Russia's Place Vis-à-Vis the EU28 Countries in Digital Development: A Ranking Using DEA-Type Composite Indicators and the TOPSIS Method

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1 Introduction

The International Digital Economy and Society Index (I-DESI) is a composite index comprising a set of indicators that was designed to measure progress towards a digital economy and society of all EU and selected non-EU countries, including the Russian Federation. Aiming to mirror and extend the results of the European Commission's EU-only Digital Economy and Society Index (Bánhidi et al., 2020), I-DESI measures performance in five dimensions or policy areas: Connectivity, Human Capital (digital skills), Use of Internet by citizens, Integration of Digital Technology and Digital Public Services. The latest edition of I-DESI (European Commission, 2018) combines 24 individual indicators from various databases (including those of the World Economic Forum, OECD, World Bank and ITU etc.) measured over a four-year time period from 2013 to 2016. The I-DESI composite index uses a scoring model to rank each country according to its digital performance and to track the evolution of the EU as a whole and its member states in digital competitiveness. This has the drawback that the dimension weights used in the DESI "were selected to represent the EU's digital policy priorities" (European Commission, 2016), which might not be identical to the policy priorities of the selected non-EU countries, rather than being based on objective criteria or the statistical properties of the dataset (Tokmergenova et al., 2021). Although we do not consider these to be unreasonable, and acknowledge that the rationale behind the weights are partly rooted in theoretical considerations about enablers and synergies, we are still on the opinion that the exact values selected by the Commission experts are somewhat arbitrary. In this paper, we

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sought to demonstrate how other models of decision theory can provide a viable alternative to this pre-defined weighting system.

In an earlier paper, the authors have already endeavored to assess the digital competitiveness and level of digital development of the Russian Federation vis-à-vis the countries of the European Union. Bánhidi et al. (2019) ranked the countries of the Russian Federation and the EU using six methods. Three of the methods ranked the 29 countries with equal weights. One of these methods was a scoring model with the weights proposed by the European Commission (2018). With these weights, Russia ranked 26th out of 29 countries. Another method using Data Envelopment Analysis (DEA) using the same weights was the DEA Common Weights Analysis (DEA/CWA) method. Using this method, the authors performed two analyses that are distinguished by the procedure according to which the available data were transformed. Since the DEA basically organizes the criteria for evaluating Decision Making Units (DMUs) into two groups according to whether the criteria can be considered input or output criteria, the criteria need to be transformed by some method. There are two possible options for this: one is to transform the inputs to be minimized, which are arranged according to the maximum by reciprocals, and the outputs, which are arranged to the minimum by reciprocal, are also transformed; the other option is to scale the data to a specified scale according to preference. The five dimensions of I-DESI are each arranged to a maximum, so there is the preferred one that takes on the highest value. In this sense, it is difficult to define an input here, but if we look for one, Connectivity and Human Capital are the best candidates, because the other three dimensions can be understood as a consequence of these two variables, i.e. they are the output dimensions. Performing the ranking with these two methods using the reciprocal procedure, Russia took the 29th, last place, while scaling the data to a scale of 1–20, the 25th place.

Using the multidimensional scaling (MDS) method of multivariate statistics, the Russian Federation finished in 27th place.

Using the classical method of the DEA and using two methods of data transformation, Russia can already show better results. With reciprocal data, the Russian Federation ranked 20th, while with scaled data, it ranked 19th.

As the results of the six methods used showed a fairly large standard deviation, further studies with the use of basic data seemed necessary. These methods are the DEA-type Composite Indicators (DEA/CI) method (Cherchye et al., 2007) and the TOPSIS method (Technique for Order of Preference by Similarity to Ideal Solution) proposed by Yoon and Hwang (1981).

The DEA-type Composite Indicators method is practically the same as a special case of DEA, with the difference that then each of the criteria is either an input, i.e. to be minimized; or an output, i.e. to be maximized. Since each of the DESI dimensions is to be maximized, the latter case occurs, we only have output criteria. This also means that data transformation can be omitted in this case, which can avoid the distortions caused by transformations.

The TOPSIS method is essentially a very simple, geometric approach based on a decision theory method that attempts to eliminate procedures based on data transformation. The method consists of three consecutive steps. (It is often summarized in six steps, but this is based on the three basic methods we describe.) In the first step, the scale problem between the data is brought to the same scale as a normalization transformation. That normalization can be a Euclidean distance on the unit sphere or transforming the data to a [0, 1] interval with an affine transformation. The resulting nominated data is then weighted by a weight vector. The weights can be subjective, given a priori, or objectively determined from the statistical properties of the available data by theoretical or mathematical statistical considerations. Finally, in the third step, the calculated efficiency is determined using the ratio of the distance between the normalized, weighted data to ideal and nadir (negative ideal) points, the order of which gives the ranking.

The paper will consist of the following sections. In the second part, we provide a brief literature review of the Digital Economy and Social Index and the analyses performed with it. In the next chapter, we determine the position of the Russian Federation among the 29 countries using the DEA/CI method. In chapter four, we do the same examination using the TOPSIS method. Finally, in the fifth part, we interpret our results and compare our ranking obtained with the two methods of decision theory, above all the place of the Russian Federation among the countries of the European Union.

2 Literature Review

Literature review highlights studies of DESI index analysis and its methodology problems in general and specifically for EU countries. Bilozubenko et al. (2020) applied a cluster method to evaluate the digital development of the EU-27. They divided EU countries into three clusters (using the Euclidean distance metric and the k-means algorithm) and sought to identify the key parameters of the "digital divide" that separates these groups. Jovanović et al. (2018) examined the DESI methodology and used correlation analysis to assess how the digital performance of EU countries affects the economic, social and environmental dimensions of sustainable development, highlighting the importance of digitalization as an additional, crucial component of sustainable development. Karnitis et al. (2019) developed a country-level model explaining the dependence of economic growth on the level of digitalization, focusing primarily on the Baltic countries. The results of the research indicate that two dimensions of the DESI index, Use of Internet and Digital Public Services, have a significant impact on the growth of the economy. Stavytskyy et al. (2019) analyzed three hypotheses and found that a high level of consumption and low unemployment are associated with a high DESI index score. The authors also suggest that in emerging and developing countries that are not presented in the official DESI reports, such as Ukraine, significant efforts are required to increase their digital development to levels that are comparable to those in Western European countries. Orbán (2020) combines the Digital Public Services dimension of DESI and her own survey results to assess the performance of e-administration services in Hungary. While she mainly focuses on "the causes of underperformance" in her paper, she also criticizes the European Commission's measurement framework for its lack of robustness and stability. Bánhidi (2021) analyzes the significance of broadband penetration for economic development with an econometric model for nine South American countries. According to this model, increased broadband penetration is associated with significant spillover effects, excess societal returns over and above the expected returns of other investments in financial capital. Soltész and Zilahy (2020) studied the features of a popular ride-sharing platform and a related network with a network theory approach, showing that the internal structure of this network shows scale-free characteristics. However, the authors also suggest that while these networks have significant growth potential, they should eventually run out of "free nodes" and reach a saturation point.

Literature review also highlights the main problems of digital development of Russia and studies present which specific areas of digital development in Russia require more sources. Ermolaev et al. (2019) assessed the development of the digital economy in Russia based on international indices. Their results show that further efforts are required to increase the percentage of Internet users, enhance the quality of digital infrastructure and the availability of ICT technologies. Revinova and Lazanyuk (2018) assessed the level of digitalization in the regions of Russia. The level of digital development varies highly between regions: among the Federal Districts the leading position belongs to the Northwestern district, and among subjects to Moscow and Saint-Petersburg. In lagging regions, the main problems identified by the authors are the lack of digital infrastructure and funding. Korovin (2018) indicates risks of digitalization of industry in Russia in terms of low level of technological development, equipment and software products. Labor productivity is also crucial in achieving leading positions in industrial digitalization by Russia. Statistical research demonstrates a positive trend in increasing the number of university graduates in such specialties as automation, IT and communications, but the demand for these specialists in Russia remains low. Baskakova and Soboleva (2019) analyzed functional illiteracy in Russia based on access to internet and level of computer literacy. The research shows that older generation, low educated, population with low income, rural population are associated with increased risk of functional illiteracy. The regional factor of Russia also contributes to unequal development of digital economy. Mironova et al. (2019) studied the importance of digital education and digital literacy in Russia as the main factor of development of economy and society. The factor of difference in generations development should be considered in transition to digitization. Akberdina (2018) indicates that industrial digitalization is impossible without a developed industrial sector, and demonstrates that the level of digitalization, automation determines the degree of using high technologies in industry. Certain regions of Russia are developed less that refers to historical factor and the author proves the fact that concentration of high technologies impacts differentiation in digital development. Kuvayeva (2019) assesses the readiness of Russia to digital integration. The author highlights the lack of unified statistical measures for assessing digital readiness of all countries, including Russia. Analyzed dimensions in the article such as investments in technologies, high-tech industry development, readiness to digital transitions are low in comparison to developed countries. Miethlich et al. (2020) analyzed the digital economy and its influence on national competitiveness on the examples of Switzerland, Russia and Azerbaijan. Their study suggests that Switzerland and Russia both excel in IT education services, but Russia lags behind Switzerland in the protection of intellectual property rights. The authors also performed cluster analysis based on data regarding the share of TCI (telecommunications, computer and information) in total service exports. According to their results, Russia is placed in the third cluster, which means that the country is not geared towards exporting TCI.

3 Ranking with DEA-Type Composite Indicators

The Data Envelopment Analysis (DEA) method was first described and applied by Charnes et al. (1978). In the last more than forty years, the procedure has since had numerous theoretical extensions and practical applications (Cook & Seiford, 2009).

The method used in this paper is a special property model of DEA. In the basic DEA, the criteria that evaluate DMUs can be divided into two different groups according to whether the criteria can be considered input or output. The basic DEA CCR-I (1)–(3) model can be written in the following form, where vectors ($\mathbf{u}$, $\mathbf{v}$) are the weights vectors of DEA, and vectors $(\mathbf{y}_j, \mathbf{x}_j)(j = 1, 2, \ldots, p)$ are the output and input evaluations of the jth DMU, and the number of DMUs is value p:

$$\mathbf{u} \cdot \mathbf{y}_1 / \mathbf{v} \cdot \mathbf{x}_1 \rightarrow \max \tag{1}$$

s.t.

$$\mathbf{u} \cdot \mathbf{y}_j / \mathbf{v} \cdot \mathbf{x}_j \leq 1; \; j = 1, 2, \ldots, p \tag{2}$$

$$\mathbf{u} \geq 0, \mathbf{v} \geq 0 \tag{3}$$

However, the model in its original form could not be used to rank DMUs in the absence of input criteria among our quantitative sub-indicators. In this case, we can rewrite model (1)–(3) as follows if we assume that the input does not exist or assume it to be a single one, i.e. $\mathbf{v} \cdot \mathbf{x}_1 = 1$.

$$\mathbf{u} \cdot \mathbf{y}_1 \rightarrow \max \tag{4}$$

s.t.

$$\mathbf{u} \cdot \mathbf{y}_j \leq 1; \; j = 1, 2, \ldots, p \tag{5}$$

$$\mathbf{u} \geq 0 \tag{6}$$

Table 1 Weights of dimensions in TOPSIS calculations

	CN	HC	UI	DT	PS
Weights	0.082	0.297	0.233	0.194	0.194

Source Own calculation

The latter model is called in the literature the DEA-type Composite Indicators (DEA/CI) method (Cherchye et al., 2007; Dobos & Vörösmarty, 2014). The new model (4)–(6) must be solved for each DMU, in our case for all countries, in order to determine the efficiency of that country. Dataset is Table 2 in the Appendix. We are looking for the $\mathbf{u}$ weight vector, and the $\mathbf{y}_j$ vector represents the digital dimensions of the jth country.

The solutions of the linear programming models (4)–(6) are given in Table 3 of the Appendix. This shows that the Russian Federation ranks 19th, i.e. in the second third of the countries of the European Union. This suggests that Russia's digital development is considered moderate. After the DEA/CI method, the results obtained with the TOPSIS method are presented.

4 Ranking with TOPSIS Method

In the introduction, we gave a short overview of the TOPSIS method, which is not repeated here. The three steps described are illustrated by the methods we use.

In the *first step*, we perform the normalization of the basic data. Suppose that the data for criterion i according to each country are contained in the vector $\mathbf{x}_i$. (Dataset used is Table 2 in the Appendix.) Then the data transformation is as follows

$$y_{ji} = \frac{x_{ji} - x_j^{min}}{x_j^{max} - x_j^{min}},\ (j = 1, 2, \ldots, n; i = 1, 2, \ldots, m),$$

where the minimal and maximal values of criterion i is x_j^{min} and x_j^{max}, number n is the number of countries, and number m is the number of criteria/dimensions. With this transformation, the values of each criterion for each country were transformed to the interval [0, 1]. Let the value of the new vectors be $\mathbf{y}_i$.

In the *second step*, knowing the values of the individual variables, in our case dimensions, we use the entropy-based method to determine the weights of the variables (Zhou et al., 2006). We chose entropy-based weighting because then the weights are objective, that is, they are determined from the data. The formula for the transformation is as follows:

$$H_i = -\frac{1}{\ln(n)} \cdot \sum\nolimits_{j=1}^{n} \frac{y_{ji}}{\sum_{j=1}^{n} y_{ji}} \cdot \ln\left(\frac{y_{ji}}{\sum_{j=1}^{n} y_{ji}}\right),\ (i = 1, 2, \ldots, m),$$

The weights will thus be as follows:

$$w_i = \frac{1 - H_i}{n - \sum_{i=1}^{m} H_i},\ (i = 1, 2, \ldots, m)$$

The weighted normalized values are denoted by z_{ji}, which is equal to $z_{ji} = w_i \cdot y_{ji}$. The ideal and nadir points are then determined using the z_{ji} values.

Finally, in the *third step*, we use the weighted data to determine the efficiency index using the ideal (I_i) and nadir (N_i) points, which are calculated in the following way:

$$I_i = \max_{j=1,2,\ldots,n} z_{ji},\ N_i = \min_{j=1,2,\ldots,n} z_{ji},\ (i = 1, 2, \ldots, m).$$

In this last, third step, the distances from the preferred and non-preferred dimensions are determined, after which the efficiencies can be calculated. The distance of the jth country from the ideal and nadir is determined as follows:

$$d_j^I = \sqrt{\sum\nolimits_{i=1}^{n} \left(z_{ji} - I_i\right)^2},\ d_j^N = \sqrt{\sum\nolimits_{i=1}^{n} \left(z_{ji} - N_i\right)^2},\ (j = 1, 2, \ldots, n),$$

A final calculation is the determination of the TOPSIS efficiency E_j, which shows the ratio of the distance from the two awarded points:

$$E_j = \frac{d_j^N}{d_j^I + d_j^N},\ (j = 1, 2, \ldots, n),$$

After a brief description of the TOPSIS method, we describe the results of our calculations performed on the dataset. We omit the detailed calculations, only the objective weights, and the TOPSIS efficiencies and the order are presented in Table 1 (CN—Connectivity, HC—Human Capital, UI—Use of Internet, DT—Integration of Digital Technology and PS—Digital Public Services) and Table 3 in the Appendix.

It is immediately apparent that the weight of the dimensions is highest among Human Capital and Use of Internet. This means that countries with a high level of development in education are at the top of the list. This is also true for the Russian Federation. This puts Russia in 18th place among the countries of the European Union, which corresponds to a medium level of development.

5 Conclusions

In this paper, we demonstrate how the DEA/CI and TOPSIS methods can be used to provide a viable framework for ranking the 28 countries of the European Union and the Russian Federation in the absence of explicit input criteria or predetermined weights that are required by the classical DEA method and the European

Commission's scoring model. These methods can eliminate the need for a pre-defined weighting system used by the original composite index, rather than an intrinsic one based on the statistical properties of the dataset. The entropy-based method identifies Human Capital as the dimension with the highest "objective weight" (0.297), highlighting the importance of digital literacy in driving the digital transformation of the economy and society. The original weighting system proposed by the European Commission (2020) also attributes the joint-highest weight (0.25) to this dimension and Connectivity, which they group together as "digital infrastructure" and suggest that two of the other dimensions, Use of Internet and Digital Public Services "are enabled by the infrastructure and their contribution is strengthened by the quality of such infrastructure". While we can accept this thesis as a sensible policy recommendation, we would also note that the entropy-based method attributes a much lower weight to the Connectivity dimension (0.082).

According to our rankings, the Russian Federation demonstrates respectable results in digital economic and social development relative to Eastern and Southern member states of the European Union, on account of its solid results in the field of Human Capital. In order to further improve its digital competitiveness, Russia would have to improve its scores in the Integration of Digital Technology and Connectivity dimensions. As for the latter, the Russian Ministry of Communications and Mass Media has set quite ambitious national broadband coverage targets to overcome its connectivity gap, which are not yet reflected in our I-DESI database. However, achieving these might prove extremely challenging, owing to the fairly low population density and vast territory of the country. On the other hand, the other dimension, the use of ICT by the business sector should not be neglected either, since it should be regarded as one of the most important drivers of productivity and economic growth.

Appendix

See Tables 2 and 3.

Table 2 The basic data (x_i)

Country	CN	HC	UI	DT	PS
Austria	0.63	0.59	0.60	0.59	0.72
Belgium	0.68	0.60	0.62	0.61	0.61
Bulgaria	0.61	0.47	0.42	0.36	0.45
Croatia	0.54	0.45	0.49	0.46	0.56
Cyprus	0.54	0.45	0.54	0.39	0.49
Czechia	0.67	0.58	0.58	0.39	0.43
Denmark	0.77	0.80	0.79	0.71	0.71
Estonia	0.62	0.66	0.70	0.53	0.85

(continued)

Table 2 (continued)

Country	CN	HC	UI	DT	PS
Finland	0.72	0.73	0.78	0.67	0.83
France	0.59	0.62	0.59	0.53	0.82
Germany	0.64	0,62	0.66	0.59	0.69
Greece	0.50	0.48	0.46	0.45	0.48
Hungary	0.60	0.62	0.55	0.51	0.46
Ireland	0.63	0.77	0.56	0.51	0.66
Italy	0.51	0.50	0.42	0.47	0.68
Latvia	0.65	0.47	0.58	0.32	0.56
Lithuania	0.61	0.53	0.58	0.46	0.63
Luxembourg	0.65	0.67	0.79	0.77	0.64
Malta	0.64	0.48	0.57	0.57	0.66
Netherlands	0.75	0.69	0.76	0.75	0.76
Poland	0.53	0.53	0.51	0.33	0.57
Portugal	0.60	0.43	0.47	0.39	0.55
Romania	0.61	0.43	0.48	0.27	0.39
Russia	0.39	0.64	0.49	0.30	0.57
Slovakia	0.57	0.65	0.59	0.40	0.38
Slovenia	0.60	0.44	0.53	0.43	0.67
Spain	0.64	0.62	0.58	0.55	0.82
Sweden	0.75	0.69	0.78	0.65	0.73
United Kingdom	0.74	0.65	0.72	0.68	0.90

Source https://ec.europa.eu/digital-single-market/en/news/international-digital-economy-and-society-index-2018

Table 3 DEA/CI and TOPSIS Efficiencies and ranking of countries

	DEA/CI Efficiencies	DEA/CI Ranking	TOPSIS Efficiency	TOPSIS Ranking
Austria	0.854	14	0.522	12
Belgium	0.883	11	0.521	13
Bulgaria	0.792	21	0.145	28
Croatia	0.712	27	0.230	24
Cyprus	0.700	28	0.211	25
Czechia	0.870	12	0.355	19
Denmark	1.000	1	0.855	1
Estonia	0.972	7	0.672	7
Finland	1.000	1	0.846	2
France	0.928	9	0.554	11

(continued)

Table 3 (continued)

	DEA/CI Efficiencies	DEA/CI Ranking	TOPSIS Efficiency	TOPSIS Ranking
Germany	0.860	13	0.584	9
Greece	0.653	29	0.196	26
Hungary	0.779	23	0.416	15
Ireland	0.963	8	0.616	8
Italy	0.761	25	0.289	20
Latvia	0.844	15	0.274	22
Lithuania	0.804	18	0.377	17
Luxembourg	1.000	1	0.722	6
Malta	0.844	16	0.381	16
Netherlands	1.000	1	0.787	3
Poland	0.714	26	0.264	23
Portugal	0.779	24	0.189	27
Romania	0.792	22	0.119	29
Russia	*0.801*	*19*	*0.365*	*18*
Slovakia	0.813	17	0.418	14
Slovenia	0.800	20	0.289	21
Spain	0.928	10	0.557	10
Sweden	0.990	6	0.759	4
UK	1.000	1	0.734	5

Source Own calculation

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