Digital Transformation and Economic Growth

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Abstract: Digital transformation has emerged as a driving force behind economic progress, innovation, and competitiveness in the 21st century. By facilitating the widespread integration of digital technologies into business, public services, and daily life, it enhances productivity, reduces transaction costs, and accelerates access to information. This study empirically examines the relationship between digital transformation and economic performance by analyzing the effects of internet usage, broadband subscription, mobile cellular access, and R&D expenditures on per capita GDP in six advanced economies—Sweden, Finland, Germany, South Korea, the United Kingdom, and the United States—between 2010 and 2023. Using panel EGLS estimation techniques, the findings reveal a statistically significant and positive relationship between digitalization indicators and per capita income, highlighting the transformative role of digital infrastructure in driving economic growth. The results underscore the strategic importance of digital policies in shaping future development trajectories.

Key-Words: Digital economy, digital transformation, economic growth, panel EGLS, advanced economies

Jel Codes: O33, O47, C33.

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1 Introduction

Digital transformation is more than a technological advancement; it represents one of the major transformative waves in human history. Following the transitions from agrarian to industrial societies initiated by the First and Second Industrial Revolutions, the rapid spread of digital technologies has fundamentally altered production infrastructures, business models, and economic structures. Elements of the digital revolution—such as artificial intelligence, big data, the Internet of Things, cloud computing, and 5G technologies—have ushered in a new era in which efficiency, productivity, and competitiveness are redefined across all economic sectors, including manufacturing, logistics, services, and public administration. The impact of digital transformation extends beyond the digitization of production tools. It is also shaped by structural indicators such as the prevalence of digital infrastructure, internet penetration rates, broadband connectivity, and the degree of integration of R&D activities into the economy. These indicators directly affect countries' digital capacity and, consequently, their long-term growth performance. However, the effect of digital transformation on economic growth varies across countries, and the specific conditions under which this relationship is more robust remain unclear. The aim of this study is to empirically examine the impact of digitalization indicators—such as the percentage of the population using the internet, broadband subscription density, and R&D expenditure as a share of GDP—on economic growth rates. Focusing on developed economies that have demonstrated high growth performance during the 2010–2025 period—namely Sweden, Finland, Germany, the United Kingdom, the United States, and South Korea—this analysis seeks to generate evidence on how digital transformation shapes growth and to develop concrete policy recommendations accordingly

2 Literature Review

The relationship between digital transformation and economic growth is commonly explained in the literature through technology-based growth theories. [1] endogenous growth model posits that technological advances and knowledge creation are key determinants of long-term growth. This approach has enabled a comprehensive analysis of the impact of the knowledge economy, particularly with the integration of digital technologies into production processes. Within the Schumpeterian growth framework, [2] argue that innovation and R&D activities enhance productivity and sustain economic growth.

Digitalization is not merely the adoption of new technologies; it represents a fundamental transformation of production infrastructures, economic organization, and social life. Much like the agricultural and industrial revolutions, it is viewed as a major structural shift in human history [3]. The widespread adoption of internet-based technologies has transformed not only the mechanical but also the cognitive dimensions of production through tools such as big data, algorithms, AI, cloud computing, IoT, and 5G [4]. The effects of digitalization go beyond AI-supported production and extend to the processes of data collection, analysis, and decision-making [5]. Accordingly, access to digital technologies has become a crucial factor in determining not only firms' but also countries' long-term growth performance. The rapid rise in internet usage, the proliferation of broadband technologies, and the orientation of R&D activities toward digital domains have induced irreversible changes in production models[6].

Empirical studies have demonstrated the impact of digitalization on economic growth through various indicators. [7] found that the expansion of broadband infrastructure in EU countries significantly supports growth. Similarly, [8] showed that the diffusion of information and communication technologies (ICTs) has positive effects on growth in both developed and developing economies. [9] highlighted the positive effects of digitalization on total factor productivity in OECD countries. R&D investments have also been emphasized in many studies as enhancing the impact of digital transformation on economic growth. Coe, [10] demonstrated that R&D activities contribute to other economies through knowledge spillovers beyond national borders. Countries like South Korea, Sweden, and Finland are frequently cited in this context [11]. Digitalization also creates transformative effects beyond economic growth, impacting labor markets, production organization, and competitive dynamics [12]. For instance [5], found that digitalization leads to profound changes in employment structures, reducing low-skilled jobs while increasing demand for occupations requiring advanced digital competencies. [13] emphasized that the effects of digitalization are not uniform across countries and are largely shaped by factors such as infrastructure, education levels, and institutional capacity. Therefore, comparative studies across countries are essential to comprehensively understand the growth effects of digitalization. The effects of digital transformation are expected not only to reshape today's production systems but also to become central to future economic policies and growth strategies. Like the agricultural and industrial revolutions, this process signifies an irreversible structural change. Thus, analyzing the impact of digitalization on growth in a country-specific and period-specific manner has become a strategic necessity for policymakers. Most existing studies in the literature examining the relationship between digitalization and economic growth either focus on global averages or rely on limited data in the context of developing countries. However, to accurately measure the effects of digitalization, it is essential to focus on countries with high digital performance and reliable long-term data. In this regard, developed economies such as Sweden, Finland, Germany, the United Kingdom, the United States, and South Korea provide an exemplary dataset due to their consistent digital indicators and sustainable growth performances. This study aims to fill this gap in the literature by empirically investigating the impact of digitalization on economic growth in developed countries, thereby offering a novel and original perspective.

3 Methodology

3.1. Model and Dataset

This research aims to investigate the influence of digitalization measures on per capita GDP of developed nations. For this purpose, annual data for the period 2010-2023 are used. The country group in the study consists of Sweden, Finland, Germany, South Korea, the United Kingdom and the United States of America. These countries were selected because they are leading countries in terms of digital infrastructure indicators and have reliable long-term data sets.

In the study, the following model 3.1 was estimated.

$$PGDP_{i_{i,t}} = \varphi_i + \beta_1.INT_{i,t} + \beta_2.BBAND_{i,t} + \beta_3.RD_{i,t} + \beta_4.MOB_{i,t} + \beta_5.CAP_{i,t}u_{it}$$

(1)

Below are the explanations of the variables included in the model along with their respective data sources. The entire dataset was sourced from the World Bank's World Development Indicators database.

Per Capita GDP (PGDP): In this study, Gross Domestic Product (GDP) per capita at constant prices 2005 is taken as the base year.

Internet Usage Rate (INT): Proportion of internet users in total population (%).

Broadband Subscription Rate (BBAND): Ratio of fixed broadband internet subscribers per 100 inhabitants.

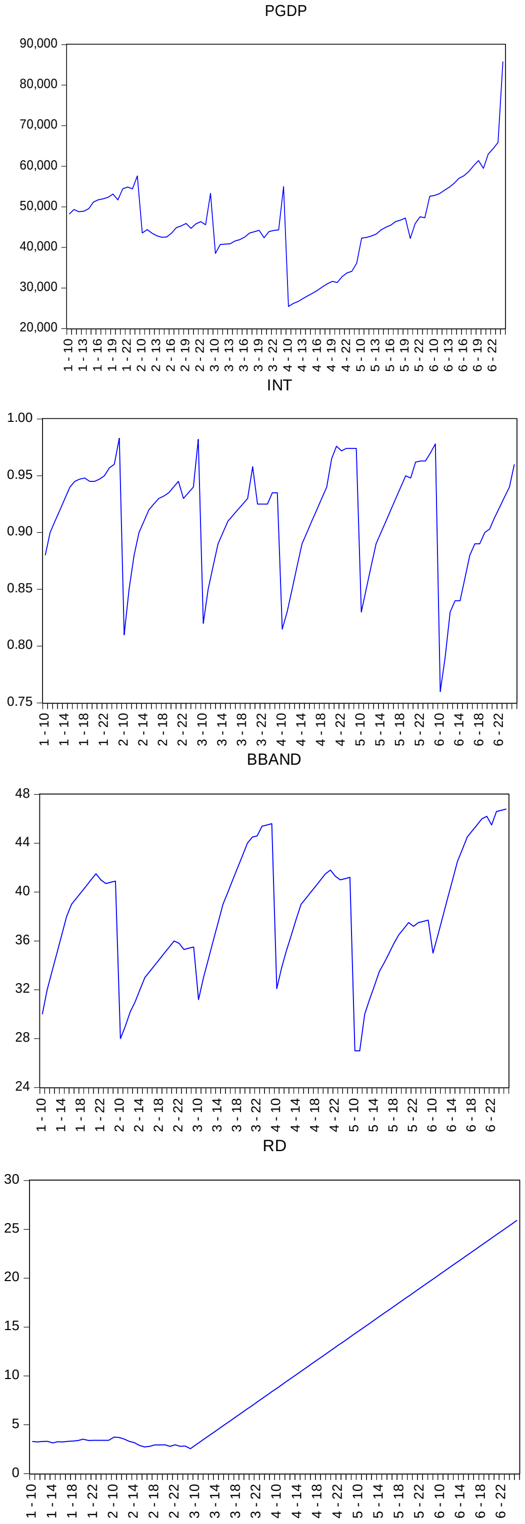
R&D Expenditure (RD): Share of R&D expenditures in gross domestic product (%).

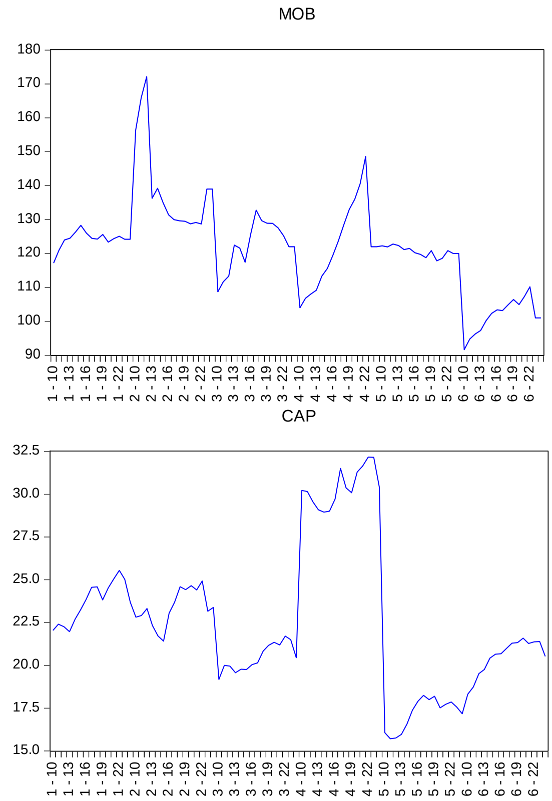
Mobile Cellular Subscriptions (MOB): Annual rate of increase in mobile phone subscriptions.

Gross Fixed Capital Formation (CAP): Annual rate of increase in gross fixed capital formation

Figure 1 presents the individual time series data of the variables utilized in the model for six countries (Sweden, Finland, Germany, South Korea, the United Kingdom and the United States of America, respectively). Accordingly, it is seen that the series have extreme values in some years and generally follow an increasing trend.

Figure 1. Individual Time Series Graphs





3.2 Econometric Methodology and Results

In this study, panel data method is applied. The panel data method makes it possible to make stronger and more reliable forecasts by taking into account both time-dependent and cross-country differences [14],[15],[16].

In this research, the panel data analysis method has been employed due to its numerous advantages over traditional time series and cross-sectional approaches. One of the key strengths of panel data analysis lies in its ability to integrate both time series and cross-sectional dimensions, thereby constructing a dataset that encompasses temporal and sectional variations simultaneously.

Compared to purely cross-sectional or time series data, panel data models provide a substantial increase in the number of observations, as they utilize both types of data. As a result, panel data techniques allow for more robust and reliable econometric estimations [17].

To ensure that the outcomes of the analysis are valid and dependable, it is crucial that the data series used in the model are stationary. If the series possess unit roots, there is a risk of encountering spurious regression, which may lead to misleading conclusions about the relationships being studied.

Prior to testing the stationarity of the series, the study first examined whether there was cross-sectional dependence among the individual units in the panel. Since the panel's time dimension surpasses its cross-sectional dimension, Lagrange Multiplier (LM) test is employed in this study. The LM test statistic is calculated based on the regression below:

$$y_{it} = \alpha_i + \beta_i{}'.x_{it} + \mu_{it} \qquad i=1,2,...,N; \quad t=1,2,...,T \qquad (2)$$

The LM test statistic is formulated as follows:

$$LM_{BP} = T.\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \sim \chi^2_{N.(N-1)/2}$$

If the p-value of the Breusch-Pagan Lagrange Multiplier (LMBP) test statistic is greater than the 0.05 threshold, the null hypothesis — which suggests no cross-sectional dependence — cannot be rejected at the 95% confidence level.

[18]'s the panel stationarity test will be utilized, as it accounts for cross-sectional dependence when assessing the stationarity of variables. This method is particularly responsive to the presence of dependence among panel units. Under the null hypothesis of the [18] test, the panel series are assumed to be stationary, meaning they do not contain unit roots. Conversely, the alternative hypothesis posits the existence of unit roots within the series. Notably, this test accommodates both serial correlation and cross-sectional dependence and is applicable in cases where the time dimension (T) is either smaller or larger than the cross-sectional dimension (N).

In their analysis, [18] employ Equation 3 as shown below:

$$y_{it} = k'_t\delta_i + f_t.\gamma_i + \varepsilon_{it}$$
$$\varepsilon_{it} = \phi_{i1}.\varepsilon_{it-1} + ... + \phi_{ip}.\varepsilon_{it-p} + v_{it} \qquad i=1,...,N, \quad t=1,...,T \qquad (3)$$

In the equation, the deterministic component is denoted by z'_t, the individual-specific effects by $k'_t\delta_i$, the unobserved common factor by γ_i , the factor loading by , and the idiosyncratic errors by ε_{it} .

[18] derives the following statistics through a regression of the specified variables y_{it} on $w_t = \left[k'_t, \bar{y}_t, \bar{y}_{t-1}, ..., \bar{y}_{t-p}\right]$ for each i to

correct for horizontal cross-sectional dependence:

$\hat{\sigma}_i^{\,2}$ denotes the long-run variance estimator. [18] derive this estimator using the following set of formulas:

$$\hat{\sigma}^2_{iSPC} = \frac{\hat{\sigma}^2_{vi}}{(1-\hat{\varphi}_i\;)^2} \quad \text{here} \quad \hat{\sigma}^2_{vi} = 1/T.\sum_{t=1}^{T}\hat{v}^2_{it}$$

$$\hat{\varphi}_i = \min\left\{1-\frac{1}{\sqrt{T}}, \sum_{j=1}^{p}\hat{\varphi}_{ij}\right\}, \quad S_{it}^{\ w} = \sum_{r=1}^{t}\hat{\varepsilon}_{ir} \quad \text{and}$$

[18]compute the $Z_A^{\ SPC}$ test statistic, which accounts for cross-sectional dependence, using the following formulation derived from all relevant equations:

$$Z_A^{\ SPC} = \frac{1}{\hat{\sigma}^2_{iSPC}.T^2}\sum_{t=1}^{T}(S_{it}^{\ w})^2$$

3.4 Empirical Results

Table 1 presents the results of the cross-sectional dependence test conducted on the series used in this analysis. Since the p-value of the test statistic for the variables in Model (1) is below the 0.05 significance level, the null hypothesis suggesting no cross-sectional dependence is rejected. PGDP_it = α + β1 * INT_it + β2 * BBAND_it + β3 * RD_it + β4 * MOB_it + β5 * CAP_it + ε_it

Table 1. Cross Section Dependence and Homogeneity Test Results

Series	**LMBP (Prob. Value)**
PGDP	178.12*** (0.00)
INT	214.17*** (0.00)
BBAND	234.66*** (0.00)
RD	175.89*** (0.00)
MOB	106.59*** (0.00)
CAP	119.47*** (0.00)
Delta-adjusted test stat.(p-value)	
-0.003 (0.501)	

*** denotes rejection of the null hypothesis at the 1% level of significance.

Given this outcome, the investigation of the unit root properties of the series will be carried out using a second-generation panel unit root test. Table 1 also presents the results of the Delta homogeneity test. The null hypothesis, which expresses the homogeneity of the coefficients, cannot be rejected.

Table 2 presents the findings of the H-K test, a second-generation approach used to evaluate the stationarity of the series. As indicated in the table, the p-values corresponding to the test statistics for all variables in the model are above the 0.01 significance threshold. Consequently, all series are deemed stationary at their level form.

Table 2. H-K Stationarity Test Results

Series	ZA-Spac	Prob. Value
PGDP	-1.85	0.96
INT	-1.64	0.95
BBAND	-1.29	0.90
RD	0.65	0.25
MOB	-1.81	0.96
CAP	-2.14	0.98

After assessing the cross-sectional dependence and the stationarity properties of the series incorporated in the model, the estimation was carried out using the Panel EGLS method. To correct for heteroskedasticity and potential cross-sectional correlation, standard errors were adjusted via White's cross-sectional covariance technique. As all variables were found to be stationary, the estimation results are reported in Table 3. The values in parentheses indicate the p-values corresponding to each variable.

Table 3. Estimation Outcomes of Panel Least Squares: Model 1

Dependent Variable	**Model 1**	
C	3037.352	0.3981
INT	13810.30***	0.0034
BBAND	112.6788*	0.0874
RD	270.5652**	0.0324
MOB	31.28080**	0.0242
CAP	832.099***	0.0000
R² value	0.99	
F-statistic	731.14*** (0.00)	

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, suggesting that the corresponding variable is significantly different from zero at those levels.

According to the findings estimated in Table 3, all digital transformation variables which are internet usage rate, broadband subscription rate, R&D expenditures and mobile cellular subscriptions significantly and positively affect per capita GDP in selected country group. In addition, it is also found that the effect of the gross fixed capital formation variable used as a control variable on per capita GDP is statistically significant and positive.

Conclusion

This study provides strong empirical evidence that digital transformation significantly contributes to economic growth in developed economies. The analysis, based on a balanced panel covering the period 2010–2023 for six digitally advanced countries—Sweden, Finland, Germany, South Korea, the United Kingdom, and the United States—demonstrates that higher internet usage, broadband subscription density, mobile cellular adoption, and R&D intensity are positively associated with increases in per capita GDP. The exceptionally high coefficient of determination ($R^2 = 0.99$) reinforces the conclusion that digitalization is not a peripheral factor but a key engine of economic development.

These findings underline the growing necessity for countries to align their economic growth strategies with digital policy agendas. First, enhancing broadband infrastructure and improving internet accessibility should be national priorities. Special attention should be paid to rural and underserved regions where digital divides persist, as digital exclusion can exacerbate regional inequalities and limit inclusive growth. Governments should therefore expand public-private partnerships to finance broadband deployment and ensure affordability of services.

Second, R&D investment must be encouraged not only through public funding but also by incentivizing private sector innovation. This includes offering tax credits for digital R&D, creating innovation clusters, and supporting startup ecosystems that develop disruptive technologies. Countries with robust national innovation systems will be better positioned to reap the productivity benefits of digital transformation.

Third, digital literacy and workforce upskilling must accompany technological adoption. As digital transformation reshapes labor markets—diminishing routine and manual jobs while increasing demand for ICT-intensive occupations—governments should prioritize lifelong learning programs, technical training, and STEM education reforms to ensure the workforce remains adaptable and competitive.

Fourth, data governance and cybersecurity should not be overlooked. As digital technologies proliferate, the importance of secure digital infrastructure, responsible data use, and transparent regulatory frameworks becomes more pronounced. Trust in digital platforms will be critical to sustaining public participation and business confidence in the digital economy.

Finally, international cooperation and knowledge transfer mechanisms can support developing economies in their digital journeys. The advanced economies analyzed in this study can play a pivotal role in setting global benchmarks for responsible and inclusive digital growth. In sum, the results of this study suggest that digital transformation should be integrated into the coreof national economic strategies. Countries that effectively institutionalize digital infrastructure, innovation policies, and digital skills development will be more resilient to economic shocks and better equipped to compete in an increasingly digitized global economy.

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