AKADÉMIAI KIADÓ

UNIVERSITY of DEBRECEN

International Review of Applied Sciences and Engineering

14 (2023) 3, 392–401

DOI:
10.1556/1848.2023.00612

ORIGINAL RESEARCH PAPER

Measurement of digital development with partial orders, Tiered DEA, and cluster analysis for the European Union

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Received: December 2, 2022 • Accepted: March 9, 2023
Published online: June 15, 2023

ABSTRACT

The digital economy is increasingly seen as an essential cornerstone in developing national strategies and industrial policies to enhance national competitiveness. On the other hand, a realistic assessment of digital readiness is essential for developing appropriate policies. In our paper, we group the countries of the European Union (EU) using three different methods applied to a dataset consisting of the four main dimensions of the EU's Digital Economy and Society Index (DESI) in order to identify Europe's main geographical "fault lines" in terms of digital readiness. DESI is a composite index aggregating several digitalization-related indicators to benchmark the progress of digital transformation in each member state. However, our methods aim not to rank countries but to identify groups of countries that are close to each other. The three methods used in the paper are partially ordered sets (poset), Tiered Data Envelopment Analysis (TDEA), and cluster analysis, known from multivariate statistics. The three types of clustering show a high degree of similarity, indicating the robustness of the results. Another research question relates to the extent to which the digital development of the EU Member States corresponds to the economic development of the countries and core–periphery relationships. While we can observe a high degree of similarity between the more and less developed clusters in terms of digital readiness and the groups that can be identified in terms of economic development and institutional quality, we also notice some peculiar exceptions (which could provide examples of best practices).

KEYWORDS

digital economy and society, index (DESI) overall index, partial orders, Hasse diagram, Tiered data envelopment analysis (TDEA), cluster analysis, European Union

1. INTRODUCTION

In recent years, digital transformation has arisen as an influential notion in information systems research related to the transformational changes in society and industry brought about by digital technologies, which has also attracted considerable interest in academia. Although this term can be easily applied to businesses and industries, it may also be considered at the country (i.e., macro) level. Digital readiness may also have considerable implications for macroeconomic stability and economic performance. If policymakers want to improve economic competitiveness effectively, they should design a solid digital transformation strategy and a sound industrial policy. However, an essential prerequisite for addressing their weaknesses and building on their strengths is to identify them in the first place, for which an adequate measurement system is crucial.

Several scoreboards, indicators, and indices have been developed to assess the state of digital transformation and its impact on societies and economies at the global, regional, national, and local (subnational) levels. In addition to general surveys describing the worldwide impact and status of digitalization, such as reports from international organizations like the UN, ITU, OECD, or World Bank, some prominent reports and indices focus on

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the development within a particular country cluster or region. A prime example of this is the European Commission's recently revised Digital Economy and Society Index (DESI), used by the European Commission to track the status of digital transformation in the EU and its member states [1].

DESI is well-known among experts and policymakers, with many advantages and serious shortcomings. Its main advantage is that it is measured in all 27 EU countries, which allows for comparisons and gives a comprehensive picture of the digital ecosystem in the EU and its Member States. On the other hand, the fact that the indicators are collected in many countries means that the methodology had to be generic and relatively simple, so the results are unsuitable for in-depth analysis and explanation of local phenomena. Furthermore, data collection and publication time can be very long, often resulting in outdated assessments. Sub-dimensions and indicators change from year to year, which makes it difficult to compare the performance of time series as these corrections and revisions are not sufficiently highlighted.

Nevertheless, it is becoming increasingly important as a monitoring tool and publicly available research database, spurring a flurry of recent activity (2021–22) in several research fields and has been the subject of numerous articles that seek to analyze the links between digitization and various micro- or macro-level indicators. While a positive relationship between digitalization and sustainability [2] and between digitalization and entrepreneurship [3] is clearly established, the impact of economic development [4] on digital readiness appears to be less clear (although a positive link is supported by tentative empirical evidence). Other authors have developed their own digital indicators and rankings on the basis of the DESI database [5] or investigated some of the main dimensions in more detail [6, 7].

In our paper, we group the countries of the EU based on the data of the four principal dimensions of the DESI, which are Connectivity, Human Capital, Integration of Digital Technology, and Digital Public Services (see Table A1 in Appendix), in order to identify Europe's main geographical "fault lines" in terms of digital readiness. These main dimensions (which are regarded as equally important and therefore carry equal weights [25%]) consist of 1–4 sub-dimensions, each comprising several digitalization-related indicators (the majority of which are sourced from Eurostat).

One of our main research questions relates to the extent to which the digital development of the EU Member States corresponds to the economic development of the countries and to the level of economic governance. In other words, to what extent can a peripheral or semi-peripheral country overcome its historical and economic disadvantages through digitalization, and to what extent can we see the emergence of new digital divides or gaps that are characteristic of development differences elsewhere?

Although the issue of convergence and the importance of economic development (as a contributing factor) have already been examined in recent literature [4, 6], our intended contribution is not directly related to this but to the identification of homogeneous country groups in terms of digital development. We also want to explore the differences between groups of countries identified by digital development and core–periphery status in order to identify countries that may be overperforming in digital transformation relative to their socio-economic status (and could provide examples of best practices).

Section 2 of our paper briefly discusses the literature on DESI and our main methodological tools (partially ordered set (poset) and TDEA). Then in the following section (3), we introduce the poset, TDEA, and cluster analysis models used for evaluating the countries in our dataset and the main results, which are then compared to our hypotheses in section 4. Finally, our conclusions are discussed in section 5.

2. LITERATURE REVIEW

The literature review is divided into four parts. The first subsection examines the measurability of the digital economy. As the European Union's DESI is used in the analysis, we review the literature discussing this particular set of indicators and some related indices. We then provide a brief overview of selected papers discussing core–periphery relations in the European Union. The third subsection briefly reviews the application of partially ordered sets in socio-economic systems, and the final subsection discusses DEA peeling based on previous applications. As the latter two methods have been used less frequently, the available literature is limited.

2.1. Measurement of the digital economy

The body of literature dedicated to the measurement and effects of digital transformation is quite diverse, and this paper only attempts to provide a short, non-exhaustive summary of a few articles on the DESI and some related indices.

Bánhidi et al. examine the five principal dimensions of the DESI (the current four and the now-defunct Internet use dimension) by employing multivariate statistical methods [8]. They first examine linear and possible causal relationships between the five dimensions with simple Pearson's analysis, partial correlation analysis, and factor analysis. They then group EU member states using cluster analysis and multidimensional scaling (MDS) and rank them using multivariate statistical methods. Their results support the thesis of the European Commission that the five principal dimensions of the DESI are interrelated but also suggest that at least one of them may be statistically redundant.

In another paper, Bánhidi et al. and Tokmergenova et al. evaluate the robustness of rankings derived from the I-DESI dataset (an extension of the DESI dataset to include non-EU countries) [9, 10]. For this purpose, they use the basic DEA and DEA/CWA methods and a one-dimensional version of multidimensional scaling (MDS), which they believe to be suitable for ranking decision-making units (DMUs, in this case, countries). Their findings indicate that these methods provide a solution comparable to the European

Commission's scoring model. However, the ranking of certain countries shows more significant variation depending on the chosen method.

Moroz reviews some major (international) indices measuring and comparing countries' levels of digital readiness and analyzes Poland's status and the progress of its digital transformation based on the DESI and the World Economic Forum's NRI (Networked Readiness Index) [11]. According to his findings, the position of Poland is somewhat unfavorable, showing a limited degree of development, a lack of digital readiness, and a slow rate of convergence.

Kotarba looks at some composite indices of digital readiness, including the DESI [12]. The author points out that digital maturity may be assessed at the level of customers, firms, sectors (industries), or the entire economy and society. Furthermore, the similarities and differences between the indicator systems are examined, and ways to improve them are suggested.

Laitsou et al. also apply the DESI and its (pre-2021) principal dimensions to assess the digital readiness of Greece, and forecast, using the Gompertz model, how the Hellenic Republic can catch up with the top EU countries regarding its digital readiness [13]. According to their results, despite the challenges the country is facing on the demand and supply side of digitalization, Greece should be able to catch up with the EU average by 2030 with the right policies.

According to Damiani and Rodríguez-Modroño, the participation of women in today's digital society is an essential part of the 2030 Agenda and a critical element of the EU's digital transformation strategy [14]. They apply a poset-based framework to the European Women in Digital (WiD) Scoreboard to investigate women's digital inclusion in Europe. Their methodology helps them identify the most relevant factors for every dimension of the WiD, taking into account the EU-28 as a whole as well as different country clusters, and establish a new assessment that overcomes the drawbacks of aggregation and data preprocessing.

Kovács et al. examine the issue of β- and σ-convergence using time series data from the DESI database [4, 6]. Their results confirm the existence of convergence for the DESI index but not for all the principal dimensions that make up the index. The authors identify the human capital dimension as a crucial factor for digital development and suggest that it could deserve more weight than the 25% defined by the Commission.

2.2. Core–periphery relationships in the European Union

Perhaps the best-known proponent of world-systems theory is Immanuel Wallerstein, who divided the world's countries into three major groups, the core (center), the semi-periphery, and the periphery, based on their role in the international division of labor (trade and investment relations) [15, 16]. High-quality factors of production, high wages, advanced technology, and high-quality products and services typically characterize core countries. On the other hand, countries belonging to the periphery generally are resource-exporting, poor and underdeveloped, while the semi-periphery has mixed characteristics.

It should also be noted here that, particularly in the context of cohesion policy, the core–periphery distinction is applied by some authors to NUTS-2 or -3 regions within European countries. In the case of Italy, for example, this may result in some regions (Lombardy) being part of the core while others (Calabria) part of the periphery [17]. In this paper, however, we have chosen to abstract from these differences within countries, as the data on the DESI dimensions are currently only available at the national level.

While there is no clear consensus on which countries belong to the core or periphery (semi-periphery), the Member States that joined the European Union after 2004 tend to be classified into the latter. At the same time, the categorization of the southern member states is often inconsistent and somewhat controversial [18, 19].

Farkas notes that the accession to the European Union itself appears to have given an impetus to the development of governance quality in the Central and Eastern European countries but also adds that a "substantial gap" remained between these and the pre-2004 core [20].

2.3. Applications of partially ordered sets in socioeconomic systems

There are two major types of ordering: partial and total. Ordering theory is a branch of mathematics that defines a binary relation between elements of a given set. In the case of total ordering, there is a relation between each element in the set; that is, it can be decided which of the two elements can be considered preferred over the other. When there is also a case where we cannot set a clear preference between the two elements in a given set, i.e., the elements of the set are incomparable, we can talk about partial ordering. In economics, total ordering is called ranking. A clear order can then be established between the elements.

In contrast, partial ordering instead sets up groups among the elements of a set to which preference can be interpreted. In economics, partial ordering is found in microeconomic consumer theory when we compare consumer baskets. The theory of partial ordering can also be applied to socioeconomic systems.

In their paper, Fattore and Maggino applied the partially ordering (poset) theory to the theory of sociological poverty and social inequality [21]. The main goal of their work is to find applications that are useful for poset practice in socioeconomic statistics and social indicators construction. The first problem is that evaluating multidimensional poverty and its multidimensional comparison leads to a ranking problem that we cannot clearly define. This is one of the most relevant examples in socioeconomic analysis.

Annoni et al. and Beycanand and Suter continued to apply poset theory in mapping multicriteria sociological poverty theory, mainly focusing on its regional aspect within Switzerland [22, 23].

Fattore and Arcagni give an overview of the Hasse-diagram technique and poset theory [24]. They list eight areas of application where poset theory has already been used, including (among others)

- Refugees' relocation in the EU,
- Temporal analysis of the Fragile/Failed State Index,
- European opinions on services,
- Comparison of fiscal policies.

The latter field of application, i.e., economic application, differs from other, mainly sociological, applications [25, 26]. The application of poset theory can extend to a wide range of social sciences.

After a brief review of the social sciences application of poset theory, we review the application of the Tiered Data Envelopment Analysis technique.

2.4. Applications of Tiered Data Envelopment Analysis in socioeconomic systems

The Data Envelopment Analysis method may be suitable for ranking DMUs. However, several assumptions must be made for this. A handful of review articles can be found in the literature on applying DEA for ranking. Recent reviews were given by Emrouznejad and Yang, Mahmoudi et al., and Labijak-Kowalska and Kadziński [27], [28], [29]. However, these methods give the total ranking. The basic DEA model virtually breaks down DMUs into two sets: efficient and non-efficient. Inefficient DMUs can be ranked in order based on their efficiency index, but efficient ones cannot. In this context, the question arises as to whether a ranking should be established or whether it is sufficient to divide DMUs into groups of nearly equal efficiency. This grouping is described by Barr et al., who proposed to examine it in DEA models [30]. A sequential algorithm has been developed in which efficient DMUs, like the onion peel, are separated from other DMUs. We then redefine the effective units on the residue and "peel the onion." We do all this until we run out of units. DMUs are then grouped according to efficiency. The methods developed by Barr et al. are relatively widely used in the social sciences, especially in management.

Port logistics proved to be the most fruitful application. The first published application was by Cheon [31]. In its application, it analyzed the efficiency of South Korean ports with this technique. The efficiency of South Korean and Russian ports was compared by Den et al. with this model [32].

Another area of application is related to higher education. Bougnol and Dulá examined 616 American universities according to their effectiveness using Tiered DEA [33]. They concluded that this method gave the same result as the measurement method used by the government administration. Among the most recent applications is the work of Johnes, who examined British universities on university lists using this method. In both articles, grouping rather than ranking dominated [34].

Finally, we mention an article on financial risk. Yemshanov et al. applied the Tiered DEA method to multicriteria risk problems [35]. The goal of this paper was to create risk maps. Onion peels can include investments with different risks.

3. RESEARCH QUESTIONS AND HYPOTHESES

For the research questions, three grouping methods were used to cluster the countries of the European Union (EU). Two of the three methods, namely the partially ordered set theory (poset) and the Tiered DEA (TDEA) method, map the sets to an ordinal scale where it is possible to determine which countries are considered to be the best performers. This feature cannot be said of cluster analysis, which groups the objects, in our case, EU countries, into groups based on distance metrics in digital development. The methods used also define the objectives of the research. The following research questions can be asked.

Research Question 1:
Using each method, how many groups can EU countries be divided into?

This question only asks how many groups will be identified but does not answer whether there is any preference between the groups. This problem is addressed in the following research question.

Research question 2:
What is the ordering of country groups in the Hasse diagram and the onion peeling (TDEA) method?

The cluster analysis does not allow for ordering the resulting groups; therefore, this method is not addressed in the research question. In our last, fourth research question, we aim to determine whether digital development is related to the historical economic development of each country.

Research question 3:
What is the stochastic relationship between the groupings obtained by the three methods?

The question seeks to answer whether the groupings obtained by the three methods are substantially different from each other, which also draws attention to the difference or differences in the ordering.

Research question 4:
To what extent does the digital development of the EU Member States correspond to the economic development of the countries, the level of economic governance, and the core–periphery relationships?

As we shall see, a Wallersteinian core-periphery relationship can be observed across groups of EU countries as the countries in the core are also (typically) more digitally advanced. However, we can identify some peculiar exceptions ("rich" laggards and "poor" digital champions).

After formulating the research questions, the groupings are made using the methods indicated.

3.1. Partial orders and dominance relation for DESI dimensions

In order theory, a partially ordered set (or poset) models the idea of ordering, sequencing, or arranging a set of DMUs. A poset is defined as a set of DMUs and a binary order relation that breaks up the set into two types of subsets: a subset (or subsets) in which for each pair of DMUs one DMU from the pair proceeds another and a subset in which the DMUs do not relate to each other. This means that not every pair of DMUs in the poset needs another DMU that satisfies the order relation. Some pairs do not comply with the relation, as neither DMU from those pairs precedes the other: they are just incomparable. Thus, the partial order concept is a generalization of the more familiar total order in which every pair is related [36].

A case of the genealogical descent of a specific population is commonly used as an example of a poset. Some sample pairs bear the ancestor–descendant relationship, but others bear no such relationship.

A finite poset can be presented through its Hasse diagram, which shows the ordering relation between certain DMUs and allows reconstructing the partial order structure. An example of a real-life ranking task assembled with the help of the partial order approach is an exemplary case of a practical application of this kind [37].

Let Q be a set of any objects, such as a collection of DMUs. For elements a and b from the set Q, if $a \leq b$ or $b \leq a$, then a and b are comparable objects. Otherwise, they are incomparable.

If elements a, b, and c belong to Q, the following properties are satisfied:

$$a\ R\ a\ (\textit{reflexivity});$$

$$\text{if } a\ R\ b \text{ and } b\ R\ a, \text{then } a = b\ (\textit{antisymmetry});$$

$$\text{if } a\ R\ b \text{ and } b\ R\ c, \text{then } a\ R = c\ (\textit{transitivity}).$$

The three properties above determine an ordering relation between the elements. The relation is written as an R relation. One can see that the related elements (i.e., the elements satisfying R) must be comparable.

The relation R is hereinafter defined as the Pareto dominance. In microeconomics, production theory uses this relation to determine the effective surface of the production set, that is, to describe the production function. Posets with a finite number of objects can be described by the Hasse matrix and visualized by its Hasse diagram [38].

The Hasse diagram is shown in Fig. 1. The maximal elements are Denmark, Finland, Sweden, Netherlands, and Estonia, on level six. These countries are not dominated by other countries, i.e., they can be understood as the best ones. The minimal elements of this graph are Greece and Bulgaria on the first level (this means that these countries do not dominate other countries). Other minimal elements countries are at different levels. Slovakia and Poland lie on the second level. Croatia, Hungary, and Romania are on the third level.

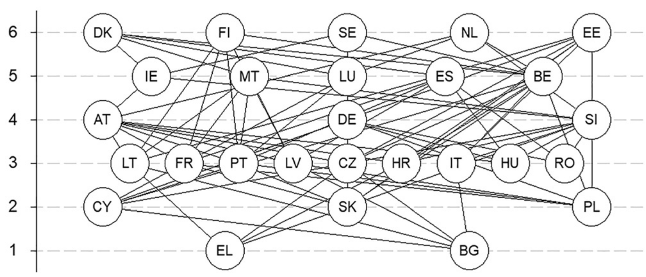

Fig. 1. The Hasse diagram of the DESI data
Source: Authors' own compilation based on data from the DESI report [1]

3.2. Using peeling technique for DESI dimensions

The Data Envelopment Analysis (DEA) method was first published and used by Charnes et al. [39]. Over the last nearly fifty years, this method has had several theoretical extensions and practical applications [40].

The method applied in this paper is an application of basic DEA. In the DEA, the criteria that evaluate DMUs can be divided into two groups considered inputs or outputs. The basic DEA CCR-I (1)–(3) model can be modeled in the following form, where vectors (u, v) are the weights vectors of DEA, and vectors (y_k, x_k) $(k = 1, 2, \ldots, n)$ are the output and input values of the kth DMU, and the sum of DMUs is n:

$$\frac{u \cdot y_1}{v \cdot x_1} \rightarrow \max \tag{1}$$

s.t.

$$\frac{u \cdot y_k}{v \cdot x_k} \leq 1; \ \ k = 1, 2, \ldots, n. \tag{2}$$

$$(u, \mathrm{v}) \geq (0, 0). \tag{3}$$

However, the model in its original form cannot be used to rank DMUs. There are no input criteria among quantitative indicators in the model used. In this model, the model (1)–(3) can be rewritten as follows, assuming no input or assuming a single input, i.e., $v \cdot x_1 = 1$.

$$u \cdot y_1 \rightarrow \max \tag{1'}$$

s.t.

$$u \cdot y_k \leq 1; \ \ k = 1, 2, \ldots, n. \tag{2'}$$

$$u \geq 0. \tag{3'}$$

The latter model is referred to in the literature as the DEA/Composite Indicator (DEA/CI) method [41, 42]. The new model (1')–(3') has to be solved for each DMU – in our case, countries – to calculate the efficiency indicators. We find the weight vector u and the vector y_j representing the digital dimensions of the jth country.

Onion peeling is a well-known method to determine which DMUs (countries) can be at which efficiency level [43]. This method is very similar to the Hasse diagram technique, but it necessarily looks for Pareto-optimal DMUs [44].

The peeling technique is a sequential method. We first analyze all countries and look for which are efficient, i.e., which countries have maximal Data Envelopment Analysis (DEA) efficiency with an efficiency level of one. We then omit these countries with maximum efficiencies and calculate a new efficiency test on the remaining countries. The DEA efficiency analysis is performed until there are no more DMUs left.

The peeling is done through the digital dimensions of EU countries, using the four main dimensions of the DESI dataset [1]. Seven onion peelings were developed using the Tiered DEA technique. These are presented in Table 1.

The analysis of Table 1 revealed that Denmark, Finland, and Estonia belong to the highest out of seven onion peels. Poland, Greece, and Bulgaria lie on the lowest level. The largest economies in the European Union, such as France, Germany, and Italy, are in the third and fourth onion levels.

3.3. Clustering countries with multivariate method cluster analysis

The multivariate statistics method Cluster Analysis allows us to group objects, in this case, the 27 countries of the EU, into clusters based on the four dimensions of the DESI. The method used for cluster analysis was the classical hierarchical cluster analysis method. The clustering procedure was the between-groups linkage method, while the traditional Euclidean distance was chosen as the distance function. No transformation was performed on the data because the data of the dimensions are of roughly the same order of magnitude.

The results of the cluster analysis are summarized in Fig. 2. The figure also presents how each cluster was formed. In the first step, the countries were divided into two clusters, one consisting of only Romania. In the second step, the group of countries was divided into three clusters. In the sixth cluster, the countries at the forefront of the digital economy were Denmark, Finland, Sweden, the Netherlands, Estonia, Malta, Ireland, Luxembourg, Spain, and Austria. In the third step, Hungary, Cyprus, Slovakia, Poland, Greece, and Bulgaria were selected from the second group. Furthermore, in the fourth step, a group of Denmark, Finland, Sweden, and the Netherlands was separated from the best-performing countries. Finally, a third cluster was created in the fifth and final step, comprising Latvia. The largest economies in the European Union, such as Germany, France, and Italy, are included in the fourth cluster. The clusters are listed in Table 2.

Table 1. DEA peels of EU countries with DEA without explicit input

Peels (number of countries)	Countries
Peel 7 (3 countries)	Denmark, Finland, Estonia
Peel 6 (3 countries)	Sweden, Netherlands, Malta
Peel 5 (4 countries)	Ireland, Luxembourg, Spain, Belgium
Peel 4 (3 countries)	Austria, Germany, Slovenia
Peel 3 (9 countries)	Lithuania, France, Portugal, Latvia, Czechia, Croatia, Italy, Hungary, Romania
Peel 2 (2 countries)	Cyprus, Slovakia
Peel 1 (3 countries)	Poland, Greece, Bulgaria

Source: Authors' own compilation based on data from the DESI report [1].

3.4. Comparison of the poset levels, Tiered DEA layers, clusters, and I-DESI ranking

We first compare the solution obtained with the poset and the TDEA methods. It can be seen in Table 3 that the levels of the two groupings are in the correct order, and therefore their correlation is positive. The Pearson correlation is 0.981, showing a strong linear relationship. The same can be said between the poset and the cluster sets, which have a correlation of 0.860 and can also be considered strong. Finally, comparing the result obtained from the TDEA and cluster analysis gives the lowest but reasonably strong relationship with a value of 0.846. All of the correlation coefficients are significant at the 0.01 two-tailed level. In conclusion, the results obtained with the three methods are very similar (see Table 3).

Our results also suggest that the richer "core" countries that joined the EU before 2004 tend to outperform the Eastern European "periphery" in digital readiness. However, there are some notable exceptions to this rule. For example, the small Baltic country of Estonia is often grouped with the top performers, while some of Europe's largest economies (e.g., Germany, France, and Italy) are in the middle of the pack.

The case of Estonia is an excellent example of a country that, despite its initial peripheral position and modest economic potential, has become a digital champion and can serve as an example of best practice, particularly in the dimension of digital public services. The Estonian government has had a clear ambition to become a "digital nation" and has pursued a coherent and well-thought-out strategy to achieve this, which has delivered the expected results [45], [46], [47]. Arguably, Slovenia could also be identified as a country that has overperformed in digital readiness relative to its socio-economic status, albeit to a lesser extent.

4. RESULTS OF INVESTIGATIONS AND ANSWERS TO THE RESEARCH QUESTIONS

The four research questions are answered in the order in which they are asked, but the questions are not repeated.

As for the first question, we wanted to determine the number of groups. The poset method identified six groups, and the TDEA method seven groups in the EU countries. The higher group number also provided a development ranking. In the case of cluster analysis, the number of groups is given exogenously by the modeler. The six clusters we have identified are based on the first two methods, taking into account the dendrogram that can be determined from the data.

As regards the second question, we only included the first two methods because they can be used to rank the clusters. The number of groups also represents a level of development.

The answer to the third research question is that there is a solid stochastic relationship between the three clustering groups, measured by Pearson's correlation. This result suggests that one method is sufficient for a future application of

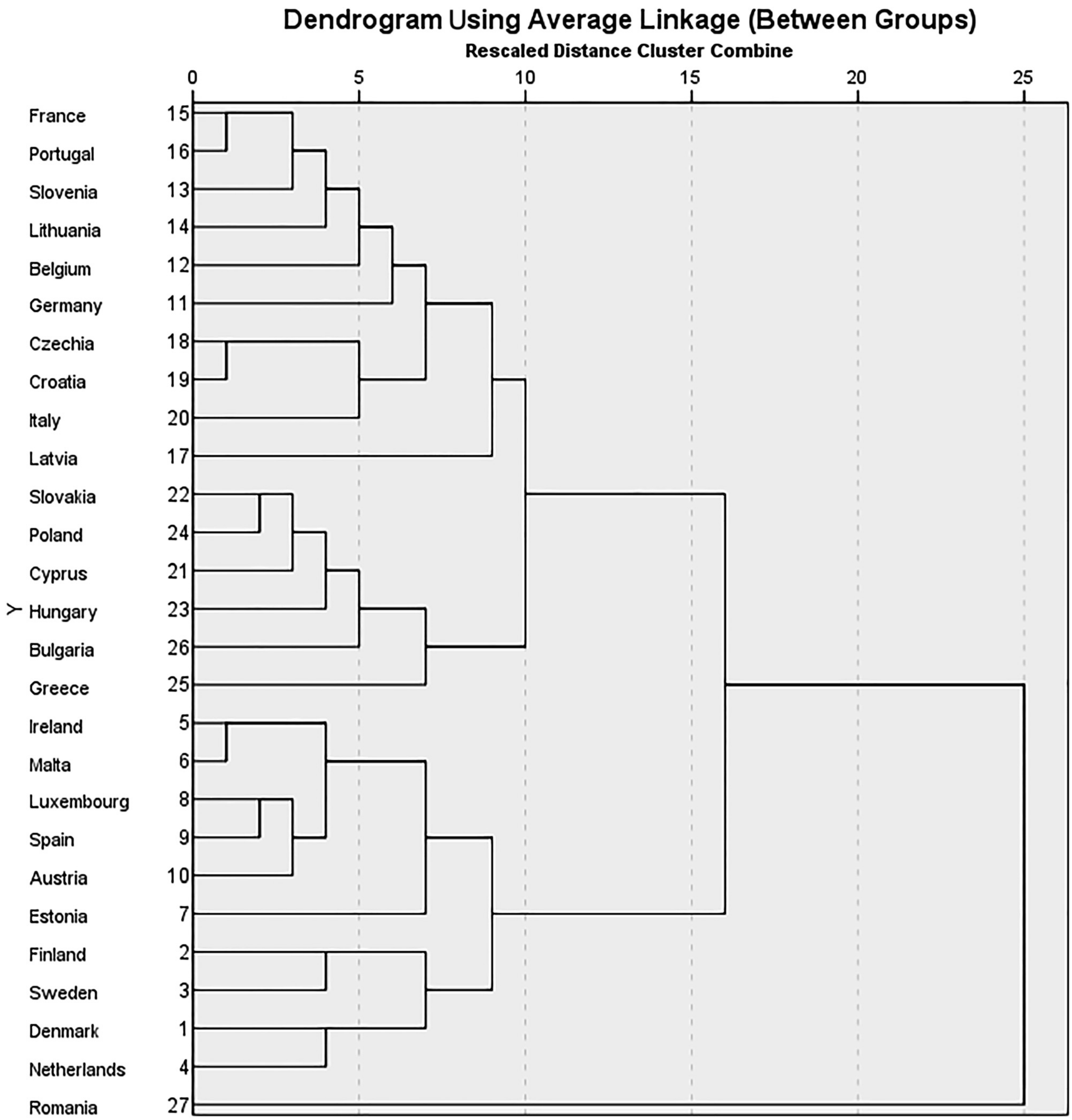

Fig. 2. Dendrogram of cluster analysis
Source: Authors' own compilation based on data from the DESI report [1]

Table 2. Grouping of countries with cluster analysis

Clusters	Countries
6	Denmark, Finland, Sweden, Netherlands
5	Estonia, Malta, Ireland, Luxembourg, Spain, Austria
4	Belgium, Germany, Slovenia, Lithuania, France, Portugal, Czechia, Croatia, Italy
3	Latvia
2	Hungary, Cyprus, Slovakia, Poland, Greece, Bulgaria
1	Romania

Source: Authors' own compilation based on data from the DESI report [1].

the three methods. Even if the ordering between the clusters is essential, it is sufficient to use one of the two methods for analysis.

The result of the last, fourth question is that the groups of countries that are digitally more advanced are those that belong to the core countries in the Wallersteinian sense. In contrast, the periphery countries are digitally less advanced. However, there are some notable exceptions: even though Estonia is usually not classified as a core country, it is consistently ranked within the most or second most developed country group (cluster) and could provide examples of best practices, especially in the Digital Public Services dimension.

Table 3. Onion peels of the countries with DEA composite indicators

Country	6 Levels (Poset)	7 Peels (TDEA)	6 Clusters (Cluster analysis)	Prior core–periphery classification
Denmark	6	7	6	Core
Finland	6	7	6	Core
Estonia	6	7	5	Periphery
Sweden	6	6	6	Core
Netherlands	6	6	6	Core
Malta	5	6	5	N/A
Ireland	5	5	5	Core
Luxembourg	5	5	5	Core
Spain	5	5	5	Core
Belgium	5	5	4	Core
Austria	4	4	5	Core
Germany	4	4	4	Core
Slovenia	4	4	4	Periphery
France	3	3	4	Core
Italy	3	3	4	Core
Portugal	3	3	4	Core
Czechia	3	3	4	Periphery
Croatia	3	3	4	Periphery
Lithuania	3	3	4	Periphery
Latvia	3	3	3	Periphery
Hungary	3	3	2	Periphery
Romania	3	3	1	Periphery
Cyprus	2	2	2	N/A
Slovakia	2	2	2	Periphery
Poland	2	1	2	Periphery
Greece	1	1	2	Periphery
Bulgaria	1	1	2	Periphery

Source: Authors' own compilation based on data from the DESI report [1], the core–periphery classification of countries is based on Chase-Dunn, Kawano, and Brewer [48].

5. CONCLUSION

The main objective of this study was to identify groups (clusters) of countries that are homogeneous in terms of their digital readiness and investigate the possible dividing lines between the more and less advanced countries. The results of the investigations are the following: The Nordic countries, notably Denmark and Finland, are in the best group or tier according to all methods (joined by the Netherlands, Sweden, and Estonia in all but one), while the South-Eastern EU countries, Bulgaria and Greece are generally in the bottom cluster (with Cyprus amongst the fellow laggards).

On the other hand, although Southern and Eastern countries are usually closer to the bottom ranks, there are no clear geographical dividing lines. Estonia is the most obvious counterexample to the mistaken presupposition that the richer Western Member States (the core) would outshine the former Eastern bloc countries (the periphery). Estonia's peculiar position is related primarily to its top-performer status in the digitalization of its administration. However, the country also outperforms the EU average in the Integration of Digital Technology and Human Capital dimensions. On the other hand, the two largest economies, Germany and France, occupy a middling rank among the EU countries in digital performance and are often grouped with some of the more advanced Central and Eastern European countries, such as Slovenia, Lithuania, and Czechia. Comparing the results of the three methods (poset, TDEA, and cluster analysis) suggests that the "pecking order" of countries is reasonably stable, and the pairwise correlation coefficients also indicate a strong association.

Our study has limitations that require future research. One of the main limitations is that the analysis is based only on the main dimensions of the 2021 edition of DESI. A more detailed picture could be obtained using the DESI's sub-dimensions or individual indicators (instead of the principal dimensions). Moreover, the analysis could be extended to include the 2022 edition and data from previous years. Future research could also answer how these persistent digital gaps could be overcome by adjusting or redesigning digital policy programs and financial instruments.

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Appendix

Table A1. The basic data (x_i)

Country	Code	Human capital	Connectivity	Integration of digital technology	Digital public services
Denmark	DK	61.20	74.04	57.93	87.09
Finland	FI	71.11	51.27	59.49	86.72
Sweden	SE	64.56	59.57	56.34	83.95
Netherlands	NL	61.55	68.44	50.70	79.90
Ireland	IE	54.07	56.41	48.02	82.61
Malta	MT	49.09	54.11	50.84	84.19
Estonia	EE	57.92	46.56	41.46	91.76
Luxembourg	LU	56.18	60.97	39.42	79.36
Spain	ES	48.33	62.03	38.75	80.68
Austria	AT	53.35	52.99	41.30	79.83
Germany	DE	55.24	58.00	35.55	67.47
Belgium	BE	50.78	48.40	49.77	65.83
Slovenia	SI	47.80	53.19	42.32	67.99
Lithuania	LT	46.14	41.71	41.21	78.05
France	FR	47.36	47.41	34.77	72.99
Portugal	PT	45.57	48.52	36.57	68.95
Latvia	LV	41.11	50.38	26.80	79.63
Czechia	CZ	47.15	44.64	39.07	58.59
Croatia	HR	46.72	45.41	39.97	51.97
Italy	IT	35.12	42.35	41.45	63.19
Cyprus	CY	39.67	41.82	30.54	61.82
Slovakia	SK	43.75	46.25	29.09	53.72
Hungary	HU	40.48	52.00	23.30	49.16
Poland	PL	37.70	45.32	25.88	55.10
Greece	EL	41.04	37.73	28.53	41.94
Bulgaria	BG	32.70	38.10	20.48	56.05
Romania	RO	33.05	53.17	23.76	21.49

Source: Authors' own compilation based on data from the DESI report [1].