IBIMA Publishing
Communications of International Proceedings
https://ibimapublishing.com/p-articles/46ECO/2025/4631625/
Vol. 2025 (25), Article ID 4631625

# The Economic Impact of Digital Competencies: A Fixed-Effects Panel Analysis for EU Countries*

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* Presented at the 46th IBIMA International Conference, 26-27 November 2025, Ronda, Spain

## Abstract

The main goal of this paper is to study the impact of digital competencies on economic growth measured by changes in the natural logarithm of GDP per capita. The study covers countries that are currently members of the European Union, and the data used to estimate the model spans the period from 2015 to 2019. To examine the relationship, a panel analysis was used. This method can isolate the impact of countries' time-invariant characteristics (fixed effects) as well as crises, business cycles, and shocks (time effects) common to all countries. The main explanatory variable for GDP per capita growth was a synthetic digital competence index created for the purposes of this study (Digital_Index). The baseline specification incorporated a number of control variables, which were subsequently removed in alternative specifications to assess changes in the quality of estimation. Models with and without lagged variables were used. A number of models with competency sub-indices and individual Internet and computer skills were tested. For the sake of comparison, OLS models were also estimated. The article indicates that digital competencies alone are not a determinant of economic growth in the short term, but this topic requires further research, the directions of which are pointed out in the conclusions.

**Keywords**: panel data analysis, fixed effects, digital competencies, digitalization

## Introduction

The progressive digitalization of economies and the economic processes is an indisputable fact, but the assessment of the effectiveness of these changes and their effects in the context of economic growth and possible benefits for people is still a subject of debate. Digitalization affects individuals and organizations such as businesses, state and local government administration equally. Due to the widespread nature of these changes, it is crucial to understand their mechanisms and impact, as negative effects can already be seen, for example in the form of digital exclusion. First of all, it is important to understand what digitalization and digital competencies are, as well as the relationship between these two concepts. There is no single correct definition of digitalization or even uniform terminology, as some authors equate digitalization with digital transformation (Parviainen et al., 2017), and even digitization, i.e., the ability to convert existing products and services into digital versions that have certain advantages over their physical counterparts (Henriette, Feki, & Boughzala, 2015). Digitalization can refer to the changes that potentially occur in society as a result of the use of digital technologies (Stolterman & Fors, 2004). Other definitions recognize that the criteria for digitalization is the increase in the use of digital or computer technologies by

**Cite this Article as:** Krzysztof SIUDA Vol. 2025 (25) "The Economic Impact of Digital Competencies: A Fixed-Effects Panel Analysis for EU Countries " Communications of International Proceedings, Vol. 2025 (25), Article ID 4631625, https://doi.org/10.5171/2025.4631625

individuals, organizations, entire industries, and countries (Brennen & Kreiss, 2016; Legner et al., 2017). In a purely economic context, it is also possible to find a definition of digitalization that ignores the process itself and focuses on the effects in the form of increased revenues from economic activity as a result of changes or the creation of new business processes that improve the company's operations (Fähndrich, 2023). The definitions mentioned above focus on the technical side of digitalization and overlook the key role of human capital, i.e., people with digital competencies that enable them to carry out digitalization. According to Calvani, Cartelli, Fini, & Ranieri (2008) „Digital competence consists in being able to explore and face new technological situations in a flexible way, to analyze, select and critically evaluate data and information, to exploit technological potentials in order to represent and solve problems and build shared and collaborative knowledge, while fostering awareness of one's own personal responsibilities and the respect of reciprocal rights/obligations". European Commission: Directorate-General for Education, Youth, Sport and Culture (2019) defines digital competencies as "…confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It includes information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and competencies related to cybersecurity), intellectual property related questions, problem solving and critical thinking". The cited definitions of digital competence focus on describing what they are, what they include, and what benefits they can bring, for example, in the form of the development of individuals or entire organizations. At best, these definitions state that digital competencies enable the use of new technologies, but they overlook the key interdependence between the implementation of these new technologies (digitalization) and digital competencies. It is difficult to imagine a situation in which people without digital competencies can implement modern technical solutions in their lives or businesses, firstly, because of a lack of awareness of the benefits this can bring, and secondly, because of a lack of the appropriate skills to carry out such implementations. This means that digitalization depends on the acquisition and development of digital competencies. Van Dijk & van Deursen (2014) recognize this connection, but consider such competencies to be a crucial phase in the appropriation of digital technologies, rather than something that must be present and continuously developed in order for newer and newer technologies to be created and used. In the context of the above definitions and the general perception of digitalization and digital competencies, this article aims to examine how these digital competencies influence economic growth. This is a key issue due to the ongoing and necessary digital transformation in the European Union, which should be carried out effectively. This necessity stems from the need to keep European economies competitive with poorer and less developed countries, which have certain comparative advantages, such as a cheaper, although less skilled, workforce. The necessary data was obtained from Eurostat websites. The study is limited to the countries of the current European Union. In the article, the primary statistical method used to assess the impact of digital competencies on economic growth in EU countries is panel analysis. Panel analysis makes a very good choice if the goal is to isolate the impact of a single variable from the surrounding noise. Panel analysis enables the separation of fixed effects (institutions, culture, geographical conditions) and time effects (common shocks, business cycles) common to all analyzed countries from the relationship under study – the impact of digital competencies on the growth of GDP per capita.

## Methodology and Data

Panel analysis uses two-dimensional data. Panel data is both cross-sectional, as it concerns entities such as countries or individual regions, and time-series, as the analysis of the aforementioned entities is carried out over a certain period (e.g., consecutive years). This two-dimensionality of data is a huge advantage of this method, as it allows the influence of unobservable heterogeneity to be removed, i.e., those characteristics of the subject of the study (e.g., a country) that are constant over time but very difficult to capture, especially in numerical form (Baltagi, 2021). For example, institutions, culture, and geographical conditions are such characteristics. We can safely assume that these characteristics have a significant impact on the phenomenon under study, but it is difficult to incorporate this impact into econometric models. The solution to this problem proposed by panel models is to introduce individual effects into the model ($\mu_i$), that are capable of capturing these time-invariant characteristics. There are two variants of panel analysis, depending on whether the individual effect representing unobservable characteristics is correlated or not with observable explanatory variables ($X_{it}$). The first of the two variants are fixed effects (FE) models, which assume that such a correlation between $\mu_i$ and $X_{it}$ exists. In this approach, the impact of the individual effect is removed using within transformation, which involves subtracting the arithmetic mean of each variable (for a given country or region) from all observations of that variable (explained and explanatory) or, more commonly, introducing so-called dummies. This may be a counterintuitive statement, because this effect is not really removed by eliminating or omitting it, but rather by capturing unobservable and time-invariant characteristics of the country and embedding them in a parameter $\mu_i$, which then allows for the correct estimation of unbiased coefficients ($\beta$). This allows countries to be compared with each other over time. Eliminating time-invariant variables over time is both an advantage (the model is not biased by omitted variables that could distort the results) and a disadvantage, because the impact of these omitted variables (e.g., geographical location, institutions) remains unknown. In addition, the fixed effects model can be expanded by adding time effects. In this case, the procedure is analogous to the individual effect, with the difference that the arithmetic mean of the variable is calculated with respect to the year rather than the unit (country, region). The advantage of introducing a time effect is that it eliminates the impact of shocks, crises, business cycles, etc., which are common to different countries (Angrist & Pischke, 2009; Cameron & Trivedi, 2005). This kind of model is called two-way FE, and this version is the one used in this article. The model can be formally specified as follows:

$$y_{it} = \alpha + \beta_1 D_{it} + \beta' X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where: $y_{it}$ – dependent variable; the (log) growth rate of GDP per capita in country i in year t, $D_{it}$ – value of the digital competencies index for country i in year t; main explanatory variable, $X_{it}$ – vector of control variables; control factors affecting economic growth, $\beta_1$ – coefficient on $D_{it}$; marginal impact of changes in the digital competencies index on GDP per capita growth, $\beta'$ – vector of coefficients on $X_{it}$; effects of the control variables on GDP per capita growth, $\mu_i$ – individual fixed effect, $\gamma_t$ – time fixed effect, $\varepsilon_{it}$ – error term; unexplained deviation for country i in year t.

Unlike the FE model, the random effects (RE) model assumes no correlation between $\mu_i$ and $X_{it}$. If there is indeed no correlation, then the individual effect is another random term, which may lead to a smaller standard error (SE) in the estimation and allows for variability between countries or regions to be taken into account (Greene, 2012). If the RE model is valid, the results obtained are consistent with the FE model, but with smaller standard errors, which means that the FE model is the safer option. The decision to use FE or RE can be made based on the Hausman test (Hausman, 1978). Another benefit of using panel analysis is the ability to analyze dynamics, i.e., to observe how changes in the values of explanatory variables in one year affect the dependent variable in the following period. By combining these two dimensions, you can obtain more data, greater variability, and, consequently, more accurate estimators (Wooldridge, 2020). In this article, it was decided, among other things, to test the variant with explanatory variables delayed by one year, which aims to eliminate the risk of reverse causality and endogeneity (Wei et al., 2025). The formal specification of the model with delayed explanatory variables is as follows:

$$y_{it} = \alpha + \beta_1 D_{i,t-1} + \beta' X_{i,t-1} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

where: $D_{i,t-1}$ – digital competencies index from the previous year, $X_{i,t-1}$ – vector of lagged control variables. Other symbols are the same as in the base model.

When comparing panel models to purely cross-sectional models, it can be seen that the former allow us to separate how countries differ from each other from the changes that occur only within a given country during the period under study. It is easy to see that countries differ significantly from one another in terms of their baseline level of digitalization, the digital competencies of their citizens, their GDP per capita, and their level of education. These baseline differences in standard models would distort the results, and it would be difficult to assess whether the growth in digital competencies has an impact on GDP per capita growth in subsequent years, or whether it is higher GDP per capita that contributes to a faster growth rate of such competencies among the citizens of a given country.

In panel models, the classic assumption of homoscedasticity and lack of autocorrelation of the error term $\varepsilon_{it}$ is often violated. In particular, macroeconomic data may exhibit differences in error variance between countries (heteroscedasticity) and correlation of errors over time within a given country (autocorrelation). If these are not taken into account, the standard errors will be underestimated, leading to inflated t-statistics and false statistical significance. This study uses clustered standard errors at the country level, which are robust to both heteroscedasticity and autocorrelation within units. This ensures that the p-values and confidence intervals obtained are reliable (Arellano, 1987; Colin Cameron & Miller, 2015).

The data comes from Eurostat resources and was converted into panel form. The study covers all current European Union member states in the period between 2015 and 2019. GDP per capita in constant prices was selected as the explanatory variable (Eurostat, 2025, sdg_08_10). Next, GDP per capita was subjected to logarithmic transformation in order to calculate logarithmic changes in subsequent years, which is a common practice in development economics research (Barro & Sala-i-Martin, post 2006], cop. 2004).

$$y_{it} = ln(GDPpc_{it}) - ln\left(GDPpc_{i,t-1}\right) \tag{3}$$

where: $GDPpc_{it}$, $GDPpc_{i,t-1}$ – Gross Domestic Product per capita for the country i in year t.

The benefits of this approach include: stabilization of variance, symmetrical increases and decreases in GDP per capita, the ability to sum changes over time, and easier interpretation. Table 1 presents the aforementioned values of two sample countries – Belgium and Bulgaria. The other tables presented are also limited to two countries, while the data used in the study covers 27 countries.

**Table 1. Example of dependent variable (dln_GDPpc); GDP per capita in EUR (GDPpc) and annual log growth rate (dln_GDPpc) for Belgium and Bulgaria, 2015–2019**

| Country | Year | GDPpc | dln_GDPpc |
|---|---|---|---|
| **Belgium** | 2015 | 40 310 | 0,87% |
| **Belgium** | 2016 | 40 590 | 0,69% |
| **Belgium** | 2017 | 41 030 | 1,08% |
| **Belgium** | 2018 | 41 610 | 1,40% |
| **Belgium** | 2019 | 42 400 | 1,88% |
| **Bulgaria** | 2015 | 8 130 | 4,66% |
| **Bulgaria** | 2016 | 8 480 | 4,21% |
| **Bulgaria** | 2017 | 8 830 | 4,04% |
| **Bulgaria** | 2018 | 9 180 | 3,89% |
| **Bulgaria** | 2019 | 9 670 | 5,20% |

The model takes into account a set of four control variables that are often used in panel studies and those concerning broadly defined digitalization. The data was also obtained from Eurostat for the years 2015–2019. The use of control variables in the model is crucial, as the GDP per capita growth rate certainly depends on many different factors, the omission of which in the model would result in a distortion of the $\beta_1$ value due to the shift of their impact to the error term $\varepsilon_{it}$, meaning an increase in its variance.

The set of control variables (Table 2) includes: percentage of the country's population with higher education – Tertiary_Edu (Eurostat, 2025, edat_lfse_03), percentage share of government, business, and household investment in total GDP – Investment_Share_GDP (Eurostat, 2025, sdg_08_11), unemployment – Unemployment_Rate (Eurostat, 2025, une_rt_a), percentage share of investment in research and development (R&D) – GERD_Share_GDP (Eurostat, 2025, rd_e_gerdtot). In the case of missing data, linear interpolation was used to maintain the continuity of panel data. Selected control variables allow for the assessment of the impact of the quality of human capital, productivity, innovation, and the potential to generate growth in the economy.

**Table 2. Control variables (tertiary education, investment share, unemployment rate, GERD) in Belgium and Bulgaria, 2015–2019**

| Country | Year | Tertiary_Edu | Investment_Share_GDP | Unemployment_Rate | GERD_Share_GDP |
|---|---|---|---|---|---|
| **Belgium** | 2015 | 32,70% | 23,15% | 8,70% | 2,43% |
| **Belgium** | 2016 | 33,20% | 23,52% | 7,90% | 2,53% |
| **Belgium** | 2017 | 35,60% | 23,50% | 7,20% | 2,68% |
| **Belgium** | 2018 | 36,00% | 23,77% | 6,00% | 2,86% |
| **Belgium** | 2019 | 36,00% | 24,23% | 5,50% | 3,15% |
| **Bulgaria** | 2015 | 24,10% | 20,86% | 10,10% | 0,95% |
| **Bulgaria** | 2016 | 24,40% | 18,41% | 8,60% | 0,77% |
| **Bulgaria** | 2017 | 24,50% | 18,30% | 7,20% | 0,74% |
| **Bulgaria** | 2018 | 24,80% | 18,79% | 6,20% | 0,76% |
| **Bulgaria** | 2019 | 24,70% | 18,68% | 5,20% | 0,84% |

The main explanatory variable is the synthetic digital competencies index (Digital_Index – equation 4), calculated as the arithmetic mean of the computer skills subindex (Computer_Skills) and the Internet skills subindex (Internet_Skills). The latter two indices were also constructed for the purposes of this study as arithmetic means using the following Eurostat data (Table 3): the percentage of people using electronic banking (Internet_Banking), the percentage of people able to search for information on goods and services on the Internet (Info_Search), the percentage of people using email (Email_Use) (Eurostat, 2025, isoc_ci_ac_i), the percentage of people able to copy and move files and folders (Copy_Move_Files), and the percentage of people able to transfer documents between different devices (File_Transfer) (Eurostat, 2025, isoc_sk_cskl_i).

$$D_{it} = \frac{Computer\_Skills + Internet\_Skills}{2} \tag{4}$$

$$Internet\_Skills_{it} = \frac{Internet\_Banking + Info\_Search + Email\_Use}{3} \tag{5}$$

$$Computer\_Skills_{it} = \frac{Copy\_Move\_Files + File\_Transfer}{2} \tag{6}$$

**Table 3. Component indicators of digital skills for Belgium and Bulgaria (2015–2019)**

| Country | Year | Internet_Banking | Info_Search | Email_Use | Copy_Move_Files | File_Transfer |
|---|---|---|---|---|---|---|
| **Belgium** | 2015 | 62,28% | 69,79% | 77,71% | 59,69% | 58,09% |
| **Belgium** | 2016 | 64,48% | 72,24% | 79,20% | 61,34% | 56,93% |
| **Belgium** | 2017 | 66,63% | 73,55% | 80,54% | 60,37% | 55,84% |
| **Belgium** | 2018 | 68,74% | 74,61% | 79,98% | 58,72% | 56,67% |
| **Belgium** | 2019 | 71,18% | 76,18% | 80,45% | 57,07% | 57,49% |
| **Bulgaria** | 2015 | 5,35% | 34,52% | 43,71% | 43,89% | 42,05% |
| **Bulgaria** | 2016 | 4,40% | 38,46% | 42,53% | 38,37% | 36,18% |
| **Bulgaria** | 2017 | 5,49% | 39,34% | 44,65% | 44,29% | 44,40% |
| **Bulgaria** | 2018 | 7,37% | 43,00% | 39,95% | 44,19% | 43,79% |
| **Bulgaria** | 2019 | 8,57% | 37,94% | 40,03% | 44,08% | 43,18% |

The first three form the Internet skills subindex (Internet_Skills), and the last two form the computer skills subindex (Computer_Skills). Equations 5 and 6 present the method of calculating the subindices (Table 4).

**Table 4. Values of Internet_Skills, Computer_Skills, and the synthetic Digital_Index for Belgium and Bulgaria (2015–2019)**

| Country | Year | Internet_Skills | Computer_Skills | Digital_Index |
|---|---|---|---|---|
| **Belgium** | 2015 | 69,93% | 58,89% | 64,41% |
| **Belgium** | 2016 | 71,97% | 59,14% | 65,55% |
| **Belgium** | 2017 | 73,57% | 58,11% | 65,84% |
| **Belgium** | 2018 | 74,44% | 57,69% | 66,07% |
| **Belgium** | 2019 | 75,94% | 57,28% | 66,61% |
| **Bulgaria** | 2015 | 27,86% | 42,97% | 35,42% |
| **Bulgaria** | 2016 | 28,46% | 37,28% | 32,87% |
| **Bulgaria** | 2017 | 29,83% | 44,35% | 37,09% |
| **Bulgaria** | 2018 | 30,11% | 43,99% | 37,05% |
| **Bulgaria** | 2019 | 28,85% | 43,63% | 36,24% |

In addition to the variables mentioned above, two further indicators (Table 5) were tested in robustness analyses. The first of these is Internet access – Internet_Access (Eurostat, 2025, isoc_ci_in_h), and the second concerns another aspect of Internet activity, specifically the percentage of people selling goods and services via the Internet – Online_Selling.

**Table 5. Internet access in households and online selling – Belgium and Bulgaria, 2015–2019**

| Country | Year | Internet_Access | Online_Selling |
|---|---|---|---|
| **Belgium** | 2015 | 81,83% | 18,61% |
| **Belgium** | 2016 | 84,79% | 20,36% |
| **Belgium** | 2017 | 85,97% | 20,13% |
| **Belgium** | 2018 | 87,27% | 18,73% |
| **Belgium** | 2019 | 89,73% | 23,70% |
| **Bulgaria** | 2015 | 59,14% | 8,97% |
| **Bulgaria** | 2016 | 63,54% | 6,39% |
| **Bulgaria** | 2017 | 67,33% | 4,93% |
| **Bulgaria** | 2018 | 72,13% | 8,20% |
| **Bulgaria** | 2019 | 75,07% | 6,34% |

## Results and Discussion

The aim of the study was to assess the link between digital competencies and real economic growth. For this purpose, a panel analysis with fixed effects for countries and time effects for years, the so-called two-way fixed effects (TWFE) model, was used. Digital competencies were the main explanatory variable, and a synthetic index (Digital_Index) was created for the purposes of this study. The dependent variable was the growth rate of GDP per capita as a measure of changes in the wealth of countries. TWFE is the reference point as the main estimation method. Table 6 contains information on all the variants compared. The values of $\beta_1$ (the most important parameter), standard errors, p-values, and the coefficient of determination ($R^2$) are compared. Standard errors and coefficients of determination were calculated in different ways depending on the model.

In the FE models, standard errors were clustered at the country level, making them robust to both heteroskedasticity and autocorrelation. The model with within transformation should always give the same $\beta_1$ values as the FE model, but in this case the errors were calculated classically, as in the OLS (Ordinary Least Squares) model, in order to show that the lack of clustering can underestimate errors and increase the significance of parameters. The classical method of calculating standard errors assumes no correlation and homoscedasticity. The last estimation variant is OLS with the assumption of heteroskedasticity, that is, a non-constant variance of the error term. Three variants of the coefficient of determination were also calculated. R2_overall(FE) was calculated for the FE model, which was cleaned of fixed and time effects using dummy variables, which are left in place when calculating $R^2$ and overestimate its value. The within transformation involves subtracting averages, so it does not create additional variables, meaning that R2_within shows the model fit for a given country over time. R2_OLS does not take into account fixed effects, which results in large residuals in the model and therefore lowers $R^2$. In addition, all model variants were tested with and without lag to assess the occurrence of reverse causality and/or delayed impact of digital competencies.

**Table 6. Estimation results for panel models — FE (fixed effects) with clustered SE (standard error), Within OLS (ordinary least squares on demeaned data, assuming homoskedasticity), and pooled OLS (HC1, heteroskedasticity-robust) — with Digital_Index as the main regressor; no lag and lag (t-1) specifications**

| No lag | | | | | | | |
|---|---|---|---|---|---|---|---|
| Spec | Model | $\beta_1$ | SE | p | R2_overall(FE) | R2_within | R2_OLS |
| Base | FE(cluster) | 0,014 | 0,076 | 0,85 | 59,13% | | |
| Base | Within(OLS) | 0,014 | 0,069 | 0,84 | | 15,30% | |
| Base | OLS(HC1) | -0,068 | 0,031 | 0,03 | | | 28,83% |
| Digit only | FE(cluster) | 0,012 | 0,054 | 0,83 | 51,76% | | |
| Digit only | Within(OLS) | 0,012 | 0,067 | 0,86 | | 0,02% | |
| Digit only | OLS(HC1) | -0,077 | 0,015 | 0,00 | | | 12,63% |
| No Education | FE(cluster) | 0,025 | 0,073 | 0,73 | 58,85% | | |
| No Education | Within(OLS) | 0,025 | 0,068 | 0,71 | | 14,71% | |
| No Education | OLS(HC1) | -0,049 | 0,019 | 0,01 | | | 27,27% |
| No GERD | FE(cluster) | 0,023 | 0,069 | 0,73 | 57,89% | | |
| No GERD | Within(OLS) | 0,023 | 0,070 | 0,74 | | 12,72% | |
| No GERD | OLS(HC1) | -0,119 | 0,028 | 0,00 | | | 21,88% |
| No Investment | FE(cluster) | -0,003 | 0,050 | 0,95 | 52,65% | | |
| No Investment | Within(OLS) | -0,003 | 0,074 | 0,97 | | 1,85% | |
| No Investment | OLS(HC1) | -0,071 | 0,032 | 0,03 | | | 27,59% |
| No Unemployment | FE(cluster) | 0,012 | 0,065 | 0,85 | 59,13% | | |
| No Unemployment | Within(OLS) | 0,012 | 0,065 | 0,85 | | 15,30% | |
| No Unemployment | OLS(HC1) | -0,048 | 0,031 | 0,13 | | | 25,34% |
| Lag t-1 | | | | | | | |
| Base | FE(cluster) | -0,067 | 0,096 | 0,49 | 69,72% | | |
| Base | Within(OLS) | -0,067 | 0,063 | 0,29 | | 7,16% | |
| Base | OLS(HC1) | -0,057 | 0,019 | 0,00 | | | 42,34% |
| Digit only | FE(cluster) | -0,052 | 0,071 | 0,46 | 67,62% | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Digit only | Within(OLS) | -0,052 | 0,060 | 0,39 | | 0,70% | |
| Digit only | OLS(HC1) | -0,074 | 0,013 | 0,00 | | | 19,83% |
| No Education | FE(cluster) | -0,064 | 0,089 | 0,47 | 69,46% | | |
| No Education | Within(OLS) | -0,064 | 0,063 | 0,32 | | 6,34% | |
| No Education | OLS(HC1) | -0,049 | 0,018 | 0,01 | | | 41,92% |
| No GERD | FE(cluster) | -0,067 | 0,095 | 0,48 | 69,72% | | |
| No GERD | Within(OLS) | -0,067 | 0,063 | 0,29 | | 7,16% | |
| No GERD | OLS(HC1) | -0,105 | 0,016 | 0,00 | | | 31,13% |
| No Investment | FE(cluster) | -0,088 | 0,099 | 0,38 | 68,94% | | |
| No Investment | Within(OLS) | -0,088 | 0,063 | 0,16 | | 4,76% | |
| No Investment | OLS(HC1) | -0,061 | 0,022 | 0,00 | | | 39,58% |
| No Unemployment | FE(cluster) | -0,042 | 0,084 | 0,61 | 69,22% | | |
| No Unemployment | Within(OLS) | -0,042 | 0,061 | 0,49 | | 5,61% | |
| No Unemployment | OLS(HC1) | -0,040 | 0,019 | 0,04 | | | 38,98% |

The base model includes the above-mentioned variables and control variables, the gradual removal of which from the model allows us to assess whether there is collinearity and correlation between them and digital competencies, which can be assessed on the basis of the obtained $\beta_1$ values. In addition, Table 7 presents the estimation results for models with single digital competence indicators and indicators of infrastructure (Internet_Access) and economic activities on the Internet (Online_Selling). In Tables 6 and 7, the $\beta_1$ values for the FE and Within models are the same in each case, confirming that the introduction of dummy variables and demeaning are equivalent and give the same results. It is worth noting the differences in values, particularly in the sign for $\beta_1$ in fixed effects and OLS models. In the case of FE models, the impact of digital competencies on economic development is statistically insignificant (p-value > 0,05) in both the no-lag and lag variants. The estimation results show that the values of the estimated coefficient $\beta_1$ (for the digitalization index) in the contemporaneous specifications are generally positive but close to zero and statistically insignificant. When introducing a one-period lag, the coefficient $\beta_1$ turns negative, yet remains close to zero and statistically insignificant. In contrast, the OLS model indicates that the impact of digital competencies is negative and statistically significant (minus sign for parameter $\beta_1$). This is an important observation, which clearly suggests that differences between countries and common shocks are responsible for this result, and that removing these factors eliminates this seemingly negative effect. More developed countries usually have a higher level of digital competencies among their citizens, but at the same time they develop more slowly, as generating growth with a high GDP per capita is more challenging.

Specifications without various control variables do not differ significantly in the level of $\beta_1$, the model is stable (no collinearity). R2_within is much lower than R2_overall(FE), as most of the model's variability is not explained by unique differences in a given country in a given year, but rather by differences between countries and common trends.

Standard errors calculated using the classical and clustered methods are similar in models without delays. In the base model, the clustered SE is 0,076 and the classical SE is 0,069, but this relationship is not consistent – the clustered SE was higher 8 times and the classical SE was higher 6 times. The situation is different in models with delays, where clustered SE is higher every time, which can be explained by a smaller number of observations, i.e., greater estimation uncertainty. The smallest standard errors are obtained by OLS models, which is to be expected due to the lack of consideration of potential autocorrelation and the lack of control of fixed effects. In addition, such models contain a lot of information (comparisons between countries over time), which ultimately leads to probable type I errors – false significance.

**Table 7. Estimation results for panel models (FE with clustered SE, Within OLS) and pooled OLS (HC1) for individual digitalization variables — Online_Selling, Internet_Access, Internet_Skills, Computer_Skills, and their components; no lag and lag (t-1) specifications**

| No lag | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Model | β | SE | p | R2_overall(FE) | R2_within | R2_OLS |
| Online_Selling | FE(cluster) | -0,094 | 0,070 | 0,18 | 59,98% | | |
| Internet_Access | FE(cluster) | 0,080 | 0,067 | 0,24 | 59,42% | | |
| Copy_Move_Files | FE(cluster) | 0,010 | 0,041 | 0,81 | 59,14% | | |
| Internet_Banking | FE(cluster) | 0,027 | 0,112 | 0,81 | 59,17% | | |
| Internet_Skills | FE(cluster) | 0,022 | 0,120 | 0,85 | 59,14% | | |
| Email_Use | FE(cluster) | 0,013 | 0,083 | 0,87 | 59,13% | | |
| Computer_Skills | FE(cluster) | 0,005 | 0,044 | 0,90 | 59,12% | | |
| Info_Search | FE(cluster) | 0,006 | 0,057 | 0,92 | 59,12% | | |
| File_Transfer | FE(cluster) | 0,000 | 0,046 | 1,00 | 59,12% | | |
| Online_Selling | Within(OLS) | -0,094 | 0,056 | 0,10 | | 17,05% | |
| Internet_Access | Within(OLS) | 0,080 | 0,081 | 0,33 | | 15,90% | |
| Internet_Banking | Within(OLS) | 0,027 | 0,071 | 0,71 | | 15,37% | |
| Internet_Skills | Within(OLS) | 0,022 | 0,081 | 0,78 | | 15,32% | |
| Copy_Move_Files | Within(OLS) | 0,010 | 0,045 | 0,83 | | 15,30% | |
| Email_Use | Within(OLS) | 0,013 | 0,068 | 0,85 | | 15,30% | |
| Info_Search | Within(OLS) | 0,006 | 0,053 | 0,91 | | 15,28% | |
| Computer_Skills | Within(OLS) | 0,005 | 0,047 | 0,91 | | 15,28% | |
| File_Transfer | Within(OLS) | 0,000 | 0,043 | 1,00 | | 15,27% | |
| Email_Use | OLS(HC1) | -0,069 | 0,017 | 0,00 | | | 29,94% |
| Internet_Access | OLS(HC1) | -0,078 | 0,023 | 0,00 | | | 27,33% |
| Internet_Banking | OLS(HC1) | -0,032 | 0,012 | 0,01 | | | 27,83% |
| Internet_Skills | OLS(HC1) | -0,047 | 0,017 | 0,01 | | | 27,89% |
| Copy_Move_Files | OLS(HC1) | -0,060 | 0,036 | 0,10 | | | 27,95% |
| Computer_Skills | OLS(HC1) | -0,060 | 0,039 | 0,13 | | | 27,85% |
| File_Transfer | OLS(HC1) | -0,053 | 0,039 | 0,17 | | | 27,44% |
| Info_Search | OLS(HC1) | -0,021 | 0,018 | 0,25 | | | 25,26% |
| Online_Selling | OLS(HC1) | -0,019 | 0,021 | 0,36 | | | 25,01% |
| Lag t-1 | | | | | | | |
| Internet_Skills | FE(cluster) | -0,164 | 0,105 | 0,12 | 71,06% | | |
| Info_Search | FE(cluster) | -0,093 | 0,063 | 0,14 | 70,64% | | |
| Email_Use | FE(cluster) | -0,101 | 0,071 | 0,16 | 70,43% | | |
| Internet_Banking | FE(cluster) | -0,082 | 0,090 | 0,37 | 69,96% | | |
| Online_Selling | FE(cluster) | -0,036 | 0,053 | 0,49 | 69,59% | | |
| Internet_Access | FE(cluster) | -0,042 | 0,077 | 0,59 | 69,50% | | |
| File_Transfer | FE(cluster) | 0,004 | 0,043 | 0,92 | 69,40% | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Computer_Skills | FE(cluster) | 0,003 | 0,063 | 0,97 | 69,40% | | |
| Copy_Move_Files | FE(cluster) | 0,000 | 0,066 | 1,00 | 69,40% | | |
| Internet_Skills | Within(OLS) | -0,164 | 0,067 | 0,02 | | 11,27% | |
| Info_Search | Within(OLS) | -0,093 | 0,044 | 0,04 | | 9,95% | |
| Email_Use | Within(OLS) | -0,101 | 0,053 | 0,06 | | 9,33% | |
| Internet_Banking | Within(OLS) | -0,082 | 0,059 | 0,17 | | 7,87% | |
| Online_Selling | Within(OLS) | -0,036 | 0,045 | 0,42 | | 6,76% | |
| Internet_Access | Within(OLS) | -0,042 | 0,070 | 0,56 | | 6,48% | |
| File_Transfer | Within(OLS) | 0,004 | 0,039 | 0,91 | | 6,17% | |
| Computer_Skills | Within(OLS) | 0,003 | 0,045 | 0,95 | | 6,16% | |
| Copy_Move_Files | Within(OLS) | 0,000 | 0,043 | 0,99 | | 6,16% | |
| Email_Use | OLS(HC1) | -0,072 | 0,015 | 0,00 | | | 47,12% |
| Internet_Access | OLS(HC1) | -0,092 | 0,025 | 0,00 | | | 43,95% |
| Internet_Banking | OLS(HC1) | -0,032 | 0,010 | 0,00 | | | 42,81% |
| Internet_Skills | OLS(HC1) | -0,048 | 0,015 | 0,00 | | | 42,94% |
| Copy_Move_Files | OLS(HC1) | -0,040 | 0,022 | 0,07 | | | 39,93% |
| Computer_Skills | OLS(HC1) | -0,039 | 0,024 | 0,11 | | | 39,70% |
| File_Transfer | OLS(HC1) | -0,034 | 0,024 | 0,16 | | | 39,28% |
| Info_Search | OLS(HC1) | -0,020 | 0,017 | 0,23 | | | 38,32% |
| Online_Selling | OLS(HC1) | -0,023 | 0,021 | 0,26 | | | 38,27% |

Introducing a lag in the models did not make the impact of digital competencies on economic growth statistically significant, but the p-values improved considerably. This may suggest that accounting for the effects of digitalization over a longer time horizon is a promising avenue for further research. In models for individual digitalization variables, significant $\beta_1$ parameters (Internet_Skills, Info_Search) appeared, but only in two cases and for SE calculated classically, which weakens the reliability of these results. In addition, the $\beta_1$ values are low, so this potentially statistically significant impact is small anyway.

In further research on this topic, it is worth extending the analysis period, as adding a delay takes away a year of observation, and this study used data from 5 years as a baseline. In the future, it is worth using dynamic GMM models and introducing longer delays. An additional area of research could be an attempt to transfer the analysis from the country level to the regional level.

## References


- Angrist, J. and Pischke, J.-S. (2009) ‘Mostly Harmless Econometrics: An Empiricist’s Companion’, in.
- Arellano, M. (1987) ‘Computing Robust Standard Errors for Within-Groups Estimators’, *Oxford Bulletin of Economics and Statistics*, vol. 49, no. 4, pp. 431–434 [Online]. Available at https://ideas.repec.org/a/bla/obuest/v49y1987i4p431-34.html (Accessed 26 September 2025).
- Baltagi, B. H. (2021) *Econometric analysis of panel data*, 6th edn, Cham (Switzerland), Springer.
- Barro, R. J. and Sala-i-Martin, X. (post 2006], cop. 2004) *Economic growth*, 2nd edn, Cambridge, Mass., London, The MIT Press.
- Brennen, J. S. and Kreiss, D. (2016) ‘Digitalization’, in *The International Encyclopedia of Communication Theory and Philosophy,* John Wiley & Sons, Ltd, pp. 1–11.

- Calvani, A., Cartelli, A., Fini, A. and Ranieri, M. (2008) ‘Models and Instruments for assessing Digital Competence at School’, *Journal of E-Learning and Knowledge Society*, vol. 4, pp. 183–193.
- Cameron, A. and Trivedi, P. (2005) *Microeconometrics: Methods and Applications*.
- Colin Cameron, A. and Miller, D. L. (2015) ‘A Practitioner’s Guide to Cluster-Robust Inference’, *Journal of Human Resources*, vol. 50, no. 2, pp. 317–372.
- European Commission: Directorate-General for Education, Youth, Sport and Culture (2019) *Key competences for lifelong learning* [Online], Publications Office. Available at https://data.europa.eu/doi/10.2766/569540.
- Eurostat (2025, rd_e_gerdtot) *GERD by sector of performance: rd_e_gerdtot* [Online], Eurostat. Available at https://doi.org/10.2908/RD_E_GERDTOT (Accessed 26 September 2025).
- Eurostat (2025, isoc_ci_in_h) *Households - level of internet access: isoc_ci_in_h* [Online], Eurostat. Available at https://doi.org/10.2908/ISOC_CI_IN_H (Accessed 26 September 2025).
- Eurostat (2025, isoc_ci_ac_i) *Individuals - internet activities: isoc_ci_ac_i* [Online], Eurostat. Available at https://doi.org/10.2908/ISOC_CI_AC_I (Accessed 26 September 2025).
- Eurostat (2025, isoc_sk_cskl_i) *Individuals' level of computer skills (2003-2019): isoc_sk_cskl_i* [Online], Eurostat. Available at https://doi.org/10.2908/ISOC_SK_CSKL_I (Accessed 26 September 2025).
- Eurostat (2025, sdg_08_11) *Investment share of GDP by institutional sectors: sdg_08_11* [Online], Eurostat. Available at https://doi.org/10.2908/SDG_08_11 (Accessed 26 September 2025).
- Eurostat (2025, edat_lfse_03) *Population in private households by educational attainment level - main indicators: edat_lfse_03* [Online], Eurostat. Available at https://doi.org/10.2908/EDAT_LFSE_03 (Accessed 26 September 2025).
- Eurostat (2025, sdg_08_10) *Real GDP per capita: sdg_08_10* [Online], Eurostat. Available at https://doi.org/10.2908/SDG_08_10 (Accessed 26 September 2025).
- Eurostat (2025, une_rt_a) *Unemployment by sex and age - annual data: une_rt_a* [Online], Eurostat. Available at https://doi.org/10.2908/UNE_RT_A (Accessed 26 September 2025).
- Fähndrich, J. (2023) ‘A literature review on the impact of digitalisation on management control’, *Journal of Management Control*, vol. 34, no. 1, pp. 9–65.
- Greene, W. H. (2012) *Econometric analysis*, 7th edn, Boston, Mass., Pearson.
- Hausman, J. A. (1978) ‘Specification Tests in Econometrics’, *Econometrica*, vol. 46, no. 6, p. 1251.
- Henriette, E., Feki, M. and Boughzala, I. (2015) ‘The Shape of Digital Transformation: A Systematic Literature Review’.
- Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P., Mädche, A., Urbach, N. and Ahlemann, F. (2017) ‘Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community’, *Business & Information Systems Engineering*, vol. 59, no. 4, pp. 301–308.
- Parviainen, P., Tihinen, M., Kääriäinen, J. and Teppola, S. (2017) ‘Tackling the digitalization challenge: How to benefit from digitalization in practice’, *International Journal of Information Systems and Project Management*, vol. 5, no. 1, pp. 63–77.
- Stolterman, E. and Fors, A. C. (2004) ‘Information Technology and the Good Life’, in Kaplan, B., Truex, D. P., Wastell, D., Wood-Harper, A. T. and DeGross, J. I. (eds) *Information Systems Research,* Boston, MA, Springer US, pp. 687–692.
- van Dijk, J. A. G. M. and van Deursen, A. J. A. M. (2014) *Digital Skills*, New York, Palgrave Macmillan US.
- Wei, D., Wang, Z., Kang, H., Sha, X., Xie, Y., Dai, A. and Ouyang, K. (2025) ‘A comprehensive analysis of digital inclusive finance's influence on high quality enterprise development through fixed effects and deep learning frameworks’, *Scientific reports*, vol. 15, no. 1, p. 30095.
- Wooldridge, J. M. (2020) *Introductory econometrics: A modern approach*, Boston, Cengage Learning.