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The Use of Selected Methods of Linear Ordering to Assess the Innovation Performance of the European Union Member States

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Abstract: The growing interest in measuring economic and social phenomena that are difficult to observe directly increases the need for researchers to broaden the use of multivariate statistical analysis methods. The ease of interpreting results presented in the form of rankings makes it common practice to use different methods of linear ordering of objects. If the appropriate assumptions are met, the determined set of variables allows for the construction of a synthetic measure whose ordered values provide a ranking. Such a statistical approach is quite often used in assessing the level of innovativeness of economies, and the literature abounds in various innovation indices. The starting point of this paper is a set of 27 variables on the basis of which the *Summary Innovation Index* is developed. After verifying the statistical assumptions and reducing the database to 21 diagnostic factors, the authors construct a total of nine innovation rankings, using different methods of linear ordering and selected procedures for normalisation of variables. The aim of the paper is therefore to assess the impact of selected methods of linear ordering (Hellwig's method, TOPSIS method, GDM method) and various procedures for normalising variables (classic standardisation, positional standardisation, quotient transformation) on the final ranking of the EU Member States due to the level of their innovation performance. The obtained results confirm that the applied method of linear ordering and the selection of the normalisation procedure have an impact on the final ranking of the examined objects – in this case, the final ranking of the EU Member States due to the level of their innovativeness analysed in the presented research.

Keywords: innovation measurement, linear ordering, Hellwig method, TOPSIS method, GDM method, normalisation of variables.

JEL codes: C38, O30.

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1. Introduction

Deep economic and technological changes that are occurring in the modern global economy have made knowledge and innovation the main factors determining the economic development and the progress of civilisation. Innovations determine not only the pace and directions of this development but also to a large extent define the forms and structure of international economic cooperation. The latest development trends of highly developed economies indicate that the scope and speed of creating and applying innovations are important factors in achieving a competitive advantage of enterprises and countries.

Innovation rankings of individual countries developed for many years prove the existence of innovativeness of economies and the need to measure it. Such rankings are very popular, especially in the context of international comparisons. Systematic research on innovativeness is conducted by a number of global institutions and organisations.

The level of innovativeness of the economy depends on many various factors among which human resources, financial resources (state budget, company and venture capital), entrepreneurship, the ability to create a network of connections between enterprises, cooperation of the R&D sector with industry, information infrastructure, institutional solutions etc. play an important role. Therefore, it is a complicated task to make a competent and comprehensive assessment of the innovativeness of the economy. There is no universal measure for this assessment; it is necessary to use a set of indices that reflect different dimensions of the innovative activity of the economy.

A popular method to measure innovation is the method proposed in the reports of the European Commission (*European Innovation Scoreboard*). In these reports, the innovative achievements of the EU Member States are assessed on the basis of the *Summary Innovation Index*, which is calculated as the weighted arithmetic mean of 27 partial indices for the European Union countries as well as Croatia, Turkey, Iceland, Norway, Switzerland, the USA, and Japan.[1]
Interesting statistical analyses showing the level of innovativeness of the world's leading economies are contained in the report prepared by the Information Technology and Innovation Foundation (ITIF), an American non-profit think tank specialising in research on innovation processes, the digital economy and labour productivity. In this report, indices that directly or

[1]The SII adopts values from 0 to 1, the closer the value is to 1, the higher the innovation level of a given country.

indirectly illustrate the level of innovativeness are used comprehensively to assess global competitiveness of economies.[2]

Innovation performance rankings published by the European Commission, despite being developed by high-class specialists based on an international and constantly improved methodology, are also criticised. Some recipients do not agree with these rankings, as they believe that these rankings do not fully reflect the actual level of innovativeness in individual countries. In economics, there is a lack of standardised, universal methods for measuring innovation. Moreover, some existing measures at the international level can be misleading when they are not, for example, adequately related to the activity of enterprises. The innovativeness of national economies is the resultant of many processes and phenomena of a social, economic and spatial nature. The multifaceted nature and complexity of this phenomenon means that the analysis of one-dimensional dependencies does not provide sufficient grounds for assessing the innovativeness of a selected country and its position in relation to others. The use of synthetic measures is therefore a necessary prerequisite in this type of analysis.

The authors of the paper, taking into account the above-presented situation and the fact that the research method (the selection of the right method of multivariate statistical analysis), and especially the different ways of approaching three detailed issues of linear ordering, i.e. normalisation, weighing and aggregation of diagnostic features, have a significant impact on the final results, proposed their own approach.

In the study presented in this paper, three methods of multivariate statistical analysis were applied to the synthetic assessment of innovation in the EU countries. The Hellwig method, the TOPSIS method and the GDM method were used, and in addition, different methods of variable normalisation were applied in each of these methods. The aim of the paper is to assess the impact of selected methods of linear ordering and different variable normalisation procedures on the final ranking of the EU Member States due to the level of their innovativeness.

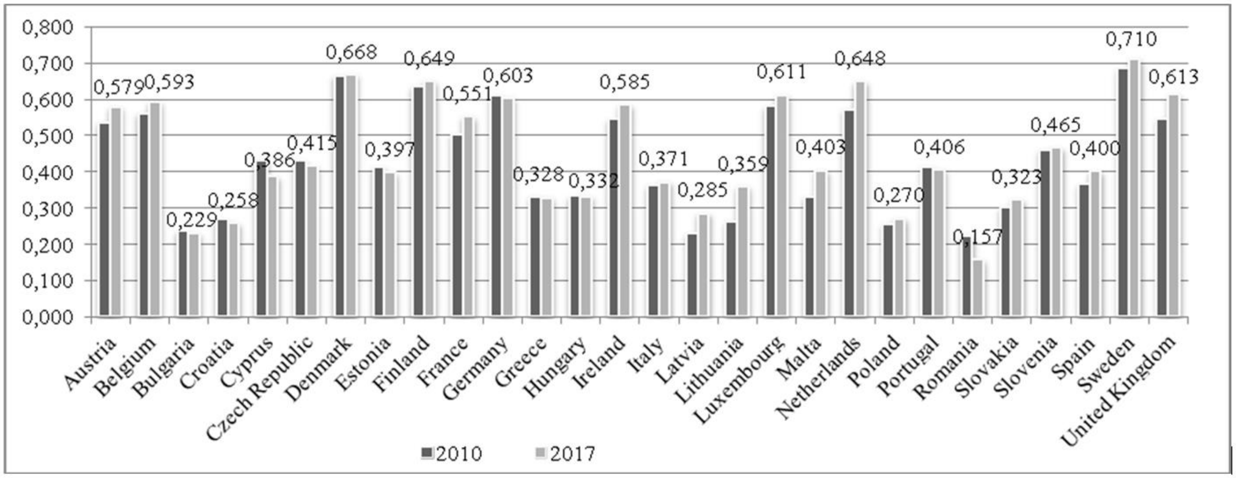
2. Measurement of innovativeness and sources of data

Innovation is a complex process due to its multidimensional characteristics for which the measurement method is difficult and ambiguous, as its evaluation requires the analysis of many

[2]The ITIF report used 16 indices divided into the following six categories: human capital, innovation capacity, entrepreneurship in the field of information technology, economic policy and economic performance.

indices. The European Union can boast of significant achievements in the field of measures to assess the level of innovativeness of various economies. The innovation performance of European countries is systematically assessed by the European Commission as part of the project *European Innovation Scoreboards* (EIS). The methodology for measuring innovation under the EIS has been evolving over recent years. Research teams focus both on the application of appropriate measurement methods and on the selection of appropriate individual measures. The results presented in the latest edition of the *European Innovation Scoreboard 2018* are based on a synthetic measure – the *Summary Innovation Index* (SII) – the construction of which includes 27 individual variables, and each of these variables was assigned to only one of four main categories (four main types of indicators: *Framework conditions* (8 indicators), *Investments* (5 indicators), *Innovation Activities* (9 indicators) and *Impacts* (5 indicators)). The main drivers of innovation performance external to the firm are included in **Framework conditions** that consist of three innovation dimensions: *Human resources*, *Attractive research systems*, and *Innovation-friendly environment*. *Public and private investment in research and innovation* are included in **Investments** that are made up of two dimensions: *Finance and support* and *Firm investments*. The innovation efforts at the level of the firm are included in **Innovation activities** described by three innovation dimensions: *Innovators*, *Linkages*, and *Intellectual assets*. **Impacts** capture the effects of firms' innovation activities grouped in two innovation dimensions: *Employment impacts* and *Sales impacts*. In the *Summary Innovation Index*, in 2010-2017, Sweden had the best rating and Denmark was right behind it. The lowest positions on the SII ranking list in those years were occupied by Bulgaria and Romania. This is also reflected in the results presented in the *European Innovation Scoreboard 2018*. Sweden once again became the EU leader in innovation, followed closely by: Denmark, Finland, the Netherlands, the United Kingdom and Luxembourg, which in 2018 joined for the first time the group of innovation leaders. Germany moved down the rating, becoming a member of the group of strong innovators. In the last 8 years, innovation performance increased in 18 EU countries and declined in ten. Lithuania, Malta, the Netherlands and the United Kingdom recorded the largest increases, while the largest decrease was recorded in Cyprus and Romania.

Figure 1. ***Summary Innovation Index*** **rating – 2017 and 2010 period comparison**



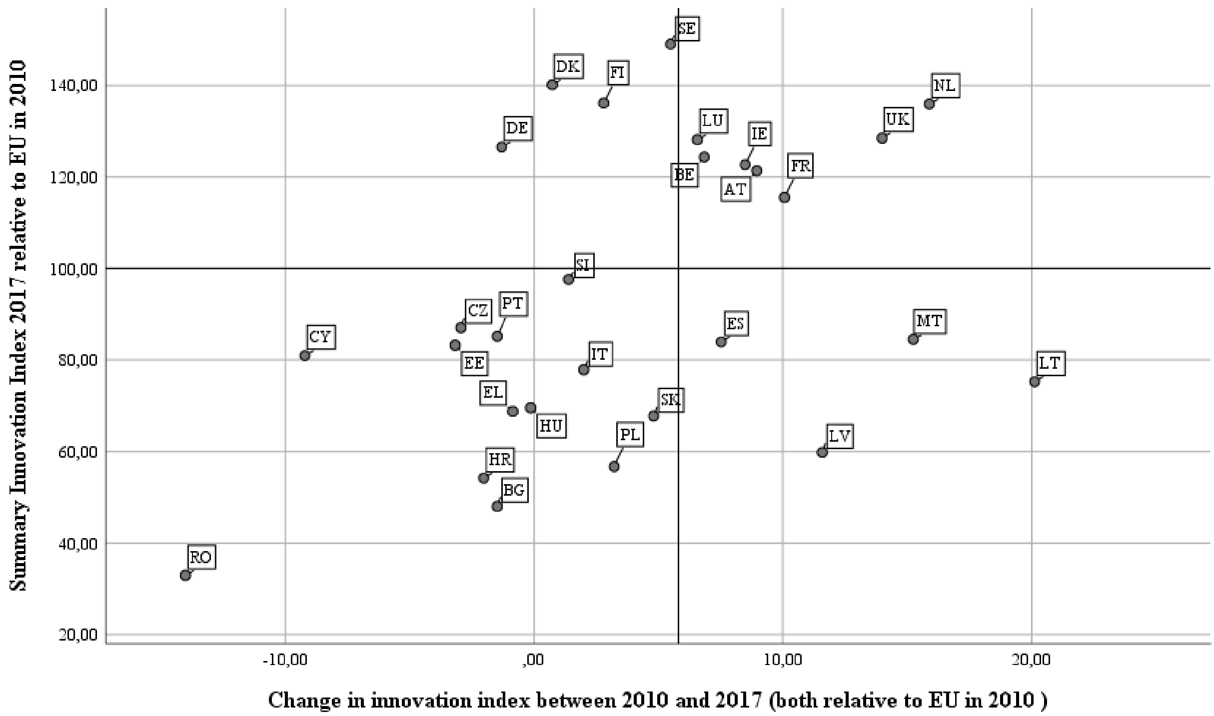
Source: own elaboration based on the European Innovation Scoreboard, https://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards_en.

In the paper, the changes in the *Summary Innovation Index* will be discussed in more detail. The ratings of *SII 2017* and *SII 2010* for each of the EU Member States in relation to the EU 2010 will be compared. A positive difference indicates an improvement in innovation performance while a negative result indicates a deterioration.

For the EU, performance between 2010 and 2017 improved by 5.8 percentage points. A similar comparison for 2010 and 2016 indicates much smaller differences in the values of *SII 2010* and *SII 2016* in relation to the EU 2010. The increase noted at that time amounted to 2.0 percentage points. In the analysed period, however, covering the years 2010 and 2017, performance improved in 18 Member States and deteriorated in 10 Member States (Figure 2).

For twelve Member States, performance improved by 5 percentage points or more: Belgium (6.8 p.p.), Ireland (8.5 p.p.), Spain (7.5 p.p.), France (10.1 p.p.), Latvia (11.6 p.p.), Lithuania (20.1 p.p.), Luxembourg (6.6 p.p.), Malta (15.2 p.p.), Netherlands (15.9 p.p.), Austria (9.0 p.p.), Sweden (5.5 p.p.), United Kingdom (14 p.p.). For six Member States, performance improved but by less than 5 percentage points: Denmark (0.7 p.p.), Italy (2.0 p.p.), Slovenia (1.4 p.p.), Slovakia (4.8 p.p.), Finland (2.8 p.p.), Poland (3.2 p.p.). For eight Member States, performance declined by up to 5%: Bulgaria (1.5 p.p.), Czech Republic (2.9 p.p.), Germany (1.3 p.p.), Estonia (3.2 p.p.), Greece (0.9 p.p.), Croatia (2.0 p.p.), Hungary (0.1 p.p.), Portugal (1.5 p.p.). For two Member States, performance declined by more than 5 percentage points; Cyprus (9.2 p.p.), Romania (14.0 p.p.).

Figure 2. The change in innovation performance between 2010 and 2017 relative to that of the EU in 2010.



Source: own elaboration based on the European Innovation Scoreboard, https://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards_en

A detailed list of diagnostic variables used in the research procedure is presented in the table below. Next to variable names, there is information about the average value of the variable

Table 1. The structure of *Summary Innovation Index* based on *European Innovation Scoreboard 2018*

		EU				EU	
	SPECIFICATION	**2010**	**2017**		**SPECIFICATION**	**2010**	**2017**
FRAMEWORK	**Human resources**			**INNOVATION**	**Innovators**		
	1.1.1 New doctorate graduates	**1.50**	**2.01***		3.1.1 SMEs with product or process innovations	**33.5**	**30.9***
	1.1.2 Population with completed tertiary education	**37.2**	**39.0**		3.1.2 SMEs with marketing or organisational innovations	**39.8**	**34.9***
	1.1.3 Lifelong learning	**10.7**	**10.9**		3.1.3 SMEs innovating in-house	**31.6**	**28.8***
	Attractive research systems				**Linkages**		

	1.2.1 International scientific co-publications	**335.9**	**517.5**		3.2.1 Innovative SMEs collaborating with others	**8.9**	**11.2***
	1.2.2 Top 10% most cited publications	**10.46**	**10.57***		3.2.2 Public-private co-publications	**40.2**	**40.9**
	1.2.3 Foreign doctorate students	**24.0**	**26.1***		3.2.3 Private co-funding of public R&D expenditures	**0.05**	**0.05***
	Innovation-friendly environment				**Intellectual assets**		
	1.3.1 Broadband penetration	**9.0**	**16.0**		3.3.1 PCT patent applications	**3.85**	**3.53***
	1.3.2 Opportunity-driven entrepreneurship	**3.0**	**3.3**		3.3.2 Trademark applications	**6.79**	**7.86**
INVESTMENTS	**Finance and support**				3.3.3 Design applications	**4.60**	**4.44**
	2.1.1 R&D expenditure in the public sector	**0.72**	**0.70***	**IMPACTS**	**Employment impacts**		
	2.1.2 Venture capital investments	**0.095**	**0.116**		4.1.1 Employment in knowledge-intensive activities	**13.4**	**14.2**
	Firm investments				4.1.2 Employment in fast-growing firms in innovative sectors	**5.1**	**4.8***
	2.2.1 R&D expenditure in the business sector	**1.19**	**1.32***		**Sales impacts**		
	2.2.2 Non-R&D innovation expenditure	**0.57**	**0.76***		4.2.1 Medium and high-tech product exports	**54.6**	**56.7**
	2.2.3 Enterprises providing training to develop or upgrade ICT skills of their personnel	**19.0**	**21.0**		4.2.2 Knowledge-intensive services exports	**66.8**	**69.2***
					4.2.3 Sales of new-to-market and new-to-firm innovations	**13.37**	**13.37***

Note: Symbol “*” denotes the variables for which the most recent available data were derived from 2015 or 2016. The tabular list includes abbreviated names of the variables. Full names of the variables are available in: European Commission (2018). *European Innovation Scoreboard* 2018.

Source: own elaboration based on European Commission (2018). *European Innovation Scoreboard* 2018.

3. Research procedure

The research procedure was carried out based on the following steps. The implementation of the research proceeded as described below.

Step 1. **Selection of diagnostic variables for the study**

Diagnostic features should be selected according to the criterion of universality. They should be characterised by substantive suitability from the point of view of the studied phenomenon and have social as well as economic significance. The selected features must be measurable, preferably expressed in the form of a structure indicator or an intensity indicator. Placement of individual, pre-selected variables in the final set requires full coverage of all objects for which statistical analysis is carried out with the variable values. When selecting variables, one should also be guided by the availability of the most recent and up-to-date data. In multivariate analyses, the fulfilment of this criterion is very difficult to achieve, especially with extensive data sets, such as the database used to determine the *Summary Innovation Index*. In the presented case, there are three reference periods: 2017 – 12 variables, 2016 – 5 variables and 2015 – 10 variables. 27 variables included in the construction of SII were the starting point in the paper. Thus, in the first step, it was necessary to reduce the data set. Due to a lack of data for Greece and Malta occurring in the whole examined period, three variables were excluded from the research proceedings – *Foreign doctorate students*, *Opportunity-driven entrepreneurship*, and *Employment in fast-growing firms in innovative sectors*. Further steps of the research procedure were carried out on a set of 24 diagnostic variables.

Step 2. **Measuring the degree of variability**

Selected features should show sufficient spatial variability and differentiate the examined objects. On the basis of the value of the coefficients of variation (V_s) determined for individual characteristics, the degree of variability is verified. Most often it is assumed that those variables for which the coefficient of variation is below 10% are eliminated. This did not apply to any of the variables contained in the set already reduced in the first step. It is worth adding that the level of variability is also an additional criterion for verification when eliminating variables with a high level of correlation. It is usually assumed that among the two strongly correlated variables, the first variable that should be removed is the one which is characterised by inferior properties discriminating objects.

Step 3. **Verifying the degree of correlation of variables**

It is assumed that strongly correlated variables are the carriers of similar information. In the case of multivariate analyses, the aim is to build such a set in which the risk of duplication of information by strongly correlated variables is minimised. Of the two strongly correlated features, the selection of the representative one should be made based on the substantive premises and the level of variability described above. In the paper, $r_{xy} = 0.85$ is assumed as the threshold level of the correlation coefficient. Based on the value of Pearson's linear correlation coefficient, three further variables were removed from the basic set – *SMEs with product or process innovations*, *Public-private co-publications*, and *PCT patent applications*. The final set consisting of 21 variables was used to construct synthetic measures and prepare rankings of the EU countries according to the level of innovation performance.

Step 4. **Transformation of variables**

Features that are destimulants should be transformed into stimulants. It is possible to use the formula for differential transformation (Kurzawa *et al.*, 2017: 130).

$$x_{ij} = a - b \cdot x_{ij}^{D}$$

where:

x_{ij} – the value of the *k*-th feature transformed into a stimulant in the *i*-th object;

x_{ij}^{D} – the value of the feature selected as a destimulant ($j \in I^D$, where I^D denotes a set of numbers of the features selected as destimulants in the *i*-th object), (i = 1, …, 28);

a, b – constant (most often a = 0, b = 1) where a = max (x_{ij}^{D}).

All variables included in the final data set are considered stimulants, hence the activities described in step 4 were not implemented.

Step 5. **Normalisation of diagnostic variables**

A detailed description of all three normalisation procedures is presented in the subsequent sections of the paper.

Step 6. **Application of selected methods of linear ordering**

A detailed description of all three linear ordering methods used in the paper is presented in its subsequent sections.

3. Research methods – comparison

The study used three selected methods of linear ordering based on a synthetic variable. Geometrically, a linear ordering consists in projecting on a straight line points of a multidimensional space representing objects. This allows us to determine the hierarchy of objects due to the established criterion. In order to systematically arrange objects, the variables that characterise them must be measured at least on the ordinal scale.

3.1. Hellwig's method

The Synthetic Development Measure (SDM) proposed by Z. Hellwig (1968) is the most commonly used reference method. Reference methods use the concept of a reference object/point for which the diagnostic variables assume optimal values. The construction of the synthetic development measure occurs in stages:

Normalisation of the values of diagnostic variables (x_{ij}),

$i = 1,\ldots\ldots, n$ – the number of objects;

$j = 1,\ldots, m$ – the number of variables.

The creation of the reference object according to the following formula:

$$z_{0j} = \begin{cases} \max\limits_i \{z_{ij}\} & for \quad stimulants \\ \min\limits_i \{z_{ij}\} & for \quad destimulants \end{cases}$$

whereis the normalised value of the j-th variable for the i-th object.

The distance of each object from the reference point (d_{i0}).

The most frequently calculated distance is based on the Euclidean metric:

$$d_{i0} = \sqrt{\sum_{j=1}^{m} \left(z_{ij} - z_{0j}\right)^2}$$

In order to normalise the synthetic development measure, the distance d_{i0} is transformed according to the following formula:

where: SDM_i – denotes the synthetic development measure for the i-th object, d_0 – is the reference point assuring that z_i takes on the values over the interval (0,1):

$$d_0 = \bar{d}_0 + 2S_0$$

where:

$$\bar{d}_0 = \frac{1}{m}\sum_{i=1}^{m} d_{i0}$$

$$S_0 = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(d_{i0} - \bar{d}_0\right)}$$

Larger values of the measure indicate a higher level of development of the studied phenomenon.

3.2. General Distance Measure

The General Distance Measure (GDM) was proposed by M. Walesiak (2002). This synthetic measure of the object's distance from the reference point, when the variables characterising the objects are measured on a quotient or interval scale and have the same weights, take on the following form:

$$GDM_i = \frac{1}{2} - \frac{\sum_{j=1}^{m}(z_{ij} - z_{0j})(z_{0j} - z_{ij}) + \sum_{j=1}^{m}\sum_{l=1}^{n}(z_{ij} - z_{lj})(z_{0j} - z_{lj})}{2\left[\sum_{j=1}^{m}\sum_{l=1}^{n}(z_{ij} - z_{lj})^2 \sum_{j=1}^{m}\sum_{l=1}^{n}(z_{0j} - z_{lj})^2\right]^{\frac{1}{2}}},$$

where z_{0j} – denotes the standardised value of the *j*-th variable for the reference object.

The synthetic variable takes on the values over the interval (0,1). The lower the value, the closer the object is to the reference point.

3.3. TOPSIS method

The TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method is the first historically method of linear ordering of multi-feature objects (Wysocki, 2010) proposed in the framework of the theory of decision (multiple-criteria decision-making). It coincides with the Hellwig parametric analysis method. The creators of the TOPSIS method, developed in 1981, are C. L. Hwang and K. Yoon. This method allows us to estimate the distance of each object from the ideal and non-ideal solution (Zalewski, 2012: 139). The best object is the one that is at the smallest distance from the ideal solution and at the same time at the largest distance from the non-ideal solution (Hwang, Yoon,1981). In Hellwig's method, only the ideal solution is used as the reference point.

To calculate the synthetic measure (R_i), it is necessary to know the coordinates of the ideal solution z_{oj}^{+} and the non-ideal solution z_{oj}^{-}, determined according to the following formulas (Zalewski, 2012: 139-140):

$$z_{oj}^{+} = \begin{cases} \max\limits_{i}\{z_{ij}\} & for \quad stimulants \\ \min\limits_{i}\{z_{ij}\} & for \quad destimulants \end{cases};$$

$$z_{oj}^{-} = \begin{cases} \min\limits_{i}\{z_{ij}\} & for \quad stimulants \\ \max\limits_{i}\{z_{ij}\} & for \quad destimulants \end{cases}.$$

Next, the distance of each object from the ideal and the non-ideal solution must be determined.

Most often, the Euclidean distance is used:

- distance from the ideal solution:

$$d_{io}^{+} = \sqrt{\sum_{j=1}^{m}(z_{ij} - z_{oj}^{+})^2};$$

- distance from the non-ideal solution:

$$d_{io}^{-} = \sqrt{\sum_{j=1}^{m}(z_{ij} - z_{oj}^{-})^2}.$$

The form of the synthetic measure (ranking factor) is as follows:

$$R_i = \frac{d_{io}^{-}}{d_{io}^{+} + d_{io}^{-}}$$

The synthetic measure R_i is normalised, taking on the values over the interval (0,1).
The higher the value of R_i in this object, the closer the object is to the ideal solution. Analogically, the more the value of the synthetic measure is closer to 1, the better the solution is from the point of view of linear ordering.

3.4. Normalisation of diagnostic variables

The main goal of normalisation of diagnostic features selected for the analysis is to obtain the dimensionless units of variables and unify the order of their magnitude. The basic requirement for normalisation procedures is that the transformation maintains interdependence (correlation) between the features and basic indicators regarding the shape of their distributions (skewness, kurtosis). These conditions are met by the linear transformation of the variable $X_j = (x_{1j}, x_{2j}, ..., x_{nj})^T$ into the variable $Z_j = (z_{1j}, z_{2j}, ..., z_{nj})^T$ in the following form (Zeliaś, 2000: 792):

$$z_{ij} = \frac{x_{ij} - a_j}{b_j}, \quad (j = 1, ..., m),$$

$$z_{ij} = \frac{a_j - x_{ij}}{b_j}, \quad (j = 1, ..., m),$$

for stimulants (1) and destimulants (2) respectively, where, if: a_j is the measure of the position of a given feature, e.g.: arithmetic mean $a_j = \bar{x}_j$, and b_j is the measure of its variability, e.g.: standard deviation $(b_j = s_j)$, then it is a **standardisation** transformation; if b_j the measure of its variability – range $b_j = \max_i x_{ij} - \min_i x_{ij}$, then it is a **unitary** transformation; and if $a_j = 0$ $(b_j > 0)$, then a **quotient** transformation is obtained.

There are many normalisation transformations presented in the literature, as it is possible to substitute the parameters a_j and b_j with other features of the analysed variables[3], such as: the minimum and maximum value, the median; as well as the median absolute deviation, the sum of value x_{ij} or the sum of the squares of the value x_{ij}. The complexity of the subject of normalisation of variables makes it difficult to choose the best – from the point of view of the quality of ordering – transformation for the needs of the research.

In the presented study, after a prior analysis of the properties of individual methods of normalisation, three normalisation formulas were selected and applied as the representatives of two basic types of normalisation: standardisation transformation and quotient transformation. The selected methods of normalisation include: classic standardisation, positional standardisation, and quotient transformation.

Classic standardisation aims to obtain the standard deviation of variables equal to 1 and the arithmetic mean equal to 0. The transformation takes on the following form:

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{S(x_j)}.$$

Positional standardisation aims to obtain the median absolute deviation equal to 1. The transformation takes on the following form:

$$z_{ij} = \frac{x_{ij} - med_j}{mad_j}$$

[3] On the subject of normalisation procedures: Grabiński et al. 1989, pp. 27-28 indicate the three transformations most commonly used in practice; Domański et al. 1998, pp. 49-48 present 5 standardisation transformations and 10 quotient transformations; Kukuła 2000, pp. 106-110 adopts another division of normalisation methods and describes 10 normalisation transformations; Zeliaś 2002, pp. 792-794 presents 2 standardisation methods, 4 unitary and 6 quotient transformation methods; Walesiak 2006, pp. 16-22 analyses a total of 11 transformations; and Młodak 2006, pp. 39-42, respectively 4 standardisation methods, 7 unitary transformation methods and 8 quotient transformation methods, including also proposals of the author that use positional statistics.

where:

x_{ij} – the value of the *j*-th feature in the *i*-th country (Panek, 2016: 78-79])

med_j – median for the *j*-th variable at the specified time;

mad_j = median absolute deviation for the *j*-th variable described by the formula $med\left|x_{ij} - med_j\right|$;

In addition, Lira, Wagner, Wysocki (2002: 91) propose to multiply the denominator by a constant 1.4826. The proposed value of the constant was taken into account in the normalisation performed by positional standardisation.

The selected quotient transformation takes on the following form:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}.$$

4. Research results – presentation and discussion

On the basis of the results obtained, the following conclusions can be formulated.

1. From the point of view of the three compared methods of linear ordering – the Hellwig method, the TOPSIS method, and the GDM method – the following results were obtained:
   a. When applying the standardisation procedure, the most similar rankings were obtained with the use of Hellwig's method and the GDM method (r_{yx} = -0.9890), a strong correlation also exists between the GDM and TOPSIS methods (r_{yx} = -0.983).
   b. When applying the positional standardisation procedure, the greatest ranking similarity was obtained with the use of the GDM and TOPSIS methods (r_{yx} = -0.990).
   c. When applying the quotient transformation procedure, the most similar results were obtained with the use of the GDM and TOPSIS methods (r_{yx} = -0.943).
2. The following results were obtained taking the selected normalisation procedures as the reference point:
   a. In the case of the Hellwig method, the rankings are the closest to one another when the normalisation of variables is carried out by means of classic standardisation or positional standardisation (r_{yx} = 0.995).

b. The situation with regard to the TOPSIS method is similar. The strongest correlation occurs in the case of rankings in which the normalisation of variables is carried out in accordance with the classic standardisation procedure or the positional standardisation procedure (r_{yx} = 0.995).
c. In the case of the GDM method, the most similar rankings were obtained with the use of the normalisation of variables based on the standardisation procedure or the quotient transformation procedure (r_{yx} = 0.997).

Table 2. Comparison of rankings of the EU Member States due to their level of innovation performance – comparison of results for different normalisation procedures

Code	Classic standardisation						Positional standardisation						Quotient transformation					
	Hellwig's method		TOPSIS method		GDM method		Hellwig's method		TOPSIS method		GDM method		Hellwig's method		TOPSIS method		GDM method	
	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank
AT	0.537	6	0.581	8	0.172	6	0.574	5	0.575	7	0.183	6	0.374	5	0.554	6	0.115	5
BE	0.542	5	0.585	7	0.180	7	**0.587**	**3**	0.590	4	0.176	5	**0.539**	**1**	0.521	9	0.137	8
BG	0.084	27	0.233	27	0.654	27	0.078	27	0.235	28	0.653	27	0.067	27	0.190	27	0.659	27
HR	0.133	25	0.293	26	0.609	26	0.148	25	0.310	26	0.587	26	0.105	25	0.244	25	0.605	26
CY	0.267	18	0.440	13	0.429	16	0.254	18	0.427	16	0.459	17	0.167	21	0.443	12	0.449	18
CZ	0.331	15	0.424	17	0.397	14	0.369	15	0.434	14	0.390	14	0.262	13	0.350	19	0.362	14
DK	0.549	4	0.602	4	0.169	4	0.545	7	0.580	6	0.196	7	0.224	15	**0.662**	**2**	0.120	6
EE	0.345	13	0.429	14	0.358	13	0.369	14	0.432	15	0.354	13	0.264	12	0.435	13	0.301	13
FI	**0.568**	**3**	**0.608**	**2**	0.157	3	0.578	4	**0.602**	**3**	**0.166**	**3**	0.313	8	**0.644**	**3**	**0.098**	**2**
FR	0.474	9	0.526	11	0.238	10	0.512	9	0.520	11	0.250	9	0.388	4	0.427	14	0.169	9
DE	0.535	7	**0.606**	**3**	0.170	5	0.549	6	**0.609**	**2**	**0.164**	**2**	**0.450**	**2**	0.479	10	**0.100**	**3**
EL	0.203	21	0.349	22	0.525	21	0.195	23	0.341	23	0.537	23	0.169	20	0.285	21	0.504	21
HU	0.196	23	0.343	23	0.552	23	0.222	21	0.371	21	0.517	21	0.155	22	0.258	24	0.549	23
IE	0.461	11	0.557	10	0.245	11	0.493	10	0.539	10	0.267	12	0.346	6	0.521	8	0.212	11
IT	0.275	17	0.373	20	0.473	20	0.288	17	0.360	22	0.502	20	0.213	16	0.290	20	0.452	19
LV	0.146	24	0.318	24	0.581	24	0.150	24	0.337	24	0.557	24	0.118	24	0.271	22	0.572	24
LT	0.220	20	0.425	16	0.439	17	0.226	20	0.456	13	0.392	15	0.185	18	0.384	16	0.403	16
LU	0.464	10	0.579	9	0.220	9	0.440	12	0.554	9	0.256	10	0.265	11	0.606	5	0.190	10
MT	0.228	19	0.427	15	0.450	18	0.227	19	0.425	17	0.461	18	0.180	19	0.365	18	0.482	20
NL	**0.573**	**2**	0.600	5	0.157	2	**0.609**	**2**	0.589	5	0.172	4	0.333	7	0.613	4	0.111	4
PL	0.130	26	0.301	25	0.592	25	0.135	26	0.312	25	0.580	25	0.102	26	0.242	26	0.584	25
PT	0.299	16	0.385	19	0.455	19	0.310	16	0.388	19	0.462	19	0.213	17	0.403	15	0.430	17
RO	0.004	28	0.223	28	0.727	28	-0.002	28	0.250	27	0.710	28	-0.019	28	0.156	28	0.762	28
SK	0.197	22	0.357	21	0.540	22	0.217	22	0.371	20	0.528	22	0.155	23	0.262	23	0.546	22
SI	0.429	12	0.494	12	0.278	12	0.488	11	0.501	12	0.264	11	0.309	9	0.474	11	0.247	12
ES	0.335	14	0.416	18	0.403	15	0.370	13	0.419	18	0.403	16	0.257	14	0.381	17	0.384	15
SE	**0.622**	**1**	**0.653**	**1**	0.109	1	**0.613**	**1**	**0.652**	**1**	**0.111**	**1**	0.265	10	**0.703**	**1**	**0.045**	**1**
UK	0.516	8	0.586	6	0.184	8	0.535	8	0.568	8	0.205	8	**0.395**	**3**	0.538	7	0.124	7

Source: own elaboration based on European Commission (2018).

Table 3. Comparison of rankings of the EU Member States due to their level of innovation performance – comparison of results for different methods of linear ordering

Code	HELLWIG'S METHOD						TOPSIS METHOD						GDM METHOD					
	standardisation		positional standardisation		quotient transformation		standardisation		positional standardisation		quotient transformation		standardisation		positional standardisation		quotient transformation	
	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank	d_{i0}	rank
AT	0.537	6	0.574	5	0.374	5	0.581	8	0.575	7	0.554	6	0.172	6	0.183	6	0.115	5
BE	0.542	5	**0.587**	**3**	**0.539**	**1**	0.585	7	0.590	4	0.521	9	0.180	7	0.176	5	0.137	8
BG	0.084	27	0.078	27	0.067	27	0.233	27	0.235	28	0.190	27	0.654	27	0.653	27	0.659	27
HR	0.133	25	0.148	25	0.105	25	0.293	26	0.310	26	0.244	25	0.609	26	0.587	26	0.605	26
CY	0.267	18	0.254	18	0.167	21	0.440	13	0.427	16	0.443	12	0.429	16	0.459	17	0.449	18
CZ	0.331	15	0.369	15	0.262	13	0.424	17	0.434	14	0.350	19	0.397	14	0.390	14	0.362	14
DK	0.549	4	0.545	7	0.224	15	0.602	4	0.580	6	**0.662**	**2**	0.169	4	0.196	7	0.120	6
EE	0.345	13	0.369	14	0.264	12	0.429	14	0.432	15	0.435	13	0.358	13	0.354	13	0.301	13
FI	**0.568**	**3**	0.578	4	0.313	8	**0.608**	**2**	0.602	3	**0.644**	**3**	0.157	3	**0.166**	**3**	**0.098**	**2**
FR	0.474	9	0.512	9	0.388	4	0.526	11	0.520	11	0.427	14	0.238	10	0.250	9	0.169	9
DE	0.535	7	0.549	6	**0.450**	**2**	**0.606**	**3**	**0.609**	**2**	0.479	10	0.170	5	**0.164**	**2**	**0.100**	**3**
EL	0.203	21	0.195	23	0.169	20	0.349	22	0.341	23	0.285	21	0.525	21	0.537	23	0.504	21
HU	0.196	23	0.222	21	0.155	22	0.343	23	0.371	21	0.258	24	0.552	23	0.517	21	0.549	23
IE	0.461	11	0.493	10	0.346	6	0.557	10	**0.539**	**10**	0.521	8	0.245	11	0.267	12	0.212	11
IT	0.275	17	0.288	17	0.213	16	0.373	20	0.360	22	0.290	20	0.473	20	0.502	20	0.452	19
LV	0.146	24	0.150	24	0.118	24	0.318	24	0.337	24	0.271	22	0.581	24	0.557	24	0.572	24
LT	0.220	20	0.226	20	0.185	18	0.425	16	0.456	13	0.384	16	0.439	17	0.392	15	0.403	16
LU	0.464	10	0.440	12	0.265	11	0.579	9	0.554	9	0.606	5	0.220	9	0.256	10	0.190	10
MT	0.228	19	0.227	19	0.180	19	0.427	15	0.425	17	0.365	18	0.450	18	0.461	18	0.482	20
NL	**0.573**	**2**	**0.609**	**2**	0.333	7	0.600	5	0.589	5	0.613	4	0.157	2	0.172	4	0.111	4
PL	0.130	26	0.135	26	0.102	26	0.301	25	0.312	25	0.242	26	0.592	25	0.580	25	0.584	25
PT	0.299	16	0.310	16	0.213	17	0.385	19	0.388	19	0.403	15	0.455	19	0.462	19	0.430	17
RO	0.004	28	-0.002	28	-0.019	28	0.223	28	0.250	27	0.156	28	0.727	28	0.710	28	0.762	28
SK	0.197	22	0.217	22	0.155	23	0.357	21	0.371	20	0.262	23	0.540	22	0.528	22	0.546	22
SI	0.429	12	0.488	11	0.309	9	0.494	12	0.501	12	0.474	11	0.278	12	0.264	11	0.247	12
ES	0.335	14	0.370	13	0.257	14	0.416	18	0.419	18	0.381	17	0.403	15	0.403	16	0.384	15
SE	**0.622**	**1**	**0.613**	**1**	0.265	10	**0.653**	**1**	0.652	1	**0.703**	**1**	0.109	1	**0.111**	**1**	**0.045**	**1**
UK	0.516	8	0.535	8	**0.395**	**3**	0.586	6	**0.568**	**8**	0.538	7	0.184	8	0.205	8	0.124	7

Source: own elaboration based on European Commission (2018).

1. In more general terms, based on the results obtained, it can be said that from the point of view of the normalisation methods under consideration, the GDM method is the least sensitive to the method of normalisation of variables. In its case, the values of Pearson's linear correlation coefficients for all compared pairs are not lower than 0.995. The choice of the variable normalisation method had the greatest impact on the final ranking of countries in the case of the Hellwig method. On the basis of the obtained results, it can be assumed that Hellwig's method is the most sensitive from the point of view of the selection of normalisation procedures. This is particularly evident in relation to the ranking in which the synthetic measure is based on variables subjected to the quotient transformation procedure.
2. However, with the comparison of normalisation procedures as the starting point, the analyses show that the smallest discrepancies in the innovation rankings were obtained with the application of the classic standardisation procedure. The biggest differences in the final ordering of countries arise when normalisation is carried out in accordance with the quotient transformation procedure.
3. The two most similar rankings were obtained using the GDM method when the normalisation of variables was carried out in accordance with the classic standardisation procedure and the quotient transformation procedure.

Correlations between the individual rankings for each selected normalisation procedure and linear ordering method are presented in the table 4.

Table 4. Comparison of results for three selected methods of linear ordering and three procedures for normalising variables

	CLASSIC STANDARDISATION					HELLWIG'S METHOD			
		Hellwig's method	TOPSIS method	GDM method			standardisation	positional standardisation	quotient transformation
r_{yx} Pearson	Hellwig's method	1.000	.979**	-.993**		standardisation	1.000	**.995****	.863**
	TOPSIS method	.979**	1.000	-.991**		positional standardisation	**.995****	1.000	.890**
	GDM method	-.993**	-.991**	1.000		quotient transformation	.863**	.890**	1.000
rho Spearman	Hellwig's method	1.000	.961**	-.987**		standardisation	1.000	**.991****	.890**
	TOPSIS method	.961**	1.000	-.982**		positional standardisation	**.991****	1.000	.915**
	GDM method	-.987**	-.982**	1.000		quotient transformation	.890**	.915**	1.000
	POSITIONAL STANDARDISATION					TOPSIS METHOD			
		Hellwig's method	TOPSIS method	GDM method			standardisation	positional standardisation	quotient transformation
r_{yx} Pearson	Hellwig's method	1.000	.960**	-.983**		standardisation	1.000	**.995****	.959**
	TOPSIS method	.960**	1.000	**-.989****		positional standardisation	**.995****	1.000	.947**
	GDM method	-.983**	**-.989****	1.000		quotient transformation	.959**	.947**	1.000
rho Spearman	Hellwig's method	1.000	.953**	-.975**		standardisation	1.000	**.982****	**.962****
	TOPSIS method	.953**	1.000	**-.990****		positional standardisation	**.982****	1.000	.933**
	GDM method	-.975**	**-.990****	1.000		quotient transformation	**.962****	.933**	1.000
	QUOTIENT TRANSFORMATION					GDM METHOD			
		Hellwig's method	TOPSIS method	GDM method			standardisation	positional standardisation	quotient transformation
r_{yx} Pearson	Hellwig's method	1.000	.698**	-.872**		standardisation	1.000	.995**	**.997****
	TOPSIS method	.698**	1.000	**-.939****		positional standardisation	.995**	1.000	.995**
	GDM method	-.872**	**-.939****	1.000		quotient transformation	**.997****	.995**	1.000
rho Spearman	Hellwig's method	1.000	.799**	-.900**		standardisation	1.000	.988**	**.991****
	TOPSIS method	.799**	1.000	**-.943****		positional standardisation	.988**	1.000	.990**
	GDM method	-.900**	**-.943****	1.000		quotient transformation	**.991****	.990**	1.000

Note: **. Correlation significant at 0.01 (two-tailed).

Source: own elaboration based on European Commission (2018).

5. Conclusions

The presented study indicates that there is a need to assess the impact of selected methods of linear ordering and various normalisation procedures on the final ranking of the EU Member States due to their level of innovation performance. A comparative analysis was carried out for rankings developed using three selected methods for normalising variables, taking into account their theoretical properties, and three methods of linear ordering.

The multivariate statistical analysis methods used in the study allowed the EU countries to be ranked due to their innovativeness. The paper compares as many as nine different innovation rankings of the EU Member States. Each of the rankings is an independent construct, and the common element of all the analysed rankings is the final set of variables containing 21 diagnostic features. The results of research using the Hellwig, Topsis and GDM methods as well as classic standardisation, positional standardisation and quotient transformation procedures are not conclusive. Comparing the constructed innovation rankings, it can be noted that the results of the ordering differ, which stems from applying three different methods of linear ordering of countries and three different procedures for normalising variables. However, the study is not limited to providing the confirmation of the hypothesis presented in the *Introduction* that different methods of determining the synthetic measure of innovation result in different positions of the EU Member States in the innovation ranking. The study has also evaluated the quality of linear ordering results of countries in terms of linear and rank correlation. The use of Pearson's linear correlation coefficient and Spearman's rank correlation coefficient to assess the convergence of the results obtained allows us to conclude that the synthetic measures proposed in the study provide different, but similar, convergent classification results. To conclude, the choice of the method of linear ordering and partial calculation procedures has an impact on the final ranking of the EU Member States in terms of their innovation performance. Therefore, the application of multivariate statistical analysis methods to measure latent variables and, consequently, to organise objects in a linear manner must be supported by insightful literature studies. Due to the differences in the final

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innovation rankings shown in the paper, in practice, statistical analyses in which an attempt is made to compare results supported by the use of various methods should be considered as the most reliable ones.

The conducted innovativeness assessments of the EU countries indicate the directions of further research which may include performing the analysis in dynamic terms in a specific time interval to explore trends of changes and comparing the results of rankings based on other measures of quality of linear ordering methods, particularly compliance mapping methods.

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Zastosowanie wybranych metod porządkowania liniowego do oceny poziomu innowacyjności krajów członkowskich Unii Europejskiej

Streszczenie

Rosnące zainteresowanie pomiarem zjawisk ekonomicznych i społecznych, trudnych do bezpośredniego zaobserwowania, wzmaga potrzebę badaczy do szerszego stosowania metod wielowymiarowej analizy statystycznej. Łatwość interpretacji wyników przedstawianych w formie rankingów sprawia, że powszechnością staje się korzystanie z różnych metod porządkowania liniowego obiektów. Przy spełnieniu odpowiednich założeń, wyodrębniony zbiór zmiennych pozwala na budowę zmiennej syntetycznej, której uporządkowane wartości dają ranking. Takie podejście statystyczne jest dość często stosowane w ocenie poziomu innowacyjności gospodarek, literatura przedmiotu obfituje w różne indeksy innowacyjności. Punktem wyjścia w tym artykule jest zestaw 27 zmiennych, na podstawie których opracowywany jest *Summary Innovation Index*. Po sprawdzeniu założeń statystycznych i zredukowaniu bazy do 21 czynników diagnostycznych, autorzy konstruują łącznie 9 rankingów innowacyjności, stosując różne metody porządkowania liniowego oraz wybrane procedury normalizacji zmiennych. Celem artykułu jest zatem ocena wpływu na ostateczny ranking krajów członkowskich UE ze względu na poziom ich innowacyjności wybranych metod porządkowania liniowego (metoda Hellwiga, metoda Topsis, metoda GDM) oraz różnych procedur normalizacji zmiennych (standaryzacja klasyczna, standaryzacja pozycyjna, przekształcenie ilorazowe). The obtained results confirm that the applied method of linear ordering and the selection of the normalisation procedure have an impact on the final ranking of the examined objects – in this case, the final ranking of the EU Member States due to the level of their innovativeness analysed in the presented research.

Słowa kluczowe: pomiar innowacyjności, porządkowanie liniowe, metoda Hellwiga, metoda Topsis, metoda GDM, normalizacja zmiennych.