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Uncovering the Pillars of National Competitiveness through a Multicriteria Decision Making Framework

Abstract. *In a globalized and volatile economic environment, national competitiveness plays a crucial role in long-term economic performance and investment attractiveness. Although composite competitiveness indices are widely used, empirical research often applies one-dimensional approaches that fail to capture deeper structural differences among countries. This study addresses this gap by integrating multi-criteria and multidimensional analytical methods to assess national competitiveness in an international context. The methodological framework combines the TOPSIS method to construct a composite ranking of countries based on economic, institutional, and innovation indicators with discriminant analysis to identify statistically significant factors distinguishing groups of countries by competitiveness level. The empirical analysis relies on internationally comparable secondary data from recognized global databases. The results reveal substantial heterogeneity in competitiveness, with developed economies consistently outperforming emerging and transition countries. Discriminant analysis, applied with an accession-cohort grouping that is independent of the TOPSIS indicators and validated by leave-one-out cross-validation (91.0% classification accuracy), identifies infrastructure quality, the tax burden, and unemployment as the strongest joint discriminators between the pre-2004 and post-2004 EU accession cohorts, with business freedom and the corruption rate also significant on their own but not adding further explanatory power once infrastructure and macroeconomic conditions are accounted for, confirming the multidimensional and systemic nature of national competitiveness.*

Keywords: *national competitiveness, TOPSIS, discriminant analysis, multi-criteria decision making, institutional quality, innovation capacity, macroeconomic performance.*

JEL Classification: C38, C61, O47.

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1. Introduction

In the context of deepening economic integration, globalization, and technological transformation, the competitiveness of countries is becoming one of the key determinants of their long-term economic growth, social stability, and ability to respond to global challenges. The current understanding of competitiveness goes beyond traditional macroeconomic indicators and reflects the multidimensional

nature of economic development, in which innovation, institutional quality, digitalization, human capital, sustainability, and the business environment play a fundamental role. Several recent studies confirm that it is the combination of these factors that forms the basis for the sustainable and inclusive competitive advantage of countries in the global environment. Attention is paid in the literature to national innovation competitiveness as the core of modern competitiveness. Empirical findings show that the paths to high innovation performance vary significantly across countries depending on their level of economic development. While high- and upper-middle-income economies benefit from diversified configuration scenarios, lower-middle-income countries exhibit more homogeneous patterns, with the ability to commercialize innovation playing a key role (Zhang et al., 2023). These findings point to the need for analytical approaches that can capture not only the intensity of individual determinants, but also their combinations and structural differences between groups of countries.

The Global Competitiveness Index (GCI) remains the dominant tool for assessing competitiveness at the global level, integrating a wide range of pillars from institutional quality and infrastructure to innovation and digital readiness. However, research also points out that the relationships between GCI pillars, country risk, and sustainable development are complex and heterogeneous. For example, low adoption of information and communication technologies or weak innovation capacity can significantly increase macroeconomic and financial risks, while strong institutions and an innovative environment contribute to mitigating them (Qazi, 2023). Similarly, it appears that the relationship between competitiveness and sustainable development dimensions varies across countries with different levels of competitiveness, requiring differentiated policy approaches (Canatay et al., 2025). At the same time, empirical literature identifies several key determinants of competitiveness, such as macroeconomic stability, research and development, digitalization, foreign direct investment, openness to trade, and quality of governance. Factor and cluster analyses within the European Union point to the existence of different development trajectories, in which the importance of individual factors varies depending on the structure of the economy and its degree of integration into global value chains (Boikova et al., 2021). At the same time, the mediating role of entrepreneurship between innovation and competitiveness has been demonstrated, with corruption potentially modifying this relationship in significant and often counterintuitive ways (dos Santos et al., 2025). Despite the wealth of empirical approaches, the methodological debate on how to effectively combine synthetic competitiveness assessments with the identification of structural differences between countries remains open. Traditional regression models, including ordered probit approaches, allow countries to be classified according to their level of competitiveness and significant determinants to be identified (Kalansuriya & Jayathilaka, 2025), they capture only to a limited extent the multidimensional nature of the assessment and the relative position of countries vis-à-vis the ideal state. In this context, a promising solution appears to be a combination of multi-criteria decision-making methods with multivariate statistical techniques.

The TOPSIS method allows for the creation of a synthetic ranking of countries based on their relative proximity to the ideal competitiveness profile, while discriminant analysis provides a tool for identifying the variables that most significantly distinguish countries with high and low levels of competitiveness. Such an integrated approach bridges the gap between the assessment of "who is competitive" and the analytical question of "why there are differences between countries".

2. Literature Review

In current economic literature, national competitiveness, technological development, and the ability to attract foreign direct investment are increasingly understood as the result of complex interactions between economic, institutional, technological, and social factors. Empirical studies repeatedly point out that the performance of countries cannot be satisfactorily explained by isolated indicators, as their interaction and contextual conditions play a decisive role. This multidimensional nature of development is particularly evident in the areas of innovation, technological efficiency, and international investment flows. The importance of innovation and technological development as key determinants of competitiveness is confirmed by a number of empirical studies. Marčeta and Bojnec (2021) show that research and development expenditure, university-industry collaboration, and the quality of research institutions are positively correlated with the global competitiveness index in EU countries, with the strength of these links varying depending on the macroeconomic context. Similarly, Khyareh and Rostami (2022) emphasize that innovation activities not only have a direct positive impact on competitiveness, but their effect is significantly enhanced by a favorable macroeconomic environment and stability. Regional and structural differences in the impact of technological factors are also documented by Tung et al. (2025), who point to the heterogeneity of the effects of technological development on competitiveness between Asian and American developing economies.

The role of foreign direct investment as a channel for the transfer of technology, innovation, and managerial know-how receives particular attention in literature. Kwilinski (2025) shows that technological leadership in advanced economies is largely conditioned by FDI inflows, with external sources of technology playing a key role, especially in countries with high economic performance. This view is complemented by Kowalski (2022) and Liao and Li (2024), who point to the nonlinear nature of the relationships between innovation efficiency, financial development, and economic growth, as well as the growing dependence of technological progress on international knowledge transfer. The institutional environment and the quality of regulation play an important role in mediating these effects, as confirmed by the findings of Ibraimi et al. (2025) in the context of the Western Balkan countries. In the context of the European Union, fiscal and institutional conditions play an irreplaceable role in shaping foreign direct investment inflows. Andrejkovicova and Andrejovská (2025) address the impact of corporate income tax rates on FDI. They conclude that the tax does not have an

immediate impact on FDI, but its effect is delayed and varies significantly between eastern and western EU countries. These findings highlight the regional heterogeneity of investment behavior and support the need for a differentiated analytical approach.

In addition to technological and economic factors, the literature increasingly emphasizes the importance of social and demographic characteristics. Wanke et al. (2024) point out that FDI performance is influenced not only by the level of GDP per capita, but also by the quality of the social system, demographic structure, and degree of urbanization, with investments concentrated mainly in high-tech sectors with high added value. The importance of institutional and network factors is complemented by Godlewska et al. (2022), who emphasize the role of formal institutions and innovation networks in promoting innovative behavior and limiting institutional pathologies. Beyond formal institutional structures, individual-level behavioral characteristics of SME owners and managers also shape competitiveness outcomes within the V4 region. Hudakova et al. (2025), surveying 1,090 SME owners and managers across Poland, Czechia, Slovakia, and Hungary, document pronounced cross-country differences in risk-taking tendency, analytical decision-making, and judgment independence: Hungarian managers exhibit the highest risk readiness (73.6%) and analytical orientation (94.0%), Polish managers show moderate-to-high risk readiness with a comparatively lower analytical orientation, while Czech and Slovak managers display more risk-averse, judgment-dependent profiles. These findings suggest that the institutional and macroeconomic disparities identified in the present study are complemented by, and may partly stem from, divergent managerial decision-making cultures across the V4 countries.

From a methodological point of view, however, the majority of existing studies use mainly regression and panel econometric approaches, which are suitable for identifying causal relationships but only allow for limited synthetic comparisons of countries across multiple dimensions. In response to this challenge, multi-criteria decision-making (MCDM) methods are gaining ground in the literature, as they can integrate heterogeneous indicators into a single evaluation framework. The contribution of these approaches is illustrated by Wanke et al. (2024), who combine MCDM with robust regression techniques to capture the complex performance of FDI at the country level.

Despite the growing use of multi-criteria approaches, however, relatively little research has been done on the extent to which countries can be systematically divided into homogeneous groups based on synthetic performance scores and which factors are decisive for distinguishing them from one another. Most existing studies focus either on compiling rankings or estimating average effects, rarely combining ranking assessments with classification statistical techniques. This gap in the literature creates space for an integrated analytical framework that combines multi-criteria evaluation of country performance with discriminant analysis to identify the key variables responsible for differentiation between performance groups.

3. Methodology

The study focuses on analyzing the business environment of European Union countries through the application of appropriate mathematical and statistical methods. In conditions of growing global competition, it is crucial to create a solid analytical framework for objective assessment of the economic environment. The TOPSIS method was used to compare the business environment between EU member states. The analysis included several important macroeconomic indicators that adequately reflect the business and macroeconomic conditions of individual EU countries and also served as input variables for the TOPSIS method; these are shown in Table 1.

Table 1. Selected Factors of Analysis

Macroeconomic factors	Fiscal factors	Institutional factors	Innovation and infrastructure factors
f1 – Gross domestic product (in billions of USD) f2 – Average annual unemployment (%) f3 – Average annual inflation (%) f4 – Foreign direct investment inflows (in billions of USD)	F5 – Taxes (%) F6 – Economic openness (%)	f7–Business freedom (score) f10–Corruption rate (score)	f8 – Infrastructure (score) f9 – Innovation rate (score)

Source: Authors' processing.

Once the evaluation criteria had been defined, it was necessary to ensure the availability of relevant data for individual European countries. Malta was excluded from the analysis as complete statistical data were not available for the period under review. After collecting data for 26 European Union countries for the years 2017–2024 and dividing them into the pre pandemic period until 2019, the pandemic period between 2020 and 2021, and the post pandemic period from 2022 onwards, the average values of the indicators were calculated. These are economically homogeneous periods in terms of exogenous shocks. Given that the COVID-19 pandemic acted as a significant catalyst for change in national markets and fundamentally affected the dynamics of macroeconomic variables, it was necessary to distinguish between three separate time phases when assessing the performance and competitiveness of the business environment. This periodisation is consistent with Vojtekova et al. (2025), who confirm, on a sample of 11,110 V4 manufacturing enterprises, a statistically significant impact of the COVID-19 pandemic on business activity indicators across all enterprise-size categories, supporting the treatment of the pre-pandemic, pandemic, and post-pandemic periods as economically distinct phases. After processing the input data, a calculation phase followed, in which preferences between individual criteria were first determined. A quantitative comparison was performed using Saaty's pairwise comparison matrix, which allows

a pair of criteria to be evaluated and then the degree of their mutual preference to be determined. This matrix organizes the evaluated elements into a hierarchical structure based on subjective judgments, which are assigned numerical values reflecting their relative importance in relation to the set goal (Saaty, 1990). The recommended point scale ranges from 1, expressing equal importance of criteria, to 9, indicating the absolute superiority of one criterion over another (Table 2).

Table 2. Saaty Matrix

	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10
f1	1	1/3	1/4	5	1/4	5	2	1/5	1/5	1/5
f2	3	1	1/5	5	1/4	4	2	1/5	1/5	1/5
f3	4	5	1	5	1	4	3	1/5	1/5	1/5
f4	1/5	1/5	1/5	1	1/5	1/3	1/2	1/5	1/5	1/5
f5	4	4	1	5	1	5	5	1/4	1/4	1/4
f6	1/5	1/4	1/4	3	1/5	1	1	1/5	1/5	1/5
f7	1/2	1/2	1/3	2	1/5	1	1	1/5	1/5	1/5
f8	5	5	5	5	4	5	5	1	1	1
f9	5	5	5	5	4	5	5	1	1	1
f10	5	5	5	5	4	5	5	1	1	1

Source: Authors' processing.

To minimize the subjectivity of the evaluation, a consistency ratio was calculated, which represents the ratio of the consistency index to the average consistency index derived from a large number of randomly generated matrices. If the value of this ratio exceeds 0.1, the decision matrix needs to be reevaluated due to inconsistent factor evaluation (Salomon & Gomes, 2024).

$$CR = \frac{CI}{RI} = \frac{0,099}{1,49} \approx 0,067 \quad (1)$$

The consistency coefficient of the pair comparison reached a value of $CR = 0.067$, which is significantly below the recommended limit of 0.10. The criteria preferences can therefore be considered consistent and the resulting criteria weights reliable.

We arranged the criteria into a Saaty matrix, which represents approximations of the weight ratios of individual criteria:

$$s_{ij} \approx \frac{v_i}{v_j}, i, j = 1, 2, 3 \dots n \quad (2)$$

Saaty's matrix is square with dimensions $n \times n$, and the following applies to its elements:

$$s_{ii} = 1; i = 1, 2, 3 \dots n \quad (3)$$

$$s_{ij} = \frac{1}{s_{ij}}, i, j = 1, 2, 3 \dots n \quad (4)$$

To calculate the weights, Saaty created his own vector corresponding to the largest eigenvalue of matrix A. The solution is then the normalized geometric mean of matrix S.

$$v_i = \frac{[\prod_{j=1}^k s_{ij}]^{\frac{1}{k}}}{\sum_{i=1}^k [\prod_{j=1}^k s_{ij}]^{\frac{1}{k}}} \quad (5)$$

The relationships between the selected criteria were determined using a nine-point scale. The subjective assessment of criterion importance remains a limitation of the method. The consistency ratio evaluates the internal coherence of the pairwise comparisons but does not eliminate the subjectivity of the underlying judgements. Since the comparison of a criterion with itself takes on a value of one, the resulting comparison matrix is reciprocal in nature, with only unit values on the main diagonal. The elements above the main diagonal express the subjectively determined degree of preference for individual criteria, while the values below the diagonal represent their reciprocal values. The selected evaluation criteria gross domestic product, foreign direct investment, freedom of enterprise, openness of the economy, quality of infrastructure, level of innovation performance, and degree of corruption were defined as maximization criteria for the purposes of applying the TOPSIS method. Conversely, unemployment, inflation, and tax burden were classified as minimization criteria. Since the TOPSIS method itself works exclusively with maximization criteria, it was necessary in the next step to transform the minimization criteria into equivalent maximization criteria. In the following phase, a weighted matrix of criteria was compiled by multiplying each j-th column of the normalized matrix by its respective weight v_i . Based on the data adjusted in this way, it was possible to determine the ideal and baseline variants for individual criteria, with the upper limit set as the maximum value in a given column and the lower limit as its minimum. In the final stage, the Euclidean distance of each alternative from the ideal (+id) and baseline (-id) solutions was calculated. The ideal and baseline variations were then determined using the appropriate mathematical formulas.

$$d_i^+ = \left(\sum_{j=1}^k (w_{ij} - H_j)^2 \right)^{\frac{1}{2}} \quad i = 1, 2, 3 \dots n \quad (6)$$

$$d_i^- = \left(\sum_{j=1}^k (w_{ij} - D_j)^2 \right)^{\frac{1}{2}} \quad i = 1, 2, 3 \dots n \quad (7)$$

After calculating the baseline and ideal variants, we proceeded to the final step of quantifying the relative indicators of the distance of the variants from the baseline variant $c_i \in (0; 1)$. We used the following relationship to quantify the relative indicators:

$$c_i = \frac{d_i^-}{d_i^- + d_i^+} \quad (8)$$

After calculating the relative indicators, individual variations were obtained, which were then arranged in descending order according to the decreasing values of the coefficient c_i , thus achieving a comprehensive ranking of all analyzed variants. Based on the identification of relevant criteria and the ranking of countries according to their level of national competitiveness and macroeconomic maturity, a discriminant analysis was then applied using the same set of input variables. Its aim was to determine a linear combination of characteristics that would allow the two accession cohorts to be clearly distinguished: EU member states that joined before 2004 and those that joined in or after 2004. Discriminant analysis is based on the construction of a discriminant function, which represents a linear combination of predictor variables ensuring maximum discrimination between individual groups of European countries. The standard assumptions of linear discriminant analysis include independent observations, multivariate normality of the predictors within each group, homogeneity of the group covariance matrices, and mutually exclusive group membership.

The ten input indicators were compiled from internationally comparable secondary sources for the period 2017–2024: gross domestic product (current prices, billions USD), unemployment (annual average rate, % of the labour force), inflation (annual average HICP change, %), and foreign direct investment inflows (billions USD) from Eurostat; economic openness (trade-to-GDP ratio, %, authors' own calculation from Eurostat trade and national-accounts data); the tax burden (f5) and business freedom (f7) as the corresponding named component scores (0–100 scale) of the Heritage Foundation's Index of Economic Freedom; infrastructure quality (f8) from the World Economic Forum's Global Competitiveness Index infrastructure pillar; the innovation rate (f9) from the WIPO Global Innovation Index overall score; and the corruption rate (f10) from Transparency International's Corruption Perceptions Index. All ten indicators were available for every country-year combination retained in the sample; because Malta was excluded precisely on the grounds of incomplete series (see below), no missing-value imputation was required for the 26 countries analyzed. For the discriminant analysis, group membership was defined independently of the ten TOPSIS indicators, using EU accession cohort as the classification criterion: the 14 pre-2004 member states present in the sample (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden) form the pre-2004 accession group, and the 12 post-2004 member states (Bulgaria, Croatia, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia) form the post-2004 accession group. These labels denote accession timing only, replacing the evaluative terms “developed”/“lagging” business environment, which are reserved for the TOPSIS ranking. This a priori, accession-based grouping was adopted in place of a split derived from the TOPSIS composite score itself, because the latter would use the same ten indicators to both define and then “predict” group membership, which is circular and mechanically inflates the

apparent discriminatory power of the model. The discriminant model was estimated on the pooled cross-section of all 26 countries observed in each of the three sub-periods ($n = 78$ country-period observations), which provides sufficient degrees of freedom for a ten-predictor model and allows classification accuracy to be assessed by leave-one-out cross-validation.

4. Results and discussion

In order to fulfill the main objective of the work and in accordance with the established methodological procedure, the c_i indicator was calculated for all three periods under review, i.e., before the pandemic, during the pandemic, and in the post-pandemic period, using selected macroeconomic indicators that adequately reflect the quality and attractiveness of the business environment. As detailed in the methodological section of the thesis, the analytical approach is based on ten key indicators that provide a comprehensive picture of macroeconomic developments in the Member States. Table 3 summarizes the results obtained based on the calculated values of the c_i indicator in the first period analyzed.

Table 3. Cross-country Ranking of EU Member States in 2017-2019

Rank	Country	c_i indicator	Rank	Country	c_i indicator
1.	Ireland	0,6159	14.	Slovenia	0,4272
2.	Denmark	0,6106	15.	Spain	0,4183
3.	Finland	0,6027	16.	Hungary	0,4168
4.	Germany	0,5918	17.	Czech Republic	0,4167
5.	Sweden	0,5880	18.	Poland	0,4156
6.	Netherlands	0,5762	19.	Lithuania	0,3972
7.	France	0,5217	20.	Estonia	0,3918
8.	Austria	0,4931	21.	Bulgaria	0,3795
9.	Luxembourg	0,4862	22.	Croatia	0,3625
10.	Cyprus	0,4810	23.	Greece	0,3625
11.	Italy	0,4508	24.	Latvia	0,3469
12.	Portugal	0,4495	25.	Romania	0,3066
13.	Belgium	0,4329	26.	Slovak Republic	0,3053

Source: Authors' processing.

The results of the study point to Ireland as the country with the most favorable business environment. Denmark, Finland, Germany, and Sweden also show above-average values, particularly in the areas of competitiveness, economic freedom, innovation performance, perception of corruption, and environmental efficiency.

Conversely, when comparing the countries at the top of the ranking with those at the bottom, several problematic characteristics are identified in the case of the Slovak Republic, including weaker economic growth, an unfavorable labor market situation, higher inflation, less effective tax policy, underdeveloped infrastructure, low level of innovation, and a relatively high level of corruption.

The same methodology was used for the calculations for 2020 and 2021. Based on the calculation of relative indicators, individual variants were obtained, which were then ranked in descending order according to the decreasing values of the coefficient c_i , which made it possible to achieve a complete and clear arrangement of all evaluated variants, presented in Table 4.

Table 4. Cross-country Ranking of EU Member States in 2020-2021

Rank	Country	c_i indicator	Rank	Country	c_i indicator
1.	Ireland	0,6008	14.	Estonia	0,4330
2.	Sweden	0,5836	15.	Italy	0,4262
3.	Denmark	0,5807	16.	Hungary	0,4245
4.	Finland	0,5789	17.	Bulgaria	0,4158
5.	Germany	0,5598	18.	Lithuania	0,4148
6.	Netherlands	0,5559	19.	Spain	0,4011
7.	France	0,5394	20.	Czech Republic	0,3935
8.	Luxembourg	0,4822	21.	Latvia	0,3739
9.	Cyprus	0,4754	22.	Croatia	0,3551
10.	Austria	0,4735	23.	Poland	0,3456
11.	Slovenia	0,4494	24.	Greece	0,3350
12.	Portugal	0,4465	25.	Romania	0,3194
13.	Belgium	0,4426	26.	Slovak Republic	0,3042

Source: Authors' processing.

Table 4 presents results that are largely comparable to those from the pre-pandemic period but also shows some changes in the ranking of individual countries. Ireland once again ranked first, Sweden moved to second place, Denmark and Finland each fell by one position, and Germany ranked fifth. By comparing the countries with the most and least favorable business environments, namely Ireland and Slovakia, it is possible to identify key areas for improvement, particularly in terms of economic growth, employment, inflation, tax policy, infrastructure quality, innovation potential, and corruption levels.

The same methodological approach was applied to the calculations for 2022 and 2024. By calculating relative indicators, individual variants were identified and then ranked in descending order according to decreasing values of the

coefficient c_i . This procedure resulted in a comprehensive and transparent ranking of all evaluated variants, which is presented in Table 5.

Table 5. Cross-country Ranking of EU Member States in 2022-2024

Rank	Country	c_i indicator	Rank	Country	c_i indicator
1.	Sweden	0,6163	14.	Hungary	0,4179
2.	Denmark	0,6136	15.	Slovenia	0,4163
3.	Finland	0,6042	16.	Portugal	0,4094
4.	Ireland	0,5904	17.	Lithuania	0,4020
5.	France	0,5883	18.	Estonia	0,4018
6.	Germany	0,5786	19.	Czech Republic	0,3967
7.	Netherlands	0,5772	20.	Bulgaria	0,3828
8.	Austria	0,5193	21.	Poland	0,3480
9.	Luxembourg	0,5036	22.	Romania	0,3413
10.	Belgium	0,4926	23.	Latvia	0,3348
11.	Cyprus	0,4625	24.	Greece	0,3249
12.	Italy	0,4425	25.	Croatia	0,3091
13.	Spain	0,4249	26.	Slovak Republic	0,2784

Source: Authors' processing.

During this period, there was a change in the ranking of countries, with Sweden taking first place, followed by Denmark and Finland. Ireland moved up to fourth place, while Germany dropped out of the top five and was replaced by France. This shift reflects changes in the relative performance of the business environment between countries during the period under review.

Discriminant analysis was subsequently applied using the same input variables as the TOPSIS assessment. Its purpose was to identify the factors that most clearly distinguish the pre-2004 and post-2004 EU accession cohorts. Before estimating the discriminant functions, the relevant assumptions were evaluated, including the equality of group covariance matrices and the statistical significance of differences in the predictor means.

Univariate tests of equality of group means (one-way ANOVA on the accession-cohort grouping defined above, $n = 78$) indicate that eight of the ten indicators differ significantly between the two groups: GDP ($F = 20.66$, $p < 0.001$), unemployment ($F = 7.20$, $p = 0.009$), inflation ($F = 9.36$, $p = 0.003$), the tax burden ($F = 52.05$, $p < 0.001$), business freedom ($F = 16.42$, $p < 0.001$), infrastructure ($F = 81.92$, $p < 0.001$), the innovation rate ($F = 55.54$, $p < 0.001$), and the corruption rate ($F = 57.93$, $p < 0.001$); FDI inflows and economic openness were not significant on their own ($p = 0.191$ and $p = 0.545$, respectively). Box's M test rejects the null hypothesis of equal group covariance matrices ($M = 273.17$, $\chi^2(55) = 235.44$, $p < 0.001$). This result indicates a violation, rather than confirmation, of

the homogeneity-of-covariance assumption. Consequently, the pooled covariance matrix used in linear discriminant analysis may not be strictly appropriate, and the classification results should be interpreted cautiously as descriptive evidence. The full ten-predictor canonical discriminant function was estimated on the pooled sample ($n = 78$): it yields a canonical correlation of 0.839 and Wilks' $\Lambda = 0.296$ (equivalently, $F(10, 67) = 15.97$, $p < 0.001$), confirming that the predictor set as a whole discriminates strongly between the two groups. The standardized coefficient of the innovation rate (f9) is positive (0.40), and its structure-matrix correlation with the discriminant function is likewise positive (0.77). The three largest structure loadings belong to infrastructure (0.86), the corruption-perception score (0.78), and the innovation score (0.77). Infrastructure (f8) carries a positive coefficient in both specifications (unstandardized $b = 0.199$ in the full ten-predictor model, $b = 0.217$ in the reduced model below), so its direction of effect is consistent regardless of which specification is used; only f9 changes sign between the circular and corrected grouping, as noted above. A forward stepwise procedure (entry criterion $p < 0.05$), which avoids overfitting a ten-variable model to 78 observations, retains three predictors: infrastructure, unemployment, and the tax burden ($R^2 = 0.672$, canonical correlation 0.82). Classification performance was evaluated both by resubstitution and by leave-one-out cross-validation: the full model classifies 94.9% of countries correctly in-sample and 91.0% correctly under cross-validation (34/36 post-2004-group and 37/42 pre-2004-group observations correctly classified).

Table 6. Univariate Tests of Equality of Group Means, pre-2004 vs. post-2004 Accession Cohort ($n = 78$; $F(1,76)$)

Indicator	F	p	Indicator	F	p
f1 GDP	20.663	<0.001	f6 Openness	0.370	0.545
f2 Unemployment	7.198	0.009	f7 Business freedom	16.423	<0.001
f3 Inflation	9.356	0.003	f8 Infrastructure	81.919	<0.001
f4 FDI inflows	1.744	0.191	f9 Innovation rate	55.539	<0.001
f5 Tax burden	52.047	<0.001	f10 Corruption rate	57.933	<0.001

Source: Authors' calculation.

Table 7. Full Ten-predictor Discriminant Function: Coefficients and Structure Matrix ($n = 78$; Canonical corr. = 0.839; Wilks' $\Lambda = 0.296$, $F(10,67) = 15.97$, $p < 0.001$)

Indicator	Unstd. b	Std. b	Structure r
f1 GDP	0.0015	1.290	0.551
f2 Unemployment	0.8589	2.200	0.350
f3 Inflation	0.0164	0.043	-0.394
f4 FDI inflows	-0.00001	-0.264	0.178
f5 Tax burden	20.2272	0.849	0.760
f6 Openness	0.0143	0.953	-0.083
f7 Business freedom	0.0285	0.229	0.502
f8 Infrastructure	0.1990	2.226	0.858
f9 Innovation rate	0.0671	0.402	0.774

Indicator	Unstd. b	Std. b	Structure r
f10 Corruption rate	0.0029	0.030	0.784
(Constant)	-30.744		

Source: Authors' calculation.

Table 8. Classification Results for the Full and Stepwise-reduced Discriminant Models (overall LOOCV accuracy: full model 91.0%; reduced model 89.7%)

Model	Evaluation	n post-2004	n pre-2004	Correct post-2004	Correct pre-2004
Full (10 pred.)	Resubstitution	36	42	34/36 (94.4%)	40/42 (95.2%)
Full (10 pred.)	LOOCV	36	42	34/36 (94.4%)	37/42 (88.1%)
Reduced (f2,f5,f8)	LOOCV	36	42	35/36 (97.2%)	35/42 (83.3%)

Source: Authors' calculation.

Using the unstandardized coefficients of the stepwise-selected canonical discriminant function, the resulting discriminant function as a predictive model for European Union countries has the following form:

$$Z = -23,918 + 0,598 \cdot f2 + 30,454 \cdot f5 + 0,217 \cdot f8 \quad (9)$$

Table 9 reports the group centroids for both discriminant specifications. In the full model, the centroid equals 4.312 for the pre-2004 accession group and -5.031 for the post-2004 accession group. In the reduced model, the corresponding centroids are 3.699 and -4.316. Assuming equal prior probabilities and equal misclassification costs, the classification cut-off for the reduced model is the midpoint between its group centroids, $Z_c = (3.699 - 4.316)/2 = -0.309$. Observations with discriminant scores above -0.309 are classified into the pre-2004 accession group, whereas observations with scores below -0.309 are classified into the post-2004 accession group. Infrastructure, unemployment, and the tax-burden score define the stepwise-selected function. The full ten-predictor model is reported as a complementary specification together with its structure matrix and cross-validated classification performance.

Table 9. Unstandardized Canonical Discriminant Functions Evaluated at Group Centroids (mean Z-score per accession cohort).

Model	Pre-2004 group (n=42)	Post-2004 group (n=36)
Full model (10 predictors)	4.312	-5.031
Reduced model (f2, f5, f8)	3.699	-4.316

Source: Authors' calculation.

The empirical results obtained by applying the TOPSIS method provide quantitative confirmation of the theoretical and empirical conclusions presented in the existing literature on competitiveness and the tax environment. The fact that the highest values of the composite indicator in the analyzed periods are achieved mainly by the Nordic countries, Ireland, and selected Western European economies points to the synergistic effect of a stable tax system, high institutional quality, and

a strong innovation ecosystem. These results are consistent with the findings of Moshenets et al. (2025), according to whom effective international tax planning requires predictable legislation and low reputational risk, as well as with the arguments of Dooley (2025) and Saqer (2025), who emphasize the importance of domestic political and economic actors in shaping the competitiveness framework.

From the perspective of the TOPSIS construction, it is essential that the countries ranked at the top do not excel in isolation in one criterion, but achieve above-average values across several dimensions, from innovation performance and infrastructure quality to low levels of corruption and favorable tax burdens. This result confirms the conclusions of Malik and Poliakova (2025) on persistent regional differences in government efficiency and infrastructure, as well as empirical evidence of a close link between human capital and competitiveness (Zarska & Smetanova, 2024). Conversely, low TOPSIS coefficient values in countries with an unstable regulatory environment and weaker institutions indicate that the mere existence of tax breaks or nominally low rates is not a sufficient prerequisite for improving competitiveness.

At the same time, the TOPSIS results indirectly confirm Duman's (2025) argument that in eurozone countries where instruments of relative competitiveness are absent, instruments of absolute competitiveness, including tax policy, take on key importance. However, the empirical ranking of countries suggests that the effectiveness of these instruments is conditional on their anchoring in a broader institutional and innovation framework, as documented by studies focusing on Northern European economies, clusters, and intrapreneurship (Calinescu, 2023; Medeiros et al., 2020; van Egeraat and Curran, 2022). From this perspective, the TOPSIS method not only assesses the relative "attractiveness" of the business environment but also reveals deeper structural determinants that determine whether tax planning is a sustainable source of competitive advantage or just a short-term optimization tool.

The results of the discriminant analysis provide a deeper insight into the structural determinants of competitiveness and complement the composite assessment of countries obtained through multidimensional indices. While aggregate competitiveness indices capture the resulting position of economies, discriminant analysis allows the identification of those variables that have the highest discriminatory power between groups of countries with different levels of competitiveness. In this context, the results confirm that competitiveness is not determined by isolated factors: the discriminant function that survives stepwise selection rests on infrastructure quality together with macroeconomic conditions (unemployment and tax burden). Business freedom and the corruption rate remain statistically significant on their own and contribute to the full ten-predictor model, but do not add further discriminatory power once infrastructure and macroeconomic conditions are already included; foreign direct investment inflows and economic openness did not, on their own, significantly distinguish the two groups of countries in this sample.

The findings can be compared with Kalansuriya et al. (2023), who identify logistics performance, foreign direct investment inflows, and GDP per capita as significant correlates of global competitiveness. The present results provide only partial support for these findings. GDP differs significantly between the two accession cohorts, whereas FDI inflows do not independently discriminate between them ($p = 0.191$). The corruption-perception score is significant in the univariate comparison and exhibits a strong structure loading in the full discriminant model, but it does not enter the reduced stepwise function once infrastructure, unemployment, and the tax-burden score are considered jointly.

At the level of Central and Eastern European countries, the results can be interpreted alongside Tiganasu et al. (2022), who emphasize the importance of fiscal policy and the quality of public spending for external competitiveness. Public expenditure was not included among the indicators examined in the present study; therefore, no direct conclusion about its independent effect can be drawn. Nevertheless, the discriminatory roles of the tax-burden score and infrastructure indicate that fiscal and structural conditions contribute to differences between the two accession cohorts. This interpretation is also consistent with Rontos et al. (2020), who emphasize the relationship between structural competitiveness and institutional quality.

The results can also be interpreted alongside Santoso et al. (2024), who identify productivity, technological sophistication, and the quality of public administration as important determinants of manufacturing competitiveness. These dimensions were not directly measured in the present study and therefore cannot be treated as findings of the discriminant analysis. Nevertheless, the strong discriminatory role of infrastructure and the tax-burden score is broadly consistent with their emphasis on the institutional and structural conditions supporting national competitiveness.

From a regional perspective, the findings are consistent with Stratan et al. (2024), who emphasize the importance of infrastructure and the innovation environment for international competitiveness. Infrastructure is among the strongest discriminators identified in the present analysis and remains in the reduced stepwise function. The innovation score is significant in the univariate comparison and has a strong positive structure loading in the full model, but it does not provide sufficient additional discriminatory power to enter the reduced function. It should therefore be interpreted as an important correlate of accession-cohort differences rather than as an independently selected predictor.

A methodologically significant finding is that some factors that are often considered key determinants of competitiveness may not have high discriminatory power in the empirical distribution of countries. This aspect corresponds with the conclusions of Prabawani et al. (2020), who point to differences between results based on primary and secondary data. Discriminant analysis thus confirms the need to combine different methodological approaches when assessing competitiveness, as individual methods capture different dimensions of reality.

From the perspective of broader conceptual frameworks, the results can be interpreted in line with Timbalari's (2021) 8-D model of international competitiveness, which emphasizes the multidimensional nature of competitiveness, including investment, economic freedom, corruption, innovation, digitalization, and sustainability. Discriminant analysis supports part of this model: governance (the corruption rate) and, to a lesser degree, business freedom are significant univariate discriminators, though neither adds explanatory power once infrastructure and macroeconomic conditions are in the stepwise model. Digitalization was not among the ten indicators analyzed here, so the results below are drawn on the cited literature rather than our own estimates. The importance of digitalization and technological readiness is also supported by the findings of Galindo-Martin et al. (2023) and Lyenonov et al. (2020), who point to a strong link between the digital environment, entrepreneurial activity, and competitiveness.

5. Conclusions

The aim of this study was to comprehensively examine the determinants of business environment competitiveness in an international context through a combination of multi-criteria and multivariate statistical methods. By integrating the TOPSIS method and discriminant analysis, the research provided both a comparative assessment of country performance and an examination of the factors distinguishing the pre-2004 and post-2004 EU accession cohorts. This methodological approach made it possible to go beyond the traditional assessment based on a single aggregate index and offer a more comprehensive view of the mechanisms shaping competitiveness.

The results of applying the TOPSIS method confirmed significant heterogeneity between countries, with the highest composite indicator values in the long term being achieved mainly by the Nordic and Western European economies. Their stable position across the periods monitored points to the synergistic effect of a high-quality institutional framework, high innovation performance, developed infrastructure, and a favorable business environment. In contrast, Central and Eastern European countries, including the Slovak Republic, are characterized by persistent structural weaknesses, which are reflected in lower competitiveness scores even in the post-pandemic period. This macro-level pattern is echoed at firm level by Rech et al. (2025), who find that profitability, cash flow, and liquidity remain the strongest predictors of financial distress among Slovak SME manufacturers up to three years before failure. These findings suggest that short-term economic recovery alone is not sufficient to bring about a fundamental change in competitive position unless it is accompanied by deeper institutional and innovation reforms.

Discriminant analysis subsequently identified the factors with the greatest discriminatory power between the pre-2004 and post-2004 EU accession cohorts. Using an accession-cohort grouping defined independently of the TOPSIS indicators, the full model achieved a leave-one-out cross-validated classification

accuracy of 91.0%. Infrastructure, unemployment, and the tax-burden score were retained in the reduced stepwise function. Business freedom and the corruption-perception score differed significantly between the cohorts in the univariate tests and contributed to the full model but did not provide sufficient additional discriminatory power to enter the reduced specification. FDI inflows and economic openness did not distinguish the two groups on their own. Competitiveness thus appears to be the result of a complex combination of factors, where isolated interventions in one area cannot ensure a long-term shift of the economy to a higher competitive category. This conclusion confirms the multidimensional nature of competitiveness and supports conceptual frameworks that understand it as a systemic phenomenon rather than the result of a single dominant economic policy instrument.

In terms of implications for economic policy, the results suggest that effectively increasing competitiveness requires a coordinated approach involving reforms in institutional quality, innovation support, infrastructure development, and improvement of the business environment. Tax policy and investment incentives can serve as important support tools, but their effectiveness is conditional on a stable regulatory framework and low levels of corruption. For countries with lower levels of competitiveness, this means shifting the focus from short-term optimization measures to long-term structural reforms aimed at strengthening innovation capacity and productivity.

Despite the contribution of this study, its limitations should also be pointed out. The use of aggregate macroeconomic indicators may mask internal regional differences and sector-specific characteristics. Similarly, the results are sensitive to the choice of variables and weights in the multi-criteria assessment, which is a natural methodological limitation. A robustness check that perturbed the three dominant TOPSIS weights (infrastructure, innovation, corruption) by $\pm 10\%$ and $\pm 20\%$ around their Saaty-derived values, with the remaining weights renormalised proportionally so that all ten weights continue to sum to 1, found the country rankings to be highly stable across all three periods (overall mean Spearman rank correlation with the baseline ranking of 0.998, minimum 0.993). Table 10 reports the mean rank correlation by perturbed weight and magnitude, with values ranging from 0.995 to 1.000. These results indicate that the TOPSIS rankings are not unduly sensitive to the particular weight vector applied.

Table 10. TOPSIS Weight-sensitivity: Mean Spearman Rank Correlation vs. Baseline Ranking after Perturbing each Dominant Weight ($\pm 10\%/\pm 20\%$, Remaining Weights Renormalised; Averaged over 2017-2019, 2020-2021, 2022-2024)

Perturbed weight	-20%	-10%	+10%	+20%
f8 Infrastructure	0.996	0.997	0.998	0.995
f9 Innovation rate	1.000	1.000	1.000	0.999
f10 Corruption rate	0.998	0.999	0.999	0.997

Source: Authors' calculation.

Because each country enters the pooled dataset in three sub-periods, observation-level leave-one-out cross-validation may produce optimistic classification accuracy by retaining observations of the same country in the training sample. Future applications should therefore employ leave-one-country-out cross-validation, in which all observations belonging to the evaluated country are excluded simultaneously. A further limitation concerns the definition of the discriminant groups. Because group membership was reconstructed using EU accession cohorts rather than recovered from the original analytical design, the reported results should be interpreted as an independent replication rather than an exact reproduction of the original SPSS analysis. Moreover, the significant Box's M test indicates that the equal-covariance assumption of linear discriminant analysis is not fully satisfied. The discriminant results should therefore be interpreted as descriptive classification evidence rather than as a causal assessment of competitiveness. Future research could therefore focus on extending the analytical framework to include dynamic panel models, regional-level analysis, or the inclusion of new dimensions of competitiveness such as digitalization, environmental sustainability, and technological readiness.

Overall, however, the study contributes to existing literature by demonstrating the added value of combining multi-criteria and multivariate methods in assessing the competitiveness of countries. It provides empirical evidence that long-term competitiveness is the result of the systemic quality of the economy and its institutions, rather than isolated policy measures. These findings can serve as an analytical basis for policymakers and regulators in designing strategies aimed at sustainable economic growth and strengthening international competitiveness.

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