

Modelling Complex Relationships Between Sustainable Competitiveness and Digitalization

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Abstract

Digitalization is the core component of future development in the 4.0 industrial era. It represents a powerful mechanism for enhancing the sustainable competitiveness of economies worldwide. Diverse triggering effects shape future digitalization trends. Thus, the main research goal in this study is to use sustainable competitiveness pillars (such as social, economic, environmental and energy) to evaluate international digitalization development. The proposed empirical model generates comprehensive knowledge of the sustainable competitiveness-digitalization nexus. For that purpose, a nonlinear regression has been applied on gathered annual data that consist of 33 European countries, ranging from 2010 to 2016. The dataset has been deployed using Bernoulli's binominal distribution to derive training and testing samples and the entire analysis has been adjusted in that context. The empirical findings of artificial neural networks (ANN) suggest strong effects of the economic and energy use indicators on the digitalization progress. Nonlinear regression and ANN model summary report valuable results with a high degree of coefficient of determination ($R^2 > 0.9$ for all models). Research findings state that the digitalization process is multidimensional and cannot be evaluated as an isolated phenomenon without incorporating other relevant factors that emerge in the environment. Indicators report the consumption of electrical energy in industry and households and GDP per capita to achieve the strongest effect.

Keywords: digital technology, competitiveness, human capital, economic development, electrical energy

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1. INTRODUCTION

The development of Industry 4.0 has caused numerous changes in terms of the overall progress of society and the economy. The primary focus of the third industrial revolution from the early 1970s until the Internet experienced diffusion around the 1990s has been on incorporating information technology (IT) in the industry with the ambition to accelerate economic growth (Sadorsky, 2012). After the third industrial revolution, the paradigm of Industry 4.0 emerged, representing the evolution of information society. A real technological boom (Jin & Cho, 2015)

that drives the core of Industry 4.0 is associated with digitalization. In theory, the broad concept of digitalization is explained as an expansion of information and communication technology (ICT) in the economy and contemporary society (Lange et al., 2020). The development of ICT technologies is seen as a powerful tool for economies to achieve global competitiveness and, as a result of their application, new sources of economic growth emerge (Nair et al., 2020). The core of digital technology is to improve the characteristics of conventional technology by converting it into "smart" systems that are competitive, efficient, and easy to use (Coskun-Setirek & Tanrikulu, 2021).

The digital transformation towards new business systems is followed by changes on several organizational levels. In particular, the labor market has not remained immune to changes in the world of digitalization. To stay competitive and follow global trends, the labor market constantly adjusts to the digital age by leading workforce to gain cognitive skills identified as crucial skills that the digitalization process imposes (Laar et al., 2020). Another important aspect of the digitalization process is environmental degradation that emerges from increased usage of ICT and it is one of the concerns in this study. The most recent literature provides evidence that the diffusion of ICT is directly associated with negative effects on environmental sustainability because this sector is considered to be a large consumer of energy (Lange et al., 2020). Today, it is impossible to talk about ICT development phenomena without considering its growing electricity demand (Salahuddin & Alam, 2016), especially if blockchain technology or other cryptocurrencies are considered.

The motive for writing this scientific paper is grounded on the need to examine the impact of social, economic, environmental and energy aspects of the sustainable competitiveness concept in the scope of the digitalization process. Other authors have already investigated the phenomenon of digitalization solely from particular perspectives such as economic, environmental or social (Li et al., 2020; Lange et al., 2020). Besides considered indicators, various authors have also investigated technological (Pelikánová, 2019) and governmental/public indicators (Dobrolyubova et al., 2019). There is a theoretical and research gap in discovering how improvements in sustainable competitiveness can be used to trace digitalization development. In that sense, the novelty of this study originates in investigating the role of straightening sustainable competitiveness in the future digital transformation progress. This paper contributes to a body of knowledge of sustainable competitiveness and digitalization, connecting these phenomena that are viewed as driving forces of economic development. The structure of the study is organized as follows. Section 2 reports contemporary research outcomes concerning the nexus between sustainable development and digitalization. Section 3 provides a brief data review and theoretical overview of the employed methodology. Section 4 illustrates the most noticeable results and a comprehensive discussion of the research outcome. Section 5 provides the final remarks of the study and proposes future research directions.

2. THEORETICAL BACKGROUND

2.1 Digitalization process

Dramatically fast introduction of new digital technology in everyday life and turbulent business

environment fosters managers, employees, governments, and all other stakeholders to change the way they work and live (Coskun-Setirek & Tanrikulu, 2021). The industrial sector has gone through digital transformation, so industrial activities nowadays are characterized by a high degree of automation and dependency on ICT services. Contemporary literature about ICT diffusion provides many ways to express ICT development (Belabbes et al.). Some international organizations go a step forward and develop ICT development indexes, like Portulans Institute that measures Network Readiness Index (NRI, 2020), United Nations that measure E-government development index (EDGI, 2020), or European Commission that estimates Digital Economy and Society Index (DESI, 2020). In this study, an ICT Development Index (IDI) is considered as the most appropriate framework to assess the ICT development. It was established by the International Telecommunications Union, which is a measure calculated from 2009 annually (International Telecommunication Union, 2020). It represents a comprehensive measure that incorporates eleven sub-indicators in its calculation procedure, thus providing a broad perspective. Its annual estimation is found to be the most suitable to compare with the rest of the data that are used in the research. IDI conceptual framework considers three indexes of ICT development such as ICT access, ICT use, and ICT skills (International Telecommunication Union, 2020). The importance weights of IDI indexes are respectively 40%, 40%, and 20% (International Telecommunication Union, 2017). The low importance weight of ICT skills is explained by using proxy indicators rather than the actual measurement of ICT skills (International Telecommunication Union, 2017). IDI has been used by various scholars to assess the development of digitalization in a specific country, region, or wider (Pérez-Castro et al., 2021).

2.2 Sustainable competitiveness

Sustainability is recognized as a future development path of society (Demartini et al., 2019). It consists of the three main pillars - social, economic, and environmental (Figge et al., 2002; Govidan et al., 2013). In that sense, sustainable competitiveness is defined as an advantage that is social, economic, and environmentally acceptable and that an organization or a company can achieve in comparison to its competitors, taking into account that this advantage is not easily reachable for others (Knudsen et al., 2021). Ferreira et al. (2019) highlight that ability to adapt past business practice to new technology and implement it in the most efficient way to gain competitiveness is a crucial factor in evaluating the effects of implementing new technology. Digital transformation does not provide a competitive advantage for companies. It has to be supported by organizational capabilities to exploit the benefits of going digital (Hirvonen & Majuri, 2020). It should be born in mind that digital transformation is not a single-step procedure. It has to be planned with the special attention of the top management and government. In order to obtain comprehensive insight into sustainable competitiveness meaning, its main pillars (social, economic, and environmental) along with energy use will be explained in detail in the context of digitalization progress.

Social perspective. The social wellbeing in one country is primarily reflected in possibilities for employment and earning income necessary to meet basic needs. The digitalization process significantly influenced the labor market worldwide and caused several changes in employment practices. Emerging digital trends already tackle the digital division of employees to "digital

natives" and "digital immigrants" (Dittes et al., 2019). A newly reported survey addressed the question of digital technology use among employees. It argued that intensive digital technology use is closely connected to high-skilled professionals rather than low-skilled workers (Cirillo et al., 2021). The leading conclusion of the survey states that nowadays, digital intensive occupations have better employment chances, especially in companies with technological-competitiveness strategies. Today, many digital workers belong to the so-called gig economy. The term gig economy explains individuals (for example, freelancers) who are occasionally on-demand or in the short term, engaged to perform some jobs (Tan et al., 2021). The gig economy has the power to modify the labor market structure in terms of reporting false employment data. For example, around 30% of the American adult population is engaged in the gig economy, and part of gig workers are classified as unemployed (Bracha & Burke, 2021). The context of the gig economy is differentiated by the size of the available industries and workers, dependency on digital technologies and flexibility in work (Tan et al., 2021). But, on the other hand, as a result of accelerated digitalization, the "digital shadow economy" emerged, which significantly affected results achieved in the formal sector. The term addresses those individuals who are achieving all legal production and provision of goods and services through cyberspace channels without authority's knowledge to avoid taxes or standard procedures (Gasparėnienė et al., 2018). The digital shadow economy is part of the total shadow economy, which is the largest in weak states and/or developing nations. Estimates show that the largest shadow economies worldwide can be found in Georgia, while the lowest in developed European countries like Switzerland and the USA (Medina & Schneider, 2018). It is unclear how large the digital shadow economy is compared to the total shadow economy. However, it is clear from before mentioned sources that the digital shadow economy is rising.

Economic perspective. Digitalization is set as an accelerating engine of economic growth. Together with the innovation process and information society, it is the fundament of the digital economy (Li et al., 2020). It boosts economic growth in both developed and developing economies, thus representing a sector of the economy that provides breakthrough opportunities in the global market for all economies worldwide (Myovella et al., 2020). As such, governments should accelerate it (Nair et al., 2020).

Adopting digital technology is not always simple for companies since investments in digital innovation are high and depend on the technology domain; therefore, the role of financial institutions like banks is fundamental in supporting digital progression (Yuan et al., 2021). Gerschenkron (1962) has even formed a special name "backwardness" advantage for developing countries that are prone to achieve greater benefits of adopting technology that is produced in developed economies than developed countries by itself due to their readiness to risk as well as lower path dependencies based on earlier developments in the economy. The main reason for increased competition is that digital technology is shaping new global trends in the markets through changing the transaction costs on both supply and demand-side, bringing potentially very positive benefits for developing nations (Abeliansky & Hilbert, 2017). Institutional economists have argued that the most essential precondition for developing countries is the quality of the institutions of a country (Acemoglu et al., 2005). Improving the institutions will therefore remove many barriers for international competition and stimulate export, especially in

the digital sphere. Recent discoveries report that national export is primarily affected by the level of productivity that is constrained by both technological prosperity and technological transfer and by the strength of the national economy (Cieřlik & Parteka, 2021). Digital technology expands markets across international borders and provides new online channels of distribution (Glocker & Piribauer, 2021). In developed economies, investments in research and development are an essential source of technology and achieve a strong impact on decisions about engaging in export (Sharma, 2018). Other authors have studied the effects that globalization has on technology adoption, especially digital, and concluded that this phenomenon fosters technology transfers and spillovers (Skare & Soriano, 2021). The process of globalization shapes the global trend of competitiveness.

Environmental perspective and energy use. For years, scientists have been dismissive of the negative ecological impact that ICT use leaves on energy demand, justifying it as very low and insignificant until the rise of Internet use and mobile phones. Underestimating the effects of ICT growth can lead to shortages in electricity supply, causing instability in energy sectors across countries (Sadorsky, 2012) and causing environmental degradation. Authors (Kallal et al., 2020) have already stated the presence of a variety of papers dealing with this problem in developed countries. Still, on the other side, they emphasized the existing shortage of such documents for developing countries. Two positive effects can be achieved by establishing more energy-efficient ICT infrastructure, and those are saving energy (electrical) and preventing environmental degradation (Shahbaz et al., 2016). The current energy goal of nations is to achieve sustainable energy use, which means satisfying current energy needs without compromising the future (Holden et al., 2021).

Salahuddin & Alam (2016) confirmed the existence of interdependence among economic growth and electricity consumption variables and highlighted the enhanced electrical energy demand for ICT use. Sadorsky (2012) revealed stunning trends of ICT growth rate in developing countries, where the average growth rate of Internet users leads to a more than 5% increase in electricity consumption. Using the panel analysis, Saidi et al. (2017) explore the nexus between ICT, economic growth, and electricity consumption. From 2000 to 2010, the number of mobile cellular subscriptions per 100 inhabitants increased by more than a hundred percent in developed economies and almost three times more in developing economies. The same situation is recorded in the number of Internet users. The empirical evidence deriving from the study indicates a higher rate of ICT development in developing countries than developed countries. Salahuddin & Alam (2016) research results demonstrate the positive long-run relationship between economic growth and electricity consumption, stating that 1% of economic growth rate induces a rise of 0.13% in electrical energy consumption in OECD countries. Household electricity consumption has the potential to increase by making houses smarter with different smart devices and appliances (Fjellså et al., 2021).

3. RESEARCH OBJECTIVE, METHODOLOGY, AND DATA

The research aims to provide a better understanding of sustainable competitiveness' pillars impact on digitalization progress in considered European countries. The study has an international

character and covers 33 economies located in Europe from 2010 to 2016. The time framework is partially constrained by available IDI information from 2009 and partially by other available data. A comprehensive dataset is created by gathering valuable annual data about input indicators reported in Table 1.

Fixed and random effects models, which are commonly used as effective methodologies for studying panel data, could not yield adequate model fits at first. The Durbin-Watson test for determining data stationarity yielded a result of 0.310. The problem of stationarity was overcome after computing the first difference on each variable. However, both fixed and random effects models revealed that most variables were not statistically significant ($p > 0.05$). Therefore, the proposed methodological framework included a nonlinear regression model and artificial neural network (ANN) that was generated in the SPSS v.17 software. The decision about employing nonlinear regression (Zhang et al., 2021) was made based on the empirical findings of the data normality test.

Moreover, the extended analysis included ANN methodology for constructing a scientific model for evaluating the digitalization process when multiple aspects are incorporated. ANN represents an intelligent engineering tool for solving complex challenges, and its functioning is simulating the human nervous system using algorithms (Elsheikh et al., 2019). It is used for modeling relationships between input and output variables and pattern recognition (Şahin et al., 2013). Multilayer perceptron neural network (MLP) is a type of ANN which is employed in this research. It consists of one input layer, one or more hidden layers, and one output layer (Şahin et al., 2013).

Tab. 1 – Sources of indicator data. Source: own research

Group	Indicator name	Source
Social	X1: Employment rate (% of the total population)	World data bank, 2021; Ilostat, 2021
	X2: Working-age population rate with advanced education (% of the total population)	Ilostat, 2021
	X3: People at risk of poverty or social exclusion (% of the total population)	Eurostat, 2021
Economic	X4: GDP per capita PPP (US\$ per capita)	World data bank, 2021
	X5: Research and development expenditure (% of GDP)	
	X6: Exports of goods and services (% of GDP)	
Environmental	X7: Electricity generation from coal (TWh)	Our world in data, 2021
	X8: Electricity generation from oil (TWh)	
	X9: Share of GHG emissions MTCO _{2e} from energy production in total GHG emission (% of total GHG emission)	Climate watch, 2021



Energy use	X10: Final electricity consumption - industry sector (TWh)	Eurostat, 2021
	X11: Final electricity consumption - other sectors household (TWh)	
	X12: Energy intensity (kw per hour / US\$)	Our world in data, 2021
Digital	Y: ICT Development Index	International Telecommunication Union, 2021

4. RESULTS AND DISCUSSION

The structural model consists of 12 predictors and 1 output variable, presented in Table 1. A brief overview of the descriptive statistics is reported in Table 2. Presented descriptive statistics clearly indicate that the dataset consists of countries of different sizes, development levels, economic systems and other characteristics. Considering economic and social indicators, the lowest values are recorded in North Macedonia or Turkey, whereas Western economies like Luxembourg and Iceland are the top-performers in these two areas. The lowest employment rate (X1), GDP per capita (X4) and R&D investments are recorded in North Macedonia. Such results are consequences of the long term political and economic crisis in this country and, together with the relatively low level of the working-age population with advanced education (X2) and a high risk of poverty (X3), lead to a considerable migration of the people to developed countries (Pollozhani, 2020). Also, due to the economic and political crisis (Öniş, 2019), the lowest levels of the working-age population with advanced education (X2) and exports (X6), as well as the highest high risk of poverty (X3), are recorded in Turkey. On the other hand, maximum values for the working-age population with advanced education (X2), GDP per capita (X4) and exports (X6) are achieved in Luxemburg as a result of the developed and sophisticated financial services sector in this country (European Commission, 2016). The highest employment rate (X1) and the lowest risk of poverty (X3) are recorded in Iceland, while the maximum value of R&D investments (X5) is recorded in Finland. It should be emphasized that the maximum values recorded in the developed countries mentioned are several times higher than the minimum values recorded in North Macedonia and Turkey.

Tab. 2 – Descriptive statistics. Source: own research

Var.	Min	Max	Mean	Std. Dev.	Variance	Skewness	Kurtosis
X1	31.05	60.21	43.55	5.55	30.76	-.10	.03
X2	10.50	39.60	25.11	7.58	57.42	-.05	-1.24
X3	11.20	65.70	26.20	10.25	104.99	1.16	1.32

X4	11283.00	110661.00	35481.84	16399.84	2.69	1.72	4.74
X5	.22	3.73	1.52	.86	.74	.65	-.62
X6	21.19	221.20	61.23	36.52	1332.99	2.09	5.16
X7	.00	288.21	27.71	53.24	2834.28	3.29	11.58
X8	.00	21.71	2.82	4.31	18.58	2.21	4.58
X9	.00	127.65	36.29	18.77	352.19	1.40	4.21
X10	.40	234.23	35.96	48.59	2360.94	2.31	5.85
X11	.59	166.13	27.86	38.55	1486.05	2.09	3.63
X12	.68	4.65	1.39	.69	.47	2.92	10.04
Y	4.38	8.88	7.06	1.00	1.01	-.20	-.59

The differences among the considered economies are evident in terms of ecological indicators. Iceland, Estonia, Cyprus, Latvia, Lithuania, Luxembourg, Malta, and Norway are the only countries that do not use coal to generate electricity, so they have X7 amounting to 0. Furthermore, Sweden, Belgium, Slovakia, and Austria reduced their share of coal-fired energy (Rodrigues et al., 2020). On the other hand, the maximum value of this indicator is recorded in Germany. Taking into account that, besides Germany, only the UK and Poland have considerably high values of X7 and that there are numerous countries where this indicator amounts to 0 or near 0, it is not surprising that the standard deviation is almost twice as high as the mean. This fact is also shown by the Skewness and Kurtosis range. In terms of oil-based electricity generation (X8), Iceland, Latvia, Luxembourg, Norway, Macedonia, and Serbia have 0 value in X8. In addition, Romania, Slovenia, Lithuania, Belgium, Denmark, Ireland, Croatia, and Hungary have a low share of this energy source in their electricity production. The country having the highest value for this indicator is Italy. Such data values resulted in a twice higher standard deviation than the mean, like in the case of X7. Considering GHG emissions (X9), it should be emphasized that the minimum value is recorded in Iceland, whereas the Czech Republic has the highest level of this indicator.

In the area of energy consumption, Malta, along with Estonia, has the lowest final energy consumption of both industry (X10) and households (X11). In contrast, the minimum energy intensity value (X12) is recorded in Ireland. Germany recorded the highest final energy consumption in the industry (X10), while France recorded the highest final electricity consumption in the household sector (X11). Iceland has the highest energy intensity (X12), but it can meet its energy needs by developing the production of energy from renewable sources (Sveinsson, 2016). Finally, the lowest value of the IDI indicator (Y) is recorded by Turkey, followed by Macedonia, Romania, Serbia, and Bulgaria, which have relatively no value for this indicator due to low digital adoption. Denmark has the highest Y value, followed by Iceland and the UK.

The data were translated into the SPSS program using the Rescaling Method for Scale Dependents for further analysis. A Kolmogorov-Smirnov (KS) test is applied to satisfy the assumptions of parametric statistics in testing the normality of the gathered data. The outcome of the KS test failed to confirm the normal distribution ($p < 0.05$). Therefore, further analysis is constrained to nonlinear regression. A described model on which nonlinear regression analysis and ANN are applied is shown in Figure 1. The outcome of Spearman's correlation underlines the high

impact of social and economic indicators on the ICT development index. The highest positive correlation is reported between income and digitalization ($\rho=0.853$, $p<0.005$), where any increase in income is followed by an improvement in digitalization. A significant positive relationship is also acknowledged between R&D expenditures and digitalization ($\rho=0.750$, $p<0.005$), and this relationship is expected and natural. The strongest negative correlation is shown in the relationship between people at risk of poverty and digitalization ($\rho=-0.740$, $p<0.005$), and it discovers that an increase in poverty population leads to a decrease in digitalization, meaning that as much as an economy is weak it tends to achieve poor results in digital development, that was also expected. To apply regression analysis, binominal Bernoulli's distribution has been applied to divide the dataset into training sample (72.7% randomly selected data) and testing sample (27.3% data).

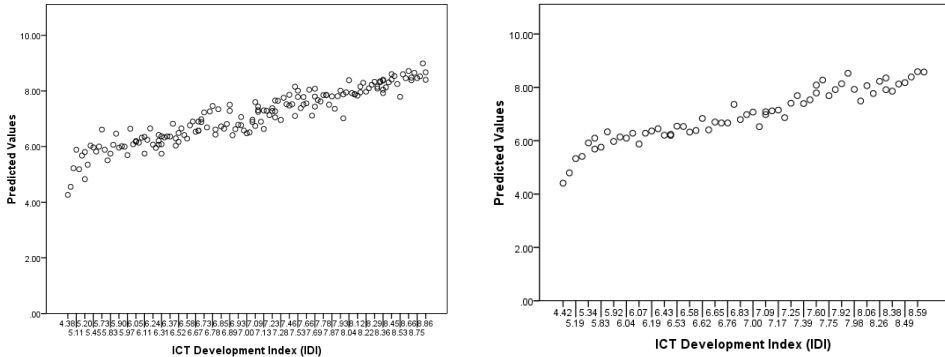
Independent indicators		Spearman's CC (ρ)	
		Social	
		Employment rate (X_1)	0.662
		Working-age population rate with advanced education (X_2)	0.683
		People at risk of poverty or social exclusion (X_3)	-0.740
		Economic	
		GDP per capita PPP (X_4)	0.853
		Research and development expenditure (% of GDP) (X_5)	0.750
		Exports of goods and services (% of GDP) (X_6)	0.113
		Environment	
		Electricity generation from coal (X_7)	-0.175
		Electricity generation from oil (X_8)	0.016
		Share of GHG emissions MTCO ₂ e from energy production in total GHG emission (X_9)	-0.245
		Energy use	
		Final electricity consumption - industry sector (X_{10})	0.279
		Final electricity consumption - other sectors household (X_{11})	0.169
		Energy intensity (X_{12})	0.041

Fig. 1 – Structural model. Source: own research

Selecting the best fitting nonlinear model was done by engaging curve estimation analysis that indicates a statistically significant ($p<0.05$) cubic nonlinear equation for all indicators. Cubic regression was used since curve estimate analysis in SPSS revealed the greatest and statistically significant coefficient of determination for each independent variable separately. Curve analysis considers linear, logarithmic, inverse, quadratic, cubic, compound, power, s growth, exponential, and logistic functions. All functions were considered in the empirical investigation. Accordingly, the outcome of the curve estimation provided unstandardized coefficient values for the nonlinear cubic regression equations that are presented as equations (1) and (2). Empirical findings based on the nonlinear cubic regression model are reported in Figure 2 for both datasets. ANOVA results for nonlinear regression confirm valuable regression equation with $R^2=0.904$ for the training and $R^2=0.930$ for the testing sample.

$$\begin{aligned}
 PRED_70\% = & 2.991 + 0.067 * X_1 + 0.001 * X_1^{**2} + 0 * X_1^{**3} + 1.763 + 0.387 * X_2 - 0.008 * X_2^{**2} + 0 * X_2^{**3} \\
 & + 10.322 - 0.19 * X_3 + 0.003 * X_3^{**2} + 0 * X_3^{**3} + 3.232 + 0 * X_4 + 0 * X_4^{**2} + 0 * X_4^{**3} \\
 & + 4.785 + 2.632 * X_5 - 0.773 * X_5^{**2} + 0.089 * X_5^{**3} + 6.273 + 0.034 * X_6 + 0 * X_6^{**2} + 0 * X_6^{**3} \\
 & + 7.345 - 0.027 * X_7 + 0 * X_7^{**2} + 0 * X_7^{**3} + 7.11 - 0.078 * X_8 + 0.021 * X_8^{**2} - 0.001 * X_8^{**3} \\
 & + 8.332 - 0.062 * X_9 + 0.001 * X_9^{**2} + 0 * X_9^{**3} + 6.603 + 0.038 * X_{10} + 0 * X_{10}^{**2} + 0 * X_{10}^{**3} \\
 & + 6.946 + 0.001 * X_{11} + 0 * X_{11}^{**2} + 0 * X_{11}^{**3} + 7.838 - 1.166 * X_{12} + 0.442 * X_{12}^{**2} - 0.032 * X_{12}^{**3}
 \end{aligned} \tag{1}$$

$$\begin{aligned}
 PRED_{30\%} = & 0.247 + 0.185 * X1 - 0.001 * X1^{**2} + 0 * X1^{**3} + 1.116 + 0.517 * X2 - 0.015 * X2^{**2} + 0 * X2^{**3} \\
 & + 8.031 + 0.013 * X3 - 0.003 * X3^{**2} + 0 * X3^{**3} + 3.885 + 0 * X4 + 0 * X4^{**2} + 0 * X4^{**3} \\
 & + 4.234 + 3.908 * X5 - 1.502 * X5^{**2} + 0.195 * X5^{**3} + 5.925 + 0.032 * X6 + 0 * X6^{**2} + 0 * X6^{**3} \\
 & + 7.13 - 0.019 * X7 + 0 * X7^{**2} + 0 * X7^{**3} + 6.952 - 0.025 * X8 + 0.008 * X8^{**2} + 0 * X8^{**3} \\
 & + 8.435 - 0.091 * X9 + 0.001 * X9^{**2} + 0 * X9^{**3} + 6.746 + 0.018 * X10 + 0 * X10^{**2} + 0 * X10^{**3} \\
 & + 7.004 - 0.019 * X11 + 0 * X11^{**2} + 0 * X11^{**3} + 8.079 - 1.747 * X12 + 0.729 * X12^{**2} - 0.077 * X12^{**3}
 \end{aligned} \tag{2}$$



(a) Nonlinear regression training sample. (b) Nonlinear regression testing sample.

Fig. 2 – Comparison of nonlinear regression prediction results and actual IDI indicator. Source: own research

The formation of the artificial neural network is based on the model described in Figure 1. The proposed ANN architecture consists of one hidden layer with eight nodes. There are 12 input neurons (representing input variables X1: X12) and 1 output layer, with one output neuron (Y). The relative error of the training sample is low, equals 0.066, while the relative error of the testing sample is slightly higher and equals 0.147.

Figure 3 illustrates the relationship between the observed and predicted values of the dependent IDI variable using the ANN model. The graph indicates the existence of linear growth of the IDI indicator with a high coefficient of determination that is $R^2=0.946$, which confirms the existence of a valid prediction model. Namely, ANN model can be used with a prediction accuracy of 94.6 %. Empirical evidence implies a high-quality ANN model with a lower deviation than the nonlinear regression model.



Fig. 3 – Comparison of ANN prediction results and actual IDI indicator. Source: own research

Countries with high electricity consumption in the industrial sector have robust economies that rely on industrial activities, and their economic prosperity is recognized in increased household electricity consumption. By considering this relationship, the secondly ranked GDP per capita is reasonably among the top priority indicators. High electricity consumption by industry and households, resulting in high GDP per capita, indicates an appropriate environment for digitalization development in terms of financial resources and all other essential requirements. Digital technologies such as blockchain technology or cryptocurrencies are expensive. Application in some countries is constrained by the lack of available financial resources (Yuan et al., 2021) and/or electrical energy (Bozorgmehr, 2021). Therefore, it is considered that economic welfare is imperative for digital development. Empirical results verify the existence of the important role of electrical energy consumption and income in planning further digital expansion. The next indicators, by their importance weights, are the generation of electrical energy using coal and oil. High-energy consumption must be supported by high-energy generation to underpin the economic growth. The study considers only conventional energy sources to prove to what extent is the digitalization progress affected by this type of energy. In the first place, the use of coal is important and followed by the use of oil. Simple justification for the given energy generation structure is recognized based on the primary use of coal and oil for producing electrical energy in most of the economies (Saidi et al., 2017). Approximately the same importance is derived for the indicator representing the country's export of goods and services. The export-GDP ratio is strongly connected with the process of globalization because globalization allows access to the global market with global competitors where all participants can compete. The high export-GDP ratio is a result of trade policies that accept globalization and international competitiveness as a path for the development of the country, and this goes, given the trends described before, hand in hand with further digital development. Based on the research of Elia et al. (2021), companies have to invest in digital technology and digital capabilities to develop a competitive advantage based on the export of digital services. Countries with a high export-GDP ratio are the ones who dictate development trends and follow the trends that are already settled. They are acknowledged as pioneers in digital transformation since they are the ones who impose it with their activities

in the global market and are open to introducing digital transformation in their economies. Governments should support digital technology diffusion because, in that way, technological advancement is enabled, and as a result, countries develop their economies (Myovella et al., 2020). However, to start the digital transformation and achieve good transformation results, governments should be aware of the educational structure of the population. This is confirmed with presented results taking into account the high importance of the working-age population with advanced education. Digitalization diffusion is partly constrained by the educational skills that the population possess since digital development must be supported by the right digital skills (Solomon & Klyton, 2020). Some of the presented studies confirm the increased use of digital technology in those workplaces where white-collar employees are required compared to the blue-collar workplace requirements (Cirillo et al., 2021). Eller et al. (2020) claim the key role of managers is to develop an adequate digital strategy and at the same time to support employees to develop their knowledge and skills to adapt to new digital framework and help to build the competitive advantage of the organization

Besides being expensive to introduce, digital technology is also a considerable energy consumption source that triggers environmental issues in terms of whether economies can secure clean energy sources with GHG emissions nearly zero for their energy needs or they plan to satisfy the needs by exploiting fossil fuels. This represents a profound question for experts and scientists about managing the future development of digital transformation when thinking about environmental sustainability. Managers should integrate digital development initiatives and environmentally friendly behavior into the core of organizational culture and tend to introduce green ICT into the business with nearly zero GHG emissions to support the future development of the 4.0 Industry (Isensee et al., 2020). Digital technology should be responsible for allowing environmental stewardship since it is the focus of the 4.0 Industry and should overcome the problem of energy sustainability through smarter and cleaner products and processes. Accordingly, higher government expenditure for R&D activities should support digitalization in its further expansion and sustainability. However, by the results of the analysis, their impact is not predominant, and empirical evidence reports that it is not crucial when digitalization diffusion is considered. The reason for this can be found in the easy access to the global market due to the fast globalization process where everyone can take part. Poverty set as a social factor is evaluated through people at risk of poverty or social exclusion, and according to the empirical results of the ANN, it is not recognized as much important for digitalization diffusion. However, it is confirmed that digitalization can improve the quality of life of ICT users. For example, authors Alhassan & Adam (2021) propose the government's financial intervention in providing access to affordable ICT, pointing out that such measures can lead to lower social exclusion. Energy intensity observed as a measurement of energy inefficiency of a country is among indicators characterized by lower importance weight and achieves low impact on future digitalization progression. It can be explained by the booming of services more than industrial production and therefore, as representative of a low energy intensity sector, it does not depend on energy efficiency. However, having in mind high household consumption of electrical energy, it can be assumed that part of this consumption belongs to performing digital services from a home office. The employment rate is seen as the least important indicator for the future digitalization process. In a recent study, authors Shapiro & Mandelman (2021) received similar empirical results that underpin the

absence of a link between digital adoption and unemployment. The main reason for this can likely be found in the specific skills needed for employees. There may very well lead to structural unemployment, where jobs skills in demand do not match with the skills of job searchers on the labor market. Given that most workers in the digital sector are younger and higher educated, this leads to the conclusion that even without digital adoption among companies, these people would be likely to find jobs. Gaspareniene & Remeikiene (2016) propose introducing new educational programs to increase the level of human capital, securing an adequate business environment with the regulation application. As a drastic measure, they propose engaging individuals that could discover illegal transactions.

The overall strong impact of environmental and energy use indicators can be utilized as a benefit in developing strategies for digital prosperity by simultaneously affecting several stakeholders. The first group of stakeholders consisting of the policymakers that have the key role in defining a legal framework for accelerating the growth of generating clean energy in the total share of energy that would decrease the dependence for exploiting conventional fuels. The second group is considering the role of business organizations and companies that have the task to be socially and environmentally responsible and lead their organizations towards sustainable business. In that sense, managers are seen as crucial in establishing strategies that reflect environmentally sustainable activities and outcomes, along with employees responsible for the implementation. The third group of stakeholders is comprised of households that are identified as an important factor in electricity consumption. One of the possibilities for reaching population awareness is through providing financial, social, and environmental incentives for the transition to clean energy. The research results highlight the prime effect that income achieves on digitalization, which means that financial resources are extremely important in shaping the digital progression. In line with this goes the importance weight that the export rates of economies have on digitalization. A strong national economy is a pillar for developing and supporting a successful digital environment. Future digitalization progression is still highly anticipated by producing conventional fuels such as coal and oil, which leads to the conclusion that sustainable competitiveness of nations can be achieved only if this dependency is minimized. Social indicators obtain poor predictive power towards digitalization prosperity, meaning that there can be some hidden effects on the transparency of social data, such as the impact of the gig-economy or digital shadow economy.

5. CONCLUSION

The research objective of this study was to create a model that synthesizes the influence of basic segments of sustainable competitiveness on digitalization development. The main reason for choosing social, economic, environmental and energy use predictors is found in the fact that digitalization is constrained by many factors and many scholars adopt these factors among the most important. To confirm the impact of selected four groups of indicators on the digitalization results, a nonlinear regression equation model with high prediction power and ANN analysis has been incorporated for creating an ANN model. The outcome of the ANN model presented more accurate results than nonlinear regression with a great value of the coefficient of determination. Major findings imply on prime effects that energy use indicators, such as electricity consumption

in industry and household achieve on the digitalization improvement along with an economic indicator that is analyzed through GDP per capita. Proposed measurements can be used as a guideline for planning future digitalization development through achieving sustainable competitiveness. The main limitation in this research is found in the limited timespan that is considered in the analysis and constraints about the number of indicators that are selected to create the model with the optimal number of predictors. Future research can be focused on a longer time span and can incorporate other relevant factors such as technological and governmental in examining the phenomenon of digitalization prosperity.

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References

1. Abeliatsky, A. L., & Hilbert, M. (2017). Digital technology and international trade: Is it the quantity of subscriptions or the quality of data speed that matters?. *Telecommunications Policy*, 41 (1), 35–48. <http://dx.doi.org/10.1016/j.telpol.2016.11.001>
2. Acemoglu, D., Johnson, S., & Robinson, J. A. (2005). Institutions as a fundamental cause of long-run growth. *Handbook of economic growth*, 1, 385–472.
3. Alhassan, M. D., & Adam, I. O. (2021). The effects of digital inclusion and ICT access on the quality of life: A global perspective. *Technology in Society*, 64, 101511.
4. Belabbes, I., El Moustafid, S., & Oubrich, M. ICT Development Index (IDI) as a statistical tool for measuring ICT uptake and assessing ICT policy: Morocco case.
5. Bozorgmehr, N. (2021). Iran bans bitcoin mining as power cuts grip country. Retrieved February 01, 2021 from Financial Times, New York: <https://www.ft.com/content/be0c8a04-9a58-4926-83f3-b99141c4f721>
6. Bracha, A., & Burke, M. A. (2021). How Big is the Gig? The Extensive Margin, The Intensive Margin, and The Hidden Margin. *Labour Economics*, 69, 101974.
7. Cieřlik, A., & Parteka, A. (2021). Relative Productivity, Country Size and Export Diversification. *Structural Change and Economic Dynamics*, 57, 28–44.
8. Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2020). Digitalization, routineness and employment: an exploration on Italian task-based data. *Research Policy*, 104079. <http://dx.doi.org/10.1016/j.respol.2020.104079>
9. Climate watch. (2021). Retrieved February 01, 2021 from <https://www.climatewatchdata.org/>
10. Coskun-Setirek, A., & Tanrikulu, Z. (2021). Digital innovations-driven business model regeneration: A process model. *Technology in Society*, 64, 101461.
11. Demartini, M., Evans, S., & Tonelli, F. (2019). Digitalization technologies for industrial sustainability. *Procedia Manufacturing*, 33, 264–271.
12. Dittes, S., Richter, S., Richter, A., & Smolnik, S. (2019). Toward the workplace of the future: How organizations can facilitate digital work. *Business Horizons*, 62 (5), 649–661. <http://dx.doi.org/10.1016/j.bushor.2019.05.004>

13. Dobrolyubova, E., Klochkova, E., & Alexandrov, O. (2019). Digitalization and Effective Government: What Is the Cause and What Is the Effect? In International Conference on Digital Transformation and Global Society, 55–67. Springer, Cham.
14. E-government Development Index (EDGI). (2020). Retrieved February 01, 2021 from <https://publicadministration.un.org/egovkb/en-us/About/Overview/-E-Government-Development-Index>
15. Elia, S., Giuffrida, M., Mariani, M. M., & Bresciani, S. (2021). Resources and digital export: An RBV perspective on the role of digital technologies and capabilities in cross-border e-commerce. *Journal of Business Research*, 132, 158–169.
16. Eller, R., Alford, P., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research*, 112, 119–127. <http://dx.doi.org/10.1016/j.jbusres.2020.03.004>
17. Elsheikh, A. H., Sharshir, S. W., Abd Elaziz, M., Kabeel, A. E., Guilan, W., & Haiou, Z. (2019). Modeling of solar energy systems using artificial neural network: A comprehensive review. *Solar Energy*, 180, 622–639. <http://dx.doi.org/10.1016/j.solener.2019.01.037>
18. European Commission. Country Report Luxembourg 2016; Commission Staff Working Document; European Commission: Brussels, Belgium, 2016; Retrieved: March 05, 2022 from: http://ec.europa.eu/europe2020/pdf/csr2016/cr2016_luxembourg_en.pdf
19. Eurostat. (2021). Retrieved February 01, 2021 from <https://ec.europa.eu/eurostat>
20. Ferreira, J. J., Fernandes, C. I., & Ferreira, F. A. (2019). To be or not to be digital, that is the question: Firm innovation and performance. *Journal of Business Research*, 101, 583–590. <http://dx.doi.org/10.1016/j.jbusres.2018.11.013>
21. Figge, F., Hahn, T., Schaltegger, S., & Wagner, M. (2002). The sustainability balanced scorecard—linking sustainability management to business strategy. *Business strategy and the Environment*, 11 (5), 269–284.
22. Fjellså, I. F., Silvast, A., & Skjølsvold, T. M. (2021). Justice aspects of flexible household electricity consumption in future smart energy systems. *Environmental Innovation and Societal Transitions*, 38, 98–109.
23. Gaspareniene, L., & Remeikiene, R. (2016). Economic and demographic characteristics of the subjects, operating in digital shadow economy. *Procedia Economics and Finance*, 39, 840–848. [http://dx.doi.org/10.1016/S2212-5671\(16\)30253-2](http://dx.doi.org/10.1016/S2212-5671(16)30253-2)
24. Gasparėnienė, L., Remeikienė, R., & Ginevičius, R. (2018). Attitudes of European Consumers towards Digital Shadow Economy: Lithuanian and Spanish Cases. *Acta Polytechnica Hungarica*, 15 (4), 121–142.
25. Gerschenkron, A. (1962). Economic Backwardness in Historical Perspective. *The Political Economy Reader: Markets as Institutions*, 211–228.
26. Glocker, C., & Piribauer, P. (2021). Digitalization, retail trade and monetary policy. *Journal of International Money and Finance*, 112, 102340.
27. Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner production*, 47, 345–354.

28. Hirvonen, J., & Majuri, M. (2020). Digital capabilities in manufacturing SMEs. *Procedia Manufacturing*, 51, 1283–1289.
29. Holden, E., Linnerud, K., & Rygg, B. J. (2021). A review of dominant sustainable energy narratives. *Renewable and Sustainable Energy Reviews*, 144, 110955.
30. Ilostat. (2021). Retrieved February 01, 2021 from <https://ilostat.ilo.org/>
31. International Telecommunication Union, The ICT Development Index (IDI): conceptual framework and methodology. (2021). Retrieved April 01, 2021 from <https://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis/methodology.aspx>
32. International Telecommunication Union. (2017). Measuring the Information Society Report 2017, Volume 1. Retrieved January 18, 2022 from https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2017/MISR2017_Volume1.pdf
33. Isensee, C., Teuteberg, F., Griese, K. M., & Topi, C. (2020). The relationship between organizational culture, sustainability, and digitalization in SMEs: A systematic review. *Journal of Cleaner Production*, 122944.
34. Jin, S., & Cho, C. M. (2015). Is ICT a new essential for national economic growth in an information society?. *Government Information Quarterly*, 32 (3), 253–260. <http://dx.doi.org/10.1016/j.giq.2015.04.007>
35. Kallal, R., Haddaji, A., & Ftiti, Z. ICT diffusion and economic growth: Evidence from the sectorial analysis of a periphery country. *Technological Forecasting and Social Change*, 162, 120403. <http://dx.doi.org/10.1016/j.techfore.2020.120403>
36. Knudsen, E. S., Lien, L. B., Timmermans, B., Belik, I., & Pandey, S. (2021). Stability in turbulent times? The effect of digitalization on the sustainability of competitive advantage. *Journal of Business Research*, 128, 360–369.
37. Laar, E., van Deursen, A. J., van Dijk, J. A., & de Haan, J. (2020). Determinants of 21st-century skills and 21st-century digital skills for workers: A systematic literature review. *Age Open*, 10 (1), 2158244019900176.
38. Lange, S., Pohl, J., & Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecological Economics*, 176, 106760. <http://dx.doi.org/10.1016/j.ecolecon.2020.106760>
39. Li, K., Kim, D. J., Lang, K. R., Kauffman, R. J., & Naldi, M. (2020). How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electronic Commerce Research and Applications*, 44, 101004.
40. Medina, L., & Schneider, F. (2018). Shadow economies around the world: what did we learn over the last 20 years? <http://dx.doi.org/10.5089/9781484338636.001>
41. Myovella, G., Karacuka, M., & Haucap, J. (2020). Digitalization and economic growth: A comparative analysis of Sub-Saharan Africa and OECD economies. *Telecommunications Policy*, 44 (2), 101856. <http://dx.doi.org/10.1016/j.telpol.2019.101856>
42. Nair, M., Pradhan, R. P., & Arvin, M. B. (2020). Endogenous dynamics between R&D, ICT and economic growth: Empirical evidence from the OECD countries. *Technology in Society*, 62, 101315. <http://dx.doi.org/10.1016/j.techsoc.2020.101315>

43. Network Readiness Index (NRI). (2020). Retrieved February 02, 2021 from <https://networkreadinessindex.org/>
44. Öniş, Z. (2019). Turkey under the challenge of state capitalism: The political economy of the late AKP era. *Southeast European and Black Sea Studies*, 19 (2), 201–225.
45. Our world in data. (2021). Retrieved February 02, 2021 from <https://ourworldindata.org/>
46. Pelikánová, R. M. (2019). R&D expenditure and innovation in the EU and selected member states. *Journal of Entrepreneurship, Management and Innovation*, 15 (1), 13–34.
47. Pérez-Castro, M. Á., Mohamed-Maslouhi, M., & Montero-Alonso, M. Á. (2021). The digital divide and its impact on the development of Mediterranean countries. *Technology in Society*, 64, 101452. <http://dx.doi.org/10.1016/j.techsoc.2020.101452>
48. Pollozhani, P. (2020). Economic Effects Of Migration To North Macedonia. *Economic Vision-International Scientific Journal in Economics, Finance, Business, Marketing, Management and Tourism*, 7 (13–14), 170–180.
49. Rodrigues, J. F., Wang, J., Behrens, P., & de Boer, P. (2020). Drivers of CO2 emissions from electricity generation in the European Union 2000–2015. *Renewable and Sustainable Energy Reviews*, 133, 110104.
50. Sadorsky, P. (2012). Information communication technology and electricity consumption in emerging economies. *Energy Policy*, 48, 130–136. <http://dx.doi.org/10.1016/j.enpol.2012.04.064v>
51. Şahin, M., Kaya, Y., & Uyar, M. (2013). Comparison of ANN and MLR models for estimating solar radiation in Turkey using NOAA/AVHRR data. *Advances in Space Research*, 51 (5), 891–904.
52. Saidi, K., Toumi, H., & Zaidi, S. (2017). Impact of information communication technology and economic growth on the electricity consumption: Empirical evidence from 67 countries. *Journal of the Knowledge Economy*, 8 (3), 789–803. <http://dx.doi.org/10.1007/s13132-015-0276-1>
53. Salahuddin, M., & Alam, K. (2016). Information and Communication Technology, electricity consumption and economic growth in OECD countries: A panel data analysis. *International Journal of Electrical Power & Energy Systems*, 76, 185–193. <http://dx.doi.org/10.1016/j.ijepes.2015.11.005>
54. Shahbaz, M., Rehman, I. U., Sbia, R., & Hamdi, H. (2016). The role of information communication technology and economic growth in recent electricity demand: fresh evidence from combine cointegration approach in UAE. *Journal of the knowledge economy*, 7 (3), 797–818. <http://dx.doi.org/10.1007/s13132-015-0250-y>
55. Shapiro, A. F., & Mandelman, F. S. (2021). Digital adoption, automation, and labor markets in developing countries. *Journal of Development Economics*, 151, 102656.
56. Sharma, C. (2018). Exporting, access of foreign technology, and firms' performance: Searching the link in Indian manufacturing. *The Quarterly Review of Economics and Finance*, 68, 46–62. <http://dx.doi.org/10.1016/j.qref.2017.11.015>
57. Skare, M., & Soriano, D. R. (2021). How globalization is changing digital technology adoption: An international perspective. *Journal of Innovation & Knowledge*, 6 (4), 223–233, <https://doi.org/10.1016/j.jik.2021.04.001>

58. Solomon, E. M., & van Klyton, A. (2020). The impact of digital technology usage on economic growth in Africa. *Utilities Policy*, 67, 101104.
<http://dx.doi.org/10.1016/j.jup.2020.101104>
59. Sveinsson, O. (2016). Energy in Iceland: Adaptation to Climate Change. UNU-FLORES Policy Briefs, United Nations University Institute for Integrated Management of Material Fluxes and of Resources (UNU-FLORES), Dresden.
60. Tan, Z. M., Aggarwal, N., Cowls, J., Morley, J., Taddeo, M., & Floridi, L. (2021). The ethical debate about the gig economy: a review and critical analysis. *Technology in Society*, 65, 101594.
<http://dx.doi.org/10.2139/ssrn.3669216>
61. The Digital Economy and Society Index (DESI). (2020). Retrieved February 03, 2021 from <https://ec.europa.eu/digital-single-market/en/digital-economy-and-society-index-desi>
62. World data bank. (2021). Retrieved February 03, 2021 from <https://data.worldbank.org/>
63. Yuan, S., Musibau, H. O., Genç, S. Y., Shaheen, R., Ameen, A., & Tan, Z. (2021). Digitalization of economy is the key factor behind fourth industrial revolution: How G7 countries are overcoming with the financing issues? *Technological Forecasting and Social Change*, 165, 120533.
64. Zhang, K., Li, W., Han, Y., Geng, Z., & Chu, C. (2021). Production capacity identification and analysis using novel multivariate nonlinear regression: Application to resource optimization of industrial processes. *Journal of Cleaner Production*, 282, 124469.

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