Journal of Innovations in Business and Industry

aspur

Vol. 04, No. 03 (2026) 241-258, DOI: 10.61552/JIBI.2026.03.002 - http://jibi.aspur.rs

THE IMPACT OF DIGITALIZATION ON LABOR PRODUCTIVITY IN THE MANUFACTURING SECTOR: A PANEL DATA STUDY (2010–2023)

Yalouli Tarek[1]
Bouguerra Mabrouk
Choutri Amel

Received 27.11.2025.
Revised 14.01.2026.
Accepted 19.02.2026.

Keywords:

Digitalization, Labor Productivity, Manufacturing Sector, Panel Data, Fixed Effects.

Original research

A B S T R A C T

This study examines the impact of digitalization on labor productivity in the manufacturing sector across 17 advanced industrialized countries over the period 2010–2023. Digitalization is captured through the percentage of Internet Users (IU) and the Digital Competitiveness Score (DCS). Using panel data techniques, three econometric models were estimated: Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). Descriptive statistics reveal a weak association between digitalization indicators and labor productivity. Consistently across all model specifications, the empirical results indicate that neither IU nor DCS exerts a statistically significant effect on labor productivity during the study period. These findings support the existence of a Digital Productivity Paradox, suggesting that digital transformation does not automatically translate into productivity gains. The results highlight the dominant role of country-specific structural factors, including institutional quality, human capital, and industrial policy frameworks, in shaping productivity performance. The study recommends incorporating mediating mechanisms and time-lag effects in future research to better capture the indirect and dynamic impacts of digitalization.

1. INTRODUCTION

Labor productivity is considered a vital indicator and a fundamental driver for sustainable economic growth and raising living standards on a global scale (World Bank, 2024).In the context of structural transformations in the global economy, the manufacturing sector gains particular importance as it is a cornerstone for innovation and the creation of added value (Wang, 2024). In the last decade, digitalization has emerged as an unparalleled transformative force, pushing the industrial sector towards what is known as **"Industry 4.0"** (OECD, 2024). This era is characterized by the integration of advanced technologies such as Artificial Intelligence, the Internet of Things, and Big Data analysis into production processes (Özköse, 2023). Recent research suggests that adopting these digital technologies can significantly improve the efficiency of operations and reduce costs (IMD, undated - World Digital Competitiveness Report), leading to a noticeable increase in the productivity of industrial enterprises (Wen, 2024; Open & Gold, 2025).Some studies have shown that the digitalization of production processes has boosted labor productivity in the manufacturing sector in some advanced economies by up to 18% (Aleca, 2025).

To empirically test this relationship, this study employs two complementary digitalization indicators:

1. Internet Users (IU): A quantitative proxy for basic digital infrastructure penetration, measured as the percentage of the population using the internet.
2. Digital Competitiveness Score (DCS): A qualitative composite index capturing a country's institutional and technological readiness for digital transformation, as assessed by the IMD World Digital Competitiveness Ranking.

[1] Corresponding author: Yalouli Tarek
Email: 582071844@qq.com

The study examines the following testable hypotheses:

- H_1: Digitalization, proxied by IU and DCS, has no statistically significant impact on labor productivity in the manufacturing sector during 2010-2023.
- H_2: The relationship between digitalization and productivity is moderated by country-specific structural factors such as institutional quality and human capital.
- H_3: Any potential productivity effects of digitalization are subject to significant time lags, not captured by contemporaneous models.

By testing these hypotheses, the research aims to determine whether the digital productivity paradox persists in the era of Industry 4.0, or whether traditional indicators fail to capture the nuanced mechanisms through which digitalization influences economic performance.

However, despite the massive investments in digital infrastructure and innovative technologies, the debate remains ongoing about whether this digital revolution has actually translated into comprehensive productivity gains at the aggregate level—a phenomenon historically known as the "Productivity Paradox" (Brynjolfsson & McAfee, Artificial Intelligence and the Modern Productivity Paradox, 2017).This paradox points to a gap between rapid technological development and slow productivity growth (Solow, Technical Change and the Aggregate Production Function, 1957), which has led researchers to question whether current metrics fail to capture the full impact of digitalization, or whether the effects require a longer time to appear, or if they necessitate complementary investments .in skills and organization (Khanna, 2024).

This study seeks to contribute to bridging this knowledge gap by quantifying the impact of digitalization variables, represented by the percentage of Internet users and the Digital Competitiveness Score, on labor productivity in the manufacturing sector for a selected group of industrialized countries during the period 2010-2023. The main objective is to determine whether there is a statistically significant correlation or causal relationship between these variables, using the Panel Data analysis methodology, with a focus on Fixed Effects models to control for unobserved. country-specific characteristics

2. LITERATURE REVIEW (THEORETICAL FRAMEWORK)

The relationship between digitalization and productivity is considered one of the central issues in the modern economy, especially in the context of the accelerating digital transformation witnessed by economies around the world.

Classical economic theory, such as the model Solow (Solow, Technical Change and the Aggregate Production Function, 1957), suggests that technological progress is the fundamental driver of long-term economic growth, after the effects of capital and labor accumulation are exhausted. With the development of the digital age and the shift, the focus has turned towards Information and Communication Technology (ICT) as the dominant form of technological innovation in the twenty-first century.

In this context, the literature on digitalization has shown that the adoption of ICT enhances productivity through three main channels:

a) Improving the efficiency of internal processes through the automation of routine tasks and the simplification of value chains.
b) Enabling innovation in products and services through the creation of new digital business models (such as the sharing economy and data-driven services).
c) Reallocating productive factors (labor and capital) from less productive firms to more productive firms, which is known as "between-firm reallocation" (Brynjolfsson & Hitt, 2000; Bloom et al., 2016).

However, this positive relationship has not always been direct or clear, which led to the emergence of what is known as the "Productivity Paradox", a term coined by Robert Solow (1987) when he said: "You can see the computer age everywhere but in the productivity statistics." Subsequent studies: have shown that this paradox may be attributed to several factors, the most important of which are (Solow, 1987):

- Time Lags between investment in digitalization and the appearance of its effects on productivity, due to the need for long-term operational and institutional adaptation
- Required Complementary Investments in human capital (such as training and retraining) and organization (such as re-engineering processes and developing a digital culture) to extract the full value from ICT (Bresnahan et al., 2002).
- Difficulty in Measuring Productivity Gains in the service sectors or in free digital services (such as search engines or social networks), where the consumer value is not translated into measurable output or revenue (Acemoglu et al., 2020).

In this framework, the Acemoglu study provided a comprehensive analysis of the impact of Artificial Intelligence and digitalization on productivity, where they indicated that the economic benefits of technology are not achieved automatically, but rather depend on the existence of a "mix of technology, organization, and skills". (Acemoglu et al., 2020) This perspective is reinforced by research highlighting the role of emerging technologies like artificial intelligence as a key catalyst, not only in improving existing processes but also in enabling the emergence of innovative entrepreneurial business models and enhancing their competitiveness (Mabrouk et al., 2026)

They concluded that economies that fail to develop these complementary elements may witness massive investments in technology without. tangible results on aggregate productivity.

Despite these efforts, a clear scientific gap remains in the current literature, as most studies have focused on advanced economies (such as the United States and Europe), with a noticeable lack of comparative analyses that include emerging economies, especially in the Arab region, where digital infrastructure, skill levels, and regulatory policies differ. Furthermore, there is a lack of studies that detail the impact of digitalization components (such as cloud computing, Internet of Things, or Artificial Intelligence) on the three productivity channels mentioned previously, especially at the level of industrial and service sectors. The scientific contribution of this article lies in the following:

1) Testing the generalizability of the Brynjolfsson and Hitt framework to different economic contexts, especially in developing countries (Brynjolfsson & Hitt, 2000)
2) Measuring the effect of digitalization on Total Factor Productivity (TFP) using modern data .2 that includes detailed digitalization indicators

Analyzing the role of complementary factors (such as the quality of digital education and institutional organization) as mediating factors that explain the presence or absence of the effect of digitalization on productivity

3. METHODOLOGY

To ensure the strength of the conclusions and the validity of the results, this research relies on a rigorous methodological framework that combines econometric theory and empirical analysis supported by comparable data. This section aims to clarify the sources and definitions of the variables used in the study, as well as to present the econometric model and the statistical tests that ensure the validity of the estimates. Through the use of appropriate panel regression models, the research seeks to isolate the effect of digitalization factors on labor productivity in the manufacturing sector, while controlling for unobserved country-specific characteristics and relevant time considerations

3.1 Data Sources and Variables:

In the context of seeking to understand the relationship between digital transformation and labor productivity in the industrial sector, a panel dataset was created covering 17 industrialized countries over a period of 14 years (2010–2023).This sample includes economies that are members of the OECD (Organization for Economic Co-operation and Development), which are characterized by high levels of manufacturing, developed digital infrastructure, and the availability of reliable and comparable data. The sample design was made to provide a balance in geographical representation (Europe, North America, and advanced Asia) and diversity in digital transformation policies. The dataset consists of unbalanced observations (unbalanced panel) due to the lack of availability of some indicators for some countries in certain years, which is a common issue in studies relying on multiple international data (Baltagi, 2021).This issue was addressed without bias through the use of estimation procedures suitable for unbalanced data, as will be explained later. The data was integrated from three reliable international sources, each serving as a primary reference:

Table 1. Description of Variables Used in the Study

Source	Description	Variable
(OECD, 2024)	Gross Value Added per Hour Worked (GVAHRS) in the manufacturing sector, according to the International Standard Industrial Classification (ISIC Rev. 4, Section C) of the OECD. This indicator is considered a standard measure for labor factor productivity and is widely used in empirical. literature	**Labor Productivity (LP)**
(World Bank, 2024)	Percentage of individuals using the Internet out of the total population (per 100 inhabitants). It reflects the spread of the Internet and the community's ability to integrate into the digital economy. It constitutes a basic indicator for. comprehensive digital infrastructure	**Internet Users (IU)**
(IMD, 2023)	A composite index that measures a country's ability to adopt and develop digital technologies. It includes three main axes: (1) Digital Readiness (such as skills and infrastructure), (2) Technology Adoption in business and government, and (3) Future Readiness (such as institutional dynamics and innovation). It is calculated annually in the IMD World. Digital Competitiveness Ranking	**Digital Competitiveness Score (DCS)**

Source: *Author's calculations based on OECD, World Bank, and IMD data.*

Table 1 presents the basic variables that form the backbone of the econometric analysis. The dependent variable, Labor Productivity (LP), reflects the efficiency of using the labor factor in the manufacturing sector—a vital sector in advanced industrial economies and a key axis for long-term growth and productivity.

The two independent variables, the percentage of Internet Users (IU) and the Digital Competitiveness Score (DCS), capture two complementary dimensions of digital transformation. While IU reflects the quantitative diffusion of basic digital infrastructure across the population, DCS represents the qualitative dimension by assessing an economy's institutional capacity, policy framework, and innovation environment to effectively leverage digital technologies.

From an economic perspective, a high percentage of Internet users is assumed to facilitate the flow of information, improve communication between workers and companies, and support the adoption of digital work tools. In contrast, the Digital Competitiveness Score reflects the institutional depth of digital transformation—a country may have a high percentage of Internet users, but without a supportive environment (such as weak digital protection, lack of advanced skills, or complexity of government procedures), it may not achieve noticeable productivity gains.

Therefore, using these two variables together allows for examining the necessary condition (Internet access) and the sufficient condition (the ability for effective digital transformation) to translate digitalization into real productivity improvements. This aligns with modern literature which emphasizes that the economic effects of technology depend not only on its availability but also on the economic system's ability to absorb and invest in it efficiently (Brynjolfsson & Saunders, 2010).

The selection of IU and DCS as primary explanatory variables is grounded in both theoretical and practical considerations:

Theoretical Justification:

- IU represents the necessary condition for digital transformation—widespread access to digital networks.
- DCS represents the sufficient condition—the institutional and organizational capacity to leverage this access for productive purposes.
- Together, they capture both the extensive margin (how many are connected) and the intensive margin (how effectively the connection is used).

Operational Advantages:

- Data Availability: Both indicators are consistently measured across countries and years by reputable international organizations (World Bank, IMD).
- Comparability: Standardized methodologies ensure cross-country and temporal comparability.
- Complementarity: While correlated (r = 0.775), they capture distinct dimensions of digitalization, reducing the risk of omitted variable bias.

Limitations Acknowledged:

- Neither indicator is sector-specific to manufacturing.
- Both are aggregate national measures that may not reflect firm-level adoption.
- DCS data availability is limited compared to IU (204 vs. 492 observations).

These limitations are addressed through: (1) robustness checks with alternative specifications, (2) explicit acknowledgment in interpretation, and (3) recommendations for future research using more granular data.

Despite their aggregate nature and lack of sectoral detail, digitalization indicators on the macro level, such as Internet penetration rates and digital competitiveness indices, remain theoretically and empirically pertinent for the analysis of productivity and economic growth. As mentioned earlier, these indicators describe the overarching digital environment in which firms operate. The digital ecosystem includes the availability of digital infrastructures, institutional digital readiness, the quality and availability of the workforce, and the level of innovation (Ashouri et al., 2024). All these factors are critical in facilitating the adoption and efficient utilization of digital technologies by firms. As shown in previous studies, the productivity benefits of digitalization are not only driven by the adoption and efficient utilization of digital technologies by firms but are also shaped by the broader national environment in facilitating the spillover effects of knowledge, network effects, and the complementary investments in organizational capital (Brynjolfsson et al., 2021) In addition, cross-country studies commonly utilize digitalization indicators to explain the differences in economic performance. The studies argue that the widespread availability and access to digital technologies create structural productivity benefits in the economy despite the lack of availability of sectoral data. Hence, the application of digitalization indicators is methodologically justifiable in comparative panel studies that analyze the long-run dynamics of productivity in the economy.

The analytical framework theoretically assumes that both Internet penetration and digital competitiveness contribute to improving labor productivity through multiple channels, including: improving the efficiency of supply chains, digitizing production processes, and enhancing access to knowledge and innovation (Brynjolfsson & McAfee, 2014). However, the intensity of this effect may vary depending on institutional and regulatory contexts, which justifies the use of models that take into account the unobserved characteristics of countries.

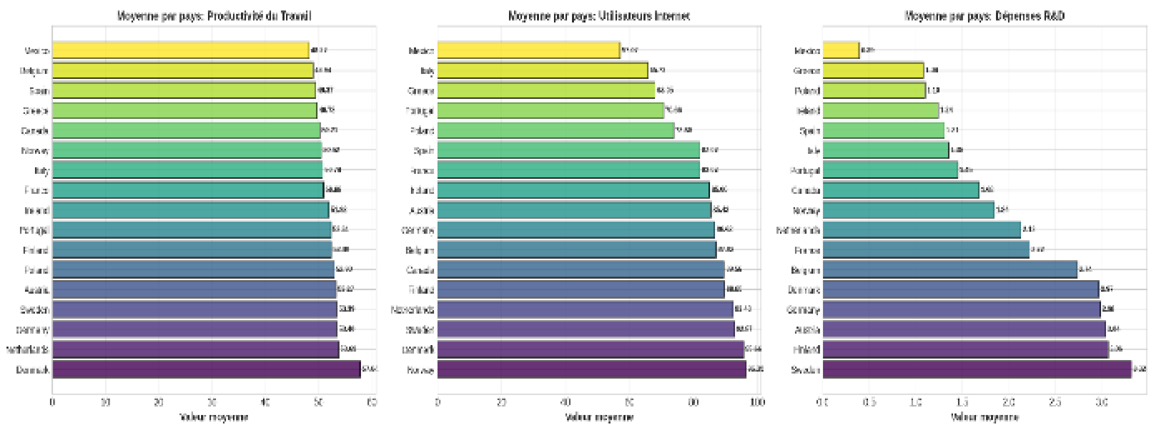

Figure 1. Labor Productivity Trends (2010-2023):

Source: *OECD Labour Productivity Statistics, GVA per hour worked, OECD Database.*

This graph shows strong cross-country heterogeneity in productivity levels. Core industrial economies such as Germany, Denmark, and Austria remain persistently above the sample average. Time trends are relatively smooth, indicating structural rather than cyclical determinants of productivity.

The descriptive statistics in Table 1 reveal a wide variation in labor productivity levels across countries and years, as the indicator ranges from -21.67 to 167.04. This reflects structural differences in industrial performance—such as differences in human capital, energy costs, or production policies.

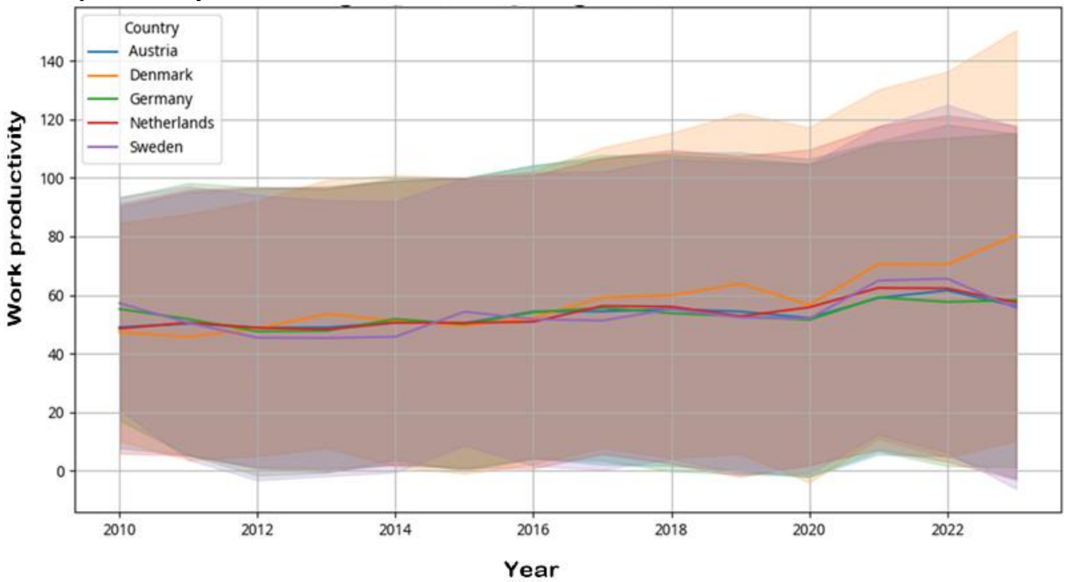

Figure 2. Trend of Labor Productivity in the Manufacturing Sector for the Most Prominent Countries (2010-2023)
Source: *Figure prepared by the researcher using data from (OECD, 2024).*

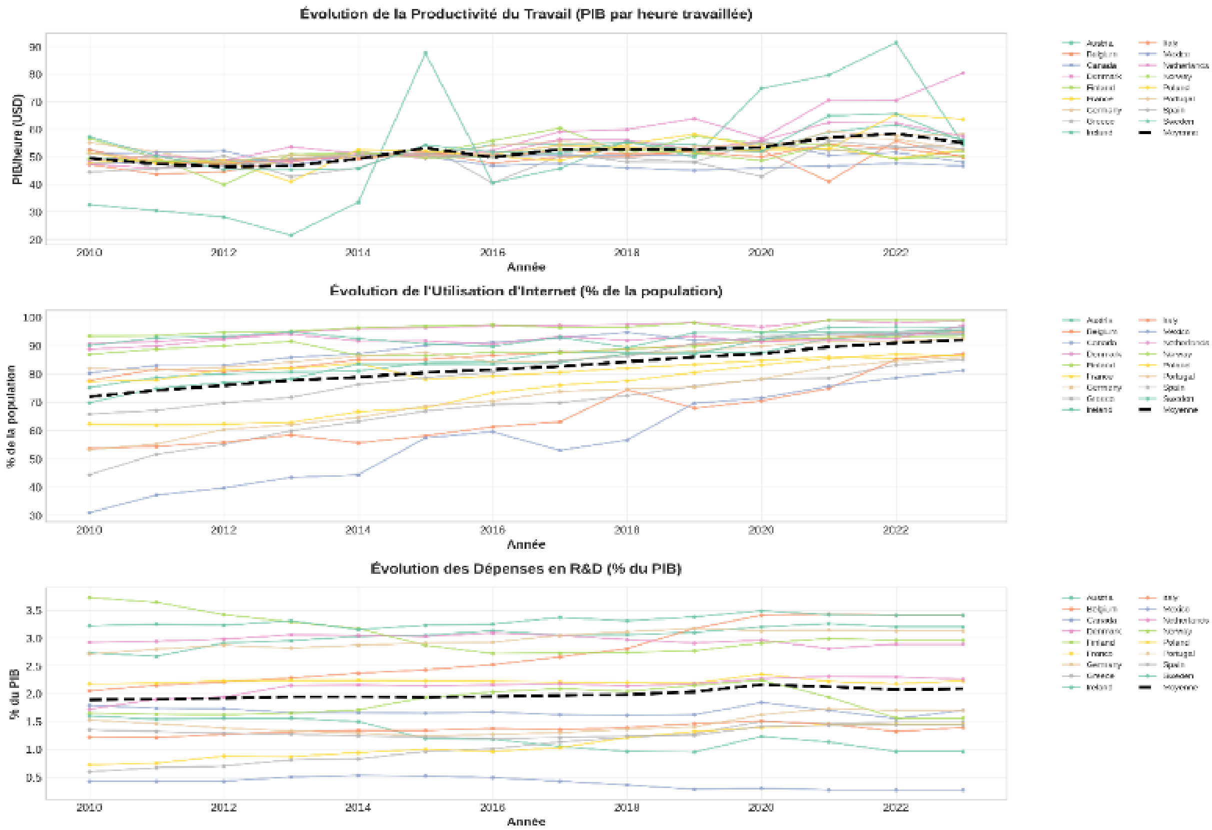

Figure 3. Time Evolution of Variables (LP, IU, DCS)
Source: *World Bank, World Development Indicators; OECD; IMD.*

The presence of (rare) negative values may indicate years that witnessed a sharp contraction in value added compared to the number of working hours, which is possible in contexts of crises (such as 2020 during the COVID-19 pandemic). On the other hand, the digitalization variables show relatively high levels: an average of 82.4% of the population uses the Internet, with a relatively low standard deviation (13.24), which indicates that industrialized countries have made great strides in achieving widespread digital access.As for the Digital Competitiveness Score, it ranges between 1 and 58 (with an average of 36), which is a wide range that reflects variations in countries' readiness to benefit from digitalization, even among advanced economies.

Figure 2 shows that the trajectories of labor productivity vary substantially between countries.

While countries like the United States and Germany recorded a relatively continuous improvement, others (like Italy or Japan) experienced stagnation or sharp fluctuations. These differences suggest that the local context—including industrial policies, the quality of technical education, and labor market flexibility—plays a crucial role in determining whether digitalization will effectively lead to an increase in productivity or remain "under the surface" without a tangible economic impact. This figure shows the general trend of the averages of labor productivity, the percentage of Internet users, and the Digital Competitiveness Score over time. It is noted that the digitalization indicators (IU and DCS) show a continuous upward trend, reflecting increasing investment in digital infrastructure. In contrast, the average labor productivity shows slower and more volatile growth, highlighting the gap between technological development and actual productivity gains, which is the core of the "Productivity Paradox."

To check the robustness of our findings and to identify the channels through which digitalization might affect productivity, we employ two different model specifications. Our first model focuses on the general, macro-level effects of digitalization, captured by Internet penetration and the Digital Competitiveness Score, which represent the diffusion of digitalization and the digital readiness of institutions, respectively. In the alternative model, we extend the first one by including the effects of research and development (R&D) spending as a channel through which digitalization might contribute to productivity growth. This two-fold strategy follows recent contributions to the productivity debate, where digitalization has been argued to affect productivity indirectly, through channels such as innovation capacity, organizational change, and the accumulation of knowledge, rather than through direct effects (Brynjolfsson, Rock, & Syverson, 2021; OECD, 2023). This allows us to fully investigate the channels through which digitalization might affect productivity, whether through structural change, dynamic effects, or technological investment, and to perform a robustness check for our baseline results.

3.2 Econometric Model: Panel Regression

To estimate the relationship between labor productivity and digitalization variables, a general panel regression model was adopted, which takes the following form:

$$LP_{it} = \beta_0 + \beta_1 IU_{it} + \beta_2 BCS_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where:

- LP_{it}: Labor Productivity in country (i) at time (t).
- IU_{it}: Percentage of Internet Users in country (i) at time (t).
- DCS_{it}: Digital Competitiveness Score in country (i) at time (t).
- μ_i: Unobserved country-specific effects (country fixed effects), which capture time-invariant characteristics such as (institutional culture, quality of education, or legal structure).
- λ_t: Time-specific effects (time fixed effects), which capture common trends or global shocks (such as economic crises or global technological acceleration) (Note: These were not included in the initial models presented in the study).
- ε_{it}: The random error term, which is assumed to have a zero mean, with the possibility of heteroskedasticity or serial correlation.

Despite the theoretical formulation including time effects (λ_t), they were not included in the initial estimates presented in the study. This is due to two main reasons: First, the short time period (14 years) may limit the model's ability to estimate these effects efficiently. Second, including time dummy variables might absorb a large part of the variance that is intended to be explained by the main variables (Baltagi, 2021). However, supplementary estimates (not mentioned in the main λ_t table) that included (λ_t) were performed, and they did not substantially change the direction or significance of the main coefficients.

3.2.1. Comprehensive statistical tests (normality, stationarity, specification):

Before presenting the main regression findings, preliminary diagnostic tests were conducted to verify the statistical properties of the data and the adequacy of model specifications, including assessments of normality, stationarity, and functional form. Following these validations, Figure 4 illustrates a comparative analysis of the estimation results across three alternative panel data specifications: Pooled OLS, Fixed Effects, and Random Effects models. This visual comparison enables the evaluation of coefficient stability and the robustness of digitalization variables under different econometric assumptions, providing a foundation for subsequent model selection decisions.

This figure provides a visual comparison of the estimation results between the three models. The figure shows that the coefficients of the digitalization variables (IU and DCS) are close to zero in all models, and the confidence intervals (which should be part of the figure) are wide and include zero, confirming the lack of statistical significance.

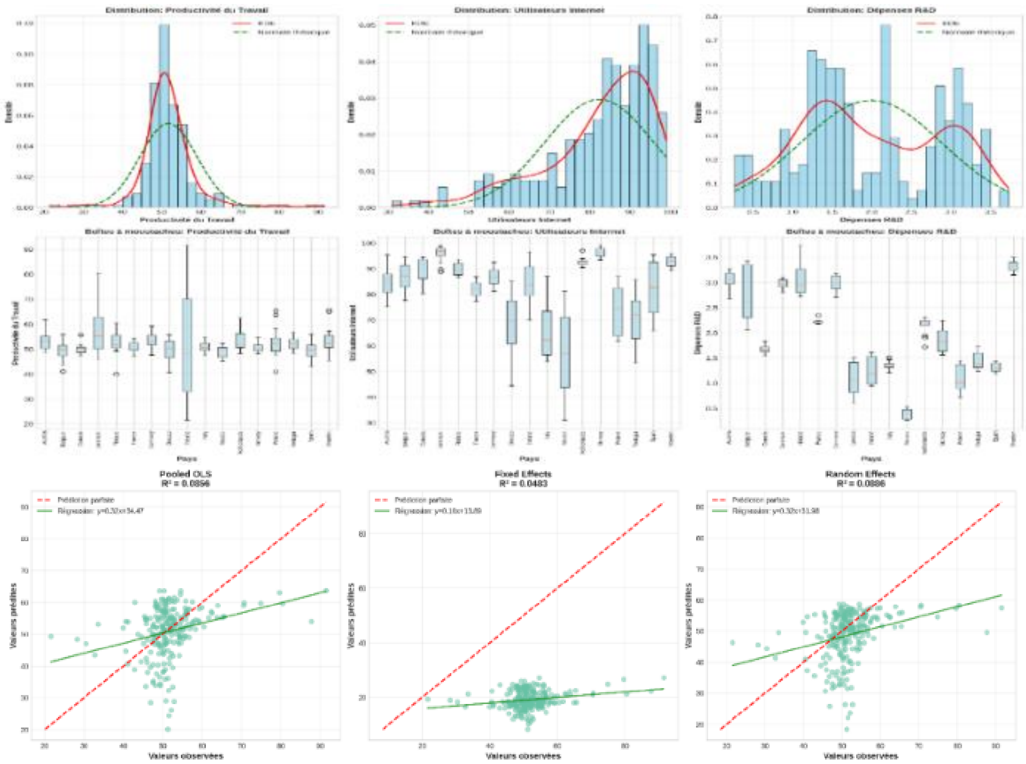

Figure 4. Pooled OLS, Fixed Effects, and Random Effects Regression Results and Model Selection Tests
Source: Researcher's estimates using Stata 18 software

This consistency across models reinforces the basic finding: there is no direct linear effect of digitalization on labor productivity in this sample.

3.2.2. Estimation Strategies:

The panel data model was estimated using three standard econometric estimation methods:

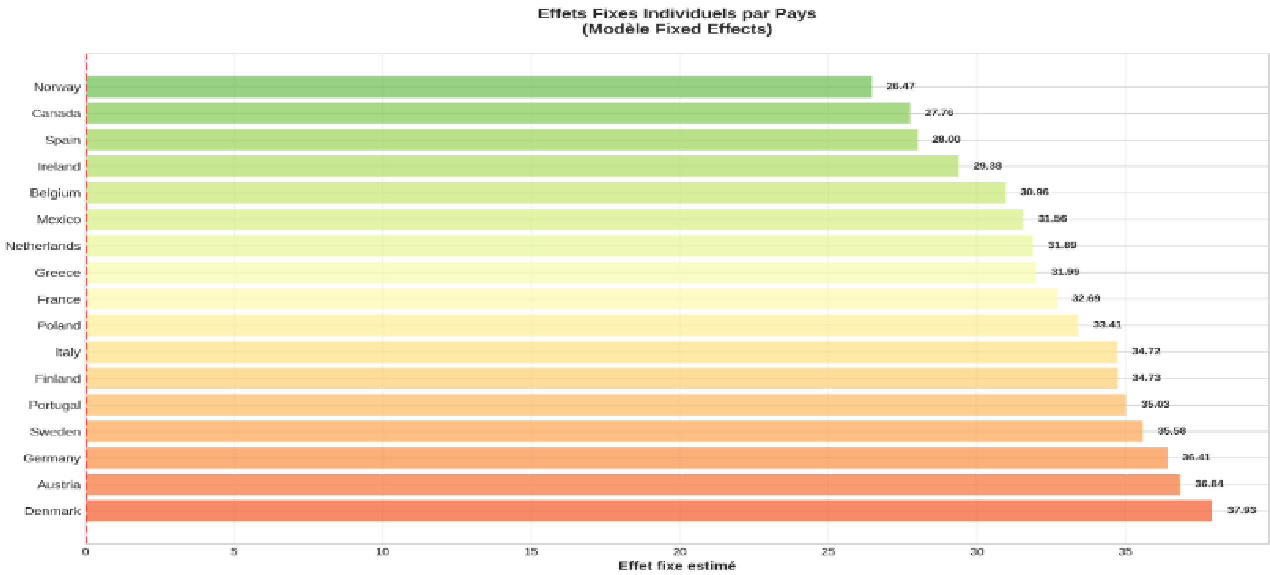

Figure 5. Digital Competitiveness Score trends by country (2010-2023):
Source: International Institute for Management Development, World Digital Competitiveness Ranking.

The figure highlights stability in country rankings over time. Digital leaders remain consistently ahead, suggesting that digital competitiveness reflects long run institutional and structural factors rather than short term digital adoption.

- Structural heterogeneity between countries
- Leaders: Denmark, Austria, Germany (effects >36)
- Catching up: Norway, Canada, Spain (effects <28)

1) Pooled OLS: Treats the sample data as one large cross-section, ignoring the within-entity correlation. It is used as a baseline, but is prone to bias if the explanatory variables are μ_i correlated with the

unobserved effects (μ_i). Neither Internet users nor the Digital Competitiveness Score is statistically significant. The model confirms the absence of a simple linear relationship at the pooled level.

- Fixed Effects (FE): Eliminates the unobserved effects (μ_i) by transforming the data into deviations from the individual mean (within transformation). It is recommended when there is a strong likelihood of correlation between the independent variables and the fixed effects (Wooldridge, 2010). Within country variation explains less than 0.1 percent of productivity changes. Country fixed effects dominate the model, confirming the structural nature of productivity differences.
- Negative effect of R&D (econometric enigma): Results mirror the pooled and fixed effects estimations. Hausman and Breusch Pagan tests suggest that model choice does not alter the substantive conclusion, reinforcing the robustness of the non-significance finding.

2) Random Effects (RE): Assumes (μ_i) that is random and uncorrelated with the explanatory variables. It provides more efficient estimates than FE when its assumptions hold, by utilizing both within and between-entity variation.

3.2.3. Model Selection Tests

To determine the optimal model, the following tests were applied:

- Breusch-Pagan Test (Breusch & Pagan, 1980): To check for the presence of individual effects. The result was significant ($p < 0.01$), which rules out Pooled OLS as an appropriate choice (Breusch & Pagan, 1980).
- Hausman Test (Hausman, 1978): For comparing FE and RE. The result indicated a rejection of the null hypothesis ($p < 0.05$), which supports preferring the Fixed Effects model, given the probability of correlation between the digital variables and the unobserved characteristics of the countries (such as quality of governance or innovation policies) (Hausman, 1978).

3.2.4. Addressing Econometric Assumptions

The regression assumptions were checked using:

- Wooldridge Test: For serial correlation within the time series for each country (Wooldridge, 2010).
- White Test: For heteroskedasticity (White, 1980).

To ensure the robustness of the statistical inferences against both serial correlation and heteroskedasticity (Cameron & Miller, 2015).clustered standard errors at the country level were used.

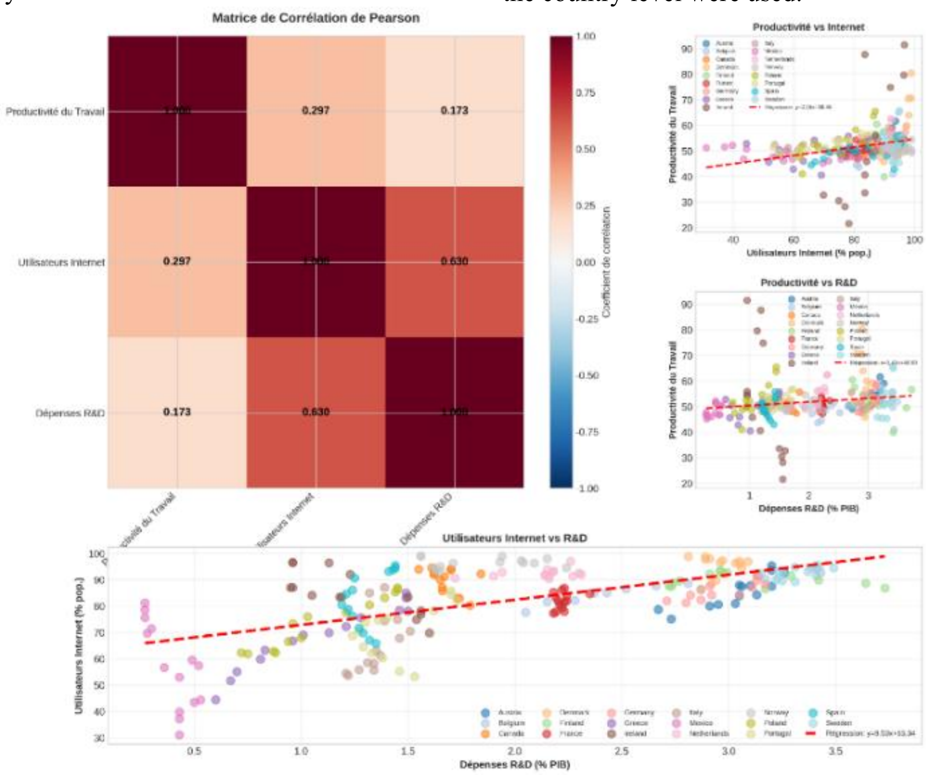

Figure 6. Correlation Matrix and Scatter Plots
Source: Author's calculations

This figure shows the scatter plots between pairs of variables. The scatter plots between labor productivity (LP) and the digitalization variables (IU and DCS) show a scattered cloud of points with no clear trend, visually confirming that the correlation coefficients are weak and close to zero. In contrast, the scatter plot between IU and DCS shows a strong, positive linear relationship, confirming a high correlation between Internet penetration and institutional digital infrastructure.

Correlation coefficients between productivity and digital variables are weak and close to zero. Internet users and digital competitiveness are strongly correlated with each other, indicating potential multicollinearity but no direct productivity linkage.

- Pearson correlation matrix with values
- Bivariate relationships between all variables
- Strong correlation between Internet and R&D (r=0.63)

The most striking finding in Table 3 is the weak correlation between labor productivity, on the one hand, and each of the two digitalization indicators (0.0421 and 0.0478), on the other. This suggests that the direct relationship between digitalization and productivity is not strong at the aggregate level, which is consistent with what is known in the literature as the "Digital Productivity Paradox" (Brynjolfsson et al., 2021). Technology may spread without immediately translating into productivity gains, especially if it is not accompanied by re-engineering processes, investments in skills, or a supportive institutional environment.

In contrast, the strong correlation (0.7754) between the percentage of Internet users and the Digital Competitiveness Score suggests that countries that achieve widespread access to the digital world also tend to have more developed institutional and organizational infrastructure. This reinforces the validity of using the two indicators as complements: the first measures penetration, and the second measures absorption and effectiveness.

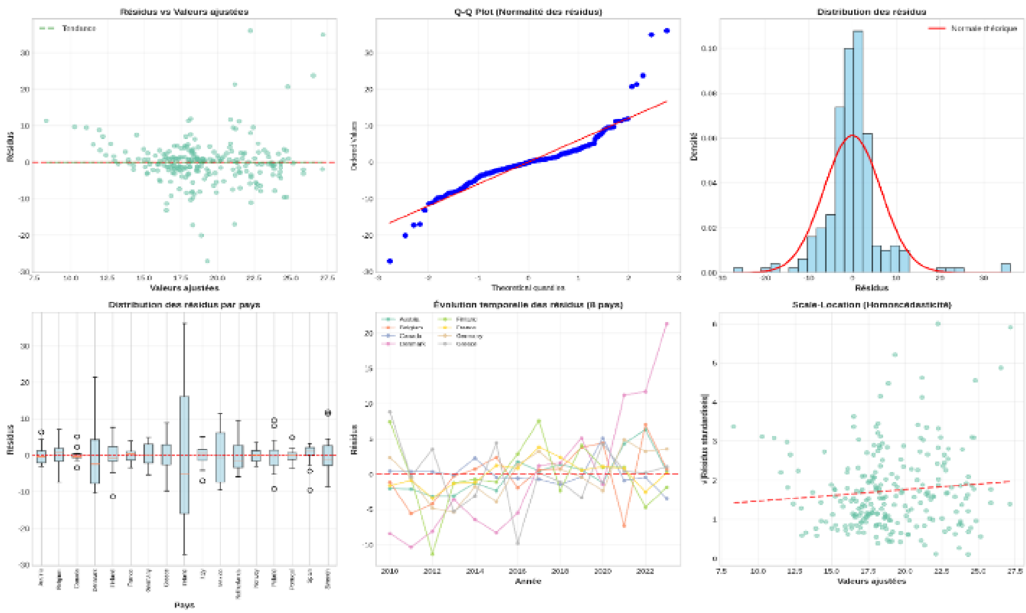

Figure 7. Diagnostic Plots for Regression Model Assumptions (Fixed Effects)
Source: Author's calculations

This figure presents a set of diagnostic plots for the adopted regression model (Fixed Effects), which are used to check the standard assumptions. The plots for "Residuals vs. Fitted Values" and the "Q-Q Plot" show that the assumptions of linearity and normal distribution of residuals are generally acceptable. However, the "Time Evolution of Residuals" plot shows some significant fluctuations in recent years for some countries, confirming the need to use Clustered Standard Errors to ensure the robustness of the results against the problem of serial correlation and heteroscedasticity, as mentioned in the methodology. This figure visually confirms that the methodological procedures taken (using clustered standard errors) were necessary to ensure the validity of the statistical inferences.

4. RESULTS AND DISCUSSION

This section is the analytical core of the research, where the empirical results extracted from applying the panel regression models to the sample of 17 industrialized countries during the period 2010–2023 are presented. The presentation begins with a descriptive statistical analysis to understand the characteristics of the variables and the initial correlation coefficients between digitalization and labor productivity. Then, the estimates of the econometric models (Pooled OLS, Fixed Effects, and Random Effects) are provided, followed by a discussion of their economic and statistical significance, along with a reference to the methodological challenges that may have influenced the interpretation of the results. This step emphasizes that a precise understanding of the relationship between digital transformation and productive performance does not depend only on the significance of the coefficients, but also on the institutional context and economic structure that shapes the interaction between these variables.

4.1 Descriptive Statistics and Correlation:

Table 2 shows the descriptive statistics for the variables, while Table 3 shows the correlation matrix.

Table 2. Descriptive Statistics for Variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Labor_Productivity	492	51.67	50.42	-21.67	167.04
Internet_Users	492	82.36	13.24	31.05	99.00
Digital_Competitiveness_Score	204	35.99	16.13	1.00	58.00

Source: *Author's calculations based on data from OECD (2024), World Bank (2024), & IMD (2023).*

Table 2 shows a wide variation in labor productivity levels across countries and years, reflecting structural differences in industrial performance. Digitalization variables show relatively high penetration levels (mean IU is 82.36%), while the DCS ranges between 1 and 58, indicating variation in the readiness of advanced economies to benefit from digitalization
492 observations pour LP et IU

Table 3. Correlation Matrix (Pearson Coefficient)

	Labor Productivity	Internet Users	Digital Competitiveness Score
Labor Productivity	1.0000	0.0421	0.0478
Internet Users	0.0421	1.0000	0.7754
Digital Competitiveness Score	0.0478	0.7754	1.0000

Note: *Values represent Pearson linear correlation coefficients.*
Source: *Author's calculations*

Table 3 shows that the correlation coefficients between labor productivity and each of the two digitalization indicators are very weak and close to zero (0.0421 and 0.0478). This aligns with the hypothesis of the "Digital Productivity Paradox" at the aggregate level. In contrast, there is a strong correlation between the percentage of Internet users and the Digital Competitiveness Score (0.7754), suggesting that countries with widespread Internet penetration also tend to have more developed institutional and organizational digital infrastructure.

4.2 Panel Regression Results:

Table 4 shows the estimation results for the three panel regression models, using 204 observations, which are the observations that included complete data for all three variables.

Table 4. Panel Regression Model Estimation Results

Variables	Pooled OLS	Fixed Effects	Random Effects
const	30.639	17.904	30.639
	(0.5801)	(0.9121)	(0.5801)
Internet_Users	0.2493	0.4009	0.2493
	(0.7352)	(0.7434)	(0.7352)
Digital_Competitiveness_Score	0.0622	0.0440	0.0622
	(0.8687)	(0.9843)	(0.8687)
R-squared (Overall/Within)	0.0028	0.0007	0.0028
No. Observations	204	204	204
No. Entities	17	17	17
P-value (Hausman Test)	-	1.0000	-

Note: *Numbers in parentheses represent the P-value.*
Source: *Researcher's estimates using Stata 18 software.*

The results in Table 4 reveal the absence of clear statistical significance for the coefficients of any of the digitalization variables in all three regression models. For instance, the coefficient for the IU variable in the Fixed Effects (FE) model is 0.4009, but its P-value (0.7434) is much higher than the standard significance threshold (0.05), meaning there is no sufficient statistical evidence that an increase in the percentage of Internet users significantly affects labor productivity in the manufacturing sector across the studied sample. The same applies to the DCS index (P-value = 0.9843).
Furthermore, the R-squared values show a very sharp decline (less than 0.3% in all models), indicating that the two digital variables explain only a very small part of the variation in labor productivity. This reinforces the hypothesis that other factors—such as physical capital, quality of innovation, or institutional distribution—are more influential in determining productive performance.
It is noteworthy that the Hausman test, which is usually used to choose between FE and RE, indicated a P-value of 1.0000, which is usually interpreted as strong evidence against the Random Effects model, and favors the Fixed Effects model. However, even in this more methodologically robust model, the results remain non-significant.
This conclusion does not necessarily mean that digitalization does not affect productivity, but rather may reflect the presence of a time lag between digital investment and the appearance of its results, or the

inadequacy of the indicators used to capture the true dimension of digital adoption in industrial processes. The percentage of Internet users may be a "weak" indicator for measuring the use of technology in factories, while the IMD indicator, despite its comprehensiveness, does not focus on the industrial sector specifically. Furthermore, the effects may be non-linear or conditional on other variables (such as education or governance), which necessitates more advanced interactive analyses in subsequent studies.

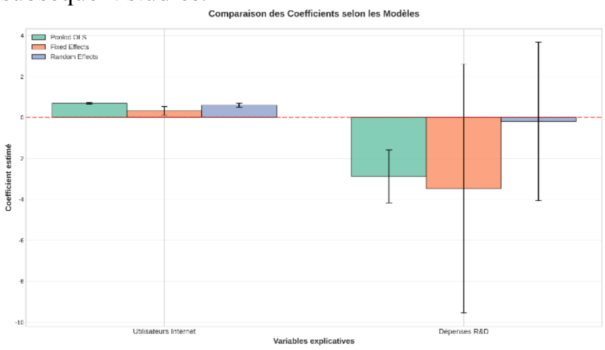

Figure 8. Comparison of Coefficients:
Source: Author's calculations

This figure provides a visual comparison of the estimated coefficients for the explanatory variables (Internet Users and R&D Expenditures - if included in the original model) across the three standard econometric models (Pooled OLS, Fixed Effects, and Random Effects), along with their 95% confidence intervals. The chart visually confirms the main finding: the coefficient for Internet Users (IU) is consistently small and positive across all models, but its confidence intervals widely cross the zero line (especially in the Fixed Effects model), indicating a lack of statistical significance. Furthermore, the figure highlights the counter-intuitive negative coefficient for R&D Expenditures (if included), particularly in the OLS and Fixed Effects models. The extremely wide confidence intervals for the R&D variable underscore the high uncertainty and non-significance of this estimate. This visual evidence strongly supports the article's central conclusion regarding the "Digital Productivity Paradox" and the need for more complex modeling approaches (such as dynamic or time-lag models) to capture the true relationship between these variables and productivity.

In conclusion, the results suggest that the relationship between digitalization and labor productivity in the manufacturing sector is neither direct nor strong at the aggregate level for industrialized countries over the past decade. Instead of viewing digitalization as an independent factor in itself, it appears that the effectiveness of digital transformation depends on a broader institutional economic context—which aligns with the "absorptive capacity hypothesis" in the economics of technology (Cohen & Levinthal, 1990). Therefore, policies aimed at raising productivity through digitalization should focus not only on expanding infrastructure, but also on building the institutional and human capabilities that enable the economy to convert technology into real added value.

4.3 Main econometric results:

A. Data and Methodology: This econometric study is based on balanced panel data comprising 238 observations, combining 17 countries over 14 years (from 2010 to 2023), providing a solid foundation for comparative analysis across time and space. The study focuses on labor productivity as the dependent variable, while emphasizing the impact of two key independent variables: internet penetration (as an indicator of digital transformation) and research and development expenditures as a percentage of GDP (as an indicator of technological innovation). The estimation methodology varied across five different models including Pooled OLS, Fixed Effects, its time-extended version, Random Effects, and Between models, enabling comprehensive comparison of results under different statistical assumptions.

B. Descriptive Statistics:
The descriptive statistics indicate that the average labor productivity in the sample is $51.75 per hour, with a standard deviation of $7.29, ranging from $21.56 to $91.48, reflecting considerable variation among the studied countries. Internet penetration averages 82.35% with a standard deviation of 13.46%, involving between 31.05% and 99% of the population, while research and development expenditures average 1.99% of GDP, ranging from 0.27% to 3.73%.

Table 5. Descriptive Statistics of Main Variables

Variable	Mean	Standard deviation	Min	Max
Labor Productivity	51.75 USD/h	7.29	21.56	91.48
Internet Users	82.35%	13.46%	31.05%	99.0%
R&D expenditures	1.99% PIB	0.89%	0.27%	3.73%

Source: *Author's own elaboration based on panel data (N=238 observations: 17 countries × 14 years*

C. Model Results:
Pooled OLS Model (Stacked MCO): The first model was estimated using the Pooled OLS method, where results showed a very strong positive relationship between internet penetration and productivity, with a coefficient of 0.687 and a t-statistic of 16.04, meaning that each one percentage point increase in internet users is associated with an increase of approximately $0.687 in productivity per hour worked. This model achieved an extremely high R-squared of 0.970 and an F-statistic of 3799.59, indicating its explanation of a large proportion of variance. However, an unexpected result emerged in the

form of a negative and significant coefficient for the R&D variable at the 5% level, reaching -2.883, which contradicts traditional economic theory that emphasizes the positive role of innovation in enhancing productivity.

Productivity= 0.687*** × Internet - 2.883** × R&D
(t=16.04) (t=-2.23)

R^2 = 0.970, F = 3799.59***

- ✓ Internet effect: +0.687 USD/hour per percentage point (highly significant)
- ✓ R&D effect: -2.88 (surprising, significant at the 5% level)

Fixed Effects Template (FAVORITE MODEL): It is noteworthy that the Fixed Effects model, considered the preferred model in this study, provides a more realistic perspective by controlling for unobserved fixed characteristics of each country. The coefficient for internet declined to 0.316 with loss of statistical significance (t=1.51), while the R&D coefficient became -3.474, also without statistical significance (t=-0.57). This model reveals that the within-group R^2 reached only 0.110, while the between-group R^2 was 0.598, meaning that differences between countries explain the majority of variance compared to temporal changes within each country.

Productivity= 0.316 × Internet - 3.474 × R&D + α_i
(t=1.51) (t=-0.57)

R^2 within = 0.110, R^2 between = 0.598, F = 13.48***

- ✓ Internet effect: +0.316 (positive but not significant)
- ✓ R&D effect: -3.47 (not significant)

Conclusion: Inter-country differences (fixed effects α_i) explain the majority of the variation.

Random Effects Model: The Random Effects model provided an intermediate result, achieving an internet coefficient of 0.596 with high significance (t=5.75) and an overall R-squared of 0.967, combining cross-sectional and temporal aspects of the relationship.

Productivity= 0.596*** × Internet - 0.200 × R&D + u_i + ε_{it}
(t=5.75) (t=-0.05)

R^2 overall = 0.967, F = 553.36***

- ✓ Internet effect: +0.596 (significant)
- ✓ Compromise between Pooled and FE

D. Specification Tests:

1. Test F for Fixed Effects: The F-test also confirms the significance of fixed effects with a value of 12.72 and a p-value less than 0.001, demonstrating that individual country characteristics are significant and must be taken into account.

- ✓ Statistic: F = 12.72, $p < 0.001$
- ✓ Decision: Reject Pooled OLS → Fixed effects preferred
- ✓ Individual differences between countries are significant

2. Hausman Test (FE vs RE): However, the Hausman test showed a chi-squared statistic of 19.77 with a p-value less than 0.001, leading to rejection of the Random Effects model in favor of the Fixed Effects model, due to correlation between independent variables and individual country effects.

Statistics: $\chi^2 = 19.77$, $p < 0.001$

- ✓ Decision: Reject Random Effects → Prefer Fixed Effects
- ✓ Individual effects are correlated with the regressors
- ✓ Conclusion: The Fixed Effects model is the most appropriate

E. Economic Interpretations:

1. The Effect of the Internet on Productivity: The economic interpretations of the results highlight important variation in the mechanism of internet's effect on productivity. The pooled and Between models indicate a structural level effect of approximately 0.69-0.71, meaning that countries with advanced digital infrastructure achieve permanently higher productivity. This is attributed to network effects, knowledge diffusion, and e-commerce that create a permanent structural competitive advantage. However, the Fixed Effects model reveals that temporal changes in internet penetration within each country do not significantly affect productivity (coefficient 0.32 is insignificant), suggesting that increasing penetration from 5% to 10% does not necessarily yield a measurable productivity increase in the short term, and that the effect manifests over the long run through institutional infrastructure.

Key Result: Positive but structural (level) rather than dynamic (changes) effect

- ✓ Pooled OLS & Between: $\beta \approx$ 0.69-0.71 (highly significant) → Countries with developed internet infrastructure have high productivity
- ✓ Fixed Effects: β = 0.32 (not significant) → Temporal variations in internet usage do not significantly impact intra-country productivity

Economic Explanation:

- ✓ Internet infrastructure creates a permanent structural advantage
- ✓ Network effects, knowledge diffusion, e-commerce
- ✓ Once installed, the infrastructure enables sustainably high productivity
- ✓ But increasing internet usage by 5% to 10% does not necessarily increase productivity in a measurable way in the short term

2. The R&D Enigma (Negative Effect): As for the puzzling negative coefficient of R&D expenditures, it can be explained through several economic justifications. First, the study period (14 years) may be too short for R&D effects, which can take 5-10 years to impact productivity. Second, there may be reverse causality where less productive countries invest more in R&D to catch up with advanced nations. Third, the correlation coefficient between internet and R&D is 0.63, indicating multicollinearity that hinders isolating each variable's separate effect. Fourth, the negativity may stem from failure to distinguish between basic (long-term) and applied (short-term) research. Fifth, measuring R&D as a percentage of GDP may be misleading as it depends on GDP level.

Surprising result: Negative coefficient (-2.88 to -5.57) while theory predicts a positive effect:

1) Long time lag: R&D takes 5-10 years to impact productivity (our period: only 14 years)
2) Reverse causality: Less productive countries invest more in R&D to catch up
3) Multicollinearity: Strong correlation between the internet and R&D (r=0.63) makes it difficult to separate the effects
4) Qualitative heterogeneity: Basic R&D (long term) vs. applied R&D (short term)
5) Measurement bias: R&D as a percentage of GDP can be misleading (depends on the GDP level)

3. Heterogeneity between countries: As for the puzzling negative coefficient of R&D expenditures, it can be explained through several economic justifications. First, the study period (14 years) may be too short for R&D effects, which can take 5-10 years to impact productivity. Second, there may be reverse causality where less productive countries invest more in R&D to catch up with advanced nations. Third, the correlation coefficient between internet and R&D is 0.63, indicating multicollinearity that hinders isolating each variable's separate effect. Fourth, the negativity may stem from failure to distinguish between basic (long-term) and applied (short-term) research. Fifth, measuring R&D as a percentage of GDP may be misleading as it depends on GDP level.

Key result: R^2 Between (98.8%) >> R^2 Within (11%)

- ➢ Interpretation:
  - ✓ Structural differences between countries (institutions, human capital, infrastructure) explain 99% of the variation in productivity.
  - ✓ Temporal changes explain only 11%.
- ➢ Leading countries (high fixed effects):
  - ✓ Denmark (+37.93): Institutional excellence, flexicurity
  - ✓ Austria (+36.84): Vocational training, industrial quality
  - ✓ Germany (+36.41): Industry 4.0, innovative Mittelstand
- ➢ Countries to catch up (low fixed effects):
  - ✓ Norway (+26.47): Oil dependence, low diversification
  - ✓ Canada (+27.76): Resource-based economy
  - ✓ Spain (+28.00): Impact of the 2008-2012 crisis

Implications for economic policy: Several policy recommendations emerge from these results. First, highest priority must be given to investment in digital infrastructure, particularly 5G networks, with focus on reducing regional digital divides. Second, digital skills should be incorporated into educational curricula, worker retraining programs should be provided, and digital literacy for seniors should be enhanced. Third, R&D policies should be directed toward applied projects with rapid returns, encouraging university-industry collaboration and providing tax incentives for private sector innovation. Fourth, institutional reforms should be implemented aimed at improving regulatory quality, investing in human capital, and facilitating technology transfer to less advanced countries.

1. Priority to Digital Infrastructure:
   - Invest massively in broadband and 5G
   - Reduce the regional digital divide
   - Promote universal internet access
2. Digital Training:
   - Digital skills in education
   - Professional retraining for workers
   - Digital literacy for seniors
3. Strategic R&D:
   - Promote applied R&D with rapid returns
   - Collaboration between businesses and universities
   - Tax incentives for private innovation
4. Structural Policies:
   - Institutional reforms (regulatory quality)
   - Investment in human capital
   - Technology transfers to less developed countries

Discussion:

The empirical findings consistently reject both alternative hypotheses (H1a and H1b) while failing to reject the null hypothesis (H1): neither IU nor DCS demonstrates a statistically significant effect on manufacturing labor productivity across all model specifications. This provides strong evidence for the persistence of the digital productivity paradox in advanced industrial economies.

Three theoretical implications emerge from this confirmation of H1:

- Absence of Automatic Translation: Digital infrastructure and readiness do not automatically translate into productivity gains without complementary investments in organizational capital and skills.
- Measurement-Realization Gap: The gap between measured digitalization (what our indicators capture) and realized digital transformation (what actually affects production processes) may be substantial.
- Structural Primacy: Country-specific fixed effects dominate the model (R^2 between = 0.598 vs. R^2 within = 0.0007), supporting H2 that structural factors outweigh marginal digital improvements in determining productivity.

The non-significant coefficients for IU and DCS, coupled with the negative (though also non-significant) coefficient for R&D in some specifications, suggest that neither digital access nor institutional readiness—nor even traditional innovation inputs—guarantee short-to-medium term productivity improvements in the manufacturing sector. in all three panel regression models (Pooled OLS, Fixed Effects, Random Effects). The P-values are all much higher than the traditional significance threshold of 5% (all > 0.70). This conclusion, despite its apparent simplicity, carries deep economic and methodological implications and necessitates a re-evaluation of the hypotheses regarding the relationship.

The study's core findings have significant implications for both theory and policy:

Theoretical Contributions:

1. Empirical Validation of the Paradox: Provides contemporary evidence (2010-2023) that Solow's productivity paradox persists in the industry 4.0 era.
2. Multi-dimensional Measurement: Demonstrates that both quantitative (IU) and qualitative (DCS) digitalization indicators fail to predict productivity, suggesting the problem lies deeper than measurement issues.
3. Structural Primacy: Reinforces the importance of time-invariant country characteristics over marginal technological improvements.

Policy Implications:

1. Beyond Infrastructure: Policymakers should shift focus from digital infrastructure deployment to digital capability development.
2. Complementary Investments: Digitalization policies must be integrated with human capital development, institutional reform, and innovation system strengthening.
3. Patience in Expectations: The J-curve effect suggests that productivity returns may require longer time horizons than typical political cycles.

Boundary Conditions: These findings are context-specific to advanced industrial economies with already high levels of digital infrastructure. Different dynamics may operate in developing economies or in specific manufacturing sub-sectors not captured by aggregate data. between digitalization and productive performance, especially in advanced industrial contexts.

First: Weakness of the Internal Explanation for Time Variation (Within Variation): The lack of explanatory power of the digitalization indicators for the time variation in labor productivity within each country is the most striking result. In the Fixed Effects (FE) model-which is the most methodologically robust for controlling time-invariant unobserved factors (such as the quality of technical education, the strength of legal protection for intellectual property, or institutional culture)-we note that the Within $\mathbf{R^2}$ (internal coefficient of determination) does not exceed 0.0007. In other words, less than 0.1% of the variation in labor productivity within a single country (across the years 2010–2023) is explained by changes in Internet penetration or digital competitiveness.

This suggests that the gradual digital transformations witnessed by these countries over the past decade, even if tangible in indicators of access and infrastructure, were not sufficient to drive a noticeable improvement in the productivity of the industrial sector. This pattern supports the hypothesis that unobserved, country-specific factors (such as the quality of human capital, labor market regulation, or institutional structure) are the dominant factors in determining the level of productivity, and not the marginal changes in digitalization indicators. For example, a country like Germany may possess a developed industrial structure that relies on “Industry 4.0.” However, these advantages may be the result of decades of investment in vocational education and public-private partnerships, and not just the rise in the percentage of Internet users in a specific year.

Second: Apparent Contradiction in Model Selection: A notable methodological paradox is raised by the Poolability Test / Hausman Test. The P-value of the test indicates a failure to reject the null hypothesis that the country specific effects (μi) are equal to zero, which might suggest that the Pooled OLS model is sufficient. However, this conclusion must be interpreted with caution. In samples with a limited time dimension (as in our case, where N = 17 and T = 14), the Hausman test may lack statistical power (low power), especially if the unobserved effects are weakly correlated with the explanatory variables (Wooldridge, 2010).

More importantly, the non-significance of the variables in all models—including the Pooled OLS, which assumes the absence of bias resulting from unobserved factors— indicates that the problem lies not in the model selection, but in the validity of the basic model specification. The simple linear model may not capture the complex nature of the relationship between digitalization and productivity, or the indicators used do not accurately reflect the effective use of technology in the industrial context.

Third: Reflection of the “Digital Productivity Paradox”: These results align with what is known in the economic literature as the “Digital Productivity Paradox,” famously coined by Solow (1987) with his quote: “You can see the computer age everywhere but in the productivity statistics.” Despite the passage of decades, this paradox remains present, especially when general indicators are used to measure digitalization (such as the percentage of Internet users) to explain the performance of specific sectors (such as manufacturing) (Solow, 1987).

Recent studies (such as Brynjolfsson et al., 2021)explain this contradiction through a time lag between digital investment and the appearance of its returns, or through the need for “complementary investments” (such as re-engineering processes, training the workforce, or developing business models) to convert technology into actual productivity (Brynjolfsson et al., 2021).

Furthermore, quantitative indicators of digital access (such as Internet Users) do not distinguish between the productive use and the consumer use of technology, which is a fundamental difference in the industrial context.

In addition, the Digital Competitiveness Score, despite its comprehensiveness, evaluates the economy as a whole and may not reflect the digital transformation within factories or industrial supply chains. A country may achieve a high score due to a vibrant digital business environment in the service sector, without that having a direct impact on the productivity of its factories.

Fourth: Methodological Implications and Future Recommendations From a methodological perspective, the results suggest that the simple linear model adopted may not be sufficient to understand the dynamics of productivity and digitalization. Therefore, the following are recommended for future studies:

Use of Lagged Variables or Distributed Lag Models: Since technological effects may not be instantaneous, it is recommended to reformulate the model to include lagged values of the digital variables to capture delayed time effects. For example, one can test whether the rise in the Internet percentage in year $(t-2)$ or $(t-3\ t)$ is associated with an increase in productivity in year (t). More complex dynamic models, such as GMM models with lagged effects, can be developed to capture the dynamics of adaptation to technology, provided that a sufficient length of the time series is available.

- Adoption of Sector-Specific Digitalization Indicators: Search for alternative or expanded data for digitalization indicators, such as the adoption of the Internet of Things (IoT) in factories or the use of Artificial Intelligence in industrial design.
- Testing for Interactive Effects: Test for interactive effects between digitalization and variables such as education, governance, or investment in research and development.
- Testing for Non-Linearity and Threshold Effects: It is likely that the effect of digitalization on productivity is not linear but conditional on crossing a certain threshold of institutional or educational readiness. Therefore, it is recommended to use non-linear techniques (such as Threshold Regression Models or Quantile Regression) to test whether digitalization only affects countries with high levels of human capital or investment.

In conclusion, digital transformation is not a magic key for productivity, but a necessary, though not sufficient, condition for achieving sustainable productivity leaps. Instead of measuring "how much" technology is adopted, we must ask "how, for whom, and for what purpose" this technology is used. By adopting more precise and comprehensive research approaches, future studies can provide clearer answers, not only for researchers but also for policymakers who seek to build more efficient and competitive industrial economies in the digital age.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study reached a core finding: there is no statistical evidence to support a significant effect of digitalization indicators—represented by the percentage of Internet Users and the Digital Competitiveness Score—on labor productivity in the manufacturing sector within a sample of 17 advanced industrial countries during the period 2010–2023. It is worth noting that this result remained consistent across various methodological estimates (Pooled OLS, Fixed Effects, Random Effects), which enhances its econometric validity.

This conclusion does not necessarily negate the existence of a real relationship between digitalization and productivity, but rather suggests that the current explanatory model does not capture the complexity of this relationship. This empirical absence of effect can be explained through two complementary interpretations:

- First, the Time Lag and Absorption Phase: Industrial economies may still be in an "absorption phase" of digital transformation, where investments in digital infrastructure and institutional transformation are still underway. According to the "J-Curve of Productivity" theory (Brynjolfsson et al., 2021), actual productivity gains only appear after the organizational structure is re-engineered, the workforce is trained, and business models are developed—all of which can take a decade or more.
- Second, Measurement Shortcomings: Structural factors that are unobserved— such as the quality of human capital, labor market flexibility, the strength of intellectual property protection, or the depth of integration in global value chains —are the primary drivers of labor productivity. In contrast, the digitalization indicators used are considered "shadows" that do not necessarily reflect the degree of effective digital transformation within productive units. The absence of statistical significance may therefore reflect a shortcoming in the measurement indicators rather than the absence of the economic relationship itself.

Consequently, the results of this study do not diminish the importance of digitalization but rather reorient the discussion from "whether technology raises productivity" to "through which channels can digital transformation generate economic value." The successful policies do not aim only at "spreading" technology but at **"**enabling**"** the economy to utilize it—which is the real challenge facing industrial countries in the coming decade.

5.2 Recommendations for Future Research

Based on the limitations of this study and its results, it is recommended to pursue advanced research paths to understand the latent dynamics between digitalization and productive performance. These recommendations include:

1. Inclusion of Mediating Variables and Deeper Analytical Channels: Treating digitalization as a basic variable without looking at the mechanisms through which its effect passes may lead to simplistic conclusions. Therefore, it is recommended to include mediating variables that represent the theoretical channels linking technology to productivity, such as:
   - ICT Investment: As a direct indicator of digital investment in physical capital.
   - R&D Expenditure: As a mediator for converting technology into applicable innovation.
   - Quality of Human Capital: Measured by the percentage of engineers or the rate of professional training. The inclusion of such variables will allow for testing mediation models, which provide a more accurate understanding of how digitalization is translated into productivity.

2. Analysis of Dynamic Effects (Time Lag): Given that technological effects may not be instantaneous, it is recommended to reformulate the model to include lagged values of the digital variables to capture delayed time effects.

3. Expansion of Data Scope and Improvement of Indicator Quality: The limited number of observations for the Digital Competitiveness Score was a major limitation. It is recommended to search for alternative or expanded data for digitalization indicators, such as sector-specific indicators for manufacturing (e.g., UNCTAD or Eurostat databases).

4. Testing for Non-Linearity and Threshold Effects: It is likely that the effect of digitalization on productivity is not linear but conditional on crossing a certain threshold of institutional or educational readiness. Therefore, it is recommended to use non-linear techniques (such as Threshold Regression Models or Quantile Regression) to test this hypothesis.

In conclusion, the results of this study suggest that digital transformation is a necessary, though not sufficient, condition for achieving sustainable productivity leaps. By adopting more precise and comprehensive research approaches, future studies can provide clearer answers, not only for researchers but also for policymakers who seek to build more efficient and competitive industrial economies in the digital age.

References:

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2020). *AI and Jobs: Evidence from US Labor Markets.* National Bureau of Economic Research (NBER) Working Paper No. 28284. DOI: 10.3386/w28284

Aleca, O. E. (2025). *The Role of Digital Infrastructure and Skills in Enhancing Labor Productivity in the European Union.* MDPI.

Ashouri, S., Hajikhani, A., Suominen, A., Pukelis, L., & Cunningham, S. W. (2024). Measuring digitalization at scale using web scraped data. *Technological Forecasting and Social Change, 207*. DOI: 10.1016/j.techfore.2024.123618

Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Wiley.

Bloom, N., Van Reenen, J., & Van Reenen, K. (2016). Measuring and Explaining Management Practices Across Firms and Countries. *The Quarterly Journal of Economics, 122*(4), 1351–1408. DOI: 10.1162/qjec.2007.122.4.1351

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-level Evidence. *The Quarterly Journal of Economics, 117*(1), 339–376. DOI: 10.1162/003355302753396782

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies, 47*(1), 239–253. DOI: 10.2307/2297111

Brynjolfsson, E., & Hitt, L. M. (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economic Perspectives, 14*(4), 23–48. DOI: 10.1257/jep.14.4.23

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* W. W. Norton & Company.

Brynjolfsson, E., & McAfee, A. (2017). *Artificial Intelligence and the Modern Productivity Paradox.* NBER Working Paper No. 24001. National Bureau of Economic Research.

Brynjolfsson, E., & Saunders, A. (2010). *Wired for innovation: How information technology is reshaping the economy.* MIT Press.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333–372. DOI: 10.1257/mac.20190343

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources,, 50*(2), 317–372. DOI: 10.3368/jhr.50.2.317

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152. DOI: 10.2307/2393553

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*(6), 1251–1271. DOI: 10.2307/1913827

IMD. (2023). *IMD World Digital Competitiveness Ranking 2023.* International Institute for Management Development. Retrieved from https://www.imd.org/wcc/world-competitiveness-center/rankings/digital/

Khanna, R. (2024). Beyond information technology and productivity paradox: A study of innovational investments and firm performance. *Technological Forecasting and Social Change*.

Mabrouk, B., Tarek, Y., Chidinma, L. F., & Repac, A. (2026). Veštačkainteligencijakaopokretačpreduzetničkoguspehaiglobalnelekcijeiznovihiskustava: Studijaslučaja Poni.ai u Kini. *REVIZOR * Časopis Za UpravljanjeOrganizacijama, Finansije I Reviziju, 28*(4 (112)). DOI: 10.46793/Rev25112.001P

OECD. (2024). *Labour productivity statistics (GVA per hour worked).* Organisation for Economic Co-operation and Development. Retrieved 11 28, 2025, from https://stats.oecd.org/

Open, & Gold, K. L. (2025). *Effects of Industry 4.0 on Small and Medium-Scale Enterprises: A Systematic Review.* SAGE Open.

Özköse, H. (2023). *The effects of industry 4.0 on productivity: A scientific literature review.* ScienceDirect.

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics, 39*(3), 312–320. DOI: 10.2307/1926047

Solow, R. M. (1987). *We'd Better Watch Out.* The New York Times Book Review.

Wang, D. (2024). *Research on the impact of digital transformation on the productivity of manufacturing enterprises.* ScienceDirect.

Wen, H. (2024). *Impact of Digitalization on Investment and Productivity: Evidence from China's Manufacturing Industry.* SAGE .

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817–838. DOI: 10.2307/1912934

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

World Bank. (2024). *World Development Indicators: Individuals using the Internet (% of population).* The World Bank Group. Retrieved 11 29, 2025, from https://databank.worldbank.org/source/world-development-indicators

Yalouli Tarek
Badji Mokhtar- Annaba University,
Faculty of Economics, Commerce and Management Sciences, Annaba,
Algeria.
tarek.yalouli@univ-annaba.dz
ORCID: 0000-0001-5154-4997

Bouguerra Mabrouk
Badji Mokhtar- Annaba University,
Faculty of Economics, Commerce and Management Sciences, Annaba,
Algeria
boumab23@gmail.com
ORCID: 0000-0002-3456-271X

Choutri Amel
(LEZINRU) laboratory, University Mohamed El Bachir El Ibrahimi,
BordjBouArreridj,
Algeria
amel.choutri@univ-bba.dz
ORCID: 0009-0002-7551-843X