde edilen bulgular, bölgesel rekabet gücünün ve uzun dönemli ekonomik kalkınmanın artırılabilmesi için bilgi temelli, teknolojik ve yaratıcı çıktıları güçlendirmeye yönelik politikaların stratejik önemini vurgulamaktadır.

Anahtar Kelimeler: *Balkan Ülkeleri, İnovasyon, ÇKKV*

1. Introduction

Innovation has become one of the primary determinants of sustainable economic development by fostering technological progress, facilitating knowledge creation, and enhancing productivity. Beyond its contribution to economic growth, innovation strengthens international competitiveness, accelerates structural transformation, and improves countries' capacity to adapt to rapidly changing global markets (Romer, 1990; Aghion & Howitt, 1992; OECD, 2023; Mtar & Belazreg, 2021). As global competition increasingly shifts from resource-based production toward knowledge-driven economies, countries with stronger innovation capabilities gain substantial advantages in achieving long-term economic prosperity and sustainable development (Porter, 1990; Martí & Puertas, 2023; Silvestre & Țircă, 2019).

The strategic importance of innovation is particularly evident in the Balkan region. Although Balkan countries have made notable economic and institutional progress during the last two decades, considerable disparities in innovation performance remain across the region. Compared with the European Union average, many Balkan economies continue to experience relatively low research and development intensity, insufficient commercialization of scientific knowledge, limited technology transfer, fragmented innovation ecosystems, and weaker institutional capacities that constrain innovation-driven growth (Radosevic, 2002; Cvetanović & Nedić, 2013; Cvetanović et al., 2014; Fedajev et al., 2024). These structural challenges not only reduce international competitiveness but also hinder the region's long-term economic convergence with the European Union. Consequently, accurately evaluating innovation performance has become increasingly important for identifying national strengths and weaknesses, supporting evidence-based policy formulation, and promoting sustainable regional development (Hysaj & Sulçaj, 2024; Lukić, 2024).

Assessing innovation, however, is inherently challenging because innovation systems consist of multiple interconnected dimensions rather than a single measurable attribute. A comprehensive evaluation therefore requires an analytical framework capable of simultaneously capturing the institutional, technological, economic, and knowledge-based components of national innovation systems. In this respect, the Global Innovation Index (GII) developed by the World Intellectual Property Organization (WIPO) has become one of the most comprehensive and internationally recognized instruments for measuring innovation performance. The GII evaluates countries using seven complementary dimensions, namely Institutions, Human Capital and Research, Infrastructure, Market Sophistication, Business

Sophistication, Knowledge and Technology Outputs, and Creative Outputs. Unlike conventional single-indicator assessments, this multidimensional structure enables a more comprehensive representation of national innovation capacity while facilitating meaningful international comparisons (WIPO, 2023).

Despite its comprehensive structure, the GII primarily provides a composite ranking of countries and does not explicitly evaluate the relative contribution of individual innovation dimensions to overall performance. Countries with similar GII scores may exhibit considerably different strengths and weaknesses across specific innovation pillars, making it difficult to identify the factors primarily responsible for differences in innovation capacity. Consequently, relying solely on composite GII rankings may provide only limited guidance for policymakers seeking to design targeted innovation strategies. Multi-Criteria Decision-Making (MCDM) methods overcome this limitation by simultaneously evaluating multiple criteria while incorporating their relative importance into the decision process. This allows innovation performance to be interpreted from a multidimensional perspective, providing richer analytical insights than conventional composite rankings alone (Hwang & Yoon, 1981; Behzadian et al., 2012; Keshavarz-Ghorabae et al., 2021).

The growing application of MCDM methods has substantially expanded innovation performance assessment in recent years. Nevertheless, studies specifically focusing on Balkan countries remain relatively limited and generally employ different weighting techniques or alternative MCDM algorithms (Cvetanović & Nedić, 2013; Çobanoğulları et al., 2026; Stojanović et al., 2022; Lukić, 2024). Although these studies provide valuable evidence regarding regional innovation performance, comparatively less attention has been devoted to evaluating Balkan countries through the integration of Entropy-based objective weighting and the TOPSIS method within a unified analytical framework. Furthermore, previous studies have generally emphasized country rankings without comprehensively examining the robustness and consistency of the obtained results through multiple validation procedures.

To address these research gaps, the present study evaluates the innovation performance of ten Balkan countries using the seven core dimensions of the Global Innovation Index within an Entropy-based TOPSIS framework. The Entropy method objectively determines criterion weights directly from the information contained in the dataset, thereby minimizing subjective judgment in the weighting process (Shannon, 1948; Zeleny, 1982). Subsequently, the TOPSIS method ranks countries according to their relative distances from the positive and negative ideal solutions, providing a transparent and data-driven assessment of innovation performance (Hwang & Yoon, 1981; Wang & Lee, 2009; Behzadian et al., 2012). Beyond generating innovation rankings, this study further examines the robustness of the proposed framework through rank-reversal analysis, comparative evaluation with twelve Entropy-based MCDM methods, Spearman correlation analysis, and normalized performance distribution analysis. By integrating objective weighting with comprehensive validation procedures, the study provides a more robust, transparent, and methodologically comprehensive assessment of innovation performance across Balkan countries while offering evidence-based implications for strengthening regional competitiveness and innovation-driven economic development.

2. Literature

2.1. Definition of Innovation and Its Strategic Importance for Countries

Innovation represents a systemic, multidimensional process where knowledge is translated into economic and social value, transcending mere technological breakthroughs (Lee & Chen, 2025; Schumpeter, 1934; Freeman, 1987). As a structural pillar of endogenous growth, it drives total factor productivity and long-term resilience (Romer, 1990; Aghion & Howitt, 1992; Lee & Chen, 2025). In the contemporary global economy, competitiveness has shifted from cost-based advantages toward knowledge intensity and product differentiation, facilitating ascension within global value chains (Porter, 1990; Mtar & Belazreg, 2021). This structural transformation necessitates robust institutional frameworks and coherent policies to foster technological upgrading (Nelson, 1993; Kattel & Mazzucato, 2018). Furthermore, the synergy between innovation and digital transformation enhances adaptive capacity, allowing economies to mitigate external shocks and sustain long-term welfare (Brynjolfsson & McAfee, 2014; Nelson & Winter, 1982; Ziesemer, 2025). Ultimately, consistent investment in human capital and digital infrastructure remains critical for securing a strategic position within the global economic system (Porter, 1990; Mtar & Belazreg, 2021).

2.2. The Relationship between Balkan Countries and Innovation

Evaluating innovation and its performance in Balkan countries goes well beyond tracking technological progress; it serves as a key analytical perspective for understanding long-term growth potential, productivity improvements, and the extent of convergence with the European Union (EU). This relevance becomes clearer when considering the region's limited R&D capacity, the dominance of medium-low technology production structures, and enduring institutional weaknesses, all of which influence how effectively innovation inputs are converted into observable outcomes. Within this setting, the Global Innovation Index (GII) has gained prominence as a reference framework, offering a multidimensional structure that supports cross-country comparisons across institutions, human capital and research, infrastructure, market and business sophistication, and innovation outputs (WIPO, 2023).

A substantial body of empirical work on the Western Balkans relies on GII-based indicators to identify regional gaps relative to selected EU economies and to examine the input-output dynamics of innovation systems. For instance, Cvetanović and Nedić (2013) provide an early comparative analysis, pointing to persistent differences in innovation capacities and outcomes between Western Balkan countries and EU counterparts. Extending this line of inquiry, Cvetanović et al. (2014) analyze similar dimensions and highlight systematic relationships between innovation inputs, outputs, and broader competitiveness patterns, reinforcing the view that these disparities are rooted in structural conditions rather than short-term fluctuations. Alongside these descriptive studies, a smaller but growing strand of research applies MCDM techniques to GII indicators to generate explicit country rankings. Stojanović et al. (2022), for example, construct a multi-criteria framework for the 2019–2021 period and rank Montenegro first, followed by Serbia, with Albania at the bottom. In a different approach, Lukić (2024) employs the FUCOM–CoCoSo method and reports North Macedonia as the leading country, followed by Serbia and Montenegro, while Bosnia and Herzegovina ranks last. This study also emphasizes the importance of institutional efficiency, infrastructure, market and

business sophistication, and innovation outputs in shaping overall performance. Taken together, these ranking-oriented analyses offer two important insights. First, they provide transparent and comparable ordinal results, helping to identify which countries consistently occupy higher or lower positions in terms of innovation performance under GII-based frameworks. Second, variations in rankings across methods and weighting schemes point to a critical methodological issue: although performance gaps across Balkan countries are well established, relative country positions can shift depending on the chosen MCDM approach, weighting strategy, and time frame. This reinforces the need for objective weighting techniques and systematic sensitivity analyses in comparative innovation studies.

3. Material and Method

3.1. Data Set

The empirical dataset is constructed from the indicators associated with the seven core dimensions of the Global Innovation Index (GII) 2025 (WIPO, 2025). The data were accessed from the official World Intellectual Property Organization (WIPO) database on 26 March 2026 and include ten Balkan countries: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Greece, Montenegro, North Macedonia, Romania, Serbia, and Slovenia. Kosovo was excluded because comparable values for the selected indicators are not available in the GII database. For clarity and consistency throughout the analysis, the abbreviations assigned to the seven GII dimensions are presented in Table 1.

Table 1. Abbreviations of GII criteria

Components	Abbreviations
Institutions	C1
Human Capital and Research	C2
Infrastructure	C3
Market Sophistication	C4
Business Sophistication	C5
Knowledge and Technology Outputs	C6
Creative Outputs	C7

Reference: WIPO, 2025

3.2. ENTROPY Method

The Entropy method is widely recognized as an objective, data-driven weighting technique within the MCDM literature (Ayçin, 2019). It determines criterion weights solely on the basis of observed data, without incorporating subjective preferences, thereby ensuring results that are both impartial and empirically grounded (Dinçer, 2019). At its core, the method assumes that greater irregularity in the distribution of a criterion implies higher informational uncertainty (Aksakal & Çalışkan, 2020). In this sense, high entropy values correspond to weaker discriminative capacity, whereas lower entropy indicates that a criterion more effectively differentiates among alternatives. This property makes the method particularly suitable for capturing variability and the informational contribution of criteria within a decision matrix (Ecer, 2020). In practice, entropy values are first computed for each criterion to quantify uncertainty, followed by the calculation of diversification degrees based on these measures (Öztel & Alp, 2020). The

proportion of each diversification value within the total then defines the final weights assigned to the criteria (Demir et al., 2021).

Entropy method has been widely applied in recent years across diverse decision-making domains, including sustainability assessment, disaster management, environmental evaluation, energy systems, and spatial planning (Erbey et al., 2025; Guo & Zhu, 2025; Xu et al., 2026; Sharma et al., 2025; Yıldırım & Şişman, 2025; Yu et al., 2025; Zhao et al., 2025). These studies consistently highlight the effectiveness and flexibility of the Entropy method as an objective weighting technique when integrated with various MCDM approaches. Nevertheless, its application to the evaluation of national innovation performance remains relatively limited, particularly in the context of cross-country comparisons. This gap further underscores the methodological contribution of the present study by extending the application of the Entropy-based framework to the assessment of innovation performance in Balkan countries. Within this framework, the computational procedure of the Entropy method has been extensively documented in the literature, and the methodological steps of its implementation are summarized below (Uludağ & Doğan, 2021).

A_i : i -th decision alternative ($i = 1, 2, \dots, m$)

C_j : j -th evaluation criterion ($j = 1, 2, \dots, n$)

x_{ij} : Performance value of the i – th alternative with respect to the j – th criterion

p_{ij} : Normalized value of the i – th alternative with respect to the j – th criterion

e_j : Entropy value

k : Entropy coefficient

d_j : Degree of diversification

w_j : Weight of the j – th evaluation criterion ($j = 1, 2, \dots, n$)

Step 1: Construction of the Decision Matrix (D)

$$D = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: Normalization of the Decision Matrix (p_{ij})

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad \forall i, j \quad (2)$$

Step 3: Determination of Entropy Values of the Criteria (e_j)

$$k = (\ln(m))^{-1} \quad 0 \leq e_j \leq 1 \quad (3)$$

$$e_{ij} = -k \cdot \sum_{j=1}^n p_{ij} \cdot \ln(p_{ij}) \quad i=1,2,\dots,m; j=1,2,\dots,n \quad (4)$$

Step 4: Calculation of the Degree of Diversification (d_j)

$$d_j = 1 - e_j \quad j=1,2,\dots,n \quad (5)$$

Step 5: Determination of Entropy-Based Criterion Weights (w_j)

$$w_j = \frac{d_j}{\sum_{j=1}^n d_j} \quad (6)$$

3.3. TOPSIS Method

The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), introduced into the MCDM literature in 1980, has become one of the most widely employed ranking methods (Başdar, 2019). Its core rationale is based on evaluating alternatives with respect to two reference points, namely the positive and negative ideal solutions (Özbek et al., 2021), which enable systematic comparison within a multidimensional decision space (Yıldırım & Çiftci, 2021). In this context, the positive ideal represents a hypothetical alternative that maximizes benefit criteria while minimizing cost criteria (Tepe, 2021), whereas the negative ideal corresponds to the least desirable case, where benefit criteria are minimized and cost criteria are maximized (Paksoy, 2017). This dual structure establishes clear performance bounds (Çakar, 2020) and implies that an alternative is preferred as it approaches the positive ideal and moves away from the negative ideal (Demirci, 2020); thus, those with the smallest distance to the ideal and the greatest distance from the worst-case scenario achieve higher rankings (Çelikkilek, 2018). This distance-based mechanism provides a transparent and internally consistent evaluation framework (Özari and Eren, 2019). The literature further indicates that TOPSIS has been extensively applied in performance evaluation, ranking, and selection problems across diverse fields (Avcı Öztürk, 2018), and its conceptual simplicity, computational efficiency, and strong discriminative capability underpin its continued prominence in both theoretical and applied MCDM research (Atan & Altan, 2020).

TOPSIS method across a wide range of decision-making problems, including urban redevelopment, supply chain resilience, cloud service selection, sustainable tourism, employability prediction, artificial intelligence evaluation, transportation management systems, and energy planning (Anes & Abreu, 2025; Ilieva, 2025; Kütahya et al., 2025; Nouib et al., 2025; Park et al., 2025; Samhoury et al., 2025; Swathi et al., 2025; Yang et al., 2025; Ye et al., 2025). These studies demonstrate the versatility and effectiveness of the TOPSIS method in ranking alternatives across diverse application domains. However, relatively few studies have employed the Entropy-based TOPSIS framework to evaluate national innovation performance, particularly within the context of Balkan countries. This highlights the methodological relevance of the present study in extending the application of TOPSIS to a multidimensional assessment of regional innovation performance.

The application steps of the method are explained below (Kaya & Karaşan, 2020).

Step 1: Decision Matrix (D)

$$D = \begin{matrix} & \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \end{matrix} \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (7)$$

Step 2: Standard Decision Matrix (D^*)

$$d_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^m x_{kj}^2}} \quad i = 1, 2, \dots, m \text{ ve } j = 1, 2, \dots, n \quad (8)$$

Step 3: Weighted Standard Decision Matrix (wD^*_{ij})

$$wD^*_{ij} = \begin{bmatrix} w_1 d_{11} & w_2 d_{12} & \cdots & w_n d_{1n} \\ w_1 d_{21} & w_2 d_{22} & \cdots & w_n d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 d_{m1} & w_2 d_{m2} & \cdots & w_n d_{mn} \end{bmatrix} \quad (9)$$

Step 4: Determination of the Positive Ideal (PIV^+) and Negative Ideal (NIV^-) Solution Values

$$PIV^+ = \{ \max_i d_{ij} | j \in J \}, (\min_i d_{ij} | j \in J') \quad (10)$$

$$PIV^+ = \{d_1^*, d_2^*, \dots, d_n^*\} \quad (11)$$

$$NIV^- = \{ \min_i d_{ij} | j \in J \}, (\min_i d_{ij} | j \in J') \quad (12)$$

$$NIV^- = \{d_1^-, d_2^-, \dots, d_n^-\} \quad (13)$$

Step 5: Distance to Positive (PID_i^+) and Negative Points (NID_i^-)

$$r_{ij} = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2} \quad (14)$$

$$\text{Positive ideal distance: } PID_i^+ = \sqrt{\sum_{j=1}^n (d_{ij} - d_j^+)^2} \quad (15)$$

$$\text{Negative ideal distance: } NID_i^- = \sqrt{\sum_{j=1}^n (d_{ij} - d_j^-)^2} \quad (16)$$

Step 6: Relative Proximity to the Ideal Solution (IS_i^*)

$$IS_i^* = \frac{NID_i^-}{NID_i^- + PID_i^+} \quad (17)$$

4. Results

4.1. Computational Analysis

At the first stage, the decision matrix was formulated in accordance with Equation 1 within the Entropy framework. This was followed by the normalization of the matrix using Equation 2, after which the entropy values for each criterion were computed through Equations 3 and 4. In the subsequent step, the diversification levels of the criteria were obtained using Equation 5, and these values were then used to derive the final entropy-based weights via Equation 6. The detailed results corresponding to each of these stages are reported in Table 2, Table 3 and Table 4.

Table 2. Decision Matrix

Decision Matrix							
Countries	C1	C2	C3	C4	C5	C6	C7
Albania	58.7	22.4	52.3	41.1	30.5	16.5	20
Bosnia and Herzegovina	28.5	28.7	41.5	33.5	18.4	20.3	13.1
Bulgaria	46	32.7	57.1	45.6	32.7	33.2	37.5
Croatia	51	40.3	58	39.9	31.7	30.3	32.1
Greece	52	46.8	52	39	28.7	28.1	33.8
Montenegro	42.8	33.3	48.8	41.2	24.6	19.8	23
North Macedonia	47	30.4	47.5	35.6	26.9	24.7	19.5
Romania	43.4	30.2	54.4	37.9	31.2	28.7	29.5
Serbia	48.1	37.5	52.8	34.6	24.2	30.8	17.3
Slovenia	58.5	48.1	57.1	37.8	38.2	35.1	29.4

Table 3. Normalized Decision Matrix

Countries	C1	C2	C3	C4	C5	C6	C7
Albania	0.123	0.064	0.100	0.106	0.106	0.062	0.078
Bosnia and Herzegovina	0.060	0.082	0.080	0.087	0.064	0.076	0.051
Bulgaria	0.097	0.093	0.109	0.118	0.114	0.124	0.147
Croatia	0.107	0.115	0.111	0.103	0.110	0.113	0.126
Greece	0.109	0.134	0.100	0.101	0.100	0.105	0.132
Montenegro	0.090	0.095	0.094	0.107	0.086	0.074	0.090
North Macedonia	0.099	0.087	0.091	0.092	0.094	0.092	0.076
Romania	0.091	0.086	0.104	0.098	0.109	0.107	0.116
Serbia	0.101	0.107	0.101	0.090	0.084	0.115	0.068
Slovenia	0.123	0.137	0.109	0.098	0.133	0.131	0.115

Table 4. Entropy, Differentiation Scores and Weights of Criteria

[illegible]

w _j	0.117	0.176	0.033	0.028	0.124	0.184	0.337
Rank	5	3	6	7	4	2	1

Table 4 reveals pronounced weight variations, aligning with the Entropy method's logic where data variability dictates discriminatory power. C7 ($w_7 = 0.337$, creative outputs) and C6 ($w_6 = 0.184$, knowledge outputs) emerge as the primary innovation determinants for Balkan countries. This suggests that regional performance is driven more by the capacity to transform knowledge and creative assets into tangible outcomes than by infrastructure alone. Consequently, strategic policies should prioritize C7 and C6 specifically through enhanced commercialization, university-industry synergy, and high-technology exports to bolster long-term regional competitiveness and innovation capacity.

In the next phase of the analysis, innovation performance is evaluated using the Entropy-based TOPSIS framework. The weights obtained from the Entropy method are first incorporated into the TOPSIS procedure, allowing performance scores to reflect both the informational contribution of criteria and the relative positioning of countries. The decision matrix is initially constructed using Equation 7, based on the Entropy-derived weights (Equation 1) and the results presented in Table 2. This is followed by normalization through Equation 8 and the computation of the weighted normalized matrix via Equation 9. Subsequently, the Positive Ideal Solution (PIV) and Negative Ideal Solution (NIV) are determined using Equations 10–11 and 12–13, respectively. The resulting weighted values and all intermediate computations are reported in detail in Table 5.

Table 5. Standardized and Weighted Standardized Decision Matrices

Standardized Decision Matrix							
Countries	C1	C2	C3	C4	C5	C6	C7
Albania	0.384	0.197	0.316	0.335	0.331	0.191	0.237
Bosnia and Herzegovina	0.187	0.253	0.251	0.273	0.199	0.234	0.156
Bulgaria	0.301	0.288	0.345	0.372	0.354	0.383	0.445
Croatia	0.334	0.355	0.350	0.325	0.344	0.350	0.381
Greece	0.340	0.412	0.314	0.318	0.311	0.324	0.401
Montenegro	0.280	0.293	0.295	0.336	0.267	0.229	0.273
North Macedonia	0.308	0.268	0.287	0.290	0.292	0.285	0.232
Romania	0.284	0.266	0.328	0.309	0.338	0.331	0.350
Serbia	0.315	0.331	0.319	0.282	0.262	0.356	0.205
Slovenia	0.383	0.424	0.345	0.308	0.414	0.405	0.349
Weighted Standardized Decision Matrix							
Countries	C1	C2	C3	C4	C5	C6	C7
w	0.117	0.176	0.033	0.028	0.124	0.184	0.337
Albania	0.045	0.035	0.010	0.009	0.041	0.035	0.080
Bosnia and Herzegovina	0.022	0.045	0.008	0.008	0.025	0.043	0.052
Bulgaria	0.035	0.051	0.011	0.010	0.044	0.071	0.150
Croatia	0.039	0.063	0.012	0.009	0.043	0.064	0.128
Greece	0.040	0.073	0.010	0.009	0.039	0.060	0.135
Montenegro	0.033	0.052	0.010	0.009	0.033	0.042	0.092
North Macedonia	0.036	0.047	0.009	0.008	0.036	0.052	0.078
Romania	0.033	0.047	0.011	0.009	0.042	0.061	0.118
Serbia	0.037	0.058	0.011	0.008	0.033	0.065	0.069

Slovenia	0.045	0.075	0.011	0.009	0.051	0.075	0.118
PIV and NIV Score							
Criteria	C1	C2	C3	C4	C5	C6	C7
PIV	0.045	0.075	0.012	0.010	0.051	0.075	0.150
NIV	0.022	0.035	0.008	0.008	0.025	0.035	0.052

In the following phase, corresponding to the fourth step of the TOPSIS procedure, the distances of each alternative (country) to the Positive Ideal Distance (PID) were computed using Equations 14–15, and their distances to the Negative Ideal Distance (NID) were then obtained via Equations 14–16. This step establishes, in quantitative terms, how each country is positioned relative to both the ideal and the worst-case reference points, forming the basis for comparing alternatives in the decision space. In the final step, relative closeness coefficients to the ideal solution were calculated using Equation 17, allowing a comprehensive assessment of innovation performance within an integrated analytical framework. The resulting PID and NID values, along with the corresponding performance scores and rankings, are reported in Table 6.

Table 6. PID, NID, IS_i^* and Rank Scores of Alternatives

Alternatives	PID	NID	IS_i^*	Rank
Albania	0.090	0.040	0.305	9
Bosnia and Herzegovina	0.113	0.013	0.101	10
Bulgaria	0.027	0.108	0.799	1
Croatia	0.029	0.090	0.757	3
Greece	0.025	0.097	0.794	2
Montenegro	0.074	0.046	0.383	6
North Macedonia	0.082	0.038	0.316	8
Romania	0.047	0.075	0.613	5
Serbia	0.086	0.045	0.346	7
Slovenia	0.032	0.093	0.741	4
Mean			0.516	

Table 6 demonstrates the high discriminative capacity of the Entropy–TOPSIS framework in evaluating innovation performance across the Balkan region. Bulgaria (0.799), Greece (0.794), Croatia (0.757), Slovenia (0.741), Romania (0.613) lead the rankings, exhibiting the closest proximity to the Positive Ideal Solution. Conversely, Bosnia and Herzegovina (0.101) reflects the lowest performance, trailing significantly below the regional average (0.516) alongside Montenegro, Serbia, North Macedonia, and Albania. The marginal difference between Slovenia and Croatia suggests emerging innovation clusters. To bridge these gaps, lagging economies must prioritize Knowledge and Technology Outputs (C6), focusing on R&D commercialization and university–industry synergy to enhance regional competitiveness.

4.2. Sensitivity Analysis

Assessing the robustness of weighting methods typically involves intentional modifications to the evaluation structure, such as introducing additional criteria or removing those with limited impact in the initial model. In this setting, robustness refers to the capacity of a method to maintain a consistent ordering of criteria despite such structural changes. Ensuring this type of stability is essential for preserving the reliability and validity of decision-making outcomes, especially in environments

marked by uncertainty or shifting evaluation conditions (Demir & Arslan, 2022). Accordingly, the criteria were sequentially removed from the analysis, beginning with the criterion assigned the lowest weight in the initial weighting results. Following each removal, the innovation performance rankings of the countries were recalculated for the corresponding scenario. This procedure enabled the impact of the progressive elimination of criteria on the ranking results to be systematically evaluated through rank reversal analysis. The country rankings obtained under each scenario are presented in Table 7, while the corresponding graphical representation of the ranking changes is illustrated in Figure 1.

Table 7. Rank Reversal

Scenario	S0	S1	S2	S3	S4	S5	S6	S7
Bosnia and Herzegovina	10	10	10	10	10	10	10	10
Albania	9	9	9	9	9	9	9	9
North Macedonia	8	8	8	8	8	8	8	8
Serbia	7	7	7	7	7	7	7	7
Montenegro	6	6	6	6	6	6	6	6
Romania	5	5	5	5	5	5	5	5
Slovenia	4	4	4	4	4	4	4	4
Croatia	3	3	3	3	3	3	3	3
Greece	2	2	2	2	2	1	2	2
Bulgaria	1	1	1	1	1	2	1	1
Removed Criteria	--	C4	C3	C1	C5	C2	C6	C7

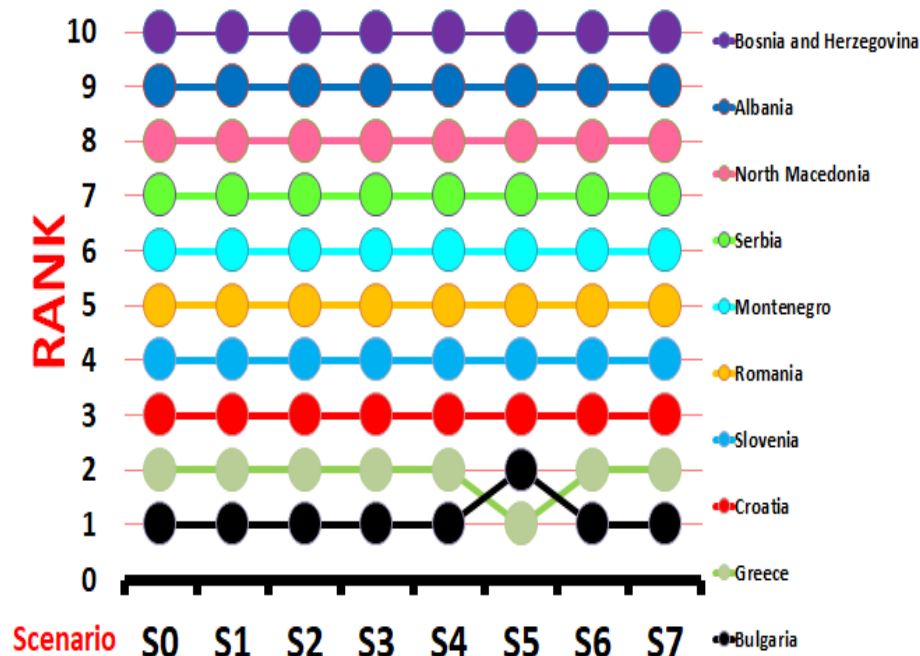


Figure 1. Rank reversal graph

Table 7 and Figure 1 present the results of the rank reversal analysis performed to evaluate the sensitivity of the Entropy-based TOPSIS model to sequential criterion removal. The initial ranking obtained from the complete decision matrix (S0) was considered the reference scenario, and seven additional scenarios (S1–S7) were generated by removing one criterion at a time. Accordingly, the excluded criteria were C4 (Market Sophistication), C3 (Infrastructure), C1 (Institutions), C5 (Business Sophistication), C2 (Human Capital and Research), C6 (Knowledge and Technology Outputs), and C7 (Creative Outputs), respectively. As shown in Table 7, the alternative rankings remain almost entirely unchanged across all scenarios. Bosnia and Herzegovina, Albania, North Macedonia, Serbia, Montenegro, Romania, Slovenia, and Croatia preserve their original ranking positions throughout the sequential elimination process, indicating that the exclusion of any single criterion does not alter their relative ordering within the decision set. This finding suggests that the relative performance of these countries is largely independent of the contribution of any individual criterion. The only ranking variation is observed under Scenario S5, in which C2 (Human Capital and Research) is excluded from the analysis. Under this scenario, Greece moves from the second to the first position, while Bulgaria shifts from the first to the second position. No other changes are observed among the remaining alternatives. This isolated exchange indicates that the Human Capital and Research criterion plays a relatively greater role in distinguishing the two highest-performing countries, whereas its removal has a negligible influence on the ranking of the remaining alternatives. Figure 1 provides a graphical representation of the results presented in Table 7 and further illustrates the stability of the ranking structure. The nearly horizontal trajectories of the ranking profiles across scenarios indicate that the relative positions of the alternatives are preserved despite successive criterion removal. The only intersection observed between the ranking curves corresponds to the position exchange between Bulgaria and Greece under Scenario S5, confirming the numerical results reported in Table 7. Overall, the sequential removal of individual criteria produces only a single local ranking change, while the remaining ranking structure is preserved across all scenarios. The persistence of the original ordering for eight of the ten alternatives demonstrates that the Entropy-based TOPSIS framework exhibits a high degree of ranking stability under criterion elimination and that the obtained results are not driven by the dominance of any single evaluation criterion.

4.3. Comparative Analysis

The purpose of the comparative evaluation is to examine the degree of convergence and divergence between the proposed method and a set of well-established MCDM techniques. Through this analysis, the study seeks to reinforce the robustness, internal consistency, and methodological soundness of the proposed framework by clarifying its relationship with existing approaches and by highlighting statistically meaningful correspondences (Keshavarz-Ghorabae et al., 2021). Within this context, the present analysis evaluates the innovation performance of countries by employing several widely used MCDM methods that are frequently adopted in the literature for measuring alternative performances and solving selection problems. The corresponding performance scores and ranking results obtained from these methods are presented in Table 8 and Figure 2.

Table 8. Performance Score in scope of other MCDM methods

ENTROPY based MCDM Methods	WPM		SAW		WASPAS		CODAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Albania	0.595	9	0.619	9	25.92	9	-0.211	6
Bosnia and Herzegovina	0.477	10	0.490	10	20.45	10	-0.657	10
Bulgaria	0.881	2	0.889	2	36.86	2	0.496	1
Croatia	0.857	4	0.857	4	36.02	4	0.360	3
Greece	0.871	3	0.873	3	36.71	3	0.375	2
Montenegro	0.647	7	0.651	7	27.48	7	-0.255	8
North Macedonia	0.638	8	0.646	8	27.18	8	-0.345	9
Romania	0.765	5	0.768	5	32.07	5	0.116	5
Serbia	0.658	6	0.680	6	28.34	6	-0.229	7
Slovenia	0.916	1	0.921	1	38.69	1	0.353	4
ENTROPY based MCDM Methods	MAUT		MARCOS		WEDBA		ROV	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Albania	0.185	7	0.408	9	0.346	9	0.178	9
Bosnia and Herzegovina	0.011	10	0.316	10	0.116	10	0.044	10
Bulgaria	0.623	2	0.556	3	0.756	3	0.423	2
Croatia	0.438	4	0.546	4	0.745	4	0.397	4
Greece	0.502	3	0.558	2	0.763	2	0.402	3
Montenegro	0.096	9	0.421	7	0.376	7	0.197	8
North Macedonia	0.097	8	0.417	8	0.349	8	0.199	7
Romania	0.255	5	0.485	5	0.590	5	0.311	5
Serbia	0.189	6	0.441	6	0.401	6	0.238	6
Slovenia	0.742	1	0.590	1	0.778	1	0.472	1
ENTROPY based MCDM Methods	CRADIS		RAFSI		MABAC		EDAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Albania	0.544	9	4.612	9	-0.133	9	0.273	9
Bosnia and Herzegovina	0.444	10	2.455	10	-0.402	10	0.000	10
Bulgaria	0.761	2	8.655	2	0.357	2	0.942	2
Croatia	0.734	4	8.221	4	0.304	4	0.834	4
Greece	0.747	3	8.372	3	0.314	3	0.885	3
Montenegro	0.568	7	4.992	7	-0.096	8	0.326	7
North Macedonia	0.564	8	4.951	8	-0.091	7	0.308	8
Romania	0.662	5	6.775	5	0.132	5	0.608	5
Serbia	0.591	6	5.601	6	-0.014	6	0.394	6
Slovenia	0.787	1	9.330	1	0.455	1	0.999	1

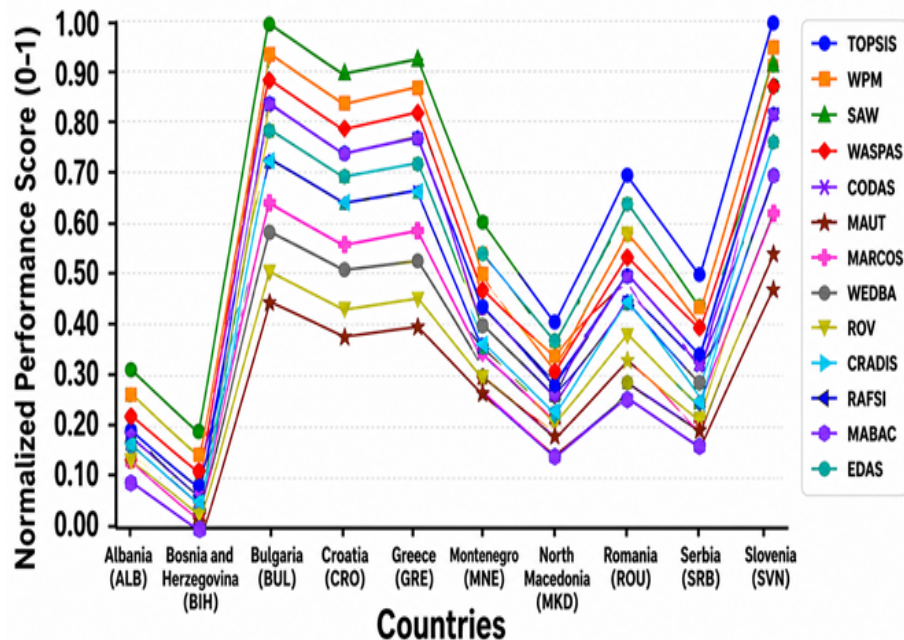


Figure 2. Comparative Distribution of Normalized Innovation Performance Across Entropy-Based MCDM Methods

According to the comparative results presented in Table 8 and Figure 2, the Entropy-based MCDM methods exhibit a highly consistent innovation performance structure across the Balkan countries. Although slight variations in the ranking positions are observed among the methods, the overall performance pattern remains remarkably stable. In particular, Bulgaria, Greece, Croatia, and Slovenia consistently constitute the leading group, whereas Albania and Bosnia and Herzegovina remain at the lower end of the rankings regardless of the decision-making technique employed. This consistency indicates that the identification of both high- and low-performing countries is largely insensitive to the choice of Entropy-based MCDM method. Among the compared techniques, WPM, SAW, and WASPAS exhibit the closest ranking pattern to the Entropy-TOPSIS results. While these methods interchange the positions of Slovenia and Bulgaria at the top of the rankings, they preserve the same cluster of high-performing countries and maintain identical rankings for most of the remaining alternatives. Likewise, Romania consistently occupies the fifth position across these approaches, demonstrating a highly stable innovation profile. Such findings suggest that the ranking differences are primarily limited to local position exchanges rather than substantial changes in the overall performance structure. A similar level of agreement is observed for MAUT, MARCOS, WEDBA, ROV, CRADIS, RAFSI, EDAS, and MABAC. These methods preserve the same upper and lower performance clusters while introducing only minor rearrangements among the middle-ranked countries, particularly Montenegro, Serbia, and North Macedonia. Such variations are expected because each method employs different aggregation mechanisms, normalization procedures, and distance or utility functions. Nevertheless, these methodological differences do not fundamentally alter the overall ranking configuration. Overall, the comparative analysis demonstrates that the Entropy-TOPSIS results are highly robust with respect to alternative Entropy-

based MCDM techniques. The persistence of the same leading and lagging country groups across twelve different decision-making methods provides strong evidence that the obtained innovation rankings reflect an inherent performance structure rather than a method-specific outcome. Consequently, the findings support the reliability and generalizability of the proposed evaluation framework.

This local ranking variation can be explained by the mathematical structure of the CODAS method, which simultaneously employs Euclidean and Taxicab distances when evaluating alternatives. In cases where low-performing alternatives exhibit very similar distances from the negative ideal solution, the Taxicab distance acts as an additional discriminative measure, amplifying otherwise minor performance differences. Consequently, limited ranking changes may occur among lower-ranked countries without altering the overall performance structure or the identification of the leading and lagging groups. Therefore, the discrepancies observed for CODAS should be interpreted as methodological characteristics of the distance metric rather than substantive inconsistencies in the evaluation results.

To provide a more comprehensive comparison of the results obtained from the Entropy-based MCDM methods, the distribution of innovation performance scores was further examined through graphical visualization. Since the compared methods employ different mathematical formulations and generate performance scores on different numerical scales, a direct comparison of the original scores is methodologically inappropriate. Therefore, the performance scores produced by each method were transformed onto a common 0–1 scale using Min–Max normalization. This transformation preserves the relative performance structure within each method while eliminating the influence of differences in scoring scales, thereby enabling a direct visual comparison of innovation performance across the Entropy-based MCDM approaches. The resulting normalized performance distributions are presented in Figure 3, which provides an integrated visualization of the relative performance profiles of the Balkan countries across all evaluated methods. To support these observations with quantitative evidence, Table 7 reports correlation coefficients comparing the innovation performance scores derived from Entropy-based TOPSIS with those generated by alternative Entropy-based MCDM methods. The consistently high, often very high, levels of association observed across these comparisons reinforce the patterns identified in the ranking analysis. Taken together, these findings underline the robustness of TOPSIS, highlighting its capacity to deliver stable and reliable evaluations that remain consistent across a range of methodological perspectives.

Tablo 9. rho Correlation Scores

Methods	WPM	SAW	WASPAS	CODAS	MAUT	MARCOS
rho	0.915**	0.915**	0.915**	0.915**	0.842**	0.903**
Methods	WEDBA	ROV	CRADIS	RAFSI	MABAC	EDAS
rho	0.903**	0.891**	0.915**	0.915**	0.891**	0.915**

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

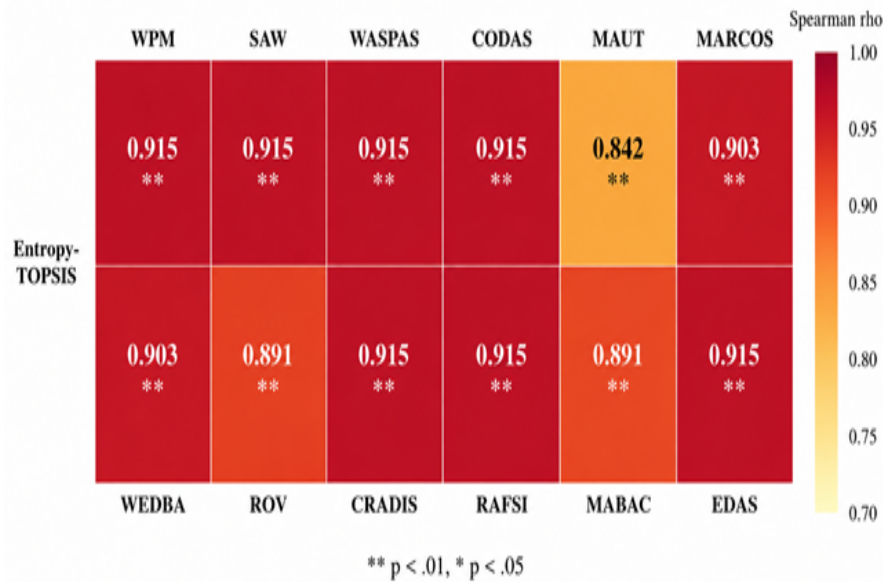


Figure 3. Heatmap of Spearman Rank Correlations Between the Entropy-Based TOPSIS Method and Other Entropy-Based MCDM Methods

Table 9 and Figure 3 present the Spearman rank correlation coefficients between the innovation performance scores obtained from the Entropy-based TOPSIS method and those generated by the remaining Entropy-based MCDM approaches. As shown in Table 9, all correlation coefficients are positive and statistically significant at the 0.01 significance level ($p < 0.01$), indicating a strong monotonic relationship between the corresponding performance scores. The correlation coefficients range from 0.842 to 0.915, demonstrating that the relative innovation performance of the Balkan countries remains highly consistent across the different Entropy-based decision-making methods. The highest correlations ($\rho = 0.915$) are observed for WPM, SAW, WASPAS, CODAS, CRADIS, RAFSI, and EDAS, indicating an almost identical performance ordering with that produced by the Entropy-based TOPSIS approach. Slightly lower, yet still very strong, correlations are obtained for MARCOS and WEDBA ($\rho = 0.903$), followed by ROV and MABAC ($\rho = 0.891$). Although MAUT yields the lowest correlation coefficient ($\rho = 0.842$), the magnitude of this relationship remains within the range generally interpreted as a strong positive association, suggesting that its performance scores largely follow the same ranking pattern as those produced by Entropy-based TOPSIS. These numerical findings are further illustrated in Figure 3, where the heatmap provides a visual representation of the correlation structure. The predominance of dark red color intensities across almost all methods reflects the uniformly high correlation coefficients, whereas the relatively lighter color corresponding to MAUT highlights

its comparatively lower, yet still substantial, level of agreement. Despite these minor differences in color intensity, the heatmap reveals a homogeneous correlation pattern, indicating that no method exhibits a weak or inconsistent relationship with the Entropy-based TOPSIS results. Taken together, Table 7 and Figure 3 consistently demonstrate that the innovation performance scores derived from the Entropy-based TOPSIS framework exhibit a high level of agreement with those obtained from alternative Entropy-based MCDM methods. The uniformly strong and statistically significant correlations indicate that the relative performance structure of the Balkan countries remains largely unchanged across different decision-making techniques employing the same objective weighting scheme. Consequently, the comparative evidence presented in both the numerical and graphical analyses supports the consistency of the innovation performance evaluation across the examined Entropy-based MCDM approaches.

Following the comparative analysis, an additional comparison was conducted between the official Global Innovation Index (GII) country rankings published by the World Intellectual Property Organization (WIPO, 2025) and the rankings obtained using the proposed Entropy-based TOPSIS framework in order to further demonstrate the original contribution of the proposed methodology. The results of this comparison are presented in Table 10.

Table 10. Comparison of Official GII Rankings and Entropy-Based TOPSIS Results for Balkan Countries

Countries	GII		Entropy-TOPSIS	
	Score	Rank	Score	Rank
Albania	34.50	7	0.305	9
Bosnia and Herzegovina	26.29	10	0.101	10
Bulgaria	40.69	2	0.799	1
Croatia	40.47	3	0.757	3
Greece	40.06	4	0.794	2
Montenegro	33.36	8	0.383	6
North Macedonia	33.09	9	0.316	8
Romania	36.47	5	0.613	5
Serbia	35.04	6	0.346	7
Slovenia	43.46	1	0.741	4
Mean	36.34	---	0.516	---

As shown in Table 10, both approaches exhibit a highly consistent representation of the overall innovation performance structure across the Balkan countries. Although the official GII ranks Slovenia as the highest-performing country, the Entropy-based TOPSIS framework identifies Bulgaria as the leading performer, followed by Greece, while Slovenia declines to the fourth position. In contrast, Croatia, Romania, and Bosnia and Herzegovina retain their respective third, fifth, and tenth positions under both evaluation frameworks. Within the lower-performing group, Montenegro improves from eighth to sixth place, North Macedonia advances from ninth to eighth, whereas Albania declines from seventh to ninth. These ranking changes indicate that the proposed Entropy-based TOPSIS framework does not merely reproduce the official GII ordering but provides an alternative assessment based on the objective informational contribution of the innovation criteria.

A comparison based on regional average performance further supports this observation. Using the official GII mean score (36.34) and the mean Entropy-based TOPSIS performance score (0.516) as reference values, Bulgaria, Croatia, Greece, Romania, and Slovenia remain above the regional average under both approaches, whereas Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia consistently remain below the corresponding average values. The complete consistency in the composition of the above-average and below-average country groups demonstrates that the proposed framework preserves the fundamental regional innovation structure while maintaining a high level of agreement with the official GII assessment.

Nevertheless, the Entropy-based TOPSIS framework introduces meaningful differences in the relative ordering of individual countries. These differences arise not from arbitrary re-ranking of the official GII results but from the methodological characteristics of the proposed framework. Specifically, criterion weights are objectively determined using the Entropy method based on the information contained in the dataset, after which country performance is evaluated according to the relative distances from the positive and negative ideal solutions within the TOPSIS framework. Consequently, countries exhibiting similar composite GII scores but differing innovation profiles across the seven GII dimensions can be distinguished more effectively. Therefore, rather than simply reproducing the official GII ranking under an alternative weighting scheme, the proposed Entropy-based TOPSIS approach provides a more discriminative, data-driven, and policy-relevant evaluation of innovation performance by revealing multidimensional differences that cannot be directly observed from the composite GII scores alone.

5. Conclusion

This study investigates the innovation performance of Balkan countries through an Entropy-based TOPSIS approach, situating the analysis within the multidimensional structure of the GII. The findings point to clear and deeply rooted disparities in performance across the region. Within the broader literature, innovation is consistently framed as a central engine of long-term growth, productivity gains, and competitive advantage, while also serving as a cornerstone of sustainable development, particularly in economies undergoing structural transition (Aghion et al., 2020).

In the Balkan setting, this role becomes even more pronounced. Compared with European Union benchmarks, the region continues to face relatively low productivity levels and limited technological sophistication (Radosevic, 2002). Against this backdrop, relying solely on descriptive indicators appears insufficient. Instead, the adoption of multi-criteria and objectively grounded evaluation frameworks becomes essential for shaping effective policy priorities and guiding resource allocation (Lukić, 2024). Building on this need, the present study seeks to evaluate innovation performance using data-driven criterion weights, thereby identifying relative country positions while reducing the subjectivity often highlighted in prior research through the Entropy-based structure.

A substantial share of earlier Balkan-focused studies relies on single indicators or preference-driven methods; in contrast, this study derives all criterion weights directly from the data and embeds them within the TOPSIS framework, providing a more consistent and discriminative basis for cross-country comparison. The Entropy

results demonstrate that indicator contributions are markedly uneven, with Creative Outputs and Knowledge and Technology Outputs emerging as the dominant drivers, indicating that performance differentials are primarily shaped by output-oriented dimensions. This finding is consistent with evidence that the economic returns of innovation stem from the transformation, commercialization, and diffusion of knowledge rather than from inputs alone (Martí & Puertas, 2023). Nevertheless, in many Balkan economies, innovation activity remains concentrated at the input stage, while the capacity to generate tangible outputs is limited, constituting a structural constraint on regional competitiveness.

The Entropy-based TOPSIS results indicate that the Entropy–TOPSIS framework provides a clear discriminatory structure for assessing innovation performance in the Balkan region. Bulgaria (0.799), Greece (0.794), Croatia (0.757), Slovenia (0.741), and Romania (0.613) occupy the leading positions, suggesting that these countries are positioned closest to the positive ideal solution. In contrast, Bosnia and Herzegovina records the lowest performance score (0.101), remaining markedly below the regional mean (0.516), together with Montenegro, Serbia, North Macedonia, and Albania. These findings align with prior studies, including Lukić (2024), who identifies Greece and Slovenia as frontrunners using FUCOM–CoCoSo, and Cvetanović and Nedić (2013) and Çobanoğulları et al. (2026), who document persistent structural deficiencies in Western Balkan innovation systems. Minor discrepancies among lower-ranked countries can be attributed to methodological differences, particularly in normalization procedures, distance measures, and weighting schemes.

Sensitivity tests via rank-reversal confirm that the Entropy-based TOPSIS model remains highly stable under criterion changes, with Greece and Bulgaria consistently leading, indicating structurally balanced performance. The preservation of overall ranking patterns and strong, statistically significant Spearman correlations with Entropy-based methods such as SAW, WPM, WASPAS, MARCOS, WEDBA, and EDAS further support the robustness and methodological reliability of the proposed evaluation framework (Keshavarz-Ghorabae et al., 2021).

Nevertheless, several limitations should be acknowledged. First, the analysis relies on cross-sectional macro-level indicators obtained from the GII, which do not capture temporal changes in innovation performance. Second, the sample comprises both European Union member states (Bulgaria, Croatia, Greece, Romania, and Slovenia) and non-EU Balkan countries (Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia). This institutional heterogeneity may influence innovation performance through differences in regulatory harmonization, access to European research and innovation funding, technology transfer mechanisms, innovation support policies, and participation in collaborative research networks. Consequently, part of the observed variation in innovation performance may reflect differences associated with the institutional environment in addition to countries' intrinsic innovation capacities. Since the primary objective of this study was to evaluate and compare innovation performance using an objective MCDM framework rather than to investigate its causal determinants, these structural differences were not explicitly incorporated into the analytical model.

From a policy perspective, the findings suggest that greater emphasis should be placed on strengthening Creative Outputs and Knowledge and Technology Outputs through enhanced R&D commercialization, stronger university–industry

collaboration, increased patenting activity, and support for knowledge-intensive entrepreneurship. In particular, Montenegro, Serbia, North Macedonia, Albania, and Bosnia and Herzegovina, which remain below the regional average in innovation performance, should prioritize strategic policies aimed at expanding innovation capacity and improving the efficiency with which knowledge is transformed into economic value. Increased investment in research infrastructure, technological capabilities, human capital, and innovation-oriented activities would not only enhance national competitiveness but also contribute more effectively to regional development and the global innovation ecosystem.

Future research could further strengthen this analytical framework by incorporating alternative objective weighting techniques (e.g., CRITIC, MEREC, and FUCOM), employing different MCDM approaches, and extending the analysis through longitudinal datasets. Furthermore, future studies may explicitly account for institutional heterogeneity by conducting subgroup analyses comparing EU and non-EU Balkan countries or by incorporating European Union membership as a dummy variable within hybrid MCDM or econometric frameworks. Such extensions would provide deeper insights into the extent to which institutional integration contributes to innovation performance while allowing methodological effects to be distinguished from structural differences among countries.

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