Prague Economic Papers
2023, Volume 32, Issue 2
https://doi.org/10.18267/j.pep.824

PRAGUE UNIVERSITY OF ECONOMICS AND BUSINESS

Efficiency of Digital Economy in the Context of Sustainable Development: DEA–Tobit Approach*

Viktorija Skvarciany [a], Indrė Lapinskaitė [a], Viktorija Stasytytė [a]

a Vilnius Gediminas Technical University, Vilnius, Lithuania
E-mail: viktorija.skvarciany@vilniustech.lt

Abstract.

The paper aims at measuring the efficiency of the digital economy in EU countries. For that purpose, data envelopment analysis (DEA) is used. Sub-dimensions of the Digital Economy and Society Index (DESI) are used as inputs and the Sustainable Development Goals Index (SDGI) as an output. The results revealed that Bulgaria, Italy and Romania are the most efficient digital economies in terms of human capital; Belgium, Bulgaria, Cyprus, Croatia, Estonia, Finland, Greece, Lithuania, Poland and Portugal in terms of connectivity; Bulgaria, Hungary and Romania in terms of integration of digital technology; and Romania in terms of digital public services. The result of tobit regression analysis showed that not all the indicators of the DESI dimensions positively influence the efficiency of the digital economy.

Keywords: digital economy, sustainable development, data envelopment analysis
JEL Classification: F43, O47

1. Introduction

The digital economy has become a widely examined topic as the whole world is now transitioning to digital, especially in COVID-19 times. According to UNCTAD (2021), the pandemic has spurred digitisation via continuing entertainment activities and switching them online. The importance of the digital economy has been indicated by one of the EU priorities, *A Europe fit for the digital age* (von der Leyen, 2019). The European Commission (2020a) established

* This project has received funding from the European Social Fund (project No 09.3.3-LMT-K-712-19-0151) under the grant agreement with the Research Council of Lithuania (LMTLT).

three activities for implementing this priority, one of which is *Shaping Europe's digital future*. It is being achieved through three pillars, one of which is a *fair and competitive digital economy*. Hence, its efficiency ought to be evaluated to make the digital economy competitive. The efficiency itself of the digital economy has not gained much attention, which is the core drawback and shows the gap in the scientific literature. Therefore, the current study aims at measuring the efficiency of the digital economy based on four Digital Economy and Society Index (DESI) dimensions (human capital, connectivity, integration of digital technology, and digital public services) as inputs, while the Sustainable Development Goals Index (SDGI) is the output.

SDGI, as an output, is selected based on the United Nations (2021), stating that data use and progress in digital technologies can be helpful to achieve sustainability goals relating to poverty reduction, climate change, energy, environment and agriculture. The digital economy can contribute to sustainability in various ways. It is most clearly seen from an environmental perspective. The digital economy has great potential to ensure environmental sustainability (Ma et al., 2022). The internet encourages people to be informed about sources of environmental pollution and, thus, they could change their behaviour to be more environmentally friendly, for example, by using cleaner energy or reducing water waste. Particularly, Li et al. (2021), Ma et al. (2022) and L. Chen (2022) found that digitisation reduces CO_2 emissions. Digitally enabled circular economy employing digital technologies in supermarkets could reduce food waste, thus contributing to corporate sustainability and social welfare (de Souza et al., 2021). On the other hand, the increased use of digital technologies simultaneously increases energy demand, which, in turn, has a negative impact on sustainability (Li et al., 2020). Another negative aspect could be seen in the new technologies, which could improve efficiency in parallel with deepening inequalities (United Nations, 2021).

The digital economy is a factor in the economic development of a country. Elmassah and Hassanein (2022) explored the impact of digitisation on well-being and determined what ICT-related elements influence life satisfaction. The use of ICT has been named as one of the critical factors representing economic performance and competitiveness globally (Mitrović, 2020). However, the use of ICT is not the only indicator of what the digital economy consists of. Hence, in the present study, a broader number of indicators represented by the DESI is used, which contributes to the existing knowledge through results obtained by more profound research.

It is worth mentioning that according to Ciocoiu (2011), a strong interrelation between the DESI and the SDGI exists. All three dimensions of sustainable development – economic, social and especially environmental – deserve special attention as components of the digital economy have both positive and negative impacts on sustainable development. From another point of view, the digital economy is considered one of the factors that can help recover from the crisis (OECD, 2009). Hence, it is vital to measure the efficiency of the digital economy of a country in order to develop strategies for its improvement. For that purpose, the DEA approach has been selected. Using the DEA method to assess efficiency, model inputs and outputs should be determined. DESI sub-dimensions were selected as inputs and the SDGI as an output.

2. Theoretical Background

2.1 Literature review

A digital economy is commonly perceived as an economy that uses digital technologies. The term "digital economy" was introduced in 1995 in Don Tapscott's book (Tapscott, 1997). This concept has drawn substantial attention of decision-makers and the community. Still, this term has no unique definition (UNCTAD – United Nations Conference on Trade and Development, 2019). Nowadays, it is so strongly linked with the traditional economy that it is hard to determine the limit. Moreover, the COVID-19 pandemic stimulated countries to focus on digital governance, which enables the digital economy as a major driver of economic and social development. Lower-income countries can especially benefit from digital technologies in the economy to move closer to the developed regions of the world (Tang et al., 2021).

Efficiency is a topic that is analysed in various fields of research. The term efficiency can be perceived in different ways: from the work output/energy input ratio to Pareto efficiency. Regardless of its infinite implications, efficiency is often limited to some particular meaning in a certain discipline. Jollands (2006) analysed the efficiency concept in ecological economics. The efficiency of the circular economy has been analysed by Robaina et al. (2020), Sánchez-Ortiz et al. (2020) and Lacko et al. (2021). Environmental efficiency in energy economics was investigated by Chen (2013). Other topics related to efficiency are production efficiency (Kolinski, 2017), management efficiency (Meng et al., 2018), education efficiency (Johnes et al., 2017), resource efficiency (Khan and Wang, 2019), etc.

Some multi-dimensional processes and complex phenomena, such as sustainability, well-being, competitiveness or education quality, are best revealed and assessed using composite indicators (Rovan, 2011; Saisana, 2014). With this methodology, the interpretation of results is easier, and measurement units are compared in a more reliable way. Composite indicators are often used to evaluate the performance of countries, cities or regions. Sometimes, ready-made indicators can be used; in other cases, synthetic indicators may be developed for a particular purpose.

The creation of such indicators must follow a clear procedure (OECD, 2008). According to Moreira and Crespo (2017), composite indicators can be viewed as mathematical functions of a set of indicators. Saisana and Tarantola (2002) point out the advantages of composite indicators, such as their suitability to assess multi-dimensional issues, ease of interpretation and comparability across countries and time periods. However, there are also some drawbacks to this type of measurement: important elements can be missing, the ability to use an indicator depends on data availability and accuracy, irrational weighting and aggregation may distort results, and such indicators can lack practical application (Booysen, 2002). Moreover, the development of composite indicators is often related to uncertainty (Cherchye et al., 2007).

Composite indicators are widely applied in research. Synthetic indicators were used by Blancas et al. (2023) to measure tourism sustainability, Drago and Gatto (2022) used them to measure institutional transparency in the energy policy sector, Jin et al. (2021) applied such indicators to assess globalisation with regard to global environmental changes. Also, some innovative approaches in composite indicator application are found, such as the separation of the benchmark selection issue from efficiency measurement (Fusco, 2022) and the use of unsupervised machine learning techniques (Jiménez-Fernández et al., 2022). Along with that, Lo-Iacono-Ferreira et al. (2022) developed an interval of composite indicators instead of using one particular indicator value to assess the sustainability performance of cities. In our research, we will use existing composite indicators – the DESI and SDGI, as they quite well describe the related phenomena and there is no need to develop new ones at this moment.

Now it is worth presenting the instruments intended to measure digital economy and sustainability. The digital economy is most often measured using the Digital Density Index, the Digital Economy and Society Index, and the Digital Society Index (Osmanbegovic and Piric, 2019). The Digital Economic Index was calculated by Pan et al. (2022). The measurement of development levels of the digital economy in China's provinces was performed using the index system, factor analysis and network analysis methods (Tang et al., 2021). Zhu and Chen (2022) analysed the link between the digital economy and urban development using spatial autocorrelation methods. Of all the mentioned indices, the Digital Economy and Society Index can be perceived as the most comprehensive and suitable to assess the digital economy. It has also been used to estimate the digital policy performance of European countries (Liu, 2022). Since its development in 2014, the DESI has had five sub-dimensions: connectivity, human capital, use of internet services, integration of digital technology, and digital public services. In 2021, the DESI was re-structured around four dimensions: connectivity, human capital, integration of digital technology, and digital public services. The index was also analysed by Rakicevic et al. (2019), Stavytskyy et al. (2019), Bánhidi et al. (2020) and Başol and Yalçın (2021).

In terms of the origin of the SDGI, it began in 2015, when the 2030 Agenda for Sustainable Development was adopted by all member states of the United Nations (UN) with the aim of accomplishing it through the implementation of 17 Sustainable Development Goals (SDG 17) which consist of 169 targets and 230 indicators to progress (United Nations, n.d.; Sustainable Development Solutions Network, 2022). To unify a large and complex measurement and monitoring framework, Bertelsmann Stiftung and Sustainable Development Solutions Network (SDSN) compiled the SDG Index as a benchmark of the performance of SDG17 countries (Diaz-Sarachaga et al., 2018; Sustainable Development Solutions Network, 2022).

The data cover 80% of the 149 UN member states with a national population greater than 1 million. Each indicator is normalised on a scale of 1 to 100 and represents absolute country performance and distance to achieving sustainable development (Sachs et al., 2017; Lafortune et al., 2018).

2.2 DESI index

As the DESI is a multi-dimensional index, it is worth presenting its decomposition in detail. Since its development in 2014, the DESI has had five sub-dimensions: connectivity, human capital, use of internet services, integration of digital technology, and digital public services. In 2021, the DESI was re-structured around four dimensions: connectivity, human capital, integration of digital technology, and digital public services.

The relevance of the DESI and its four dimensions is based on the DESI description across thematic chapters (European Commission, 2021). The human capital dimension covers internet user skills and advanced digital skills. Assessing these skills is necessary, as van Laar et al. (2017) state that digital skills are irreplaceable elements of 21st-century skills. People aiming to participate in the knowledge-based workforce should fully exploit ICT. This human capital dimension also partly reflects the dropped DESI sub-dimension – the use of internet services. Moreover, human capital aims to assess the percentage of ICT specialists, paying particular attention to women in this field. Yeganehfar et al. (2018) state that the gender gap in the professional labour force still exists even though considerable effort has been made to promote women's empowerment. Thus, the level of such indicators discloses women's participation in technical fields and, in turn, the success of the respective education and qualification-raising policies.

The connectivity dimension covers fixed broadband take-up and coverage, mobile broadband and broadband prices, 4G coverage and 5G readiness and coverage. Broadband is essential for economic development and the welfare of society. However, broadband coverage can differ across countries as well as across rural and urban areas. The fixed broadband gap is sometimes replaced with mobile broadband (Prieger, 2013); therefore, indicators of both types are important. 4G and 5G coverage represent the quality of internet service, while the price reflects its accessibility.

Integration of the digital technology dimension measures digital intensity, digital technologies for business, and e-commerce. The elements of this dimension are mainly related to digital indicators of enterprises. The usage of technologies based on artificial intelligence (AI) is analysed. AI is an important element of enterprises' digital transformation, enabling companies to provide more efficient services (Calp, 2020). Thus, the positive impact of digital services on the economy is noticed, which is worth measuring using the DESI. Cloud computing services and applications and big data analysis in companies are also estimated in the frame of this dimension. Cloud computing covers the hosting of the enterprise's databases, accounting software applications, CRM software and computing power. Cloud computing benefits cloud service providers and users (Alouffi et al., 2021). For this reason, it has been increasingly studied and applied recently.

Digital public services are related to e-government opportunities and evaluate digital public services for citizens and businesses. Services for citizens mainly cover social assistance. At the same time, services for businesses concentrate on starting a new business and conducting regular business activities. This dimension also measures the open data policy application in countries and its impact. However, the latter element strongly depends on government regulation. Government data policy can affect companies' productivity because most businesses rely on electronic data in their production or service-providing processes (Ferracane et al., 2020).

3. Methodology

Data envelopment analysis (DEA) was selected in order to measure the efficiency of the digital economy. DEA is a linear programming technique for evaluating the efficiency of units called decision-making units (DMUs) (Ji and Lee, 2010). DEA is widely used in different research areas. For example, there are many studies employing DEA for bank efficiency and performance measurement (Kamel et al., 2022; Owusu Kwateng et al., 2019; Titko et al., 2014). It is worth mentioning that using DEA for bank efficiency evaluation is one of the most widely used DEA applications. Still, there are scientists using DEA for other goals. For instance, some scientists investigate energy efficiency, savings and consumption optimisation using DEA (Karadaş and Külekçi, 2020; Rakshit and Mandal, 2020; Villa et al., 2021). Other scholars employ the approach for sustainability measurement (Ait Sidhoum et al., 2019; Keshavarz and

Toloo, 2020; Yousefi et al., 2022). Stankova and Hampel (2019) used this method in finance for bankruptcy prediction, Zhou et al. (2016) constructed an environmental performance index with the help of DEA, and Amalnick and Zadeh (2017) conducted a performance assessment of customer relationship management combining DEA and other methods.

Nonetheless, there are only a few articles investigating the digital economy using the DEA technique. For instance, Mitrović (2020) analyses the dynamics and the achieved level of digital economy development in the European Union, Central and Eastern Europe and Western Balkan countries. However, the author uses a limited number of inputs, which are all connected to ICT, which, in turn, does not cover the whole digital economy. In other words, it is believed that the digital economy could be measured through a greater number of inputs; hence, the current research is conducted in order to cover that issue. Actually, due to a limited number of articles, it could be stated that the DEA application in digital economy efficiency assessment is underestimated. In the digital economy, DEA would help distinguish the most efficient digital economies, which would help set a relative benchmark that could be used as a frontier for less efficient digital economies to improve.

In order to perform a DEA, it is vital to select inputs and outputs, which is a significant step that is conducted before the DEA application (Peyrache et al., 2020). In the current research, the input factors are selected based on the DESI sub-dimensions, as this is a methodology that measures the progress of the digital economy and society. The output is represented by the SDGI. The SDGI was chosen as an output, as there are authors claiming that there is a linkage between the digital economy and sustainability. For example, X. Chen et al. (2022) state that the digital economy is a driving force in sustainable development. Nesterenko et al. (2020) argue that digital economy technologies increase sustainability. Pan et al. (2022) claim that the digital economy acts as an innovation driver for extensive sustainable development. Hence, the selection of the SDGI as an output is supported by the literature; however, the interface between these two phenomena (digital economy expressed by the DESI and sustainable development expressed by the SDGI) has not received significant attention from scholars, which shows the novelty of the present research.

The core concept of DEA is estimating the efficiency score, which is calculated as a ratio of outputs to inputs (Charnes et al., 1978). It is worth noting that for obtaining the results, the input-oriented basic (radial) model with a constant-returns-to-scale (CRS) DEA approach was used. The linear programming problem that ought to be solved under CRS involves a measure of return to scales on the variable axis c_k, to the country k (see Equations (1)–(3)) (Huguenin, 2012).

$$\text{Maximise} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \tag{1}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \; j = 1, \; \ldots, \; n \tag{2}$$

$$u_r, \; v_i > 0, \; \forall r = 1, \; \ldots, \; s; \; i = 1, \; \ldots, \; m \; . \tag{3}$$

Where: y_{rk} is quantity of the output r produced by the country k, x_{ik} is quantity of the input i covered by the country k, u_r is the weights of the output r, v_i is the weights of the input i, n is the number of countries to be evaluated, s is the number of outputs, and m is the number of inputs.

It is worth mentioning that the DEA model allows for weights to be allocated to inputs and outputs, which are established by maximising the ratio of the weighted sum of outputs to the weighted sum of inputs (Yu et al., 2021).

Moreover, the DEA approach has three main limitations (drawbacks), which are as follows (Omrani et al., 2021):

i. it does not consider decision makers' preferences in the evaluation process;
ii. DMUs in this model are flexible in weighting the criteria to reach the maximum possible efficiency; and
iii. it ignores the uncertainty in data.

Despite the limitations, DEA is a powerful approach for technical efficiency measurement. A linear programming problem could be solved using two different approaches, i.e., input-oriented and output-oriented. For the current research, the input-oriented approach was employed. The primal equations are provided below (see Equations (4)–(6)):

$$\text{Maximise} \sum_{r=1}^{s} u_r y_{rk} \tag{4}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0, j = 1, \; \ldots, \; n \tag{5}$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1 \tag{6}$$

As alluded to above, DESI sub-dimensions are used as inputs, and the SDGI values as output. All in all, four procedures are completed, i.e., the efficiency of every dimension in terms of the SDGI is calculated.

After the efficiency is calculated, regression modelling is employed in order to find out which subdimension has a significant influence on the SDGI. Since the DEA efficiency values are truncated, the ordinary least squares method (OLS), for instance, will lead to estimation bias; hence, in order to solve this problem, the censored tobit regression modelling has been employed. The model uses the maximum likelihood estimation method when estimating the regression coefficients, which helps make the estimation of model parameters unbiased (X. Chen and Wang, 2022). Still, the tobit regression, like other methods, has limitations. As DEA efficiency estimates are serially correlated, this could affect the results of the tobit regression (Simar and Wilson, 2007). On the other hand, Wang and Wang (2022) claim that the tobit model has strong robustness and feasibility. Hence, it was decided to employ tobit regression in order to investigate the impact of DESI sub-indicators on the efficiency of the digital economy of the EU.

The tobit econometric model describing the impact of DESI sub-dimensions on the efficiency of the digital economy is provided below.

$$Y_i^* = \begin{cases} \alpha + \beta X_i + \epsilon,\ Y_i^* > 0 \\ 0,\ Y_i^* < 0 \end{cases} \tag{7}$$

All in all, four equations will be developed within each dimension. The dependent variable in all the models is the efficiency of the digital economy within the specific dimension; the independent variables are as follows:

- Model 1:
  - X_1 – Internet user skills
  - X_2 – Advanced skills and development
- Model 2:
  - X_3 – Fixed broadband take-up
  - X_4 – Fixed broadband coverage
  - X_5 – Mobile broadband
  - X_6 – Broadband price index
- Model 3:
  - X_7 – Digital intensity
  - X_8 – Digital technologies for businesses
  - X_9 – e-commerce
- Model 4:
  - X_{10} – e-government.

4. Empirical Findings

Human capital is the first DESI dimension that was investigated. The following human capital sub-dimensions have been employed: internet user skills and advanced skills and development. The results are presented in Table 1.

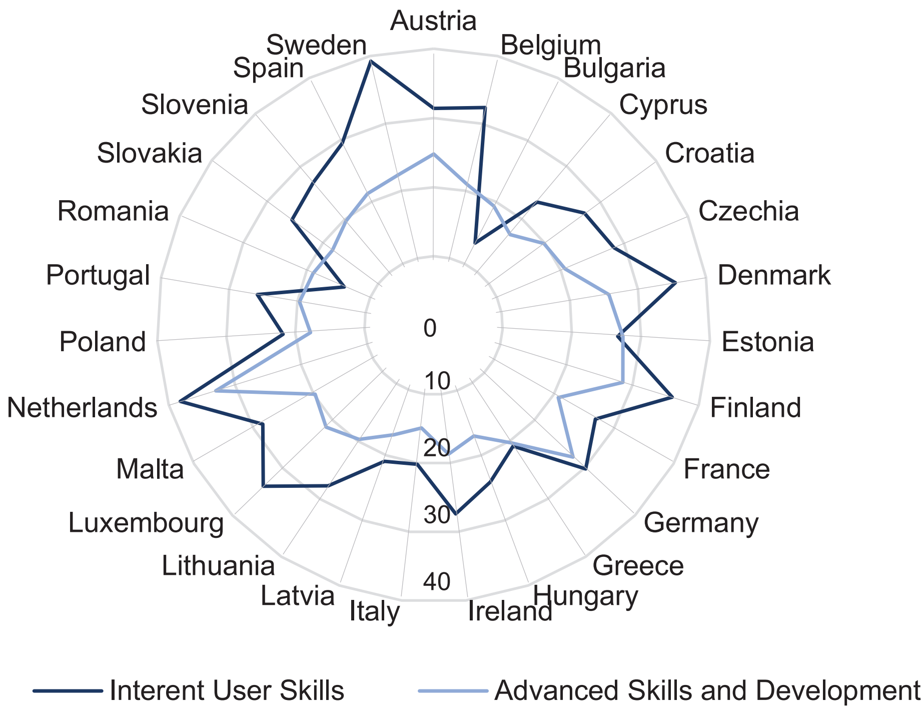
Table 1: Digital economy efficiency in terms of DESI dimension *human capital*

DMU name	Efficiency score	Efficiency	DMU name	Efficiency score	Efficiency
Austria	65.05%	Inefficient	**Italy**	100.00%	Efficient
Belgium	74.14%	Inefficient	**Latvia**	93.46%	Inefficient
Bulgaria	100.00%	Efficient	**Lithuania**	73.75%	Inefficient
Cyprus	82.46%	Inefficient	**Luxembourg**	65.67%	Inefficient
Croatia	76.54%	Inefficient	**Malta**	72.41%	Inefficient
Czechia	74.34%	Inefficient	**Netherlands**	50.99%	Inefficient
Denmark	62.42%	Inefficient	**Poland**	89.98%	Inefficient
Estonia	66.85%	Inefficient	**Portugal**	76.90%	Inefficient
Finland	59.25%	Inefficient	**Romania**	100.00%	Efficient
France	76.11%	Inefficient	**Slovakia**	82.64%	Inefficient
Germany	63.24%	Inefficient	**Slovenia**	78.40%	Inefficient
Greece	81.43%	Inefficient	**Spain**	70.50%	Inefficient
Hungary	87.62%	Inefficient	**Sweden**	72.57%	Inefficient
Ireland	81.74%	Inefficient			

Source: authors' calculations

According to Table 1, in the context of the human capital dimension, there are three countries with an efficient digital economy with the output represented by the SDGI. They are Bulgaria, Italy and Romania. Actually, some results are quite surprising, i.e., the primacy of Bulgaria and Romania – the countries with one of the lowest GDP per capita in the EU. According to the human capital sub-dimension of internet user skills, Bulgaria and Romania are ranked 26th and 27th, respectively, while Italy is ranked 26th. This means that these countries are at the bottom of the list. In terms of advanced skills and development, Bulgaria, Romania and Italy are in the 19th, 20th and 27th places, which shows their low performance. Nevertheless, the SDGI score is relatively high for these countries, which means that with the lowest DESI results, they produce a high level of sustainable development, which, in turn, shows that the digital economy works effectively compared with other EU countries. In other words, the countries with an inefficient digital economy, measured by the human capital dimension, could have higher sustainable development, but their digital economies have a potential that is not used.

Figure 1: *Human capital* sub-dimension values by country



Source: authors' calculations

The second DESI dimension that was examined is connectivity. The following connectivity sub-dimensions were used: fixed broadband take-up, fixed broadband coverage, mobile broadband, and broadband price index. The results are presented in Table 2.

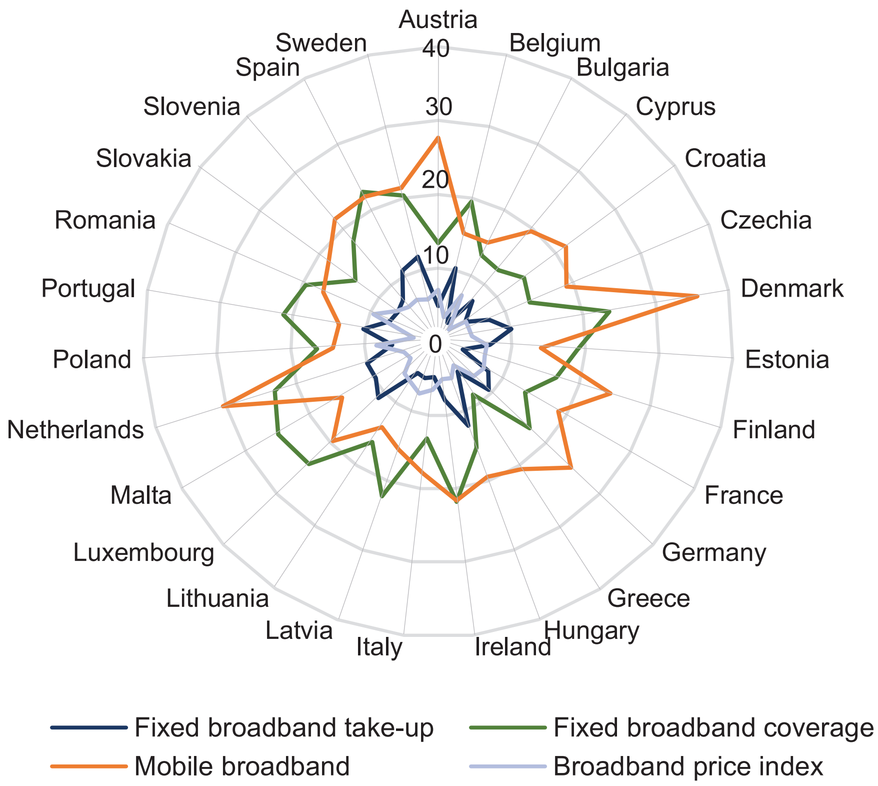
Table 2: Digital economy efficiency in terms of DESI dimension *connectivity*

DMU name	Efficiency score	Efficiency	DMU name	Efficiency score	Efficiency
Austria	87.74%	Inefficient	**Italy**	97.39%	Inefficient
Belgium	100.00%	Efficient	**Latvia**	93.69%	Inefficient
Bulgaria	100.00%	Efficient	**Lithuania**	100.00%	Efficient
Cyprus	100.00%	Efficient	**Luxembourg**	69.69%	Inefficient
Croatia	100.00%	Efficient	**Malta**	89.77%	Inefficient
Czechia	99.17%	Inefficient	**Netherlands**	68.85%	Inefficient
Denmark	69.64%	Inefficient	**Poland**	100.00%	Efficient
Estonia	100.00%	Efficient	**Portugal**	100.00%	Efficient
Finland	100.00%	Efficient	**Romania**	79.02%	Inefficient
France	96.36%	Inefficient	**Slovakia**	94.13%	Inefficient
Germany	77.07%	Inefficient	**Slovenia**	82.79%	Inefficient
Greece	100.00%	Efficient	**Spain**	71.84%	Inefficient
Hungary	90.05%	Inefficient	**Sweden**	82.60%	Inefficient
Ireland	85.41%	Inefficient			

Source: authors' calculations

As can be seen from Table 2, in terms of the connectivity dimension, there are ten efficient digital economies. They are as follows: Belgium, Bulgaria, Cyprus, Croatia, Estonia, Finland, Greece, Lithuania, Poland and Portugal. In this dimension, four sub-dimensions were used for the efficiency calculation: fixed broadband take-up, fixed broadband coverage, mobile broadband, and broadband price index. The EU monitors the connectivity of member countries, measuring both supply and demand of fixed and mobile broadband. In terms of this dimension, there are no patterns as with the previous one, i.e., all the countries are placed in the list randomly. It is worth mentioning that the connectivity dimension is the one in the context of which the number of efficient digital economies is the highest. The connectivity sub-dimension scores are presented in Figure 2.

Figure 2: *Connectivity* sub-dimension values by country



Source: authors' calculations

The third DESI dimension that was examined was integration of digital technology. The sub-dimensions that were used are digital intensity, digital technologies for businesses, and e-commerce. The results are presented in Table 3.

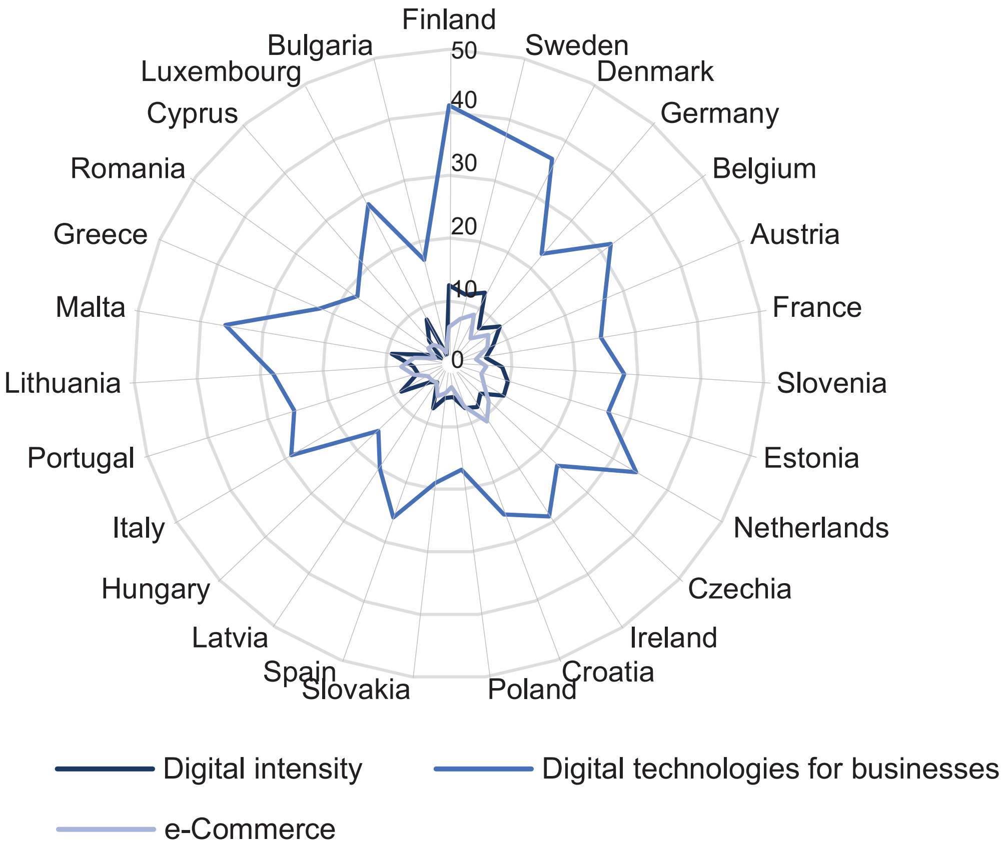
Table 3: Digital economy efficiency in terms of DESI dimension *integration of digital technology*

DMU name	Efficiency score	Efficiency	DMU name	Efficiency score	Efficiency
Austria	59.57%	Inefficient	**Italy**	61.25%	Inefficient
Belgium	50.29%	Inefficient	**Latvia**	84.91%	Inefficient
Bulgaria	100.00%	Efficient	**Lithuania**	56.85%	Inefficient
Cyprus	72.68%	Inefficient	**Luxembourg**	62.64%	Inefficient
Croatia	61.95%	Inefficient	**Malta**	45.87%	Inefficient
Czechia	67.64%	Inefficient	**Netherlands**	49.86%	Inefficient
Denmark	45.69%	Inefficient	**Poland**	95.81%	Inefficient
Estonia	63.51%	Inefficient	**Portugal**	63.70%	Inefficient
Finland	46.33%	Inefficient	**Romania**	100.00%	Efficient
France	70.80%	Inefficient	**Slovakia**	81.91%	Inefficient
Germany	71.72%	Inefficient	**Slovenia**	59.41%	Inefficient
Greece	80.21%	Inefficient	**Spain**	62.68%	Inefficient
Hungary	100.00%	Efficient	**Sweden**	47.13%	Inefficient
Ireland	54.75%	Inefficient			

Source: authors' calculations

As can be seen from Table 3, in terms of the integration of digital technology, there are three efficient digital economies, i.e., Bulgaria, Hungary and Romania. Bulgaria, as in the previous dimensions, produces quite a high SDGI level with a shallow level of digital intensity, digital technologies for businesses, and e-commerce. A similar situation is in Hungary and Romania. In order to understand the levels of the sub-dimensions investigated, a visualisation of the data is provided in Figure 3 below.

Figure 3: ***Integration of digital technology*** **sub-dimension values by country**



Source: authors' calculations

The fourth DESI dimension that was researched is digital public services. This dimension consists only of one sub-dimension, which is e-government. The results are provided in Table 4.

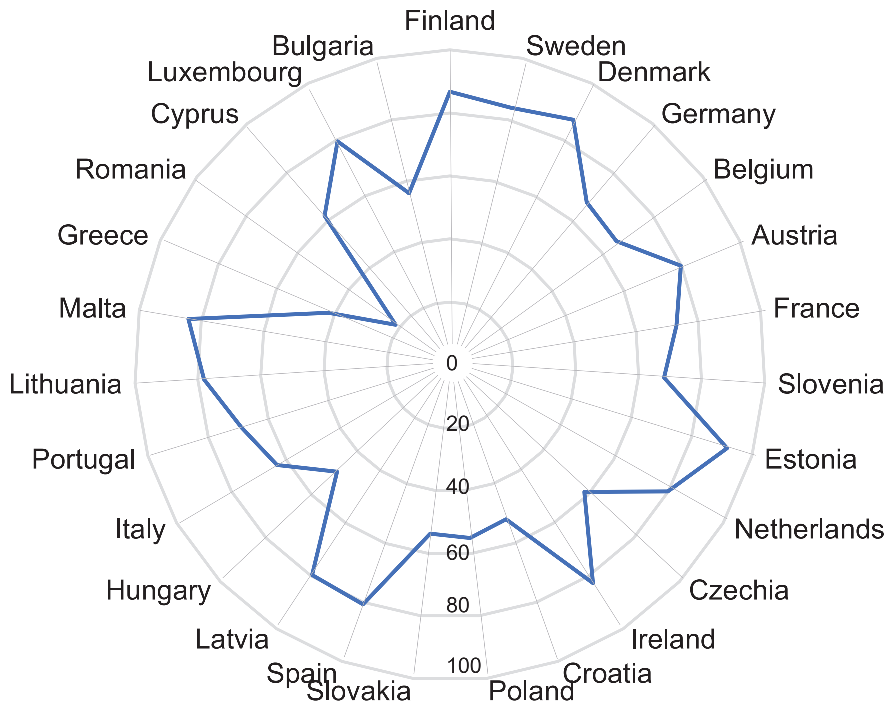
Table 4: Digital economy efficiency in terms of DESI dimension *digital public services*

DMU name	Efficiency score	Efficiency	DMU name	Efficiency score	Efficiency
Austria	29.47%	Inefficient	**Italy**	35.72%	Inefficient
Belgium	35.79%	Inefficient	**Latvia**	28.49%	Inefficient
Bulgaria	37.75%	Inefficient	**Lithuania**	28.17%	Inefficient
Cyprus	34.71%	Inefficient	**Luxembourg**	26.80%	Inefficient
Croatia	44.33%	Inefficient	**Malta**	25.79%	Inefficient
Czechia	39.82%	Inefficient	**Netherlands**	29.26%	Inefficient
Denmark	27.93%	Inefficient	**Poland**	41.73%	Inefficient
Estonia	25.48%	Inefficient	**Portugal**	32.69%	Inefficient
Finland	28.39%	Inefficient	**Romania**	100.00%	Efficient
France	32.07%	Inefficient	**Slovakia**	42.45%	Inefficient
Germany	35.04%	Inefficient	**Slovenia**	34.40%	Inefficient
Greece	51.58%	Inefficient	**Spain**	28.23%	Inefficient
Hungary	45.93%	Inefficient	**Sweden**	29.23%	Inefficient
Ireland	28.09%	Inefficient			

Source: authors' calculations

The results presented in Table 4 show that the only efficient digital economy in terms of digital public services and with an output represented by the SDGI is Romania. The results are similar to the outcomes presented above, i.e., the efficient economy has got one of the lowest GDP per capita (in terms of the EU). Romania shows the worst result in the e-government sub-dimension (see Figure 4), but with these results, the country's SDGI score is comparatively high, which means that the country's ability to perform effectively in terms of the mentioned dimension is relatively high. In order to compare the scores of sub-dimensions, see Figure 4.

Figure 4: *Digital public services* sub-dimension values by country



Source: authors' calculations

In order to evaluate the influencing factors that affected the efficiency of the digital economy, the tobit regression was adopted. As was mentioned above, the DEA calculation results are truncated discrete distribution values between 0 and 1; the OLS method would lead to an estimation bias; hence, the tobit regression was chosen for the research. All in all, four models were developed. The summary of Model 1 is presented in Table 5.

Table 5: Summary of Model 1

				LR $\chi^2(2)$	= 63.35	
Log-likelihood = 49.823				**Prob > χ^2**	= 0.0000	
				Pseudo R^2	= −1.7457	
Efficiency*	**Coefficient**	**Std. err**	**t**	**P > |t|**	**[95% conf. interval]**	
X_1	−0.011	0.002	−7.33	0.000	−0.015	−0.008
X_2	−0.014	0.002	−5.72	0.000	−0.019	−0.009
Const	1.377	0.040	34.41	0.000	1.294	1.459
var(e.Efficiency)	0.001	0.000			0.001	0.003

*Efficiency in terms of human capital

Source: authors' calculations

As can be seen from Table 5, there are two independent variables, i.e., X_1 and X_2 and both are statistically significant. Moreover, both have a negative impact on efficiency. In terms of internet user skills (X_1), the results are quite common, as in order to achieve technical efficiency, equal access to the internet should be in all the regions of a country; otherwise, it could lead to digital inequality, which, in turn, according to Hidalgo et al. (2020), could lead to economic inequality, which might be harmful particularly for the younger generation, as it could be excluded from the labour market. Advances skills and development (X_2) also have a negative influence on the efficiency of the digital economy in terms of human capital. This could be due to the fact that only a limited number of digital service users could be treated as advanced, which means that inequality exists in that field, which, in turn, could lead to non-efficiency.

The summary of the second model (Model 2) is provided in Table 6.

Table 6: Summary of Model 2

Log-likelihood = 46.446				**LR $\chi^2(4)$** = 50.05		
				Prob > χ^2 = 0.0000		
				Pseudo R^2 = −1.168		
Efficiency*	**Coefficient**	**Std. err**	**t**	**P > |t|**	**[95% conf. interval]**	
X_3	−0.017	0.004	−3.95	0.001	−0.026	−0.008
X_4	−0.008	0.003	−3.07	0.005	−0.013	−0.003
X_5	−0.012	0.002	−7.29	0.000	−0.015	−0.009
X_6	−0.024	0.006	−4.26	0.000	−0.036	−0.012
Const	1.551	0.059	26.44	0.000	1.429	1.672
var(e.Efficiency)	0.002	0.001			0.001	0.003

*Efficiency in terms of connectivity
Source: authors' calculations

The results presented in Table 6 indicate that all the indicators of the connectivity dimension are with the minus sign, which means that they could negatively influence the technical efficiency of the digital economy. The obtained result is quite surprising and brings new evidence to the scientific field of the digital economy and its efficiency. This could be due to the fact that in the EU, not all the countries are equally developed; hence, the level of connectivity indicators is different, and, as was mentioned above, inequality brings a decrease in efficiency. Therefore, it is vital for all the policy-makers to take these results into account and enhance the level of connectivity indicators for all the residents of the country in order to lower the inequality in this area.

The summary of the third model (Model 3) is presented in Table 7.

Table 7: Summary of Model 3

Log-likelihood = –56.671				**LR $\chi^2(3)$** = 6.09		
				Prob > χ^2 = 0.1071		
				Pseudo R^2 = –0.3116		
Efficiency*	**Coefficient**	**Std. err**	**t**	**P > |t|**	**[95% conf. interval]**	
X_7	–0.028	0.023	–1.24	0.228	–0.076	0.019
X_8	0.006	0.010	0.58	0.566	–0.014	0.026
X_9	0.043	0.017	2.51	0.019	0.008	0.079
Const	0.485	0.144	3.38	0.003	0.188	0.781
var(e.Efficiency)	0.023	0.006			0.013	0.040

*Efficiency in terms of integration of digital technology
Source: authors' calculations

As can be seen from Table 7, only one coefficient of X_9 is statistically significant and has a positive effect on the efficiency of the digital economy in terms of the digital technology dimension. This is quite a predictable result, as electronic commerce is often associated with sustainability, which is an output of the DEA approach. For instance, Yang et al. (2021) argue that e-commerce could help achieve sustainable development in rural areas. Zhang and Xu (2021) support the view that e-commerce could help maintain sustainable development by putting forward various subsidy programmes for retailers. Moreover, e-commerce is critical for the country's market position and its developmental perspectives (Jasińska-Biliczak, 2022). Hence, it could be stated that e-commerce is one of the drivers of the efficiency of the digital economy, as, for instance, it helps improve the efficiency and quality of services of companies with a considerable reduction in costs (Dragulanescu and Androniceanu, 2017).

The last model is Model 4, and its summary is provided in Table 8.

Table 8: Summary of Model 4

Log-likelihood = **16.087**				**LR $\chi^2(1)$** = 3.30		
				Prob > χ^2 = 0.0693		
				Pseudo R^2 = −0.1143		
Efficiency*	**Coefficient**	**Std. err**	**t**	**P > |t|**	**[95% conf. interval]**	
X_{10}	−0.003	0.002	−1.87	0.072	−0.006	0.000
Const	0.568	0.113	5.05	0.000	0.337	0.799
var(e.Efficiency)	0.018	0.005			0.010	0.031

*Efficiency in terms of digital public services
Source: authors' calculations

The outcome of Model 4 indicates that e-government representing digital public services has a negative effect on the efficiency of the digital economy. At present, in different countries, especially low-income countries, the e-government is only about to be developed. It means that in some countries, the transition to e-government is in the initial stage, which, in turn, could not influence the efficiency of the digital economy positively. Only mature systems could affect the efficiency of the digital economy. In other words, this is quite an essential result for the EU policy-makers, i.e., it is vital to develop strategies for all the countries to transit to e-government and contribute to the efficiency of the digital economy of the country.

5. Discussion

Jovanović et al. (2018) examined the link between digitisation and sustainable development. The DESI index was used as a measurable expression of digitisation. The authors analysed the DESI index by five dimensions, which were in effect before 2021. They compared DESI results with such indexes as the Global Competitiveness Index, Global Innovation Index, GDP, Global Entrepreneurship Index, Good Country Index, Sustainable Development Goal Index, and Sustainable Society Index. Our research differs in that it uses only the SDGI as a measure of sustainable development and disregards other indices. We do not treat this as a drawback of our research but rather as concentrating on one particular measure. Moreover, we used the DEA method to measure digital economy efficiency, which is far more comprehensive than measuring the correlation coefficient as performed by Jovanović et al. (2018). The DEA method gives the efficiency score of a country, while correlation only indicates the strength and direction of the relationship between the DESI and the selected variables.

Herman (2022) analysed the impact of digital entrepreneurship on sustainable development goals. After performing the correlation and regression analysis, she found that digital entrepreneurship depends on the general level of country digitisation, and it further has an impact on SDGs, distinguishing particular SDGs as major recipients of the effect. Moreover, the author performed principal component analysis and cluster analysis. In the mentioned research, the variables were divided into three groups: related to entrepreneurship, digitisation and sustainable development. The DESI index was in the second group, along with several other indices, while the SDGI was in the third group. The difference between Herman's (2022) and our research is in the fact that we aimed to obtain the efficiency of the digital economy in terms of sustainable development, and Herman (2022) estimated the relationship between entrepreneurship (including digital entrepreneurship) and sustainable development. Thus, entrepreneurship is treated as an equally important factor of Herman's (2022) analysis, while we pay attention solely to digitisation.

Stan et al. (2020) aimed to find out how digitisation affects sustainability. The research was done based on a Romanian example. Particular elements of sustainable development were examined in detail. Similar to our research, Stan et al. (2020) used the DESI and SDGI for their analysis. A correlation analysis between the DESI and SDGI was performed for Romania, selecting six SDGI elements. Most selected SDGI measures were strongly correlated with the DESI, either positively or negatively. Even though the described research was performed based on only one country, its results are interesting and open a broad field for future research.

Del Río Castro et al. (2021) state that there is an interplay between digitisation and sustainability. However, they found several gaps in previous SDG research and implementation, as well as a lack of scientific evidence about the interaction of digitisation and sustainability. Little is known about how the digital economy can help achieve sustainable development. Their main analysis instrument was a literature review. They determined that novel data sources, enhanced analytical capacities and collaborative digital ecosystems allow digitisation to contribute to SDG achievement. The three mentioned groups of actions are further divided into smaller activities. Even if Del Río Castro et al. (2021) did not apply any quantitative methods to measure the impact or relationship between the analysed phenomena, they provided a sound review and classification to present the state of the art of the digitisation-sustainability peculiarities and nexus. This is a suitable background for future research intended for quantitative estimations of their efficiency or relationship.

Contemporary technologies have applications in many areas. By developing and applying various technologies, digitisation can help strengthen the economy, protect the environment and ensure safe well-being for people. Mondejar et al. (2021) introduce the concept of digital sustainability and define it as technology to achieve sustainable economic growth. Though again, without particular quantitative estimations, these authors provide a set of trends and examples of how innovative digital technologies can help achieve SDGs.

Digitisation efficiency was measured by Yalçın (2021) using the DEA method. The author used DESI dimensions as inputs and GDP growth rate and employment rate as outputs. The sustainability aspect has not been taken into account here. DEA has also been used to measure the impact of digitisation on financial sector performance (Ekinci, 2021), retail logistics efficiency (Loske and Klumpp, 2020), and enterprise architectures (Sandkuhl et al., 2019). DEA is often applied together with other methods, such as regression. However, none of the mentioned works analysed the sustainability perspective.

To sum up, it could be noted that the previous research is mainly twofold. Part of the authors combine the DESI and SDGI in their analysis but do not measure efficiency and do not apply the DEA method. Other types of research are related to digitisation efficiency, and they often use DEA but do not consider sustainability perspectives. Thus, our research representing the measurement of digital economy efficiency concerning sustainable development is original and suitable to fill the revealed research gap.

Overall, digital technologies can affect the economy and sustainability both positively and negatively. Employees' and citizens' advanced digital skills and increased internet availability affect the development and utilisation of digital technologies in businesses and households. Novel data sources and new analytical techniques, including big data analytics, contribute to sustainability and well-being as we can recognise hidden trends in data and thus make more reasonable individual and corporate decisions. Data exchange platforms and cloud technologies enhance proactive and quick data sharing worldwide. However, the drawbacks of the use of technologies include increased energy consumption and related costs, as well as critical dependence on energy supply. In order to promote efficiency, countries should aim to adequately utilise and promote the advantages while reducing the negative effects of technologies.

6. Conclusions

For assessing the efficiency of the digital economy, four DESI dimensions and their sub-dimensions were employed. They are as follows: human capital (internet users and advanced skills and development), connectivity (fixed broadband take-up, fixed broadband coverage, mobile broadband, and broadband price index), integration of digital technology (digital intensity, digital technologies for businesses, and e-commerce), and digital public services (e-government). All the EU countries were selected for the research and the study period covered 2021, employing the latest available data. For obtaining the results, the DEA technique was used. The DESI sub-dimensions were treated as inputs and the SDGI as an output. The selection of output is backed by scientific literature, where authors that claim there is a strong connection between the digital economy and sustainability. Actually, this supports the novelty of the current study, as, at present, there is a limited number of articles measuring the efficiency of the digital economy in the context of sustainable development. In other words, the contribution of the current paper to the scientific literature and knowledge is undoubtful.

To sum up the DEA results, it is concluded that in terms of human capital, there are three efficient digital economies in the EU: Bulgaria, Italy and Romania. Regarding connectivity, there is the most significant number of efficient digital economies, which are as follows: Belgium, Bulgaria, Cyprus, Croatia, Estonia, Finland, Greece, Lithuania, Poland and Portugal. In terms of the integration of digital technology, there are three efficient digital economies: Bulgaria, Hungary and Romania. The last dimension that was analysed is digital public services with one efficient digital economy: Romania. Some results are quite surprising as, in most cases, the countries with the lowest economic development (based on GDP) have the best digital economy efficiency measurement results. The reason is that the countries with the lowest DESI sub-dimension points produce quite a high level of SDGI (compared with the world results); hence, it supports the economic efficiency concept.

The second stage of the research was regression modelling in order to find out which DESI sub-dimensions have an impact on the country's sustainable development represented by the SDGI. All in all, four models were investigated. Each model represented a DESI dimension. In terms of the first model, internet user skills appeared to be statistically significant and have a positive impact on sustainable development. In the second model, out of four independent variables, only one was considered to have an influence on the SDGI, namely mobile broadband. In the context of the third model, all the coefficients of the variables were statistically significant, which means that all the variables affect the SDGI. However, the calculations showed that while digital intensity and e-commerce influence the SDGI positively, digital technologies for businesses have a negative impact. The last model consisted only of one independent variable, e-government. The obtained results revealed that the mentioned variable has a positive influence on the SDGI.

Brief measures for countries with lower efficiency scores could be proposed. Technologies should be increasingly applied to minimise waste by *just-in-time* or similar logistics systems, optimise consumption by reducing paper and transport use, and reduce inequality through improved accessibility and online learning opportunities. Countries should strive for efficient utilisation of resources. To cope with increased energy consumption and its costs, citizens should increasingly use energy-efficient devices. Still, particular measures may greatly depend on the political decisions of countries' governments and municipalities.

References

Ait Sidhoum, A., Serra, T., Latruffe, L. (2019). Measuring sustainability efficiency at farm level: a data envelopment analysis approach. *European Review of Agricultural Economics*, 47(1), 200–225. https://doi.org/10.1093/erae/jbz015

Alouffi, B., Hasnain, M., Alharbi, A., Alosaimi, W., Alyami, H., Ayaz, M. (2021). A Systematic Literature Review on Cloud Computing Security: Threats and Mitigation Strategies. *IEEE Access*, 9, 57792–57807. https://doi.org/10.1109/ACCESS.2021.3073203

Amalnick, M. S., Zadeh, S. A. (2017). Concurrent Evaluation of Customer Relationship Management and Organizational Excellence: An Empirical Study. *Performance Improvement Quarterly*, 30(1), 55–88. https://doi.org/10.1002/piq.21240

Bánhidi, Z., Dobos, I., Nemeslaki, A. (2020). What the overall Digital Economy and Society Index reveals: A statistical analysis of the DESI EU28 dimensions. *Regional Statistics*, 10(2), 46–62. https://doi.org/10.15196/RS100209

Başol, O., Yalçın, E. C. (2021). How does the digital economy and society index (DESI) affect labor market indicators in EU countries? *Human Systems Management*, 40(4), 503–512. https://doi.org/10.3233/HSM-200904

Blancas, F. J., Contreras, I., Lozano-Oyola, M. (2023). Evaluating destinations' efforts to improve sustainability in tourism using the inter-temporal decomposition of a composite indicator. *Environmental Impact Assessment Review*, 98, 106947. https://doi.org/10.1016/j.eiar.2022.106947

Booysen, F. (2002). An Overview and Evaluation of Composite Indices of Development. *Social Indicators Research*, 59, 115–151. https://doi.org/https://doi.org/10.1023/A:1016275505152

Calp, M. H. (2020). *The Role of Artificial Intelligence Within the Scope of Digital Transformation in Enterprises* (pp. 122–146). https://doi.org/10.4018/978-1-5225-9550-2.ch006

Charnes, A., Cooper, W. W., Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, C.-M. (2013). A critique of non-parametric efficiency analysis in energy economics studies. *Energy Economics*, 38, 146–152. https://doi.org/10.1016/j.eneco.2013.03.009

Chen, L. (2022). How CO2 emissions respond to changes in government size and level of digitalization? Evidence from the BRICS countries. *Environmental Science and Pollution Research*, 29(1), 457–467. https://doi.org/10.1007/s11356-021-15693-6

Chen, X., Teng, L., Chen, W. (2022). How does FinTech affect the development of the digital economy? Evidence from China. *The North American Journal of Economics and Finance*, 61, 101697. https://doi.org/10.1016/j.najef.2022.101697

Chen, X., Wang, Y. (2022). Research on financing efficiency of China's strategic emerging industries based on super efficiency DEA and tobit model. *International Journal of Emerging Markets*, 17(2), 485–504. https://doi.org/10.1108/IJOEM-02-2020-0188

Cherchye, L., Moesen, W., Rogge, N., Puyenbroeck, T. Van. (2007). An Introduction to 'Benefit of the Doubt' Composite Indicators. *Social Indicators Research*, 82(1), 111–145. https://doi.org/10.1007/s11205-006-9029-7

Ciocoiu, C. N. (2011). Integrating Digital Economy And Green Economy: Opportunities For Sustainable Development. *Theoretical and Empirical Researches in Urban Management*, 6(1), 33–43.

de Souza, M., Pereira, G. M., Lopes de Sousa Jabbour, A. B., Chiappetta Jabbour, C. J., Trento, L. R., Borchardt, M., Zvirtes, L. (2021). A digitally enabled circular economy for mitigating food waste: Understanding innovative marketing strategies in the context of an emerging economy. *Technological Forecasting and Social Change*, 173, 121062. https://doi.org/10.1016/j.techfore.2021.121062

Del Río Castro, G., González Fernández, M. C., Uruburu Colsa, Á. (2021). Unleashing the convergence amid digitalization and sustainability towards pursuing the Sustainable Development Goals (SDGs): A holistic review. *Journal of Cleaner Production*, 280, 122204. https://doi.org/10.1016/j.jclepro.2020.122204

Diaz-Sarachaga, J. M., Jato-Espino, D., Castro-Fresno, D. (2018). Is the Sustainable Development Goals (SDG) index an adequate framework to measure the progress of the 2030 Agenda? *Sustainable Development*, 26(6), 663–671. https://doi.org/10.1002/sd.1735

Drago, C., Gatto, A. (2022). Policy, regulation effectiveness, and sustainability in the energy sector: A worldwide interval-based composite indicator. *Energy Policy*, 167, 112889. https://doi.org/10.1016/j.enpol.2022.112889

Dragulanescu, I. V., Androniceanu, A. (2017). Considerations Relating the Italian e-Commerce Development in a Global Economy. *New Challenges of Economic and Business Development - Digital Economy*, 177–188.

Ekinci, R. (2021). The Impact of Digitalization on Financial Sector Performance. In *The Impact of Artificial Intelligence on Governance, Economics and Finance. Volume I.* (pp. 99–119). https://doi.org/10.1007/978-981-33-6811-8_6

Elmassah, S., Hassanein, E. A. (2022). Digitalization and subjective wellbeing in Europe. *Digital Policy, Regulation and Governance*, 24(1), 52–73. https://doi.org/10.1108/DPRG-05-2021-0060

European Commission. (2020). *A fair and competitive digital economy*. The European Digital Strategy. http://bit.ly/2VdWQgf

European Commission. (2021). The Digital Economy and Society Index (DESI). In *Shaping Europe's Digital Future*. https://bit.ly/3Irptwq

Ferracane, M. F., Kren, J., Marel, E. (2020). Do data policy restrictions impact the productivity performance of firms and industries? *Review of International Economics*, 28(3), 676–722. https://doi.org/10.1111/roie.12467

Fusco, E. (2022). Potential improvements approach in composite indicators construction: The Multi-directional Benefit of the Doubt model. *Socio-Economic Planning Sciences*, 85,101447. https://doi.org/10.1016/j.seps.2022.101447

Herman, E. (2022). The Interplay between Digital Entrepreneurship and Sustainable Development in the Context of the EU Digital Economy: A Multivariate Analysis. *Mathematics*, 10(10), 1682. https://doi.org/10.3390/math10101682

Hidalgo, A., Gabaly, S., Morales-Alonso, G., Urueña, A. (2020). The digital divide in light of sustainable development: An approach through advanced machine learning techniques. *Technological Forecasting and Social Change*, 150, 119754. https://doi.org/10.1016/j.techfore.2019.119754

Huguenin, J.-M. (2012). *Data Envelopment Analysis (DEA): a pedagogical guide for decision makers in the public sector*.

Jasińska-Biliczak, A. (2022). E-Commerce from the Customer Panel: the Phenomenon of the Pandemic Increase and Future Challenge. *Business, Management and Economics Engineering*, 20(1), 139–151. https://doi.org/10.3846/bmee.2022.16752

Ji, Y., Lee, C. (2010). Data Envelopment Analysis. *The Stata Journal: Promoting Communications on Statistics and Stata*, 10(2), 267–280. https://doi.org/10.1177/1536867X1001000207

Jiménez-Fernández, E., Sánchez, A., Sánchez Pérez, E. A. (2022). Unsupervised machine learning approach for building composite indicators with fuzzy metrics. *Expert Systems with Applications*, 200, 116927. https://doi.org/10.1016/j.eswa.2022.116927

Jin, S., Zhang, Y., Wang, K., Zheng, C., Song, L. (2021). Global environmental changes slow down the pace of globalization highlighted by a new composite indicator. *Journal of Cleaner Production*, 318, 128538. https://doi.org/10.1016/j.jclepro.2021.128538

Johnes, J., Portela, M., Thanassoulis, E. (2017). Efficiency in education. *Journal of the Operational Research Society*, 68(4), 331–338. https://doi.org/10.1057/s41274-016-0109-z

Jollands, N. (2006). Concepts of efficiency in ecological economics: Sisyphus and the decision maker. *Ecological Economics*, 56(3), 359–372. https://doi.org/10.1016/j.ecolecon.2005.09.014

Jovanović, M., Dlačić, J., Okanović, M. (2018). Digitalization and society's sustainable development – Measures and implications. *Zbornik Radova Ekonomskog Fakulteta u Rijeci: Časopis Za Ekonomsku Teoriju i Praksu/Proceedings of Rijeka Faculty of Economics: Journal of Economics and Business*, 36(2), 905–928. https://doi.org/10.18045/zbefri.2018.2.905

Kamel, M. A., Mousa, M. E.-S., Hamdy, R. M. (2022). Financial efficiency of commercial banks listed in Egyptian stock exchange using data envelopment analysis. *International Journal of Productivity and Performance Management*, 71(8), 3683-3703. https://doi.org/10.1108/IJPPM-10-2020-0531

Karadaş, K., Külekçi, M. (2020). Optimization of energy consumption for sunflower production using data envelopment analysis approach. *Journal of Environmental Biology*, 41(2(SI)), 505–513. https://doi.org/10.22438/jeb/41/2(SI)/JEB-32

Keshavarz, E., Toloo, M. (2020). A hybrid data envelopment analysis and multi-attribute decision making approach to sustainability assessment. *Expert Systems*, 37(4). https://doi.org/10.1111/exsy.12347

Khan, M. H., Wang, D. (2019). The Impact of Green HRM Practices on Job Satisfaction and Resource Efficiency. *Education Excellence and Innovation Management through Vision 2020*, 6565–6575.

Kolinski, A. (2017). The Impact of Eco-efficiency in Production on Availability of Machines and Equipment. In *Efficiency in Sustainable Supply Chain* (pp. 161–177). https://doi.org/10.1007/978-3-319-46451-0_10

Lacko, R., Hajduová, Z., Zawada, M. (2021). The Efficiency of Circular Economies: A Comparison of Visegrád Group Countries. *Energies*, 14(6), 1680. https://doi.org/10.3390/en14061680

Lafortune, G., Fuller, G., Moreno, J., Schmidt-Traub, G., Kroll, C. (2018). SDG Index and Dashboards 2018. In *Global Responsibilities. Implementing the Goals* (Issue September).

Li, Y., Dai, J., Cui, L. (2020). The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. *International Journal of Production Economics*, 229, 107777. https://doi.org/10.1016/j.ijpe.2020.107777

Li, Y., Yang, X., Ran, Q., Wu, H., Irfan, M., Ahmad, M. (2021). Energy structure, digital economy, and carbon emissions: evidence from China. *Environmental Science and Pollution Research*, 28(45), 64606–64629. https://doi.org/10.1007/s11356-021-15304-4

Liu, T. (2021). Digital policy in European countries from the perspective of the Digital Economy and Society Index. *Policy & Internet*. 14(1), 202–218. https://doi.org/10.1002/poi3.274

Lo-Iacono-Ferreira, V. G., Garcia-Bernabeu, A., Hilario-Caballero, A., Torregrosa-López, J. (2022). Measuring urban sustainability performance through composite indicators for Spanish cities. *Journal of Cleaner Production*, 359, 131982. https://doi.org/10.1016/j.jclepro.2022.131982

Loske, D., Klumpp, M. (2020). Simulating the impact of digitalization on retail logistics efficiency. *Data Science and Innovation in Supply Chain Management: How Data Transforms the Value Chain. Proceedings of the Hamburg International Conference of Logistics (HICL)*, 77–111. https://doi.org/10.15480/882.3126

Ma, Q., Tariq, M., Mahmood, H., Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development. *Technology in Society*, 68, 101910. https://doi.org/10.1016/j.techsoc.2022.101910

Meng, W., Dou, R., Han, Y., Wang, N. (2018). The Management Efficiency of PPP Projects in Rural China. *7th International Conference on Industrial Technology and Management (ICITM 2018)*, 179–183.

Mitrović, Đ. (2020). Measuring the efficiency of digital convergence. *Economics Letters*, 188, 108982. https://doi.org/10.1016/j.econlet.2020.108982

Mondejar, M. E., Avtar, R., Diaz, H. L. B., Dubey, R. K., Esteban, J., Gómez-Morales, A., Hallam, B., Mbungu, N. T., Okolo, C. C., Prasad, K. A., She, Q., Garcia-Segura, S. (2021). Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. *Science of The Total Environment*, 794, 148539. https://doi.org/10.1016/j.scitotenv.2021.148539

Moreira, S. B., Crespo, N. (2017). *Composite Indicators of Development* (pp. 140–162). https://doi.org/10.4018/978-1-5225-0714-7.ch007

Nesterenko, N., Pakhomova, N., Richter, K. K. (2020). Sustainable development of organic agriculture: Strategies of Russia and its regions in context of the application of digital economy technologies. *St Petersburg University Journal of Economic Studies*, 36(2), 217–242. https://doi.org/10.21638/spbu05.2020.203

OECD. (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. https://www.oecd-ilibrary.org/economics/handbook-on-constructing-composite-indicators-methodology-and-user-guide_9789264043466-en

OECD. (2009). *The impact of the crisis on ICTs and their role in the recovery*.

Omrani, H., Valipour, M., Emrouznejad, A. (2021). A novel best worst method robust data envelopment analysis: Incorporating decision makers' preferences in an uncertain environment. *Operations Research Perspectives*, 8, 100184. https://doi.org/10.1016/j.orp.2021.100184

Osmanbegovic, E., Piric, N. (2019). Contemporary approaches to measuring digital economy. *6th International Scientific Conference Economy of Integration (ICEI 2019)*, 189–199.

Owusu Kwateng, K., Osei-Wusu, E. E., Amanor, K. (2019). Exploring the effect of online banking on bank performance using data envelopment analysis. *Benchmarking: An International Journal*, 27(1), 137–165. https://doi.org/10.1108/BIJ-06-2018-0154

Pan, W., Xie, T., Wang, Z., Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research*, 139, 303–311. https://doi.org/10.1016/j.jbusres.2021.09.061

Peyrache, A., Rose, C., Sicilia, G. (2020). Variable selection in Data Envelopment Analysis. *European Journal of Operational Research*, 282(2), 644–659. https://doi.org/10.1016/j.ejor.2019.09.028

Prieger, J. E. (2013). The broadband digital divide and the economic benefits of mobile broadband for rural areas. *Telecommunications Policy*, 37(6–7), 483–502. https://doi.org/10.1016/j.telpol.2012.11.003

Rakicevic, J., Rakicevic, A., Poledica, A. (2019). Logical clustering approach for analysing digital economy and society performance of countries. *Proceedings of the 11th Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT 2019)*, 550–557.

Rakshit, I., Mandal, S. K. (2020). A global level analysis of environmental energy efficiency: an application of data envelopment analysis. *Energy Efficiency*, 13(5), 889–909. https://doi.org/10.1007/s12053-020-09857-5

Robaina, M., Murillo, K., Rocha, E., Villar, J. (2020). Circular economy in plastic waste - Efficiency analysis of European countries. *Science of The Total Environment*, 730, 139038. https://doi.org/10.1016/j.scitotenv.2020.139038

Rovan, J. (2011). Composite Indicators. In *International Encyclopedia of Statistical Science* (pp. 275–276). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-04898-2_15

Sachs, J., Schmidt-Traub, G., Kroll, C., Durand-Delacre, D., Teksoz, K. (2017). *SDG Index and Dashboards Report 2017*.

Saisana, M. (2014). Composite Indicator(s). In *Encyclopedia of Quality of Life and Well-Being Research* (pp. 1156–1161). Springer Netherlands. https://doi.org/10.1007/978-94-007-0753-5_504

Saisana, M., Tarantola, S. (2002). *State-of-the-art report on current methodologies and practices for composite indicator development*.

Sánchez-Ortiz, J., Rodríguez-Cornejo, V., Del Río-Sánchez, R., García-Valderrama, T. (2020). Indicators to measure efficiency in circular economies. *Sustainability* 12(11), 4483. https://doi.org/10.3390/su12114483

Sandkuhl, K., Wißotzki, M., Schmidt, R., Zimmermann, A. (2019). On the Effect of Digitalization of Products and Services on Enterprise Architectures. *Information Systems Development: Information Systems Beyond 2020 (ISD2019 Proceedings)*.

Simar, L., Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Stan, S. E., Oprean-Stan, C., Ţîţu, A. M. (2020). Digitalization – sustainable development convergence: metrics and effects in Romania. *Management of Sustainable Development*, 12(1), 10–16. https://doi.org/10.54989/msd-2020-0002

Stankova, M., Hampel, D. (2019). Bankruptcy Prediction Based on Data Envelopment Analysis. *37th International Conference on Mathematical Methods in Economics 2019*, 31–39.

Stavytskyy, A., Kharlamova, G., Stoica, E. A. (2019). The Analysis of the Digital Economy and Society Index in the EU. *Baltic Journal of European Studies*, 9(3), 245–261. https://doi.org/10.1515/bjes-2019-0032

Sustainable Development Solutions Network. (2022). *SDG Index and Monitoring*.

Tang, L., Lu, B., Tian, T. (2021). Spatial Correlation Network and Regional Differences for the Development of Digital Economy in China. *Entropy*, 23(12), 1575. https://doi.org/10.3390/e23121575

Tapscott, D. (1997). *The Digital Economy: Promise and Peril in the Age of Networked Intelligence*. McGraw-Hill.

The United Nations. (2021). *The 17 goals*.

Titko, J., Stankevičienė, J., Lāce, N. (2014). Measuring Bank Efficiency: DEA Approach. *Technological and Economic Development of Economy*, 20(4), 739–757. https://doi.org/10.3846/20294913.2014.984255

UNCTAD. (2021). COVID-19 and E-commerce: a Global Review. In *United Nations publication*.

UNCTAD - United Nations Conference on Trade and Development. (2019). *Digital Economy Report 2019: Value creation and capture: Implications for developing countries*.

United Nations. (2021). *Digital Economy Report UNCTAD 2021* (Issue September).

van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, 72, 577–588. https://doi.org/10.1016/j.chb.2017.03.010

Villa, G., Lozano, S., Redondo, S. (2021). Data Envelopment Analysis Approach to Energy-Saving Projects Selection in an Energy Service Company. *Mathematics*, 9(2), 200. https://doi.org/10.3390/math9020200

von der Leyen, U. (2019). *A Union that strives for more: My agenda for Europe - Political Guidelines for the next European Commission 2019-2024*. https://bit.ly/30d4NnH

Wang, Z., Wang, X. (2022). Research on the impact of green finance on energy efficiency in different regions of China based on the DEA-Tobit model. *Resources Policy*, *77*, 102695. https://doi.org/10.1016/j.resourpol.2022.102695

Yalçın, E. C. (2021). Efficiency Measurement of Digitalization on EU Countries: A Study Based on Data Envelopment Analysis. *International Journal of Management, Knowledge and Learning*, 10, 323–333. https://doi.org/10.53615/2232-5697.10.323-333

Yang, S., Wang, H., Wang, Z., Koondhar, M. A., Ji, L., Kong, R. (2021). The Nexus between Formal Credit and E-Commerce Utilization of Entrepreneurial Farmers in Rural China: A Mediation Analysis. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(4), 900–921. https://doi.org/10.3390/jtaer16040051

Yeganehfar, M., Zarei, A., Isfandyari-Mogghadam, A. R., Famil-Rouhani, A. (2018). Justice in technology policy. *Journal of Information, Communication and Ethics in Society*, 16(2), 123–137. https://doi.org/10.1108/JICES-06-2017-0038

Yousefi, S., Hassanzadeh, A., Saen, R. F., Mousavi Kashi, Z. (2021). Assessing sustainability of Islamic countries via data envelopment analysis (DEA). *Clean Technologies and Environmental Policy*. 24, 1129–1143. https://doi.org/10.1007/s10098-020-02002-x

Yu, Y., Zhu, W., Shi, Q., Zhuang, S. (2022). Common set of weights in data envelopment analysis under prospect theory. *Expert Systems*, 38(1). https://doi.org/10.1111/exsy.12602

Zhang, Y., Xu, B. (2021). How Should E-Commerce Platforms Subsidize Retailers with Logistics Constraints during an Epidemic Scenario? Considering Power Structure and Altruistic Preference. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(5), 1680–1701. https://doi.org/10.3390/jtaer16050095

Zhou, P., Poh, K. L., Ang, B. W. (2016). Data Envelopment Analysis for Measuring Environmental Performance. In *Handbook of Operations Analytics Using Data Envelopment Analysis* (pp. 31–49). https://doi.org/10.1007/978-1-4899-7705-2_2

Zhu, W., Chen, J. (2022). The spatial analysis of digital economy and urban development: A case study in Hangzhou, China. *Cities*, 123, 103563. https://doi.org/10.1016/j.cities.2022.103563