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The Digital Competitiveness of European Countries: A Multiple-Criteria Approach

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Abstract

High-quality digital infrastructure is the basis of almost every sector of a modern and innovative economy and society. As a part of the overall competitiveness concept, digital competitiveness is a multidimensional structure that encompasses various factors of the process of digital transformation through the ability of learning and application of new technologies, technology factors that enable digital transformation, and digital readiness factors that assess the preparedness of an economy and citizens to assume digital transformation. The paper aims to propose a methodology for measuring digital competitiveness using a composite index approach including a variety of various indicators. To assess the digital competitiveness of European countries, a multi-criteria analysis was applied in a two-stage procedure integrating CRITIC and TOPSIS as weighting and aggregation methods. The sample includes thirty European countries and the research is based on thirteen indicators provided in the database Eurostat Digital Economy and Society. In addition, a ranking of sample countries according to digital competitiveness is presented. Finally, a cluster analysis was conducted to examine relations between digital competitiveness and several economic performances such as GDP pc, labour productivity and employment rates. The results indicate that Nordic countries have achieved the highest digital competitiveness, while most Eastern European countries still lag behind.

Keywords: digital competitiveness, CRITIC method, TOPSIS method, cluster analysis
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1. INTRODUCTION

Constant technological progress and the constant acceleration of the pace of technological change have become basic features in countries around the world. According to projections, by the end of 2020, one million new devices were set be available online every hour (Yoo et al., 2018). The impact of the Internet of Things and digitization is pervasive. The application of ICTs (information and communication technologies) can transform the way businesses operate and how people live as well as drive global innovation. However, the rapid emergence of new technologies creates many new challenges. The risks inherent in new technologies further complicate the problems facing policymakers. The role of government is becoming more and more important, as it is necessary to strike a balance between protecting the country's fundamental interests on the one hand and the ability to ensure national competitiveness and accelerate economic growth on the other through the use of new technologies. There is evidence that digitization can enable countries to maintain global competitiveness, increase GDP, stimulate innovation and create jobs (Yoo et al., 2018). It is recognized that ICTs play a crucial role in connecting people and communities, increasing innovation and productivity, improving living standards, strengthening competitiveness, supporting economic and social modernization, and reducing poverty worldwide.

The paper aims to examine the level of digital competitiveness of European countries by proposing a methodology for a composite index of digital competitiveness using multi-criteria decision-making methods in the process of aggregation data. In the primary step of the creation of a composite index, the proposed methodology determines the relative importance of indicators in the model using an objective statistical approach based on decision matrix data. In this segment, the paper contributes to existing methodologies which measure digital competitiveness by aggregation based on a linear combination, aggregation with equal criteria importance, or subjectively determined weighting coefficients. The method of choice for objective importance assessment of single indicators within the composite index is CRiteria Importance through Intercriteria Correlation (CRITIC). The methodology applied to aggregate weighted data is Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Additionally, the sub-objective of the analysis is to identify countries with similar digital competitiveness and economic performances. The basic hypothesis is that the countries with better economic performance have higher levels of digital competitiveness.

The paper is structured as follows: In the first section, the role of the digital economy for competitiveness is presented, accompanied by methods for assessment of ICT development impact on country economic performances. In the second section, the research methodology, model development and the data used are described, while in the third section, the research results and a discussion of results are offered. Concluding remarks pointing to scientific contribution and further research directions are put forth in the last section.

2. THE IMPORTANCE OF THE DIGITAL COMPETITIVENESS FOR THE ECONOMY

The digital economy and digital competitiveness are among the most commonly used terms referring to the socio-economic development perspectives of contemporary society. In a broader sense, the digital economy describes the development of a technological society and implies the widespread use of ICTs in all spheres of human activity. ICTs enable people to perform ordinary tasks more efficiently and have emerged as a response to societal needs (Sendlhofer & Lernborg, 2018). In addition to the impact on individuals, ICTs also have an important impact on companies, since they provide new opportunities for companies and facilitate the worldwide availability of their products and services (Elia et al., 2016). ICTs have contributed to transforming the nature and handling of the uncertainties typical for the entrepreneurial process and its outcomes (Nambisan, 2017). The advantages of applying ICTs in companies are numerous (Rossato & Castellani, 2020): improved efficiency and effectiveness of business processes, improved understanding of user experience, increased creation and transfer of knowledge, increased awareness of the cultural value of the company's heritage, and the development of state-of-the-art employee skills. The advent of the digital economy was facilitated by the digital revolution, also known as digitalization, which represents a transition from analogue or physical technologies to digital data systems (Dufva & Dufva, 2019).

Carlsson (2004) states that digitalization of information, combined with the Internet, creates a wide range of various combinations of information and knowledge use through which the application of modern technologies and the availability of greater technical possibilities can be turned into economic possibilities. The Internet of Everything, aided by economies of scale and platforms such as consumer electronics, mobile devices, and urban infrastructure, enable the wide availability of services to consumers as well as easier access to potential consumers (Leviäkangas, 2016).

The relationship between ICTs and economic growth is an issue of particular interest in terms of both theory and practice. There are two prevailing understandings about the impact of ICTs application on economic growth (Thompson Jr & Garbacz, 2011): direct impact, which implies productivity improvements resulting from the application of ICTs, and indirect impact, which means the materialization of externalities resulting from the application and development of ICT. Several studies have reported a positive link between the development and implementation of ICTs and economic growth (Myovella et al., (2020). Portillo et al., 2020; Vu et al., 2020; Bahrini & Qaffas, 2019; Nair et al., 2020). Evidence indicates that ICTs improve various aspects of productivity (Skorupinska & Torrent-Sellens, 2017; Corrado et al., 2017; Pieri et al., 2018; Kılıçaslan et al., 2017, Ivanović-Đukić, et al., 2019; Haller & Lyons, 2019;). The digitalization and digital economy contribute to productivity growth in many ways (Wyckoff, 2016): by creating new innovative businesses and reducing the number of businesses with outdated, non-innovative operations; enabling smarter, more efficient use of labour and capital to create so-called multi-factor productivity growth through which even older firms can improve; introducing new opportunities and services for individuals previously removed from the global economy (such as farmers and local producers); and enhancing the efficiency of inventory management and shipping.

Examining the impact of ICTs on economic growth is of great importance to policymakers, as it provides them with guidance for creating development strategies. Nevertheless, it should be borne in mind that a large number of indicators of digital development and competitiveness exist, and that most research uses only some of these as proxies, thus all aspects of digital competitiveness have not been covered. The following are most commonly used as proxies in the literature: mobile and fixed broadband (Thompson Jr & Garbacz, 2011), broadband speed (Mayer et al., 2020), fixed and mobile phone subscriptions (Albiman & Sulong, 2017), and digital subscriber line broadband services (Haller & Lyons, 2019), investments in ICT (Niebel, 2018). For a detailed overview of digital development proxies, see Vu et al. (2020).

Measuring and comparing countries based on digital competitiveness is a topical issue, where several methodologies for quantification have been proposed. World Economic Forum has offered the Networked Readiness Index (NRI) for measuring the propensity of a country to take advantage of the opportunities offered by ICTs (NRI, 2019). This index measures the performance of economies in using ICTs to boost competitiveness, innovation and well-being. Another methodology is the Digital Economy and Society Index (DESI, 2019) developed by the European Commission. It is a complex index that summarizes relevant indicators on European digital performance and tracks the development of EU Member States in digital competitiveness. In 2017 the DECA (Digital Economy Country Assessment) program was developed and tested (Ashmarina et al., 2020). DECA is a multivariate model that involves analysing the readiness, use and impact of digital transformation on national socio-economic progress. The DECA methodology is focused on assessing the current level of development of the digital economy to identify critical shortcomings, challenges and opportunities for future growth, as well as areas that require more careful analysis. The United Nations International Telecommunication Union published the ICT Development Index (IDI, 2018) aimed at comparing and monitoring the development of ICT between countries and over time. E-government Development Index (EGDI, 2021) was developed to examine the development of e-government in the member states of the United Nations. Additionally, several authors have proposed composite indices of digitalization and digital competitiveness (Yoo et al., 2018; Milenkovic et al., 2016; Nair et al., 2020; Ali et al., 2020a; Ali et al., 2020b).

The construction of composite indices has specific critical steps on which the whole process depends and which are primarily related to the determination of appropriate weighting and aggregation methods (Saisana & Tarantola, 2002). When it comes to weighting methods when constructing composite indices, they can be grouped into three main categories (El Gibari et al., 2019): equal weighting, data-based methods, and participation-based methods. The equal weighting method has the least computational complexity but has drawbacks reflected in the loss of information (Nardo et al., 2005). The participation-based methods incorporate intuition, the subjective system of values and knowledge of the decision-maker or group, which is also a disadvantage of this approach because the weighting coefficients depend on their subjective assessment and perception. The data-based methods perform criteria weights determination based on data from the decision matrix, which eliminates the subjectivity of decision-makers, and weight determination is performed using mathematical and statistical methods based on information from the model. Yet, despite the apparent shortcomings, most of the stated indices of digital competitiveness use equal weights when determining weights (Pérez-Castro et al., 2021).

When it comes to aggregation methods, criteria can be aggregated into a composite index in several ways: linear aggregation, geometric aggregation or multicriteria analysis. Each method implies different assumptions and has specific consequences (Nardo, 2005). Still, it should be noted that one of the advantages of multicriteria analysis methods is that the application of these methods leads to the creation of composite indices that are non-compensatory or partially compensatory.

The need to create an adequate composite measure for assessing and monitoring the digital competitiveness of countries stems from the fact that accelerated technological development imposes the urge to make effective strategic decisions related to the digital future, as well as to assess the level of digital development and competitiveness of countries (Alam et al., 2018). Having in mind the diversity and variety of indicators, it is desirable to create a unique composite indicator of digital development and competitiveness that will include various aspects of digitalization. The digital economy and digital competitiveness have a multidimensional nature and can be defined as a multiple-criteria phenomenon (Balcerzak & Bernard, 2017). Therefore, this paper aims to create the composite index for the measurement of digital competitiveness on the sample of European countries using multi-criteria analysis methods.

The contribution of the paper is reflected in the creation of a new composite index of digital competitiveness, which, unlike most existing composite indices, uses objectively determining weighting coefficients. Namely, most of the proposed composite indices for measuring digital competitiveness give equal importance to the indicators that make up the composite index, which makes some indicators overestimated or underestimated. The proposed model uses an objective approach to determining weights, which determines the weights of criteria in a multi-criteria model based on data from the decision matrix, thus eliminating the subjectivity of decision-makers and determining weights based on information from the model itself. To summarize, the methodology used in this analysis makes three contributes to the construction of a complex digital competitiveness index: (i) demonstrates the possibility of creating objective data-based weights of criteria by which the composite index is aggregated; (ii) points to the possibility of weights to provide adequate information to policymakers regarding the identification of priority areas when it comes to digital competitiveness of countries; and (iii) leads to the elimination of decision-maker subjectivity that may result in biased results. In addition, most of the above-mentioned composite indices were created by aggregating data from diverse sources. However, the use of data from different sources can jeopardize the correctness and reliability of the data used, which can inadvertently affect the obtained results (Akande et al., 2019). To obtain reliable and verifiable results, it is desirable to use data from a single, dependable database, such as Eurostat. Therefore, only data from the Eurostat database on the digital economy and society were used in this paper to assess the digital competitiveness of European countries.

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

The main objective of this paper is to assess the digital competitiveness of European countries using a two-step analysis. In the first step, the weighting coefficients of the criteria will be obtained using CRITIC methods. In contrast, in the second step, the assessment and ranking of countries according to the achieved level of digital competitiveness will be performed using TOPSIS methods. Additionally, the sub-objective of the paper is to identify the groups of European countries with similar digital competitiveness and economic performances.

3.1 CRITIC method

CRITIC (CRiteria Importance Through Intercriteria Correlation) was proposed by Diakoulaki et al. (1995) as one of the possible ways to determine the objective values of the weighting coefficients of criteria. The method is based on the difference and the conflict between the criteria inherent to multi-criteria decision-making problems. The CRITIC method represents a correlation method where the process of determining the criteria weights requires the use of standard deviation of the normalized criteria values, as well as the correlation coefficients of all pairs of criteria (Žižović et al., 2020). The CRITIC method algorithm consists of six steps (Diakoulaki et al., 1995):

Step 1: Normalization of criteria values using the linear normalization relations depending on the type of criteria:

$$r_{ij} = (x_{ij} - x_{ij}^{min})/(x_{ij}^{max} - x_{ij}^{min}) \quad (1)$$

$$r_{ij} = (x_{ij}^{max} - x_{ij})/(x_{ij}^{max} - x_{ij}^{min}) \quad (2)$$

wherein $x_{ij}^{max} = max(i)x_{ij}$ and $x_{ij}^{min} = min(i)x_{ij}$, $i = 1, 2,\ldots,m$, $j = 1, 2,\ldots, n$.

Step 2: Determination of the standard deviation σj of each vector rj in the normalized decision matrix.

Step 3: Construction of a symmetric matrix with elements R_{ij} representing the correlation coefficients between each pair of normalized criteria in the model.

Step 4: Determination of the measure of conflict between criteria:

$$\sum_{j=1}^{n} (1-R_{ij}) \quad (3)$$

Step 5: Determination of the amount of information C_j emitted by the jth criterion:

$$C_j = \sigma_j \sum_{j=1}^{n} (1-R_{ij}) \quad (4)$$

The larger the value of C_j, the greater is the amount of information contained in a given criterion, and, consequently, that criterion has greater relative importance.

Step 6: Determination of the criteria weighs using the relation:

$$w_j = C_j/(\sum_{j=1}^{n} C_j) \quad (5)$$

3.2 TOPSIS method

TOPSIS represents an acronym for The Technique for Order of Preference by Similarity to Ideal Solution. It is a multi-criteria analysis method developed by Hwang & Yoon (1981). The essence of this method is that the optimal solution should be closest to the Positive Ideal Solution (PIS) and farthest from the Negative Ideal Solution (NIS) in a geometric sense (Chen et al., 2020). The ideal solution is the point where the utility for the decision-maker is greatest, that is, the point where the value of the revenue criteria is the highest. At the same time, the value of the expenditure criteria is the lowest. The ideal solution is usually not achievable, but all multi-criteria analysis methods tend to keep the optimal solution as close as possible to the ideal one. The main advantage of the TOPSIS method is its low mathematical complexity and ease of use (Rajak & Shaw, 2019). In addition, the attractiveness of the TOPSIS method is enhanced by the fact that it requires minimal inputs from decision-makers, i.e., the only subjective data required are criteria weight (Olson, 2004).

The TOPSIS method can be represented by the following algorithm (Yoon & Hwang, 1995; Kuo, 2017):

Step 1. The beginning of the TOPSIS method algorithm requires the determination of a normalized decision matrix with rij coefficients, whereby rij coefficients are determined using the following relation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i = 1,2 \dots m, j = 1,2 \dots n \tag{6}$$

Step 2. In this step, the coefficients v_{ij} that form a preferentially normalized matrix are calculated. The calculation of the v_{ij} coefficients is done by applying the relation:

$$v_{ij} = r_{ij} \cdot w_j \tag{7}$$

Step 3. The third step of the TOPSIS method algorithm involves determining the PIS and the NIS. The elements of the PIS v_j^* and the NIS v_j^- are determined using relations:

$$A^* = \{v_1^*, v_2^*, \dots, v_j^*, \dots, v_n^*,\} = \left\{(\max_i v_{ij} \left| j \in J_1) \wedge (\min_i v_{ij} | j \in J_2), i = 1,2, \dots m \right.\right\} \tag{8}$$

$$A^- = \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-,\} = \left\{(\min_i v_{ij} \left| j \in J_1) \wedge (\max_i v_{ij} | j \in J_2), i = 1,2, \dots m \right.\right\} \tag{9}$$

where J_1 is a set of revenue criteria and J_2 is a set of expenditure criteria.

Step 4. The main step of the TOPSIS method involves determining the distance of an alternative from the PIS and the NIS. The relation for determining the distance between the alternative and the PIS is given by:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \quad , i = 1,2 \dots m \tag{10}$$

On the other hand, the relation for determining the distance between the alternative and the NIS is given by:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad , i = 1,2 \dots m \tag{11}$$

Step 5. In this step, the approximation index (C_i^*) is determined, that is, the relative proximity of the considered alternative to the PIS according to the relation:

$$C_i^* = (S_i^-)/(S_i^* + S_i^-), \quad i = 1,2,\dots m \tag{12}$$

Step 6. In the final step of the TOPSIS method, alternatives are ranked based on the approximation index in descending order to obtain the best alternative.

3.3. Cluster analysis

Cluster analysis represents one of the most proficient methods for data processing used to identify homogeneous sets within a heterogeneous group (Fox et al., 1991). It is an approach used to detect complex relationships between variables. Cluster analysis involves grouping a set of objects in a way that the objects in one group are similar to each other, and at the same time, differ from objects in other groups (Esmalifalak et al., 2015). The ease of use of cluster analysis is the reason for the popularity of this approach. Variables applied in the cluster analysis have the same importance (there are no dependant and independent variables) since the purpose of cluster analysis is to recognize patterns among variables rather than predicting a particular value. Each object in the cluster analysis represents a separate point in multidimensional space defined by the values of its attributes, where the similarity between the two objects is determined based on their distance (Zeng et al., 2008). The clustering process aims to identify similarities in the variable structure and create homogeneous groups of objects based on the identified similarities. Several cluster procedures can be identified, whereby an agglomerative hierarchical cluster analysis will be applied in this paper. The essence of this approach is that it starts with each of the n objects being a cluster, with similar objects being merged in each subsequent step until each of the objects is deployed into relatively homogeneous groups. Therefore, the agglomerative clustering strategy is considered a bottom-up strategy since each object represents a separate cluster at the beginning. Then the cluster pairs merge as the hierarchy increases (Chakraborty et al., 2020).

The first step in the cluster analysis is the determination of the distance between objects. There are various methods for determining the distance between objects (such as Euclidean distance, squared Euclidean distance, Manhattan distance, Maximum distance, Mahalanobis distance), whereby squared Euclidean distance will be used in this paper. In the next step, the grouping of objects is performed. There are various agglomeration methods (Olson, 1995), whereby in the paper, Ward's procedure will be applied. The essence of this method is not to calculate the distance between the clusters but to maximize the homogeneity within the cluster. Ward's method has several advantages (Ünal & Shao, 2019): it allows maximizing homogeneity within the cluster, allows minimizing cluster heterogeneity, and leads to the robustness of results. The outcomes of hierarchical clustering are usually represented in the form of a dendrogram which illustrates the clusters as the nodes of a tree-like data structure (Chakraborty et al., 2020).

3.4 Data and model development

Digital competitiveness is estimated for a sample of 30 European countries based on data regarding the digital economy and society obtained from the Eurostat Digital Economy and Society database for the year 2019 (Eurostat, 2020a). As data on the ICT sector were not available for all countries, nor for 2019, indicators related to the ICT sector were not taken into account in the analysis, as the sample size would be significantly reduced. Therefore, the indicators used to assess digital competitiveness include 13 indicators grouped into three categories.

The first category, named ICT usage in households and by individuals, encompasses indicators such as the percentage of individuals that has used the Internet in the last three months (Internet use), the percentage of households with Internet access (Connection to the Internet and computer use), the percentage of individuals that has used the Internet to obtain the services of public institutions or administrative entities within last 12 months (E-government), the percentage of individuals that used the Internet to purchase products or services in the last three months (E-commerce) and the percentage of individuals that has used computers, laptops, smartphones, tablets or other portable devices at work (ICT usage at work). The second category referred to as ICT usage in enterprises includes indicators related to the percentage of enterprises that have a website (Website and use of social media), the percentage of enterprises with ERP software package to share information between different functional areas (E-business), the percentage of enterprises with e-commerce sale (E-commerce), the percentage of employees using computers with Internet access compared to the total number of employees (Connection to the Internet), the percentage of enterprises that have Internet access relative to the total number of enterprises in the country, and the percentage of enterprises that use strong password authentication as an

ICT security measure (ICT security). The third category, named digital skills, involves indicators such as the percentage of the population with low digital skills (ICT users), the percentage of employed ICT specialists as a share of total employment (ICT specialists in employment), and the percentage of enterprises that have provided training for employees to develop or improve digital skills (ICT training).

Categories represent criteria in the model, while the indicators represent sub-criteria (Figure 1).

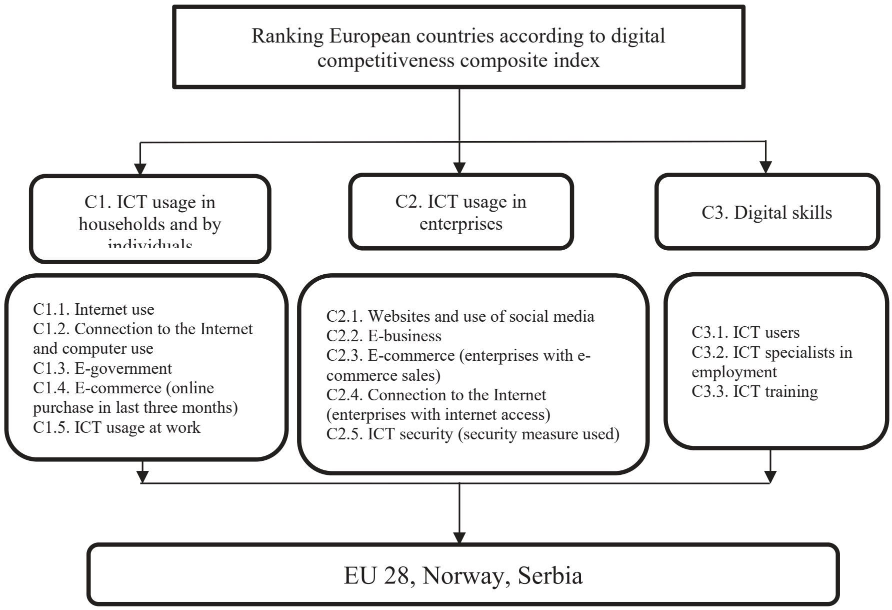

Fig. 1 – Hierarchical structure of the model. Source: own research

4. RESULTS AND DISCUSSION

Using the CRITIC methods, the following weights of criteria and sub-criteria were determined (Table 1):

Tab. 1 – Relative significance of criteria and sub-criteria. Source: own research

Criteria	Sub-criteria	Sub-criteria weights	Criteria weights
ICT usage in households and by individuals	Internet use	0.062287121	0.3201145
	Connection to the Internet and computer use	0.080473564	
	E-government	0.057049018	
	E-commerce (online purchase in the last three months)	0.065249476	
	ICT usage at work	0.055055319	

ICT usage in enterprises	Websites and use of social media	0.064372506	0.46628311
	E-business	0.111007268	
	E-commerce (enterprises with e-commerce sales)	0.092766335	
	Connection to the Internet (enterprises with internet access)	0.077118394	
	ICT security (security measure used)	0.121018607	
Digital skills	ICT users	0.080599667	0.21360239
	ICT specialists in employment	0.062194305	
	ICT training	0.070808420	

Based on the obtained results, it can be noted that the category ICT usage in the enterprises has the highest relative importance in assessing the achieved level of digital competitiveness. Regarding sub-criteria, the most important sub-criteria in assessing countries' digital competitiveness is related to ICT security and E-business. This means that the digital performance of the country is most significantly affected by the level of development of the ICT sector in enterprises. In contrast, the usage of ICT in households is not crucial. Also, the level of digital skills is less important than the importance of ICT usage in enterprises. Additionally, when looking at the sub-criteria within the criteria of ICT usage in enterprises, it can be noticed that the criteria related to the commercial use of ICT (such as e-commerce) are less important than the criteria related to non-commercial use of ICT (such as online security), which is following the results obtained by Milošević et al. (2018).

In the second part of the analysis, the TOPSIS method was applied to evaluate and rank countries based on their digital competitiveness. The results are shown in Table 2.

Tab. 2 – Country rankings according to the level of achieved digital competitiveness. Source: own research

Country	Digital competitiveness index	Rank	Country	Digital competitiveness index	Rank
Finland	0.762145886	1	Slovenia	0.484931879	16
Netherlands	0.740252087	2	Spain	0.479319590	17
Denmark	0.737697856	3	Estonia	0.476872351	18
Sweden	0.704007455	4	Portugal	0.449256463	19
Norway	0.696300532	5	Serbia	0.437748381	20
Belgium	0.664988713	6	Slovakia	0.392472813	21
United Kingdom	0.596010034	7	Cyprus	0.380482019	22
Ireland	0.576294361	8	Latvia	0.372013043	23
Austria	0.569541227	9	Croatia	0.358278487	24

Germany	0.565424996	10	Italy	0.357726914	25
Czech Republic	0.563265193	11	Poland	0.322461394	26
Luxembourg	0.539312451	12	Greece	0.318395071	27
France	0.525897882	13	Hungary	0.260716169	28
Malta	0.520077868	14	Bulgaria	0.167774072	29
Lithuania	0.487942569	15	Romania	0.105482473	30

The results indicate that Nordic countries achieve the highest values of digital competitiveness, while most of the Eastern European countries are at the bottom of the list. If the obtained results are compared with similar indices measuring the level of digital development, such as the Network Readiness Index (NRI, 2019), ICT Development Index (IDI, 2018), IMD World Digital Competitiveness Ranking (IMD, 2019), and Digital Economy and Society Index (DESI, 2019), similarities can be seen both in the countries at the top of the list and in the countries at the bottom of the list. According to DESI (2019), Finland, Sweden, Denmark and the Netherlands scored the highest. Similarly, the results of NRI (2019) indicate that eight European nations rank among the top ten countries in the world: Sweden (1), the Netherlands (3), Norway (4), Switzerland (5), Denmark (6), Finland (7), Germany (9), and the United Kingdom (10). In addition, Nordic countries, the Netherlands and Switzerland can be found among the highest-ranked countries in the IMD World Digital Competitiveness Ranking. The similarities in ranking indicate the validity of the proposed methodology.

The results of the correlation analysis indicate that the application of equal weights leads to moderate rank reversal (the value of Kendall's tau is 0.903). Therefore, whenever possible it is desirable to apply objective methods of weight determination. Regarding the sensitivity of the results, although there is a rank reversal, it is not intensely expressed, a finding which supports the robustness of the results.

To determine groups of countries with similar digital competitiveness and economic performances, a cluster analysis was performed, for which the first and the most important step is the selection of the variables. Besides the assessed digital competitiveness, three more variables were used in the analysis which reflects the economic performance of analysed countries (Table 3).

Tab. 3 – Variables for cluster analysis. Source: own research

Variable	Description	Source
Digital competitive-ness	Assessed value based on the data related to the digital economy and society using integrated CRITIC-TOPSIS method	Own research
Labour productivity	Output per worker (GDP constant 2011 inter-national $ in PPP)	ILOSTAT (2020)
Employment rate	Share of employed persons aged 20 to 64 in the total population of the same age group	Eurostat (2020b)

Median equalised net income	The median of the total income of all households after tax and other deductions that is available for spending or saving, divided by the number of household members converted into equivalised adults	Eurostat (2020c)

After selecting appropriate variables, a cluster analysis was applied and four distinct groups of countries were identified (Table 4).

Tab. 4 – Composition of clusters. Source: own research

Cluster 1	Cyprus, Czech Republic, Estonia, Latvia, Lithuania, Malta, Portugal, Slovakia, Slovenia, Spain
Cluster 2	Bulgaria, Greece, Croatia, Italy, Hungary, Poland, Romania, Serbia
Cluster 3	Denmark, Germany, Netherlands, Austria, Sweden, United Kingdom, Norway
Cluster 4	Belgium, Finland, France, Ireland, Luxembourg

Cluster 1 is the largest one, including one-third of the countries, while Cluster 4 is the smallest with five countries. The clusters obtained include a set of geographically heterogeneous countries. Cluster 1 has the highest diversity, consisting of countries primarily from Central and Southern Europe and Baltic countries. Cluster 2 encompasses Balkan countries and some of the Central European countries. Cluster 3 includes Northern and most Western European countries, while Cluster 4 includes Western and Northern European countries.

If the data are analysed by clusters, it can be noticed that high digital competitiveness is accompanied by better economic performance and vice versa (Table 5). Hence, there is a link between the level of digital competitiveness and a country's economic performance. The difference in the global competitiveness of countries and their economic performance largely depends on the availability, level of acceptance, and use of ICT (Mitrović, 2020). Regarding digital competitiveness and economic performance of the clusters, Cluster 2 has the lowest average value of digital competitiveness and also indicates the existence of considerable economic deprivation, signifying that a lower level of digital competitiveness is associated with lower economic performance. Regarding the countries in Cluster 1, they have higher average values of all variables than the countries in Cluster 2. Countries in the fourth cluster have a relatively high value of digital competitiveness and the highest values of GDP per capita and labour productivity. In contrast, countries in Cluster 3 have the highest values of digital competitiveness and the highest employment rates. Considering Clusters 3 and 4, it can be concluded that higher digital competitiveness is associated with better economic performance.

Tab. 5 – Mean value of variables within clusters. Source: own research

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Digital competitiveness	0.4607	0.2911	0.6585	0.6137
Labour productivity	69,711.00	61,755.75	98,138.29	129,323.60
Employment rate	76.01	69.21	79.37	72.86
Median equalized net income	11,600.00	7,130.00	27,094.00	26,793.00

5. CONCLUSION

The overall development of the information society should be directed towards harnessing the potential of ICTs to increase efficiency, economic growth, and higher employment to improve the quality of life of all citizens of the countries. Digital transformation is an opportunity for European countries to address a number of their structural economic, political and social challenges. In recent decades, the importance of digitalization has become the subject of numerous researches, as digitalization has changed the lives of groups and individuals in many ways. Nevertheless, when it comes to measuring digitalization and digital competitiveness of countries, no consensus has emerged regarding a composite indicator that would cover all aspects of digitalization.

This paper has proposed a multi-criteria approach to create a composite measure of digital competitiveness. Nordic countries were shown to achieve the highest degree of digital competitiveness, while countries in Eastern Europe lag behind. Furthermore, the results indicate that ICT usage in the enterprises has the highest relative importance with regard to the assessment of the achieved level of digital competitiveness, which indicates that the digital performance of a country is most significantly affected by the level of development of the ICT sector in enterprises. In contrast, the usage of ICT in households is not crucial. Also, the level of digital skills is less important than the importance of ICT usage in enterprises. Additionally, the criteria related to the commercial use of ICT (such as e-commerce) are less important than the criteria related to non-commercial use of ICT (such as online security).

Regarding the identification of groups with similar digital competitiveness and economic performances, four distinct geographically dispersed groups of countries were identified: countries primarily from Central and Southern Europe and Baltic countries, Balkan countries along with some Central European countries, Northern and most Western European countries, while the smallest fourth group includes one Western and one Northern European country. The results indicate that groups with a low average value of digital competitiveness also have lower economic performance, while economically advanced countries can be found in the groups of countries with high digital competitiveness.

These results contribute to existing research on how to measure the digital economy by offering an empirical example of assessing the digital competitiveness of European countries. Furthermore, the results may have implications for policymakers as well as serve as a guideline for making strategic decisions aimed at planning the digital future of the country.

Nevertheless, the proposed study has some limitations. Due to the unavailability of data, the research does not take into account the supply side of digitalization related to regulatory frameworks nor the countries' investments in ICTs. Future studies will be aimed at eliminating these shortcomings and including these variables, as they represent valuable indicators of digital competitiveness.

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