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Quantifying the Digital Divide: A Data-Driven Approach with EFA, Shannon Entropy and Sensitivity Testing

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Abstract. In the digital world, inequalities in digital participation often arise as a consequence of the uneven distribution of digital resources. Therefore, the objective of this study is to develop a digital divide index (DDI) that facilitates the temporal and spatial examination of disparities in the availability and quality of internet access, internet use and outcomes. Empirical data for 27 European countries were collected from online available datasets for 2014 and 2022. Exploratory factor analysis (EFA) was used to identify factors in DDI, while the weight values were calculated using the Shannon entropy method. The average difference in DDI scores indicates a spread of the digital divide facilitated by Finland, Latvia, Estonia, Germany, Poland and Slovakia. States in Northern and Central Europe like Norway, Austria and the Czech Republic are at the forefront of achieving digital equality. Spatial analysis reveals that Benelux countries along with Scandinavian countries show the highest levels of DDI, while Southern Europe lags behind. Sensitivity testing results show a stable index structure with variations in the importance of factors not significantly affecting the ranking results.

Keywords: digital divide index, exploratory factor analysis, Shannon entropy, sensitivity testing, spatial analysis.

1. Introduction

The advancement of digital technologies (DT) can be seen as a process that inevitably contributes to the creation and deepening of the digital divide and digital inequalities. Despite the widespread recognition of the transformative potential of the leading technologies of the Fourth Industrial Revolution such as artificial intelligence (AI), big data, the Internet of

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Things (IoT), blockchain, ubiquitous computing (UC) and robotics, their uneven application and availability across regions and populations exacerbate differences [56], [3], [14]. Big data analytics and AI stand out as major forces of this technological progression. This has led to significant differences in how businesses and economies take advantage of DT in terms that some regions are making fast progress while others lag behind [14], [47]. The cause-and-effect correlations of DT usage underpin the theory of resources and appropriation [65] and offer an explanation for the growth of the digital divide. Social inequalities among individuals result in a discriminatory distribution of resources, which limits access and the possibility of using digital technologies for certain social groups. This culminates in a broadening of the digital divide within the entire society, leading to adverse effects for the affected individuals [28]. When the digital divide arises as a result of flaws in society, economy or education, it is called digital exclusion [28]. As digital technologies continue to drive economic development this dual effect of progress and exclusion is expected to continue, shaping patterns of digital inequalities well into the future, with projections extending to 2050 [55], [37]. This problem is of particular importance for common free market initiatives, such as the European Union (EU) market, which has a key interest for member countries to achieve a uniform level of digital development in order to improve their competitiveness in all sectors, especially in the information and communication technologies (ICT) sector [4].

The concept of the "digital divide", often known as the "digital gap", is closely linked to the possibility of accessing and utilizing information and communication technology in one country or between countries [25]. The emergence of a digital divide within the state hinders the ability of individuals to actively engage in social processes and access information that is important in an information age [64]. The term has been discussed in academic literature since the late 1990s when the use of the internet marked the beginning of the rapid digitalization phase and the concept was further developed by a scientist Jan van Dijk [66]. van Dijk referred to an important emerging challenge in investigating the digital divide. In a review study [63] argued that the pick of interest on the topic of the digital divide occurred from 2000 to 2004, while in 2005 scientists came to the conclusion that the digital divide is no longer a rising issue because the majority of developed countries have already established a large scale of DT access. van Dijk observed that simple expansion of DT access is not a solution for such a challenge. The problem goes deeper and it integrates motivational access, material access, skills access and usage access. Prior literature has explored various approaches to tackle this issue [14]. The wide range of discoveries has led to the adoption of a classification system known as the three-level digital divide or three-order digital gap. The three levels of the digital divide are technology access and coverage (first order), technology usage and skills (second order) and technology outcomes (third level) [55]. By 2002 research studies focused on the first-order digital divide [36]. These studies were concentrated towards gaining access to computers and the internet. As a significant share of the population acquired access to DT scholarly attention shifted towards the second-order digital divide. At this stage users experienced challenges in lacking the skills to engage with DT. By 2005 the third-order digital divide become evident as a consequence of gaps in DT practical outcomes [36].

Prior research on measuring the digital divide has used a variety of approaches, such as composite indices, multivariate analyses and geographic information system (GIS) tools. However, these studies have several key shortcomings. One of the main problems is the lack of a universal measurement system, which makes it difficult to compare results [41], [52]. Authors [7] point to the limitation of available data, the dominance of quantitative or qualitative approaches and the neglect of spatial factors when analyzing differences in the speed of digital development. Many studies fail to integrate all three dimensions of the digital divide-access, use and outcomes-into a single index, or use metrics that are not strictly related to ICT, which can lead to conclusions concerning wider social inequalities [30]. For example [19] developed an index that captures access to technologies and economic factors but does not take technological outcomes into account. Authors [61] attempt to cover all three levels but use different indicators such as internet usage and mobile phone ownership. Authors [44] created an index based on Internet progress and digital financial inclusion, but without a clear definition of the factors. Other studies [34] based the index exclusively on Internet indicators, neglecting cutting-edge Internet technologies and limiting the age demographics of the respondents. In this regard [25] emphasizes that the availability of inexpensive, high-speed Internet networks can facilitate the spread of ICT and indicates the need for clearly defined indices that correlate levels of access, use and results. Despite existing indices offering significant insights, methodological uncertainties point to the need for standardized and dynamic approaches in measuring the digital divide.

Organizations such as the International Telecommunication Union (IDI index), the Portulance Institute (NRI index), the European Commission (DESI index) and the World Bank (e-government index) have developed measurement instruments to monitor the progress in digitalization [6]. These indices have a complex structure with numerous indicators, offering a broad view of the digital divide but often being impractical for analysis [24]. Studies point out a common problem of these indices, which is the double counting of the same or analogous indicators, and proposes a modified IDI index with only four indicators [24]. Authors [6] utilize the principal component approach (PCA) to reduce the dimensionality of the DESI index from 37 to 15 indicators, hence removing redundant indicators.

One of the main shortcomings of existing indices, such as DESI and NRI, is that their factor weights remain static, instead of being dynamically adjusted [12], [48]. Authors [60] state that in the NRI reports from 2013 to 2016, the weights of the pillars and indicators were uniform, failing to account for the dynamic nature of digitalization, which can lead to a distorted picture of the digital divide. Also the Australian Index of Digital Inclusion (ADII) uses three pillars (access, affordability and digital capabilities) with equal weights, which can lead to neglecting variation in the data [39]. References [19] and [36] point to the problem of equal weighting as variations in the data may go undetected. While reference [61] propose the application of PCA for data analysis, factor formation, and weight assignment, which enables accurate weight assignment. Authors [35] use exploratory factor analysis to identify factors and assign factor weighting values, which enables a more precise determination of the relationship between indicators. While on the other hand [44] form an index of digital division without determining the factors; they assign weights to the indicators only through the entropy method. This approach jeopardizes valuable information about hidden relationships and high correlations between indicators which can lead to redundancy in the model and reduction in measurement efficiency. Some authors criticize the entropy method for its shortcomings in dealing with instant large or minor fluctuations in data and the limitation in analyzing interrelationships among indicators [18].

The digital divide is based on various factors that shape the speed and extent of digitalization, including demographic, social, cultural, economic and personal aspects all of which affect digital inequality in society [55], [64], [67]. Moreover, the spatial aspect is of great importance, as the digital divide is not evenly distributed across all geographic areas.

Spatial analysis enables a better understanding of regional concentrations of digital activities and the identification of areas with a greater or lesser level of digitalization. Many studies indicate that there is spatial inequality in the use of digital technologies, with less urbanization often associated with a more pronounced digital divide [45] [69]. A number of authors have used different spatial analyses to map the geodemographic factors of Internet access and investigate the spatial distribution of the digital divide in different countries and regions. These analyses help to identify specific geographic areas where the digital divide is greater, which allows the formulation of more targeted policies to mitigate digital inequalities [42], [49], [50], [51], [71].

In line with the previous researches and their theoretical or methodological gaps the main goal of this research is to provide a spatial-temporal analysis of digital inequality in European countries. This goal is realized through four sub-goals:

1. Formation of the DDI
2. Spatial analysis
3. Sensitivity analysis
4. Robustness checking.

2. Literature Review

There have been various investigations with the objective of developing a composite index or a separate metrics of the digital divide through a combination of ICT indicators. The literature section presents a theoretical overview of more than thirty studies on the topic of the digital divide measurement and existing research results compared on several components.

Digital divide evolution. The first research on the digital divide analyzed in this paper appeared in 2002 and analyzed the increase of the digital divide in 15 EU countries between 1997 and 2000 [20]. In the same period, [52] investigated the digital divide in households, the business sector and government institutions in Italy while [7] developed a six-factor composite index to analyze the digital divide in ten developed economies. Authors [21] expanded the research focusing on measuring the digital divide in disadvantaged social groups. The rest of the research expanded methodological approaches and geographical coverage. Other studies [68] developed an index to measure the digital divide in the EU27 by analyzing five indicators of all levels of the digital divide. Authors [40] used individual indicators, such as the number of internet users, landline and mobile phones and social networks in Japan. Authors [19] analyzed global digital inequality, while [43] extended the analysis to digital skills and digital participation. [35] developed an index of the digital divide in Europe using factor analysis and [29] applied the ICT index in Turkey with spatial analysis. Reference [42] investigated local digital divide while [9] analyzed the socioeconomic dimensions of the digital divide. Reference [61] introduced a three-level digital divide model while [51] analyzed the regional digital divide in Indonesia using the IDI index. Authors [32] constructed an index for the Visegrad Group, adapted to the DESI methodology. A Study [11] used the coefficient of variation to measure digital divide. Authors [30] extended the analysis to digital participation and [10] investigated urban-rural internet access in the EU. More recent research of [46] developed an index of the digital presence of institutions in the EU. Several authors have investigated digital divide in China

[34], [44], [70], [71]. Authors [50] applied a globally accepted ICT index to Iran while [18] analyzed the digital economy in 30 Chinese provinces by applying spatial analysis to the digital divide. Early work looked at core indicators of the digital divide such as ownership and access to the Internet and digital devices [38], [41] while later work explored digital skills and participation, as well as socioeconomic aspects of the digital divide [16].

Digital divide levels. Early research such as [20], [21] and [52] focused on the first level of the digital divide - access to digital technologies. The second level which deals with use and skills was analyzed by [7] and [19]. Authors [61] introduce a third level which includes digital outcomes, while [18] and [46] investigated digital presence and the development of the digital economy. Works that combine multiple levels include [32], [35], [68] and [71] which included all three dimensions.

Indicators. Preliminary research of the digital divide used variables of a technical nature, predominantly quantitative, such as access to the Internet, ownership of computers and mobile phones [20], [52]. Later works expand the set of variables to include social, economic and regulatory aspects. For example, [19] and [34] use variables related to education, income and age structure, while [18] introduce indicators of digital industrialization and innovation. In research focusing on Internet use [35] analyze variables such as e-commerce and e-government while [40] study the number of Internet users and mobile devices. Authors [11] use variables such as internet subscriptions and administrative digitalization. [42] use variables related to media infrastructure, such as radio, TV and fixed and mobile phones, while [41] use basic variables like owning a mobile phone and internet access.

Synthetic index or individual metrics. Some studies measure the digital divide through synthetic indices. For example [7], [19] and [46] use composite indices that are formed through factor analysis while [44] and [18] apply the entropy method. Also, works like [51], [29] and [32] use different types of synthetic indices such as IDI, ICT index and DESI adjusted index. Factor analysis was key in the research of [35], [68] and [71]. In a similar approach [43] use composite indices to analyze the digital divide in correlation with economic development while [29] develop an index that integrates access, use and skills. In research such as [1] and [9], factor analysis was used to form indices focusing on digital development and the association with socio-economic status. On the other hand, some studies use individual indicators to measure the digital divide, such as [11] and [40], who focus on variables such as Internet access and e-government. Also, works like [4] and [45] analyze individual indicators, such as internet access and use of mobile devices in different social groups.

Forming factors. Factor analysis is the most commonly used method for forming factors as it enables the identification of key factors based on a set of indicators. This approach was applied in works of [7], [19] and [61] where it was used to extract significant factors that encompass different aspects of the digital divide. For example [46] used factor analysis to reduce the dimensionality of a set of indicators, while [35], [68] and [71] also used this method to form factors that capture principal dimensions of the digital divide. Authors [50] used factor analysis to identify three key factors: access, use and skills which are key to analyzing the digital divide. While authors [11] analysed digital divide using the coefficient of variation and some researchers have used cluster analysis [4], [42]. Author [16] formed two factors using subjectively allocated weights and [1] created an index by synthesizing multiple dimensions.

Importance weight of factors. Approaches to assigning weighting factors within the digital divide index vary significantly among studies. Prior works, such as the research by

[20] used subjective methods to determine weight coefficients. Later works applied more sophisticated methodologies, including factor variance [7], the entropy method [44] and H-DEA analysis [18]. Research that used factor analysis such as that of [32], [35], [68] and [71] used weight coefficients of factors. In some works as [50] weights were assigned to factors and indicators within the ICT index while [29] maintained the same weight coefficients for the IDI index with minor changes. Research by [4] and [45] analyzed the variables individually without forming factors or assigning weight coefficients. In some cases subjective weight coefficients were used, which may affect the generalizability of the results [16]. Works such as [9] and [70] used factor analysis to form the index but the approaches to assigning weights in some studies were different, with the factors having the same values, which may indicate differences in the interpretation of the results.

Spatial analysis. Spatial analysis of the digital divide has been conducted in different geographic settings with researchers applying different approaches at different levels of analysis. Studies dealing with the European digital divide show variations in the degree of digitalization between different regions with regional gaps between the technologically developed north and the less developed south [20], [21]. Authors [19] confirmed this division with a spatial scale analysis identifying differences between northern and southern Europe. [35] used spatial analysis to investigate how the digital divide manifests in different parts of Europe. Similar results are provided by [10] who examined urban and rural differences in the EU pointing to the specific challenges and advantages of different territorial areas within the EU. Reference [46] investigated institutional differences within the EU which enabled the identification of factors contributing to the digital divide at the regional level. Authors [29] analyzed the spatial distribution of the digital divide using an approach that focuses on the national context and differences among Turkish regions. Authors [11] applied the coefficient of variation to Ukrainian regions to investigate spatial differences in the digital divide. Authors [7] confirmed variations in the degree of digitalization between ten economies while [4] provided insight into specific EU regional divide. At the global level [1] conducted an analysis of the digital divide in 116 countries, while [30] investigated spatial inequalities in the digital divide among Russian cities. To investigate differences at the national level, [42] analyzed the digital divide in Kigali, while [16] investigated the digital divide in US counties.

3. Data and Methodology

Annual statistics for the 27 states were collected to analyze the digital divide in Europe. Table 1 describes all the states participating in the study. Even some studies propose evaluating the digital divide among countries with different economic scales such as [1] and [9]; this study is focused towards similarly developed economies to enable transparent comparison and mitigate significant cultural and economic influence on the results as proposed by [7]. In this way the digital divide is simply the outcome of managing digital development in a specific country. Statistics were gathered for the years 2014 and 2022 in order to assess patterns of digitalization progress in this area.

The collected data associated with the DDI concentrates on broadband usage and speed, demonstrating the manner in which digital inequality is evaluated according to Internet availability and access quality. The broadband usage indicators are integrated into the research to tackle the question by [63] and in recent research by [6] who emphasized the

Table 1. List of states

Belgium	Croatia	Austria
Bulgaria	Italy	Poland
Czech Republic	Cyprus	Portugal
Denmark	Latvia	Romania
Germany	Lithuania	Slovenia
Estonia	Luxembourg	Slovakia
Greece	Hungary	Finland
Spain	Malta	Sweden
France	Netherlands	Norway

Table 2. Index components details and sources

Indicator	Definition	Unit	Level of digital divide	Previous studies
More than 30 Mbps	Broadband internet coverage by more than 30 megabits per second.[1]		I level digital divide (access)	[31], [48]
More than 100 Mbps	Broadband internet coverage by more than 100 megabits per second.[1]	% of households		[48]
Next generation access	Broadband internet coverage by the next generation of internet technology.[1]			[54]
Households - level of internet access	Households with internet access.[1]	% of households		[29], [31], [32], [55]
Internet use: finding information about goods and services	Individuals who use the internet to find information about goods and services.[1]	% of individuals	II level digital divide (use and skills)	[31], [55]
Last internet use: in last 3 months	Individuals using the internet in the last 3 months.[1]	% of individuals		[55]
Internet use: never	Individuals who have never used the internet.[1]	% of individuals		[29], [55]
Male Internet users as a % of total male population	Male individuals who use the internet as a percentage of the male population.[2]	% of individuals	III level digital divide (outcome and benefits)	[39], [56]
Female Internet users as a % of total female population	Female individuals who use the internet as a percentage of the female population.[2]	% of individuals		[39], [56]

[1]source: [57], [2]source: [58].

need to revise digital divide measures from the basic ones such as internet or computer access to more advanced ones, such as access to emerging technology. Gathering indicator values from the World Bank and Eurostat databases allowed for the creation of the database that was initially established with fourteen indicators. All indicators have been converted into relative values and expressed as percentages, so standardization of data is not mandatory.

Table 2 reports indicators that have been integrated into analysis after several iterations within factor analysis. The indicators represent all three levels of the digital divide. The first and second levels are clear and simple to understand. Whereas the third level of the digital divide is reflected in the demographic digital divide across different social groups such as men and women. It reports which demographic/social group benefits more from the use of digital technology.

The procedure for performing the analysis includes the following steps, as presented in Figure 1.

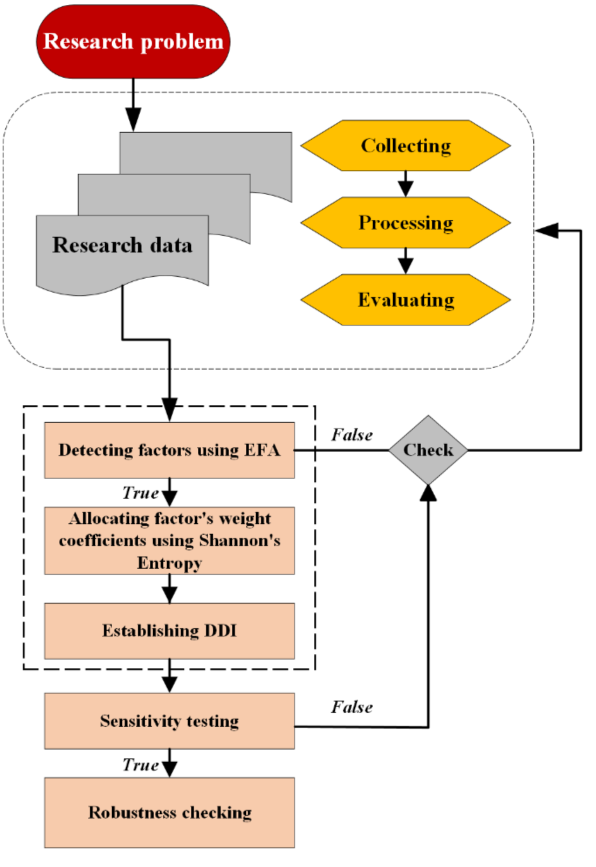


Figure 1. Research phases

Exploratory factor analysis (EFA) - is a popular statistical technique used to discover relationships within complex data sets and group them into appropriate factors to reduce the number of indicators [62]. This process involves identifying relationships among variables through correlation analysis and adopting those variables whose correlation coefficient is higher than 0.3 [59]. The basic precondition for conducting EFA includes data adequacy testing using the Kaiser-Mayer-Olkin (KMO) test and Bartlett's test of sphericity [62]. The KMO test assesses the suitability of data for factor analysis by comparing the squared correlation among variables with the squared partial correlation among the variables [2]. The KMO test estimates the proportion of variance among variables that may be shared, with the defined threshold value as follows: (1) above 0.9 (superb), (2) 0.8 to 0.9 (great), (3) 0.7 to 0.8 (good), (4) 0.5 to 0.7 (mediocre), and (5) below 0.5 (unacceptable) [15]. An additional test for checking the presence of correlation among variables is Bartlett's test of sphericity, which examines the hypothesis of correlation between variables, confirming their existence and statistical significance [2]. It investigates whether the original correlation matrix responds to the identity matrix [59]. The results of Bartlett's test of sphericity with a high value of chi-square and a low value of statistical significance ($p < 0.05$) mean that the correlation matrix is not an identity matrix and prove the suitability of the dataset for factor analysis [59].

EFA involves the application of principal component analysis (PCA) to reduce the number of indicators to a smaller number representing factors [62]. This process is called factor extraction [62]. The criterion for extracting the number of unrotated factors is Kaiser's criterion or "eigenvalues" criterion [2]. Factor extraction based on the eigenvalues criterion compares the common variance with the variance among variables in the extracted factors [59]. Those components with eigenvalues greater than 1 represent the number of retained factors [2]. For ease of interpretation, EFA includes a factor rotation procedure to simplify the display of indicators belonging to factors, allowing each indicator to be associated with only one factor [62]. There are orthogonal (uncorrelated) and oblique (correlated) rotation techniques, that depend on the correlation among factors [26]. In practice, there are several ways of orthogonal rotating, but varimax rotation is often used for maximum clarity and interpretability of the results [26]. The factor's consistency is assessed by computing the Cronbach alpha (α) coefficient, which is often used as a measure of scale reliability [8]. The value of Cronbach alpha ranges from 0 to 1, and the recommended threshold should be 0.7 and above; however, in certain instances, a 0.6 level can be acceptable [53]. The EFA is recommended when there are underlying relationships among variables that have not been examined completely so the structure of the interactions between variables is unknown [2].

The zero unitarization method was performed by implementing the following equation, which adopts the relationship among the original data [66]:

$$z_{ij} = \frac{x_{ij} - x_{j,\min}}{x_{j,\max} - x_{j,\min}} \times 100 \;, \tag{1}$$

where x_{ij} is the original value of j-th variable for i-th object that is being normalized, $x_{j,min}$ is the minimum value of j-th variable in the set of objects, and $x_{j,max}$ is the maximum value of j-th variable in the set of objects. This method has a wide practical application in agriculture, economics and other fields [67]. This study applied the method to the raw data set to alleviate the effect of drastic fluctuations in values between the indicators. The Shannon entropy method was then applied to this balanced dataset.

Shannon entropy method - The first scientist who proposed the concept of entropy in the field of information theory was Shannon in the mid-20th century [58]. The Shannon entropy approach measures the disorder in existing information [73]. The method takes into consideration the lack of order in the observed values within a particular piece of information or data and suggests that greater variability among the information results in higher uncertainty [5]. As a result, a higher amount of information leads to higher entropy values and, therefore, higher weight values for the evaluated information due to its perceived usefulness in the decision-making process [54]. It represents an objective way of calculating criteria weights [54]. Authors [22] described the calculation procedure that starts with the normalization of the values in the decision matrix in the following way:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} . \tag{2}$$

In the next step, the entropy value is calculated using the following formula:

$$E_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), \tag{3}$$

where the value of k, that is normalized factor is calculated using the following formula:

$$k = \frac{1}{\ln(m)}, \tag{4}$$

where m is the number of alternatives or instances that are being evaluated by different criteria. In this case, the number of alternatives equals the number of considered states. In the next step, the value of the weight vector is calculated using the formula:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)}, \tag{5}$$

where $1\text{-}E_j$ represents diversity degree (d_j) of the j-th criterion, n is the number of criteria and w_j represents the objective weight of the j-th criterion. The degree of diversity shows the difference in values, that is, the variability between the observed alternatives. A criterion with a higher weight has higher informational value in evaluating alternatives (e.g. states) because its values are heterogenous rather than uniform.

According to [27], the Shannon entropy method is essential for constructing composite indices as it enables an unbiased comparison of the criteria being evaluated and is relatively simple to implement.

4. Research Results and Discussion

The research results consist of multiple segments. First, the initial overview of the new index structure for examining the digital divide was presented. Then the allocation of indicators was performed using factor analysis according to the hidden patterns of connections between the data, which formed the corresponding factors. The weight values of the identified factors were calculated using the Shannon entropy method, and the DDI scores were calculated. The results are shown spatially, mapping territories that reflect similarities and differences in DDI scores, along with a study of the impact of temporal variations on these values. A sensitivity study was conducted to assess the index's stability concerning simulated scenarios of significant factor changes and to identify possible trends. In order to compare the DDI results with the existing research results, a correlation analysis was conducted.

Digital Divide Index (DDI) structure. EFA was systematically implemented on two distinct datasets corresponding to the years 2014 and 2022. The primary objective was to discover relationship among the employed indicators based on their latent interactions and establish DDI factors. The insight into the latent relationship among data forms the index architecture that is presented as follows:

$$DDI_t = \sum_{i=1}^{n} w_{j,t} \times \left(\sum_{i \in com_j}^{n} com_i \right) \tag{6}$$

where DDI_t is the calculated index value for the year t, $w_{j,t}$ is the weight coefficient for factor j-th in the year t, and com_j denotes all components that belong to the factor j-th; com_i are the actual values of the indicator i-th. Weight coefficients are obtained by applying the Shannon entropy method and these values are the same as those reported in equation (5).

Factors formation. The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were applied to assess the sample's adequateness for conducting EFA. The KMO test confirmed sample adequacy for both datasets (KMO > 0.7) and a statistically significant result from Bartlett's test of sphericity ($p = 0.000$). The analysis demonstrated the suitability of using EFA, and the Table 3 shows the total variance that the components explain. PCA was employed to extract the factors for the suggested components. Two elements with eigenvalues greater than 1 were identified in the Table 3 for both years leading to the selection of two factors for further research. Results for the 2014 highlight 95.22% of the variance in the sample can be attributed to the two main factors. Similarly, data for the 2022 discover 85.29% of the total variance explained by the two factors (F_1 and F_2). The factor loadings for the components were extracted and their impact has been determined using the varimax-rotated matrix with the Kaiser normalization process. The results are provided in the Table 4.

Table 3. Total variance explained for 2014 and 2022 data

Com	Initial Eigenvalues for 2014		Initial Eigenvalues for 2022	
	Total	Percentage of Variance (%)	Total	Percentage of Variance (%)
1	6.792	75.463	5.356	59.509
2	1.778	19.761	2.320	25.781
3	.184	2.042	.599	6.655
4	.126	1.401	.314	3.489
5	.074	.827	.183	2.034
6	.023	.255	.115	1.275
7	.015	.170	.059	.651
8	.005	.057	.039	.435
9	.002	.024	.015	.172

The rotational component matrix derived from 3 iterations indicate mainly strong positive factor loadings across all components, with the exception of the internet use component, which indicates a negative value for observed years. The factor loading values were utilized as input values for calculating the coefficient weights for each factor. To assess the reliability of the rotated results, Cronbach's alpha was employed.

Table 4. Rotation matrix components

Component (com_i)	Factor loadings for 2014		Factor loadings for 2022	
	F_1	F_2	F_1	F_2
More than 30 megabits per second (Mbps)	.946		.924	
More than 100 megabits per second (Mbps)	.921		.854	
Next generation access	.938		.976	
Internet use: finding information about goods and services		.912		.715
Households - level of internet access		.968		.913
Last internet use: in last 3 months		-.971		.972
Internet use: never		.921		-.949
Male Internet users as a % of total male population		.956		.929
Female Internet users as a % of total female population		.933		.900
Cronbach alpha (α)	0.950	0.771	0.900	0.672

EFA results for both observed years report two factors that subsequently are established of three and six components. The weight coefficients $w_{1,t}$ and $w_{2,t}$ are calculated using the Shannon entropy. The overall equation for the DDI can be described as follows:

$$DDI_t = w_{1,t} \times \left(\sum_{i=1}^{3} com_i \right) + w_{2,t} \times \left(\sum_{i=4}^{9} com_i \right) \quad (7)$$

Coefficient weights calculation. The relevance weights of the two factors were calculated individually for the years 2014 and 2022 using the Shannon entropy technique. The starting matrix in the Shannon entropy analysis was created by multiplying the factor loadings of the components from EFA and the actual values of the components, for each of the two factors independently. The calculated scores of the component values were normalized and adjusted by a normalization factor whose value equals the natural algorithm's number of alternatives, which is 27 (k = 0.303). The results summary is reported in the Table 5.

Entropy technique presented the weights for the first (w_1 = 0.736) and second factor (w_2 = 0.264) by observing the year 2014. In 2014 the first factor is evaluated as predominant on the digital divide. The computational results of the entropy approach for the year 2022 show that the importance weight of the first element (w_1 = 0.577) is marginally larger than the importance weight of the second factor ($w_2 = 0.423$). The results for 2022 are showing greater balance in the effects of both factors on digital divide, opposite from the results for 2014.

Table 5. Computational outcome of factors weight coefficients by Shannon entropy

Reference year	Parameters	F_1	F_2
2014	Entropy value (e_j)	0.982	0.994
	Diversity degree (d_j)	0.018	0.006
	Weight coefficient (w_j)	0.736	0.264
2022	Entropy value (e_j)	0.999	0.999
	Diversity degree (d_j)	0.001	0.001
	Weight coefficient (w_j)	0.577	0.423

DDI spatial analysis. The formation and calculation of the DDI simplified the comparison of countries according to the DDI scores, which range in standardized values from 0 to 100. A higher score indicates a superior rank and a smaller digital divide, while a lower score indicates the opposite results, i.e., a digital divide. The comparative results of DDI_2014 and DDI_2022 are illustrated in following Figure 2.

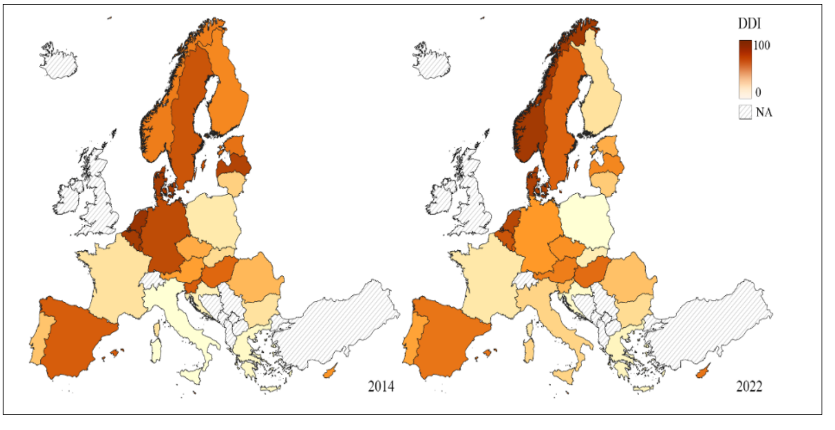


Figure 2. Distribution of DDI across Europe for 2014 and 2022

The spatial results of propound a digital divide between selected countries (Figure 2). In both period spatial clustering are identified. In general, clustering tendencies are noticeable in central-eastern and northern Europe. However, there are regional variances in observed periods. In 2014, Benelux countries are grouped in cluster with the highest DDI values (score between 93.93 and 100), with Netherland as a leader (DDI value 100). The second cluster considers Scandinavian countries with Estonia, and Latvia with Denmark as a leader (DDI value 93.67). And third cluster comprise Slovakia, Poland and Lithuania that fall in DDI range 21.50-35.21. The remaining countries do not show spatially explicit grouping. Considering 2014, on the regional scale, the prominent digital divide is noticeable between north and southern Europe, where the average difference in DDI value is 18.68 in favor to northern countries. The results of the study are supported by the results for Europe in the research of the author [19]. These authors point to a reduced digital divide in the Nordic countries, which include Denmark, Sweden, Norway, among others and an increased digital divide in the southern part of Europe especially in Bulgaria [9], [19], [35]. On the other hand, looking at the local disparities, even greater differences are more noticeable between the neighboring countries. For instance, Belgium outperforms France for 66.97 while Slovenia outperforms Italy for 63.88. The lowest rated country in 2014 are Italy, Greece and Croatia with DDI value range 0 to 19.44.

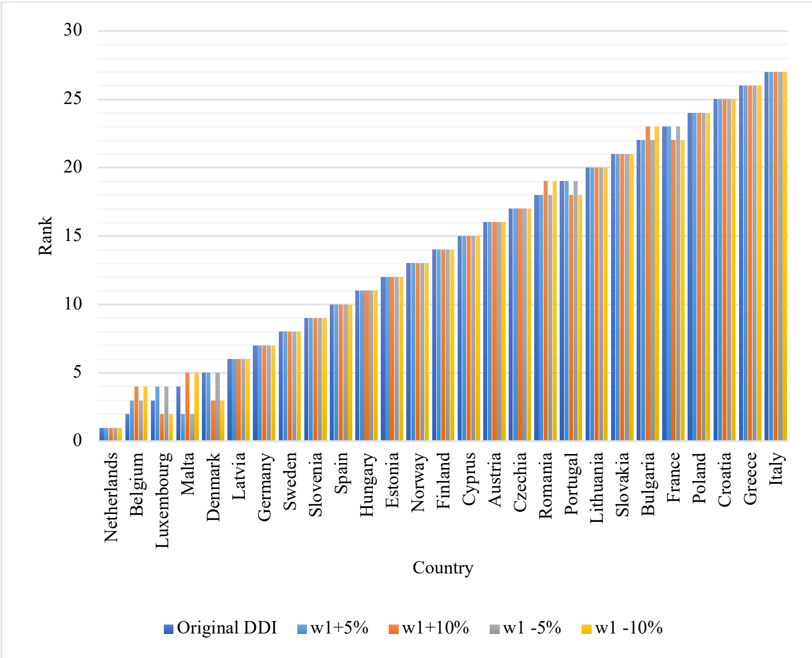
The results for 2022 results show the slowdown in digital dominance of Benelux countries that remind clustered, though, with average drop in performance of 8.45 comparing to 2014. The significant change is observed in the second cluster where Norway improved its performance from 61.26 to 100, Sweden improved its performance for 8.87, and Denmark improved for 4.90, while Finland, Latvia and Estonia down performed for 29.94, 20.86 and 12.58 respectively. Thus, this region become more divided comparing to 2014. On the other hand, Czech Republic and Austria gain the pace in the digitalization process and improved their performances for 12.03 and 16.86 respectively, and joined neighboring Germany and Hungary, forming new spatial cluster in central-eastern Europe. Also, the lagers from 2014, Greece and Italy considerably improved their performances, for 28.21 and 11.36 and decreased regional differences with northern European countries from 18.68 to 4.26. The results are supported by [9] who reported three clusters of the digital divide in the EU that are northern and western Europe as leaders in reaching digital equality, followed by moderately developed central and eastern Europe and least developed southern Europe labeled as the outsiders.

To understand the overall change between 2014 and 2022 the average difference of DDI values for each year is calculated. The average difference between the countries for 2014 is 32.56 while for the 2022 is higher 34.27. This indicate that the digital divide was more pronounced in 2022, and underwent negative changes among countries. Studies [7] and [8] identified this issue, with their research confirming the findings and highlighting that the advancement of digital technology contributes to the disparity in their adoption and implementation ability. This result primarily reflects the strengthening of the ranks of less digitally developed countries through the mitigation of the digital divide such as in the case of Norway, Italy, Cyprus and Austria. While other high digitally developed countries either maintained their previous rank or fell behind in this process especially Finland, Latvia and Germany. The conducted research affirms the assertions put forward by number of scholars regarding the spatial-temporal aspects of digitalization. In line with the results of [42], [71] and [50], this study confirms that the digitalization process is by its nature uneven at both local/urban, provincial, and regional level.

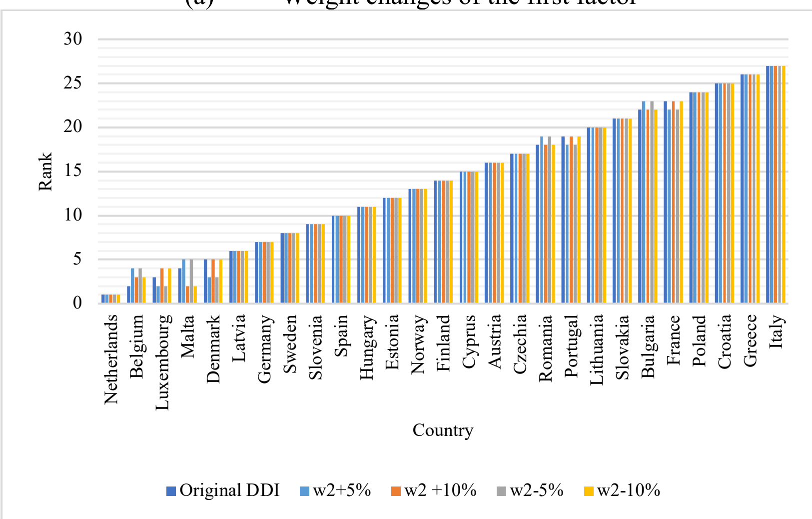
What has been noted by the comparative analysis of the successful solution of the digital divide is that investment in infrastructure and the application of new technology are of great importance for solving this problem as well as increasing the user base. For example, the remarkable growth of Norway from the 13th position according to DDI_2014 to the 1st position according to DDI_2022 was supported by measures on the development of infrastructure access and use of high-speed Internet. Empirical data shows an increase of 65.6% of households using broadband Internet access greater than 100 Mbps and a growth of 23.5% of households using broadband Internet access exceeding 30 Mbps. Less than 1% of the population declares that they have not used the Internet and that they do not have Internet access at home, which shows that the country is adequately covered by the Internet network. Italy made up for its deficit from 2014 by strengthening its position by installing broadband Internet access for more than 65% of households that actively use this technology, but there was also an exceptional increase in the use of newer generation Internet technology by 65.9%. In that country, as well as in other Southern European countries, the increase in the use of the Internet for the purposes of finding information about products and services online and the reduction of the share of the population that was digitally excluded is enviable, which speaks of raising the awareness of the population about the importance of using digital technology to facilitate life and work. In countries that have reduced the digital divide, such as Italy, an increase in the share of women in the use of the Internet can be observed to a greater extent than men, which speaks of solving the issue of the digital divide due to the unequal access of men and women as members of the socially sensitive category of the population. Cyprus has made significant progress in the area of infrastructure by expanding access to the Internet among households, which has resulted in a significant decrease in the number of individuals who have never used it. Austria solved the problem of the digital divide by progressing simultaneously across all sectors. The same results are seen in the research by [7] in who reported homogenous digitalization development across different factors in USA, UK, France, Italy and Spain.

The slow adoption of advanced Internet technology and access to high-speed Internet significantly contributed to Finland and Poland's decline. According to the figures for DDI_2022 Finland and Poland have made the least progress compared to all other countries and less than 80% of households that have adopted this technology have been recorded. Bearing in mind that the importance of these indicators is significant and that they constitute one of the two DDI factors, their influence on the final DDI ranking is huge. Finland replaced its position of 14th place according to DDI_2014 with the 22nd position in the DDI_2022 ranking. While Poland ranked last in the DDI_2022 ranking. In Germany a unique trend emerged that hasn't been observed in any other country. Specifically, from 2014 to 2022, the population's use of the Internet for product and service information declined by 18.46%, marking a significant drop in the sample and comparable to Bulgaria's findings. The same case was identified in the study by [46] which recorded a high digital divide in Hungary compared to other V4 countries due to a lack of trust, security, and interest in services and information that are available online. Less than 50% of the population in Romania uses the Internet for these purposes. In Latvia, a positive trend was recorded, but still a smaller percentage of respondents use the Internet for these needs. The highest growth in the use of high-speed Internet access technology in Bulgaria is recorded at 76.8%, but the percentage of households with enabled access is lower compared to other European countries, which contributes to digital inequality. In Southern European countries the proportion of the population that has never utilized the Internet exceeds 10% in Bulgaria, Greece, Croatia and Portugal.

Sensitivity analysis. Sensitivity analysis was conducted for both years to verify the stability and robustness of the proposed index. The parameters used in this analysis are the weight coefficients of the two identified factors. The sensitivity analysis was carried out within the range of ±5% to ±10% variation in the values of the weights. These changes were simulated individually, with the first weight coefficient changing the weight value while the second factor is constant and vice versa. This approach allows a review of how the change in the significance of an individual factor affects the final result of DDI. The position of countries is given according to the original DDI values, where a high DDI value reflects a superior rank and opposite. Figures 3 and 4 illustrate the sensitivity analysis for the investigated states.



(a) Weight changes of the first factor

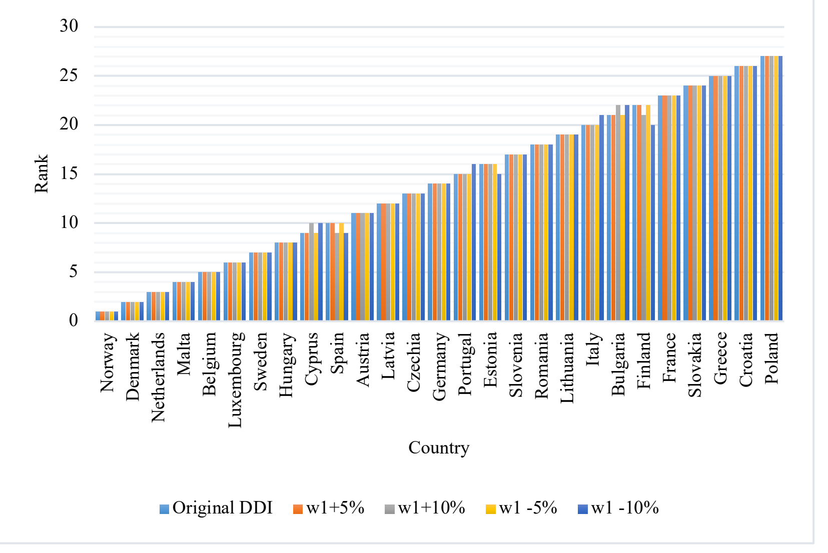


(b) Weight changes of the second factor

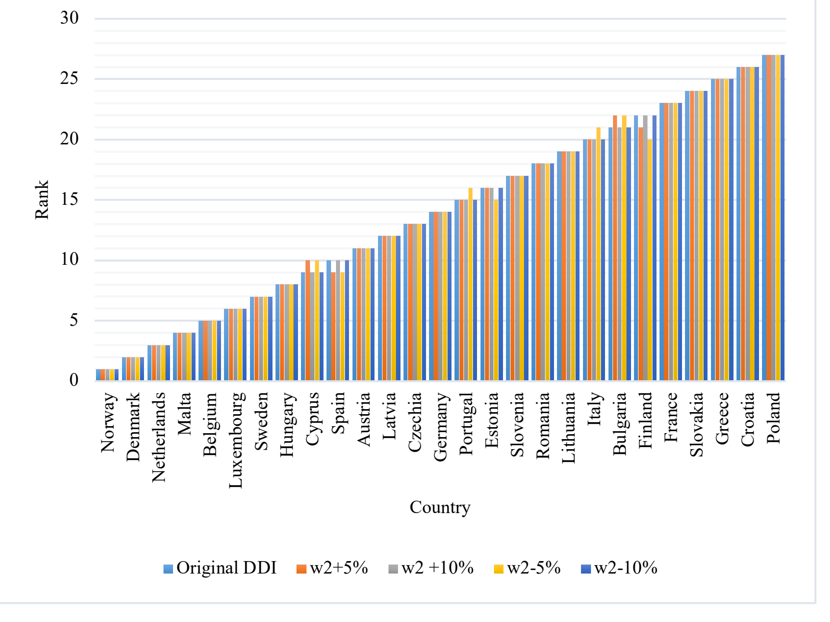
Figure 3. Sensitivity analysis of the DDI_2014

The sensitivity analysis for the year 2014 in the Figure 3 indicates the stability of DDI_2014 by simulating the variation in significance of two factors. Rank changes from the original DDI_2014 scores are limited to a maximum of ±2 positions. The largest disparities in cases a) and b) are observed in the countries ranked at the top of the list, namely Belgium, Malta, and Denmark. The rank of Belgium drops by two places when the significance of factor 1 changes by ±10% and when the value of factor 2 changes by ±5%. Belgium is unique in that any alteration in the value of factors 1 and 2 affects its ranking negatively. In the case of Malta, a growth of 2 places was observed when the importance of factor 1 changes by ±5%, while the positions oscillate the same when the importance of factor 2 varies by ±10%. In the case of Denmark, the opposite effect is noticeable when the significance of factor 1 changes by ±10%; the rank increases by 2 places, while the rank oscillates the same way when the significance of factor 1 changes by ±5%. Minor fluctuations of ±1 position of the DDI_2014 rank were recorded in the case of Luxembourg, Romania, Portugal, Bulgaria, and France. Other countries that make up the majority of the sample achieve rank consistency when conducting sensitivity analysis. Factor 1 mostly causes rankings to fluctuate at a variation of ±10%, while factor 2 causes fluctuations at a variation of ±5%. By calculating the average ranks when the importance of individual factors changes, it is found that there is no notable difference in the sensitivity of the index in relation to variations in one of the factors. Both factors have a uniform impact on DDI_2014, which indicates the stability of the ranking methodology.

A comparative analysis of the DDI_2014 sensitivity analysis with the results from the DDI_2022 year confirmed the smaller dispersion according to the latter's ranking. The oscillation of the ranks appeared in the case of seven countries, while the ranks changed by ±1 position except Finland. Finland's rank changes favorably by 2 positions due to a -10% change in the importance of factor 1, as well as with a +5% change in the importance of factor 2, reflecting the highest disparity value. Cyprus and Bulgaria recorded a decline in rank for one position when the importance of factor 1 changed by ±10% and when the importance of factor 2 changed by ±5%, while in other instances the position remained constant, while in Spain the situation was reversed. Portugal and Italy report a one-place drop in position when the importance of factor 1 changes by -10% or when the importance of factor 2 changes by -5%, but they maintain their initial position in other cases. In contrast, Estonia has an opposite effect under the same settings. It can be noted that the change in the significance of factor 1 by ±5% and the change in the significance of factor 2 by ±10% do not affect the sensitivity of the index. The highest difference in the average ranks when changing the importance of factor 1 is seen in the case of Finland, but identical outcomes are recorded when the importance of factor 2 is changed. The sensitivity analysis results of DDI_2022 indicate that variations in the significance of both parameters uniformly affect the final DDI rank. The study's conclusion remained consistent following the sensitivity analysis of the DDI demonstrating the index's resilience to data fluctuations.



(a) Weight changes of the first factor



(b) Weight changes of the second factor

Figure 4. Sensitivity analysis of the DDI_2022

Robustness checking. The computed DDI was validated by comparing its values with the globally measured network readiness index (NRI) using Pearson's correlation. The reason for selecting this specific index is found in the similarity of components that establish both of the indexes; however, the NRI index scope is much broader with a distinct set of components than the DDI. NRI is established on four pillars of technology, people, governance and impact with several indicators representing each pillar (Network Readiness Index Report, 2022). The obtained scores for NRI were standardized on a scale from 0 to 100 in order to eliminate potential disparities among scales and to prepare comparable statistics.

The Pearson's correlation analysis showed several statistically important facts. First, a statistically significant and positive relationship ($r = 0.842$, $p = 0.000$) between the calculated DDI_2014 and DDI_2022 shows that the data fit well, proving that the index is valid and reliable when it comes to collecting and measuring data. The applied method for calculating the index is consistent and produces robust results. Second, a strong positive correlation between DDI_2014 and NRI_2014 ($r = 0.638$, $p = 0.000$) and DDI_2022 and NRI_2022 ($r = 0.507$, $p = 0.007$) shows that the diverse and well-known digitalization index fits well with the composed DDI. The results indicate a positive statistical significance, suggesting that the newly developed digitalization index with a reduced number of components may serve as a simplified alternative to more complex indices like NRI.

This study offers a significant contribution to the development of the digital divide through a two-stage methodology that combines factor analysis and entropy method. Using the PCA method, the dimensions of the data were reduced, thus forming factors that more accurately reflect key aspects of the digital divide. Then, based on the values obtained by factor analysis, the entropy method was applied to assign weights to the factors, which enables dynamic monitoring of changes in the importance of index elements over time. The advantage of this approach is that the factor weights vary annually, allowing the tracking of current social and technological changes, compared to existing indices that use static or slower-changing weights. The index covers all three dimensions of the digital divide - access to technology, practical use and outcomes with a special emphasis on the Internet as the global standard for digital progress. Spatial analysis of the index provides additional insights into the spatial patterns of the digital divide, contributing to the understanding of regional differences in Internet access and use. This research framework not only identifies digital divides but also contributes to the understanding of how spatial distribution affects Internet access, allowing for better targeted interventions and research at the local level.

5. Conclusion

Measuring disparities in the development of digitalization is a challenging task that lacks a standardized measurement tool. This problem is a result of various research approaches being employed to address digital inequality. This research examines digital inequalities in European countries by creating a novel index to quantify it. The results are evaluated using spatial-temporal analysis. The theoretical contribution of this research appears through several equally important instances.

First, the structure of the DDI is composed of indicators of all three levels of digital division which are digital access, use and outcome. Unlike traditional models that emphasize some levels of digital divide, the DDI approach balances between all three levels to produce an integrative index. The originality and innovation of the index are evident in the multidimensional analysis of the digital divide based on a smaller number of indicators, which simplify its complexity. Second, the index is unique in its structure because it includes only indicators related to Internet use. In this way, the digital divide in societies is evaluated based on Internet indicators. To address potential concerns about the narrow focus of DDI, the index's structure provides the possibility for adapting such an approach with other indicators of the digital divide. Third, the application of EFA enables the discovery of hidden connections between the observed data and the formation of factors based on meaningful components. This directs the focus of the index to the key factors that are important for the issue of the digital divide. The use of Shannon entropy for the distribution of weighted factor values is a data-driven mechanism to diminish subjectivity and uncertainty in factor evaluation. This method relies on differences in the data, assigning greater importance to factors with greater variation within the dataset. This approach in assessing the weighted importance of factors enables the results to be harmonized with the information provided by the data. Traditional models for expressing the digital divide lack flexibility in changing the weighting values. Hybrid methodology provides index stability allowing it to be effectively applied across different sample sizes and timeframes. The proof is found in the results of testing the sensitivity of the index to changes in weight values. The rankings remained relatively stable between 5 and 10 percent change.

The research also presents a comprehensive array of practical implications related to development of the following:

1. Government investment programs to reduce digital inequality by integrating advanced infrastructure that enables the availability of high-speed internet. The recommendation stemmed from the results observed in Norway and Italy which have drastically reduced their digital disparity through internet infrastructure modernization projects and following global trends in the development of internet technology.
2. Government subsidies for the introduction of technological innovations in the private sector and households. The delay in the introduction of digital innovations, primarily in terms of the use of high-speed Internet access and new technologies for Internet access creates a digital divide in the public, private sector and society. A practical example can be found in the case of Finland and Poland which have slowed down their pace of adoption of advanced Internet technologies.
3. Private financing programs for the development of technological progress through innovative forms of financing such as crowdfunding. This financing model enables the acquisition of private capital for infrastructure investments alleviating the strain on public finances for investment in this sector.
4. Educational programs and media campaigns that encourage the development of digital literacy and highlight the advantage of using Internet technology. Italy and Cyprus are practical examples of countries where awareness of digital inclusion has grown significantly. Access to the Internet increases the visibility of individuals and companies and enables them to participate in the global market, which is why the importance of having digital skills in the 21st century is deep. The role of public-private partnerships is of fundamental importance for the implementation of this measure because the state could provide tax incentives to IT companies that would offer their expertise and equipment for IT training programs.
5. Digital inclusion programs for socially sensitive categories of residents that would encourage equality in the use of digital technology. This measure particularly applies to the countries of Southern Europe, where this gap is more pronounced compared to other regions. Targeted economic support of socially vulnerable categories of the population, such as women, the elderly and the rural population has a decisive influence on digital

access, use and results. They prove that the digital divide can sometimes be a result of systemic failures (economy, society, education, politics, etc.). In such instances, it is a broader social problem and it is addressed as digital exclusion.

6. Local and regional cross-border cooperation programs aimed at reducing uneven technological development in the observed areas. Huge local differences can be seen in the example of Belgium and France, but also regional differences in the example of Southern Europe and Northern Europe. This measure offers the creation of a program of local and regional policies for the harmonization of technological development. The example is „Smart Villages" project which the EU implements to mitigate digital inequality in rural regions. The cross-border program can also refer to the diversification of funding sources through foreign investment channels and the assignment of agreements on technological cooperation.
7. Customized sectoral programs for the introduction and use of digital technology that would enable the digitalization of all economic sectors. This measure was prompted by a decline in the use of the Internet for information about products and services in Germany. The decline may be the result of a weaker use of e-commerce due to the demographic structure of this country. This indicates the need for users to use digital platforms that are simple to use and offer data and personal protection.
8. Long-term digital development strategies that enable uniform development. A characteristic example is Austria, which has progressed in all areas, confirming the importance of a comprehensive approach to digital development. Long-term strategies should include infrastructure, literacy, education and encouraging the use of the Internet in different segments of society. The long-term strategy should include digital development that is sustainable and in line with environmental protection and current climate change. This strategy would include the transition to renewable energy sources as the main energy supplier of the technological development.

The limitations of this research include the accessibility of up-to-date data on digitalization, which affects the time frame utilized for comparing digitalization progress as well as the list of countries included in the study. The recommendation for future research is to broaden the scope of attributes that contribute to digital inequality and include other states that cover the entire European continent. This would allow for a comprehensive mapping of the digital divide across the area. Further investigation might also prioritize the incorporation of additional geographical variables, such as the distinction between urban and rural areas, which is also essential for analyzing digital disparity.

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