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RESEARCH ARTICLE

A Better Proxy for Technology Determinant of Economic Growth: The International Digital Economy and Society Index

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ABSTRACT

The importance of information communication technology in fueling economic growth is widely acknowledged. In the current digital era, the International Digital Economy and Society Index (I-DESI) offers a more precise depiction alternative to the ICT indicators by serving as a better proxy for changes in the factors of production. It monitors the advancement of ICT in the EU27 and 14 non-EU nations, highlighting their strides towards a technology-driven economy. The objective of the study was to evaluate the influence of the I-DESI on economic growth through the utilization of the panel data method. Hence, gross domestic product (GDP) measured at constant prices was utilized as the dependent variable in the analysis, while the Index of Digital Economy and Society Integration (I-DESI), calculated by the European Commission, served as the independent variable. However, it's important to note that the described index is current and limited at present. In line with this constraint, only four years of data, spanning from 2015 to 2018, were available. To ensure the accuracy of the model, diagnostic tests were conducted, and the Driscoll-Kraay standard error model was employed to assess the outcomes. Two models were constructed to achieve this goal, with the initial one revealing the relationship between the I-DESI and economic growth. The second model aimed to pinpoint the dimensions of the I-DESI that had the greatest impact on growth. According to findings obtained from the analysis, I-DESI and certain subdimensions which are digital skills, use of internet, integration of digital technology, and digital public services affect economic growth positively and significantly. A one percent increase in I-DESI results in a one percent increase in GDP. Similarly, each subdimension mentioned, where meaningful relationships have been identified, possesses explanatory power for GDP. Furthermore, evaluating the coefficient of these independent variables, changing the weight of dimensions can be considered.

Keywords: Digital economy, Economic growth, Technology, International digital economy and society index, Driscoll-Kraay model

JEL Classification: O14, O33, O47

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1. Introduction

For sustainable economic growth, it is essential to increase the quality, not just the quantity, of labor and capital. On the other hand, other inputs, especially technology penetration, play a substantial role in the production process (Kuznets, 1966).

There has been a continuing evolution in information and communication technology (ICT) since the early 1900s (Imran et al., 2022:1). The ICT is widely regarded as a crucial indicator of both economic growth and development (Mgadmi et al., 2021; Vishnevsky et al., 2021). These postulates provide a base for an alternative perspective to the exogenous growth model. Romer (1986) and Lucas (1988) conducted principal studies supporting these assumptions, and this alternative view is called the endogenous growth model. The growth rate can indeed increase over time, in contrast to diminishing returns. In addition to physical capital, human capital is also considered. Therefore, with an increase in physical capital, human capital also increases, and the law of diminishing returns does not apply. Romer's (1986) endogenous growth model is founded on the integration of three main assumptions. Firstly, the model proposed in Romer's (1986) paper posits that knowledge, as an input, exhibits increasing marginal productivity. Furthermore, knowledge possesses a natural externality, indicating that the new knowledge discovered by a firm can be utilized by other firms for their benefit. The primary reason for this externality lies in the non-exhaustive patenting of knowledge. Secondly, knowledge can expand limitlessly, resulting in increasing returns in the production of consumption goods. Finally, to prevent an excessively rapid increase in consumption and utility, there must be a diminishing return on new knowledge production. Additionally, the model represents a competitive equilibrium with endogenous technological change.

ICT has a catalytic effect on the country's economy. These effects are not only on the micro-scale but also on the macro-scale. Through progress in ICT, knowledge can be shared quickly, as never before. Despite an emerging awareness of the importance of protecting intellectual property rights, there are few obstacles to the diffusion of knowledge. As knowledge expands among households, firms, and countries, it can foster human capital through labor skills. It also enables individuals to make consumption or investment decisions efficiently. Similarly, firms can benefit from the ICT revolution to reduce costs and improve productivity in their production processes through R&D activities (Vu, 2011).

Moreover, developments and changes in ICT can serve as a valuable measure for assessing a country's degree of digitalization. Various techniques are employed to measure ICT and digitalization, such as the Digital Economy and Society Index (DESI), which provides a comprehensive evaluation of a country's digital progress across various dimensions. The index may be referred to as a comprehensive measurement tool that evaluates a country's digital performance. It is composed of five main dimensions, which are all equally important in determining a country's digitalization process, both economically and socially. Each one of the dimensions is equally weighted: human capital, connectivity, use of internet, integration of digital technology, and digital public services. Each of these dimensions has its own set of sub-dimensions that are evaluated to provide a more in-depth analysis of a country's digital structure (European Commission, 2022a).

The purpose of this paper is to investigate the impact of digitalization on economic growth by examining the sub-dimensions of the I-DESI. Unlike prior research, this study examines the impact of each dimension on economic growth independently to enhance comprehension of this connection. To accomplish this, a ratio is computed by dividing the value of each component by the total score of the I-DESI. This ratio reveals the proportionate contribution of each dimension to the overall performance of the I-DESI. Therefore, the main significance of the current paper is based on the variables and model employed.

This study comprises of four main sections in addition to the introduction. Section II explains the DESI and the I-DESI concepts, their sub-dimensions, and sub-indicators. In Section III, the current literature is given, and previous studies and their conclusions are briefly discussed. Section IV presents the methodology, explaining the data set, model estimation, and other diagnostic analyses. Finally, Section V is the conclusion.

2. The DESI and I-DESI: Emerging Proxies for Evaluating The ICT Advancements

The DESI and I-DESI, these two indices are used to follow countries' digitalization paths by the scale of some specific field. The DESI and I-DESI calculated by the European Commission are paving the way for tracking digital progress in EU countries (European Commission, 2021). In contrast to the DESI, non-European countries are also included in the I-DESI. The I-DESI is a more comprehensive index for the study's goals, as it includes not only the EU27 countries, but also 18 non-European Union countries. While the I-DESI is a broader version of the DESI, both indices can be used interchangeably. An applied correlation analysis shows a strong positive correlation of 0.89 between them and country rankings (European Commission, 2020; Kovács et al., 2022). It is important to point out that the DESI or I-DESI is dynamic. Their dimensions, sub-dimensions, and individual indicators can change over time.

The DESI was composed of five main dimensions until 2021. The previous version of the DESI consisted of human capital, connectivity, use of internet, integration of digital technology, and digital public services. All individual indicators were combined under the four main dimensions in the new version, as shown in Table 1. Since it is dynamic, seminal improvements and methodological changes have been made throughout the years (European Commission, 2022a). While every component is weighted equally in the modified DESI, they were weighted 0.25, 0.25, 0.15, 0.20, and 0.15 respectively in the previous version. In the DESI, human capital measures individuals' basic and advanced internet-using skills, while connectivity determines broadband features and power. In this component, fixed broadband take-up, fixed broadband coverage, mobile broadband, and broadband prices are calculated by considering their weight. The integration of digital technology represents business digitalization and e-commerce activity. Finally, digital public services inform about government services given to citizens electronically (European Commission, 2022b).

Sub-dimensions and individual indicators are collected in various units. Therefore, their values are normalized using the min-max method, assigning each indicator a value between 0 and 1. The minimum value in the series is equal to 0, while the maximum value in the series is equal to 1. The remaining values fall between 0 and 1.

The formulation of a country's DESI score, based on indicators' notation in the table, is:

$$DESI_{it} = 0{,}25HC_{it} + 0{,}25\ C_{it} + 0{,}25IDT_{it} + 0{,}25DPS_{it} \qquad \text{(I)}$$

In this notation, while *i* represents the country, *t* shows the date. *HC* and *C* denote human capital and connectivity dimensions, as *IDT* and *DPS* display integration of digital technology and digital public services, respectively. This formula can calculate a country's DESI score on a given date. The notation below can be followed if warranted, to examine digital progress in detail through sub-dimensions. In this version of the formula, sub-dimensions contribute to the score with their weight.

$$DESI_{it} = 0{,}25[0{,}5(1a)_{it} + 0{,}5(1b)_{it}] + 0{,}25[0{,}25(2a)_{it} + 0{,}25(2b)_{it} + 0{,}4(2c)_{it} + 0{,}1(2d)_{it}]$$
$$+ 0{,}25[0{,}15(3a)_{it} + 0{,}7(3b)_{it} + 0{,}15(3c)_{it}] + 0{,}25[(4a)_{it}] \qquad \text{(II)}$$

Table 1: Sub-dimensions and individual indicators of DESI

Dimensions of DESI, 2021	sub-dimensions		individual indicators
1. Human Capital **25%**	1a. Internet user skills	**50%**	1a1, 1a2, 1a3
	1b. Advanced skills and development	**50%**	1b1, 1b2, 1b3, 1b4
2. Connectivity **25%**	2a. Fixed broadband take-up	**25%**	2a1, 2a2, 2a3
	2b. Fixed broadband coverage	**25%**	2b1, 2b2, 2b3
	2c. Mobile broadband	**40%**	2c1, 2c2, 2c3
	2d. Broadband prices	**10%**	2d1
3. Integration of Digital Technology **25%**	3a. Digital intensity	**15%**	3a1
	3b. Digital technologies for businesses	**70%**	3b4 3b5, 3b6, 3b7
	3c. e-Commerce	**15%**	3c1, 3c2, 3c3
4. Digital Public Services **25%**	4a. e-Government	**100%**	4a1, 4a2, 4a3, 4a4, 4a5

Source: European Commission, Digital Economy and Society Index (2022)

Although the I-DESI is based on the components of the DESI, it only combines 24 individual indicators, while the DESI has 33 individual indicators. These indicators and sub-dimensions are listed in Table 1 and Table 2. Additionally, these tables show that individual indicators contribute to the total score based on their assigned weight.

$$I - DESI_{it} = 0{,}25C_{it} + 0{,}25\, DS_{it} + 0{,}15UI_{it} + 0{,}20IDT_{it} + 0{,}15DPS_{it} \qquad \text{(III)}$$

The differences between equation I and equation III are *DS* and *UI*, i.e., the "digital skills" and "use of internet" dimensions added in the last equation instead of , and the weight of sub-dimensions.

$$I - DESI_{it} = 0{,}25\left[\tfrac{1}{3}(1a)_{it} + \tfrac{2}{9}(1b)_{it} + \tfrac{1}{3}(1c)_{it} + \tfrac{1}{9}(1d)_{it}\right] + 0{,}25\left[\tfrac{1}{2}(2a)_{it} + \tfrac{1}{2}(2b)_{it}\right] + 0{,}15\left[\tfrac{1}{3}(3a)_{it} + \tfrac{1}{6}(3b)_{it} + \tfrac{1}{3}(3c)_{it} + \tfrac{1}{6}(3d)_{it}\right] + 0{,}20\left[\tfrac{3}{5}(4a)_{it} + \tfrac{2}{5}(4b)_{it}\right] + 0{,}15(5a)_{it} \qquad \text{(IV)}$$

Equation IV can be used to calculate every sub-dimension in the I-DESI and their weighted contribution to the score. The I-DESI score can also be derived from individual indicators. From $1a$ to $5a$, using variables are denoted in the table below.

Table 2: Sub-dimensions and individual indicators of I-DESI

Dimensions of I-DESI, 2020	sub-dimensions		individual indicators
1. Connectivity 25%	1a. Fixed broadband	33%	1a1, 1a2
	1b. Mobile broadband	22%	1b1, 1b2
	1c. Speed	33%	1c1
	1d. affodabilitiy	11%	1d1
2. Human Capital 25%	2a. Internet users skills	50%	2a1, 2a2, 2a3
	2b. Advanced skills and development	50%	2b1, 2b2
3. Use of Internet 15%	3a. Content	33%	3a1
	3b. Communications	16,5%	3b
	3c.Transactions	33%	3c1, 3c2
	3d.Ubiquitous use	16,5%	3d1
4. Inetgration of Digital Technology 20%	4a. Bussiness digitalisation	60%	4a1,4a2
	4b.e-Commerce	40%	4b1,4b2
5. Digital Public Services 15%	5a. e-Government development index	100%	5a1, 5a2, 5a3

Source: European Commission, International Digital Economy and Society Index 2018, Smart 2017/0052, Final Report, 2020.

While the DESI is more comprehensive than the I-DESI, regarding individual indicators, the I-DESI provides a broader cross-national analysis. Therefore, I-DESI is preferred in this paper since it can include non-members of the EU in the analysis. However, it should be mentioned that since the I-DESI has been calculated recently, only four years of data are available so far.

3. Literature Review

In the literature, there are numerous studies claiming a positive relationship between ICT and economic growth. This claim is based on the ability of ICT to increase productivity (Pohjola, 2000; Vu, 2011; Olczyk & Kuc-Czarnecka, 2022; Imran et al., 2022). Nevertheless, a comprehensive appraisal of these investigations reveals divergent findings. Furthermore, it should be noted that there is currently no consensus on the impact of ICT on economic growth, with some research indicating a positive effect, while others suggest a negative effect or find no significant relationship between the two. In this context, Fernández-Portillo, Almodóvar-González, and Hernández-Mogollón (2020:2-4) thoroughly summarize the literature and findings by dividing the studies according to their exogenous and endogenous growth theory.

Previous studies have utilized different variables to represent the features of ICT in countries. For instance, Nasab and Aghaei (2009) investigated the relationship between ICT and economic growth using the Generalized Method of Moments (GMM). The study focused on the OPEC countries and utilized data spanning the period from 1990 to 2007. In their model, Nasab and Aghaei (2009) used ICT input, physical capital, human capital, and the labor force as independent variables. The ICT data encompassed computer hardware, software, computer services, and communication services, including wire and wireless communication equipment. According to the results of the dynamic panel model, investments in ICT were found to positively impact economic growth within the context of OPEC member countries' data. Similarly, Vu (2011) evaluated three different issues. In the first part, he aimed to determine whether there was a structural change in the 1996-2005 interval compared to the previous two decades. He used the Chow test to analyze data from 102 countries, which revealed a significant difference between the two periods. In line with this suggestion, improving ICT can contribute to economic growth. The main objective of the study was to determine if there was a causal relationship between ICT penetration and economic growth. Personal computers, mobile phones, and internet users were used as proxies for ICT. The GMM estimator demonstrated that each of the three variables positively affected economic growth.

As distinct from preceding studies, Ishida (2015) conducted autoregressive distributed lag (ARDL) tests, revealing that, whether in the long or short run, there is no statistically significant impact of ICT investment on real GDP. Ishida (2015) employed a model for a specific sample in his analysis, focusing on Japan, one of the most important partners in ICT development, during the period 1980-2004. The model specification in this study is grounded in the production function. Consequently, the dependent variable is real GDP, while independent variables include capital stock, labor hours, energy consumption, and ICT investment. The data for these variables were sourced from reputable institutions, specifically the Cabinet Office (for the first two variables), the Ministry of Internal Affairs and Communications, the Ministry of Health, Labor and Welfare, the Agency for Natural Resources and Energy, and the Ministry of Internal Affairs and Communications. Jin and Cho (2015) conducted a study using data from Korea, another leader in ICT. They noted some essential and supportive results to confirm the presence of the effect of ICT on economic growth. They incorporated both supply and demand proxies for ICT in their analysis. Determinants on the supply side included fixed-line internet network, PC penetration rate, mobile phone subscription rate, and imports of telecommunication equipment. On the demand side, variables encompassed internet use rate, total population of ICT workers, and annual earnings in telecom service. Additionally, related ICT policies are listed under the title "policy dimension" as an independent variable. Exports of telecommunications equipment were used as a proxy for policy. They also included moderating variables in the model, namely population, inflation, corruption perception index (CPI), and education capacity. Based on the results of the fixed effect with autocorrelation panel data analysis, they found a statistically significant impact of the mobile network adoption rate on economic growth but not for others in the supply dimension variables. Variables in the ICT demand dimension, namely internet use rate and telecom profit, had a statistically significant effect on economic growth. Moreover, the ICT policy dimension was found to be a rather impactful variable for economic growth.

Another substantial study belongs to Stanley, Doucouliagos, and Steel (2018). In their study, they focused on determining whether the effect of information and communication technology (ICT) growth is a genuine phenomenon or merely a result of publication bias. To address this question, they conducted a comprehensive analysis, employing meta-regression analysis encompassing 466 estimates from 59 different empirical analyses based on the Solow or Productivity Paradox. To compile relevant data, they used keywords related to ICT and economic growth, conducting their research through Google Scholar, Proquest, and SSRN. Following filtration, the dataset was narrowed down to 59 studies specifically examining the ICT growth effect. The analysis comprised of three main steps. Initially, they conducted a meta-analysis, followed by an investigation into the presence of publication bias. Finally, they examined potential variations in results between developed and developing countries, as well as variations based on different types of ICT. The meta-regression analysis estimation suggested a small effect of ICT on economic growth. Furthermore, the study employed Cochrane's Q test to assess the heterogeneity of the reported conclusions in the studies included. According to Cochrane's test results, the effect of ICT on economic growth could be influenced by other moderating factors. Interestingly, the study revealed differing results for developed and developing countries. Additionally, the impact of ICT was found to vary depending on its type. For example, the growth effect of cell technologies was almost twice as strong as landlines. Separately, computing has the most significant impact on growth in developed countries, with cells and landlines following. However, for developing countries, cell phones have the most significant effect, followed by landlines.

There are several other studies in the literature that examine the impact of ICT on economic growth using different proxies. While the results of empirical analyses reveal various relationships, it can be stated that studies advocating and supporting the positive effects of ICT are predominant (Saidi, Hassen, & Hammami, 2015; Shodiev, Turayey, & Shodiyev, 2021; Usman, et al., 2021). On the other hand, there are limited studies on DESI or I-DESI, which are widely accepted as the main content of the current study. The main reason for choosing I-DESI as the independent variable is precisely this. Examining how technological progress in the digital world, with a new and comprehensive proxy, will affect economic growth is crucial in drawing attention to the literature on this matter.

According to the literature review, the first study to examine the relationship between ICT and economic growth using DESI as a proxy was conducted by Fernández-Portillo, Almodóvar-González, and Hernández-Mogollón (2020). They used this proxy and applied Partial Least Squares (PLS) to analyze the effects of the DESI on economic growth. They obtained data from the OECD. Firstly, they generated a global conceptual map. This map shows the variables and indicators in the DESI and the three different representatives of GDP, namely GDP per capita

USD constant 2010 Purchasing Power Parity (PPP)", "GDP per person employed USD current PPP" and "GDP per person employed USD constant 2010 PPP". Therefore, twenty-five indicators into sub-dimensions in the DESI were used as a proxy of the ICT, and three particular GDP measures were used as dependent variables. In addition to this, the conclusions of the PLS suggest that fixed broadband connectivity and the use of internet variables influence GDP positively.

On the other hand, Gherghina, Paşa, and Onofrei (2021) used descriptive statistics to investigate where there is a correlation between the constituents of the DESI and real GDP rate and real GDP per capita. The Pearson product-moment correlation analysis proved a significant positive relationship between the DESI and real GDP per capita, but there was no such relationship between the DESI and real GDP rate.

Another current study belongs to Tokmergenova, Bánhidi, and Dobos (2021). They researched the I-DESI and its essential five dimensions using data from the EU28 countries and the Russian Federation. They investigated the development of Russia by comparing it with other countries. For this reason, they used a multivariate statistical analysis known as Principal Component Analysis (PCA). They examined the relationship between these principal dimensions using partial correlation coefficients. According to the results of their analysis, two dimensions can be explained by using the other three dimensions. They then used this conclusion to compose a group of the countries involved in the research. Thus, Russia is found obviously in the developing countries group that is related to the I-DESI score.

Similarly, Olczyk and Kuc-Czarnecka (2022) examined the relationship between DESI and economic growth. Firstly, they investigated whether the defined weights of indicators in the DESI are at the optimal level or not. After that, they analyzed the effect of the DESI on economic growth using a panel data model. In this analysis, GDP per capita was utilized as the dependent variable, while DESI served as the independent variable. Besides, they employed other control variables such as total factor productivity, government consumption, ICT capital compensation, gross fixed capital formation, financial direct investment (FDI), population size and growth, life expectancy, openness, and real effective exchange. The findings from the panel data model indicate a positive impact of DESI on GDP per capita.

Ghazy, Ghoneim, and Lang (2022) elaborated on the interconnections between the two assumptions. They examined their first hypothesis, that entrepreneurship positively impacts productivity, and the second hypothesis, that digitalism can foster entrepreneurship. Based on this postulate, digitalism was assumed to affect productivity. A two-stage GLS regression model (G2SLS) was used, with the DESI and its subdimensions as determinants, to examine the mentioned relationship. Additionally, both fixed-effects and random effects Generalized Least Squares (GLS) models were employed. Their analysis shows that four dimensions have a positive and significant relationship with entrepreneurship, except for human capital.

Comprehensive studies on the I-DESI in the literature should be done to attract attention, as it is a current proxy of ICT. Only research considering this index is given in this part of the study. There is a need for more analysis to support the I-DESI explanatory force and significance.

4. Methodology

In the section below, analysis results and interpretations are provided for estimating the static panel data model, aiming to examine the relationship between GDP and I-DESI, along with its subdimensions. After the application of diagnostic statistics, the Driscoll-Kraay Standard Errors Model was employed as the appropriate estimator for standard errors. At this juncture, the time constraint of the I-DESI dataset (4 years) necessitated the preference for static panel data models over dynamic panel data models (Fernández-Portillo, Almodóvar-González, and Hernández-Mogollón, 2020).

4.1. Dataset and model

To conduct our empirical analysis, we utilized a random effects model. Before implementation, we thoroughly assessed the model's assumptions and subsequently applied the Driscoll Kraay model to evaluate the connection between economic growth (dependent variable) and the subdimensions of I-DESI (independent variables). These data were obtained for the EU27 member countries and 18 non-member states for 2015-2018. Hence, the balanced panel data is employed, and the total number of observations is 180. The I-DESI dataset was obtained from EUROSTAT, and as a proxy of economic growth GDP at constant prices (the base year 2015), was attained from OECD. Stat. Equations given below demonstrate the models examined in this paper:

$$lnG_{it} = \beta_0 + \beta_1 \ln(I - DESI_{1it}) + \beta_2 D + \mu_i + u_{it} \quad \text{(V)}$$

where G_{it} represents country i's economic growth at t time, while lnG_{it} is logged G_{it}. $\ln(I - DESI_{it})$ is the explanatory variable and indicates the I-DESI score of country i's at t time. D is the dummy variable generated based on whether countries are members of the EU in the model. Beside μ_i and u_{it} demonstrate individual effects and the error term, respectively.

$$lnG_{it} = \beta_0 + \beta_1 \ln(RC_{1it}) + \beta_2 \ln(RDS_{2it}) + \beta_3 \ln(RUI_{3it}) + \beta_4 \ln(RIDT_{4it}) + \beta_5 \ln(RDPS_{5it}) + \beta_6 D + \mu_i + u_{it} \quad \text{(VI)}$$

where, at t time, , $\ln(RC_{it})$ represents country 's ratio of the contribution of connectivity to I-DESI, as $\ln(RDS_{it})$, $\ln(RUI_{it})$, $\ln(RIDT_{it})$, $\ln(RDPS_{it})$ demonstrate country i's ratios of the contribution of digital skills, use of internet, integration of digital technology and digital public services to I-DESI, respectively. Henceforward, equation V is expressed as Model I, and equation VI is expressed as Model II.

It should be specifically emphasized here that in internal economic growth models, human capital and physical capital are used as the main determinants. As a dimension, under the "connectivity" heading, physical capital that contributes to digitization is detailed, and under the "human capital" heading, the acquisitions and skills of individuals in the path of digitization are displayed. Since the probability of creating autocorrelation is high and could compromise the reliability of the results, the use of another dataset for these variables has been avoided. Additionally, sections showing the purposes of internet usage and integration of the private sector to digital technology, and public policy are included in the model as independent variables under the headings "use of internet", "integration of digital technology," and "digital public services," respectively. Finally, whether countries are members of the European Union is included in both models as a dummy and control variable. Testing alternative hypotheses in these models is given in Table 3.

Table 3: Alternative hypothesis

	H_A
Model I	$H_1$1: I-DESI contributes to economic growth
Model II	$H_1$2: Contribution of each components of I-DESI affects economic growth
	$H_1$2a: The RC affects economic growth
	$H_1$2b: The RDS affects economic growth
	$H_1$2c: The RUI affects economic growth
	$H_1$2d: The RIDT affects economic growth
	$H_1$2e: The RDPS affects economic growth

Note: The null hypothesis, i.e., H0 for each alternative, postulates that explanatory variables do not affect economic growth.

4.2. Model specification and the other diagnostic tests

To achieve optimal parameter estimation in panel data analysis, a meticulous evaluation of individual and time effects within the model is necessary. If the model incorporates either or both of these effects, it is categorized as non-classical. The F test, Likelihood Ratio (LR) test, Breusch and Pagan (1980) Lagrange multiplier (LM) test, adjusted LM (ALM) test, and Score test are used for testing the validity of the classical model.

As presented in Table 4, the results demonstrate the rejection of the null hypothesis that assumes the absence of individual effects, while the null hypothesis that assumes the absence of time effects cannot be rejected. Also, GLS is used to estimate the random and fixed effects models after determining the one-way individual effects model. The F-test and Wald Chi-Square test results show that the null hypothesis assuming no individual and time effects in all models was rejected either for Model I or Model II. The Hausman test was conducted to determine which estimator is most efficient. This test examines whether individual effects are correlated with the independent variables. The null hypothesis of the Hausman test is predicated upon this assumption, i.e., . If the null hypothesis is rejected, it is more appropriate to use the fixed-effects model estimator instead of the random-effects model, as the fixed-effect estimator is not impacted by violating the null hypothesis. It is expected that the difference between the fixed-effects and random-effects estimators is close to zero for using random effects estimator (Hausman, 1978:1263). Hence, the random-effects estimator, consistent under the null hypothesis, was deemed appropriate.

Table 4: Individual and time effects test results

	individual effects test			time effects test		
	H_0	Model I	Model II	H_0	Model I	Model II
F test	$H_0: \mu_i = 0$	269.2**	239.13**	$H_0: \lambda_t = 0$	0.00	0.00
LR test	$H_0: \sigma_\mu = 0$	570.34**	794.65**	$H_0: \sigma_\lambda = 0$	0.00	0.00
LM test	$H_0: \sigma_\mu^2 = 0$	16.41**	15.49**	$H_0: \sigma_\lambda^2 = 0$	-1.37	-1.25
ALM test	$H_0: \sigma_\mu^2 = 0$	7.68**	7.19**	$H_0: \sigma_\lambda^2 = 0$	-1.65	-1.43
Score test	$H_0: \sigma_\mu = 0$	570.84**	1.0e+10**	$H_0: \sigma_\lambda = 0$	0.00	0.00
Hausman-Test chi2 [prob > chi2]- FE vs RE	$H_0: E(\mu_i \mid X_{it}) = 0$	0.24 [0.623]	7.64 [0.177]			
rhausman Test chi2 [prob > chi2]- FE vs RE	$H_0: E(\mu_i \mid X_{it}) = 0$	0.26 [0.610]	2.14 [0.829]			

Note: In the table, values in the brackets denote p-values. The levels of significance of 1%, 5%, and 10% are indicated by symbols *, **, and ***, respectively.

While panel analysis has heteroscedasticity, autocorrelation, cross-sectional dependence, multicollinearity, or non-normal distributions, it is commonly assumed that the classical model cannot be estimated approximately. If even one of these assumptions is not provided, robust estimators are needed to estimate the model efficiently (Elamir, 2022). Table 5 displays the results of model specification tests and several tests used to examine deviations from the assumptions.

Diagnostic tests ensure the adequacy of model specifications and estimations. One of the most popular tests of the specification is Ramsey's (1969) regression specification error test (RESET). However, DeBenedictis and Giles (1989) claimed that the Ramsey RESET test could not have high power to examine whether the model specification is appropriate. So, they described this test as biased. Hence, they developed the RESET test, and because it was based on Fourier approximation, they named it FRESET. The modified RESET test is based on linear and sinusoidal transformations. As can be seen in Table 5, linear and sinusoidal transformations are represented by RESETL and RESETS, respectively. The test results denote that the null hypothesis that supposes no model specification error was not rejected.

Afterward performing the specification test in the presented paper, another diagnostic test was conducted to determine the violation of essential assumptions. As it is known commonly, the classical F-test examining homoscedasticity is appropriate for the assumption of normal distribution. Subsequently, several alternative methods have been developed over the years. Levene's (1960) test is one of the most famous. In this analysis, homoscedasticity, i.e., equal variances, was examined by the Levene and Brown-Forsythe (1974) test, which was a robust test of Levene (Shoemaker, 2003). According to the test results, the test statistics shown by W0, W50, and W10 are greater than the critical value of the Snedecor F table with (44, 135) degrees of freedom[1]. The null hypothesis that postulates equal variances was rejected for each of the three statistics. So, the first assumption was invalid for Model I and Model II. Both models contained heteroscedasticity.

When testing the model, autocorrelation is examined as another basic assumption. To examine whether errors form random walk, Durbin-Watson, modified by Bhargava, Franzini, and Narendranathan (1982), and Baltagi-Wu (1999) locally best invariant (LBI) tests are used. The null hypothesis of these tests assumes that the errors are serially independent, i.e., there is no autocorrelation in

[1] Only W50 statistics were demonstrated in Table 5. The other statistics are for Model I, W0=3.065, W10=3.065, and for Model II, W0=3.448, W10=3.448.

the residuals $(H_0: \rho = 0)$. The alternative hypothesis tested against the null hypothesis suggests the presence of either a positive $(H_0: \rho > 0)$ or negative correlation $(H_0: \rho < 0)$ in residuals. Test results are given in Table 5. Both tests rejected the null hypothesis, which assumes no autocorrelation since the test statistics were less than 2 (Tatoğlu, 2021:267). For Model I, the Bahargava test statistic is 0.956, and it is 0.814 for Model II. Besides, Baltagi-Wu test statistics 1.744 and 1.596 for Model I and Model II, respectively. Likewise, LM and ALM tests were also performed to detect serial correlation. Baltagi and Li (1991) modified Breush-Pagan (1980) LM test. This extended version of the LM test assumes a joint hypothesis that provides both the presence of random individual effects and serial correlation. Therefore, the null hypothesis was rejected according to LM, ALM, and the joint test results.

Pesaran (2004) conducted a test that can be convenient for determining cross-section dependence in stationary and unit root heterogeneous dynamic panel data The Pesaran test is applicable for utilization, also in conditions that used panel data consisting of short T and large N. The null hypothesis of the Pesaran test is based on the assumption of no cross-section dependence in the panel data. Other common tests for determining the presence of heterogeneity in panel data belong to Friedman (1937) and Frees (1995). While Friedman's (1937) test proposes the non-parametric test using Spearman's rank correlation coefficient, Frees's (1995) test statistic is related to the sum of the squared rank correlation coefficients. Table 5 represents the conclusion of these tests. The results demonstrate that the alternative hypothesis, which suggests the presence of cross-section dependency, was not rejected (De Hoyos & Sarafidis, 2006).

Another test used to determine a violation of assumptions is related to multicollinearity. The VIF (Variance Inflation Factor) criterion measures the presence of multicollinearity between the independent variables and the remaining variables using the rule of thumb. The VIF criterion is denoted as $VIF_{(\hat{\beta}_J)} = \frac{1}{1-R_2}$, where $\hat{\beta}_J$ represents the auxiliary regression and equals the count of independent variables, and R_2 is the proportion of variance in this regression model which is estimated for the explanatory variable. If the VIF criterion is less than 5, it is interpreted that there is no collinearity between the variables and the remaining variables. On the contrary, if this criterion is higher than 10, this finding is evaluated as an indicator of multicollinearity (O'Brien, 2007; Tatoğlu, 2021:274-275). In Table 5, the mean VIF value was given in both Model I and Model II, and the results supported that there was no collinearity for any independent variable[2].

As the final assumption, the normality of the error terms was investigated by conducting the D'Agostino-Belanger-D'Agostino test (1990). This test examines both the presence of skewness and kurtosis individually and their simultaneous existence. The null hypothesis, which tests simultaneous existence, is defined on the assumption that skewness and kurtosis are zero $(H_0: S = 0)$ and three $(H_0: K = 3)$, respectively. The results of the null hypothesis testing are provided jointly in Table 5. The joint normality test for "e" shows the normal distribution of errors, while the test for "u" indicates the normal distribution of unit effects. D'Agostino-Pearson K^2 statistic is used to test the distribution (D'Agostino, Belanger, & D'Agostino, 1990).

[2] For MODEL I, VIF criterion of ln*(I-DESI)* and *D* is 1.02. In Model II, criterions are ln*(RC)*, ln*(RDS)*, ln*(RUI)*, ln*(RIDT)*, ln*(RPDS)* and *D* are 4.83, 4.41, 1.87, 1.72, 1.59, 1.21, respectively.

Table 5: Results of diagnostic tests

		H_0	Model I	Model II
Model spesification test				
DeBenedictis-Giles Specification test	ResetL test	$H_0: \in \sim N(0, \sigma_2 I)$	0.146 [0.964]	0.389 [0.816]
	ResetS test		1.860 [0.119]	0.343 [0.848]
Heteroscedasticity test				
Levene, Brown and Forsythe test		$H_0: \sigma 1^2 = \sigma 2^2 = \cdots = \sigma k^2$	2.167**	2.790**
Autocorrelation test				
Durbin-Watson test for autocorrelation		$H_0: \rho = 0$	0.956	0.814
Baltagi-Wu LBI test for autocorrelation			1.744	1.596
LM test for serial correlation			237.17**	209.53**
ALM test for serial correlation		$H_0: \rho = 0$	30.83**	25.07**
Joint LM test		$H_0: \sigma_\mu^2 = 0, \rho = 0$	300.04**	264.20**
Cross sectional dependence test				
Pesaran test			29.576**	35.021**
Frees test		$H_0: \rho_{ij} = \rho_{ji} = cor(u_{it}, u_{jt}) = 0$	5.229** (0.8391)	15.571** (0.8391)
Friedman test			64.493**	76.760**
Multicollinearity test				
VIF test		$H_0: \hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_3 = 0$	1.02	2.61
Normality test				
D'Agostino, Belanger and D'Agostino	joint nomality test on e	$H_0: S = 0, K = 3$	0.01	1.98
	joint nomality test on u		0.69	0.16

Note: In the table, values in the parentheses represent standard errors, and values in the brackets denote p-values. The levels of significance of 1%, 5%, and 10% are indicated by symbols *, **, and ***, respectively.

4.3. Estimation of robust model and results

Since Table 5 contains relevant information about deviation from substantial assumptions, it is necessary to use robust estimators to estimate the model. Driscoll and Kraay (1998) introduced a non-parametric covariance matrix that offers robust estimation against heteroscedasticity, autocorrelation, also cross-sectional dependence.

The analysis results of the Driscoll-Kraay standard error model demonstrated in Table 6 show that the estimation of both Model I and Model II is significant by Wald Chi-Square statistics at the five percent significance level. On the other hand, the values of the overall R square are significant, even though the main determinants for growth models are excluded from the analysis. Furthermore, the results from the estimate using the Driscoll-Kraay standard error model reveal that the I-DESI has a statistically significant positive effect on GDP at a confidence level of 5%. This result is partially the same line as Gherghina, Paşa, and Onofrei (2021). They defined that DESI positively impacts real GDP per capita but does not on real GDP. Nonetheless, as it is interpreted via test statistics in the present analysis, a positive relationship exists between I-DESI and GDP at constant prices.

In addition to these findings, it is essential to determine which component of the I-DESI contributes much more than others. The answer to this question can lead to countries' policy decisions about technology investment. Therefore, model II was estimated to respond to this substantial question. As mentioned above, this study emphasizes which part of the I-DESI is more explanatory for GDP. With this purpose, variables are generated as rates to measure the contribution.

Table 6: The results of Driscoll-Kraay standard error model estimation

	Model I	Model II
lnG as a dependent variable		
$ln(I-DESI)$	0.327**	
	(0.065)	-
$ln\ (RC)$		0.118
	-	(0.100)
$ln\ (RDS)$		0.109**
	-	(0.028)
$ln\ (RUI)$		0.200**
	-	(0.052)
$ln\ (RIDT)$		0.086**
	-	(0.021)
$ln\ (RDPS)$		0.068**
	-	(0.021)
D	-2.335**	-2.324**
	(0.653)	(0.463)
$constant$	13.489*	15.285*
	(0.606)	(0.763)
Wald Chi2 (prob > Chi2)	22.68 [0.000]	58.85[0.000]
Overall R-squard	0.388	0.388
rho	0.999	0.999
Number of obs	180	180
Number of groups	45	45

Note: In the table, values in the parentheses represent standard errors, and values in the brackets denote p-values. The levels of significance of 1%, 5%, and 10% are indicated by symbols *, **, and ***, respectively.

Drawing from the Driscoll-Kraay standard error model estimation, it can be inferred that, except for the rate of connectivity contribution to the I-DESI, each explanatory variable holds a statistically significant influence on GDP. Represented results in Table 6 corroborate digital skills, use of internet, integration of digital technology, and digital public services have an explanatory effect on GDP. Contrary to Fernández-Portillo, Almodóvar-González and Hernández-Mogollón (2020), there is no relationship between connectivity and GDP. Nevertheless, the results which are related to the use of internet are in the same line with their findings.

Besides, the most powerful explanatory variables are the use of internet and digital skills. Also, if digital skills are evaluated as factors for human capital, results support the theory that an increase in human capital impacts economic growth positively. Although Ghazy, Ghoneim, and Lang (2022) used dimension values without changing and different proxies for dependent variables in their analysis, this paper's findings partially support what they found. By corresponding with Vu's (2011) research on the impacts of the internet variable, this analysis confirms positive and significant impacts.

Moreover, this presented study shows that the ratio of the integration of digital technology and the ratio of digital public services can induce economic growth. These sub-dimensions and their indicators can accelerate production progress from the beginning of entrepreneurship to the last step for preparing for consumption because integrating technology brings many advantages, such as easily achieving a feasible project or target groups. This assumption can be predicated on Kuznet's (1966:286) suggestion: "*no matter where these innovations emerge… the economic growth of any given nation depends upon their adoption*". Another impressive conclusion benefit from the analysis is that, considering the coefficient of independent variables, the weight of dimensions can be reconsidered to compute the I-DESI score based on the postulation that digital technology stimulates GDP.

5. Conclusion

In the digital era, technology has been evaluated as an effective driver of economic growth. Concordantly, ICT is one of the outstanding determinants from the perspective of endogenous growth models. A huge number of analyses have enforced this assumption. Likewise, various explanatory variables have been used in the literature as a proxy for ICT. One of the most current proxies is I-DESI. Hence, to contribute to the literature, I-DESI was chosen as the main independent determinant. Also, sub-dimensions of the I-DESI and their contributions to the I-DESI were calculated as ratios and included in the second model.

As determined in the analysis results mentioned, the I-DESI can stimulate economic growth significantly. Therefore, all components and sub-indicators of the index may be evaluated as indicators of the technological gains of individuals, entrepreneurs, and governments. Especially in detail, the use of internet and digital skills variables may denote how individuals or households benefit from the technological revolution and its increasing time-saving and productivity effects. According to the results of the current empirical study, if the enhancement of individuals' human capital in alignment with the digital age is provided, positive outcomes for economic growth may be realized. Despite the absence of a statistically significant result concerning the connectivity variable, it nonetheless facilitates the potential contribution of human capital to economic output. In this context, investments in the requisite infrastructure services to effectively integrate individuals into the process of digitalization should be prioritized.

Furthermore, another variable demonstrating noteworthy and positive effects is digital integration. The digitization of e-commerce and business operations may ensure yield, economic and environmental cost reductions, facilitate the more effective functioning of the supply chain, and provide opportunities for swifter market penetration on both a national and international scale. Similarly, the migration of public services to the electronic environment in tandem with digitization may allow citizens to access public services instantly. Moreover, the transition of the required documents for bureaucratic processes into electronic format can contribute to waste reduction, resulting in a positive environmental impact.

On the other hand, reweighting these variables to calculate the index can make the I-DESI more advanced than the current version. This modification can explain economic growth more properly. Nevertheless, these findings can be considered in a policy decision about which investment is feasible or needed and which project should have priority.

Lastly, since the I-DESI is a thoroughly current calculated index, the data contains only four years, from 2015 to 2018. In this context, the present paper can be qualified to lead future research, which may be more inclusive.

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