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# The Role of Digital Transformation in Shaping Labor Productivity across EU Member States

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**Abstract.** *For labour productivity improvement, economic growth, and labour market transformation, digital transformation is required. Understanding the relationship between productivity and digitalisation is becoming more and more important as the European Union pursues its digital agenda. This study is grounded on the EUROSTAT data and machine learning to examine the contribution of digital transformation to employee productivity for a group of EU member states between 2012 and 2023. The study uses the eXtreme Gradient Boosting Regressor to investigate economic variables like GDP (Gross Domestic Product) per capita in purchasing power parity as well as crucial indicators of digitalisation like internet banking usage, the availability of internet, and digital exclusion. The results show that while productivity is substantially impacted by digital transformation, the impact is varied. The results show that while productivity is substantially impacted by digital transformation, the impact is varied. While digitalisation indicators recorded varying but comparatively modest effects, the GDP per capita was the most dominant predictor, accounting for 93.37% of the efficacy of the model. Use of SHapley Additive exPlanations analysis, which provides a profound understanding of how digital drivers drive productivity outcomes, is a significant methodological contribution of this study. The model, with R2 of 0.95, showed useful predictive accuracy, showing that it was robust. This study provides data-driven assessment of the impact of digitalisation on labour markets by the integration of machine learning and economic analysis, rather than traditional econometric methods. Policy implications are that increasing internet accessibility will maximize productivity gains, especially in the developing world. Digital infrastructure and capacity building investments are required for economic growth on an equal scale. Emerging studies need to examine the impact of digitisation across different sectors and how it can supplement labour automation.*

**Keywords**: Digital transformation, labor productivity, European Union, digital inclusion.

## Introduction

Digital transformation is a crucial part of economic progress. It changes the way people work, the way businesses are set up, and whole industries around the world. As technology gets better, more and more individuals are understanding that digitization may make tasks easier, faster, and more

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creative, which means that people can get more done at work. The use of digital tools like cloud computing, big data analytics, and artificial intelligence has changed the way people work, making them more productive in many areas (Relich, 2017; Ark, Vries & Erumban, 2019). However, the size of these benefits varies across different regions; it depends on factors such as the policy environment, the sector, and the overall digital maturity of the economy. Policymakers have a good deal to learn about how worker productivity is affected by digitalization if they hope to reap their highest economic return on digital transformation and keep disruptions small for the labor market.



In getting the economy more competitive and productive, the European Union (EU) has promoted speeding up the use of digital technologies. The Digital Single Market policy is just one example. But there are still huge gaps between EU nation states on how quickly they adopt and how much digital technology helps them do more. Some countries, like Germany and Finland, have embraced digital transformation to get their people more productive. Other countries still struggle with having too few trained individuals and weak digital infrastructure (Kovbych, 2022; Crisan et al., 2023). It is needed to study more about how worker productivity is affected by digitization across different countries to fill these gaps. This study attempts to add to our understanding of this front by answering three primary research questions:

a. How does digital transformation influence the productivity of workers among EU members?
b. Of internet banking usage, internet access, and digital exclusion due to digitization, which affects workers' productivity the most?
c. How does GDP per capita affect the connection between work productivity and digitalization?

To answer these questions accordingly, the following recommendations are put forward:

**H1:** The digital revolution contributes importantly to how productive workers are within EU states.
**H2:** Internet banking usage, internet usage, and digital exclusion are amongst the most notable indicators of the issue of digitalization that affect how productive workers are.
**H3:** The link between digitalization and productivity is conditioned upon GDP per capita. Higher-income economies benefit more from their digitization.

This research differs from other work done in the scientific literature examining broad trends on ICT because we apply a machine learning technique, the Boost Regressor algorithm, in order to identify the complex relationship between work productivity and digitalization. This prediction from our research is more accurate and trustworthy because we account for such factors as how often people use online banking, how easy it is going online, and how many people are left out from digital services (Relich, 2017; Vasilescu et al., 2020). SHAP (SHapley Additive exPlanations) analysis also shows how significant different components of digitalization are compared to one another, which does not get recognized by standard regression methods. The statistics show that becoming digital has a significant effect on how productive workers are. GDP per capita (measured in purchasing power standards) is by far the most significant predictor and accounts for 91.49% of the model's explanatory power. There are some notable indicators of digitalization, such as how people use online banking, how convenient accessing the internet is, and how many individuals are disconnected from the digital universe. But not every indicator exerts similar influence.The final model has strong determination of coefficient ($R^2$=0.96) and thus indicates that it was good at predicting after having adjusted model's parameters. SHAP research also showed that internet use for banking purposes had the greatest influence on predictions about how productive workers will be.These findings show how critical EU states must adopt selective policy adjustments stimulating digital inclusivity and maximize the productivity gains from going digital (Kovbych, 2022; Lastauskaitė & Krušinskas, 2023).

## Literature review

In recent years, scholars have focused on the relationship between digital transformation and labor productivity due to their interconnectedness with innovation, digitalization, and economic outcomes. This study examines the impact of digital transformation on productivity and the function of internet usage in influencing labor productivity.



The Solow-Swan growth model, established by Solow (1956) and further developed by Swan (1956), asserts that economic growth is propelled by capital accumulation, labor productivity, and external technical advancement. It also recognizes diminishing returns to capital, indicating that in the absence of technical progress, economies may face stagnation. Building upon this, as more capital is added to the economy, the additional output generated by each unit of capital decreases, and the economy reaches a point where capital accumulation no longer significantly increases output per worker because the diminishing returns balance out with population and technology growth (Guerrini, 2006). This is the reason why poorer economies tend to grow faster than richer ones as long as they have similar savings rates, population growth, and levels of technological progress (Sachs, 2000; Kuznets, 2019; Kraay, 2006). However, critics argue that the model's assumption of uniform technological progress across countries is unrealistic. Dowrick and Rogers (2002) examined the growth model by integrating external technical advancement and international technology transfer. To evaluate their hypothesis, they utilized data from 57 nations covering the period from 1965 to 1990, applying the Generalized Method of Moments (GMM) estimator and found out about the important role of institutional convergence and strong education in achieving economic growth.

The endogenous growth theory enhances the Solow-Swan growth model by asserting that sustained economic growth is attainable through intrinsic factors, including human capital development, innovation, and knowledge accumulation (Romer, 1994). Digital transformation aligns with endogenous growth, as investments in digital infrastructure and research and development foster innovation and facilitate information dissemination, hence enhancing productivity (Chang et al., 2024; Tang & Zhao, 2023). The theory says that human capital is utterly important, suggesting that employees who have better digital skills can use more modern technology, which can boost productivity and inspire creativity in businesses (Girlovan, et al., 2024). Digital platforms are also the ideal places to share knowledge and best practices. This makes innovation even more crucial for the economy (Bondi & Cacchiani, 2021). The feedback loop created by these factors, where investments in digital technologies foster productivity, which in turn supports further innovation, exemplifies the mechanisms of endogenous growth. The importance of leveraging intellectual resources in the context of digital transformation is also underscored by Nuriddin (2024). The study indicates that in a digital economy, enhancing labor efficiency promotes developing and utilizing new technologies that optimize individuals' intellectual capabilities. These findings enhance the broader framework of endogenous growth theory, which underscores the critical role of human capital and innovation in boosting productivity

Empirical research provides comprehensive insights into the relationship between digitalization and worker productivity. Najarzadeh et al. (2014) analyzed data from 108 nations from 1995 to 2010 using a dynamic panel data technique. Their findings indicate that a 1% increase in internet users correlates with a gain of \$8.16–\$14.6 in GDP per employed individual, highlighting the internet's significant influence on labor productivity improvement. Shahnazi (2021) examined 28 European Union countries from 2007 to 2017, using the Spatial Durbin Model to assess the effects of Information and Communications Technology (ICT) found out that a 1% increase in a nation's ICT index resulted in a 0.357% augmentation in its labor productivity and a

0.421% enhancement in the productivity of neighboring nations, underscoring the regional spillover benefits of ICT investments. Information and Communication Technology (ICT) propels digital transformation and enhances labor productivity by facilitating internet access, fostering innovation, and improving communication. Metrics such as internet banking utilization and domestic internet accessibility signify ICT adoption, whereas non-utilization underscores deficiencies in digital inclusion.



A study conducted by Baker et al. (2020) on 65 developing nations from 2000 to 2014 revealed that internet usage mediated 24.20% of the relationship between human capital and overall labor productivity, with more pronounced effects in the services (27%) and industrial (23%) sectors. This confirms that labor production is directly affected by internet usage, also internet adoption brings up the advantages of better education and upgraded skills. Li (2020) conducted an empirical study in China, using panel data from 2013 to 2017, to investigate the impacts of e-commerce transactions, software income, and computer usage on labor productivity and employment distribution, and discovered that areas with elevated e-commerce engagement observed a growth in employment within the service sector. In manufacturing, the use of e-commerce and software markedly enhanced labor productivity while diminishing the employment share, indicating pronounced labor-saving impacts. Stable internet access is crucial for supporting employee productivity, particularly with the rising need for remote jobs in the post-pandemic economy. Barrero et al. (2021) projected that universal, high-quality home internet access in the U.S. could enhance earnings-weighted labor productivity by 1.1%, resulting in yearly output improvements of $160 billion or $4 trillion when capitalized. Hsieh and Goel (2019) also studied how the use of the internet spread improved the quality of work in the US and 28 OECD countries from 2001 to 2016. They found a weak yet positive link between using the internet and productivity efficiency. However, for the US, the study found that using the internet at work can lower productivity, meaning that not all digital tools are used in the right way in the labor realm. A comprehensive analysis by Falck et al. (2024) demonstrated that efficiency improvements in digital goods-producing industries contributed to about fifty percent of the total labor productivity growth in Germany, France, and the United States from 1996 to 2020. Acemoglu (2024) shows the impact of AI on economy and its effect on worker productivity. The author projects that total factor productivity (TFP) will rise by less than 0.53% over the next decade due to the ongoing challenges in automating tasks that require human cognition and reasoning in decision-making. These results confirm the need to address skill gaps and structural barriers to ensure that digitalization leads to an increase in productivity for each industrial sector.

The literature shows that digital transformation can bring positive change, but it also has some limits. Digital technologies can greatly boost productivity, but their effects depend on other aspects, such as the skills of the workers, the quality of the institution, and how well they are interlinked with each other. For example, the data indicate that the impact of ICT on labor productivity is more pronounced in the EU compared to some OECD nations, illustrating how regional contexts and policy frameworks affect the relationship between digitalization and productivity.

Despite considerable interest in the impact of digital transformation on labor productivity, the majority of studies examining the effects of internet usage on economic outcomes have utilized traditional econometric methods such as regression and panel data models. These econometric tools give us significant information, but they don't usually take into consideration the nonlinear linkages and different effects that adopting digital technology can have. Also, most of the existing publications have looked at ICT infrastructure as a macro indicator; thus, we argue that it's important to have a granular and more specific approach for digitalization indicators, such as how many people use online banking, how many people are digitally excluded, and how many households have internet access. A significant gap in the existing research is the absence of machine learning methodologies that not only deliver enhanced forecasting accuracy but also improve interpretability concerning the impact of digital transformation on labor productivity.



This research addresses the gaps by employing SHapley Additive Explanations (SHAP) analysis in combination with the eXtreme Gradient Boosting (XGBoost) Regressor. This method offers a more refined empirical viewpoint in assessing the effect of digitalization on productivity gains. The method we employ contrasts with prior studies that prefer to utilize static modeling techniques with limited assumptions. In doing so, we pinpoint the essential indicators of digitization and illustrate their diverse effects on various EU member states. This new perspective adds to the research's rigor and provides policymakers with significant insights.

## Methodology

The research employs various EUROSTAT datasets with digital transformation measures, labor productivity measures, and GDP per capita measures. The resulting dataset has a target variable and multiple features following preprocessing. The target variable is labor productivity per person employed and hour worked, standardized tall data. The features include the percentage of people who use the Internet for banking, the percentage of people who do not use the Internet, the percentage coverage of Internet usage in households, and GDP per capita in purchasing power standards (PPS) as a control variable.

The information ranges from 2012 to 2023 based on data availability, for the EU member states below: Austria (AT), Belgium (BE), Bulgaria (BG), Croatia (HR), Czech Republic (CZ) Denmark (DK), Estonia (EE), Finland (FI), Germany (DE), Greece (EL), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Slovakia (SK), Slovenia (SI), Spain (ES).

We started data preprocessing by loading the raw data, which were European countries. Only the EU member states were chosen based on data availability, then the dataset was ready for analysis. To validate Hypothesis 2 (H2), we utilized a feature selection process in order to trim down the original set of the indicators of digitalization by excluding variables that were redundant or not necessary. Eight features were excluded, including broadband coverage indicators, based on the fact that they were found not highly related to labor productivity in this research. Therefore, the resultant variable set utilized for testing H2 was focused on the most important indicators of digitalization: use of internet banking, internet access at home, and being digitally excluded, as the hypothesis revealed. There were 62 cases with no digital transformation features, and there were 104 missing target values. We utilized complete case analysis in missing value handling within data. In other words, the exclusion of any observation with missing data. Complete case analysis was chosen because imputing data from a low sample size for each country risked inaccurate estimations and compromised data integrity We used the StandardScaler to scale features so that all have the same mean of zero and standard deviation of one. This preprocessing cleaned the dataset and made it consistent for the subsequent step of modeling.

Our machine learning model of choice was XGBoost Regressor, a gradient boosting algorithm, that builds a robust model by using an ensemble of decision trees. The default hyperparameters were used for initial exploration and testing. Hyperparameter tuning was conducted using the grid-search method to maximise prediction performance.The number of estimators, representing the total number of boosting iterations, was initialized with a value of 100.

A learning rate of 0.01 was chosen to manage the contribution of each single tree to the overall model, thus allowing for a slower and more accurate learning process. The max_depth of the decision trees was set to 3, balancing the model's complexity with computational efficiency. The subsample and colsample_bytree hyperparameters were both set to 0.8, meaning that 80% of the available data was used in each boosting iteration, and 80% of the features were sampled for each tree.



The objective function consists of the loss function and the regularization term:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

The loss function measures the difference between the predicted value ($\hat{y}_i$) and the true value ($y_i$). For regression, the most common choice is mean squared error (MSE):

$$l(y_i, \hat{y}_i) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

The regularization term for the complexity of each tree $f_k$. For a tree, this is defined as:

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{T} w_j^2$$

where:

T: The number of leaves in the tree.

wj: The weight of leaf j.

γ: Regularization parameter to penalize the number of leaves.

Λ: Regularization parameter to penalize the leaf weights.

The prediction for a given instance x is the sum of the outputs from all K trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

In addition, XGBoost also uses an additive approach to learning where trees are sequentially added with the aim of minimizing the error of the previous ones. The system adds a new tree at each iteration to minimize the objective function, which is made up of a regularization term and a loss term. Contributions of the new tree added are combined with the original predictions to enhance them so that the performance of the model is enhanced step by step. Contribution of each tree to the final model is weighted by the learning rate XGBoost uses. The algorithm minimizes the risk of overfitting by lowering the learning rate of the model using a smaller learning rate.

## Results and discussions

### Descriptive Statistics

Table 1 descriptive statistics analysis provides us with significant information regarding the economic and digital landscape of European countries in the period between 2012-2023. Even though internet access has improved, it is apparent that there are disparities in the use of the internet by individuals. Home internet accessibility is relatively high with a mean of 83.95% and a relatively low standard deviation value (10.47), signifying the presence of infrastructure at a large level. However, internet use at the individual level presents a more fragmented scenario. The rate of internet bank use by individuals varies wildly from 3.45% in some countries to near total adoption at 96.22%, with an average rate of 53.13% and a huge standard deviation of 23.91. This wide variation implies that there are prevailing disparities in confidence in financial systems in the digital economy, literacy in digitization, and access to digital services.



The non-internet users' rate confirms the digital divide. Even though the average non-user rate is 14.45%, in some regions, as high as half of the population (47.73%) remains offline. This suggests that despite technological advancements, digital exclusion remains a structural problem, perhaps driven by socio-economic status, ageing population, or lack of digital infrastructure in the countryside.

Besides electronic access, economic disparity can also be seen. Human labor productivity per head and per hour worked (EU27_2020=100-indexed) varies between 42.90 and 212.80, at a mean of 93.41 and a high standard deviation (37.16). The same applies to GDP per capita in PPS, which is a key measure of economic well-being, varying from 46.00 to 283.00, at a mean of 100.86 and standard deviation of 46.47.

**Table 1. Descriptive Statistics**

| Feature | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| Individuals using the internet for internet banking | 53.13 | 23.91 | 3.45 | 96.22 |
| % of individuals not using the internet | 14.45 | 9.94 | 0.07 | 47.73 |
| Level of internet access - households | 83.95 | 10.47 | 50.92 | 99.18 |
| Labour productivity per person employed and hour worked (EU27_2020=100) | 93.41 | 37.16 | 42.90 | 212.80 |
| GDP per capita in PPS | 100.86 | 46.47 | 46.00 | 283.00 |

Source: Authors' own elaboration based on model estimates.

The mean variation between the predictions from the model and actual values was 17.45, reported the initial evaluation of the model on the test set by the study. The test set's coefficient of determination ($R^2$) was 0.79, indicating that the model was able to account for 79% of variance in the target variable. At an importance score of 0.49, feature importance analysis found that GDP per capita in purchasing power standards (PPS) was the biggest contributor to the model. Internet banking utilization (0.06), access to the internet in the home (0.05), and the number of people not using the internet (0.4) were important variables as well. This shows economically and digitally relevant indicators have a significant role to play in employee productivity prediction. A time series cross-validation technique was used to confirm the model stability. The RMSE scores were between 16.07 and 20.66 for each fold. With a standard deviation of 1.73 and an overall average RMSE of 18.38 in all folds, the results showed consistent performance against varying validation splits. The reliability of the model and the capability to explain data patterns without affecting generalisability was also confirmed through this cross-validation.

The final evaluation demonstrated a considerable performance gain after hyperparameter tuning was employed to optimize the model. Compared to the baseline model, the test set RMSE dropped to 7.27, indicating a decreased mean prediction error. Having a test set coefficient of determination (R2) value of 0.95, the model accounted for 95% of the variance in the target variable, indicating a very strong improve in predictiveness.

Consistency of the model was also confirmed by time series cross-validation outcomes. Fold RMSE values varied from 8.62 to 10.09 with average RMSE 9.12 and standard deviation 0.73. The model is reliable and consistent in predicting labour productivity since it has a low standard deviation that reflects that it worked uniformly over various validation splits.



Feature importance analysis (Tabel 2) identified GDP per capita in purchasing power standards (PPS) as the top predictor with a contribution of 93.37% to the model. The remaining features, though less predictive, were the percentage of individuals not using the internet (2.38%), household internet access (2.04%), and internet banking usage (2.22%).

**Table 2. Feature Importance Analysis**

| Feature | Importance |
|---|---|
| **Individuals using the internet for internet banking** | 0.0222 |
| **% of individuals not using the internet** | 0.0238 |
| **Level of internet access - households** | 0.0204 |
| **GDP per capita in PPS** | 0.9337 |

Source: Authors' own elaboration based on model estimates.

To investigate the effect of digitalisation features on labour productivity, the SHAP analysis was done with only the effect of digitalisation and excluding the control variable (GDP per capita). Based on the mean absolute SHAP values, the results showed how all features contributed to making predictions by the model (Figure 1). The most contributing feature was the percentage of people who do not use the internet, with a mean absolute SHAP value of 1.473794. This was followed by contribution from internet banking usage, with a value of 1.285657, which indicates a considerable amount of contribution that is slightly less. The third to contribute to labour productivity predictions was internet banking access by households, which had some contribution to make (SHAP value of 0.446841).

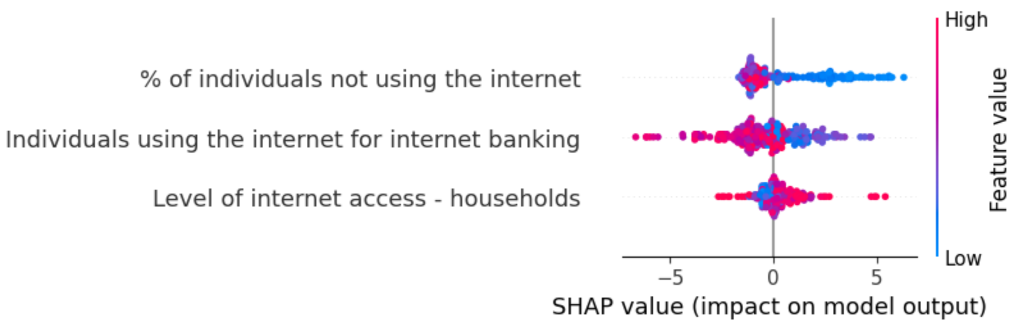


**Figure 1. SHAP Summary Plot of Digitalization Features on Labor Productivity**
Source: Authors' own elaboration based on model estimates.

Figure 2 shows the impact the usage of internet banking has on the model's predictions, according to its SHAP values. The x-axis shows to what level individuals use internet banking, and the y-axis measures to what level that component affects the model's outcome. The color gradient signals the percentage of non-internet users, with red suggesting high numbers of offline users and blue indicating zones with low numbers of non-users. The trend suggests that where there is low adoption of internet banking, this feature has an important contribution to forecasts, primarily rendering their value higher. But as adoption rises, the impact dwindles, i.e., beyond a certain number of online bank users in an area, a rise in users makes little extra difference. This is a demonstration that when online banking is the norm, other factors become important. Additionally, regions with a high proportion of offline residents (red and pink points) show lower usage of internet banking, which confirms the argument that digital exclusion limits online banking's contribution to economic activity. The relevance of digital inclusion: in less connected areas, internet banking is a significant predictor, while in highly connected regions its contribution declines as it has become a norm.



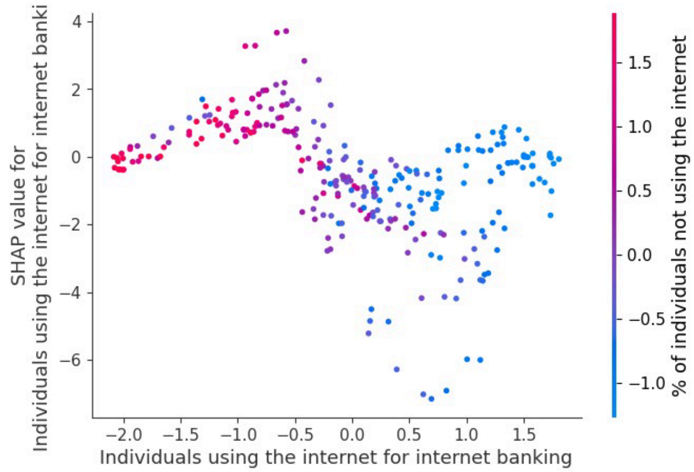


**Figure 2. SHAP Dependence Plot**

Source: Authors' own elaboration based on model estimates.

Figure 3 provides a clear assessment of the model's predictive accuracy on the testing set through two key visualizations: a Predicted vs. Actual Scatter Plot (left) and a Time-Series Comparison (right).

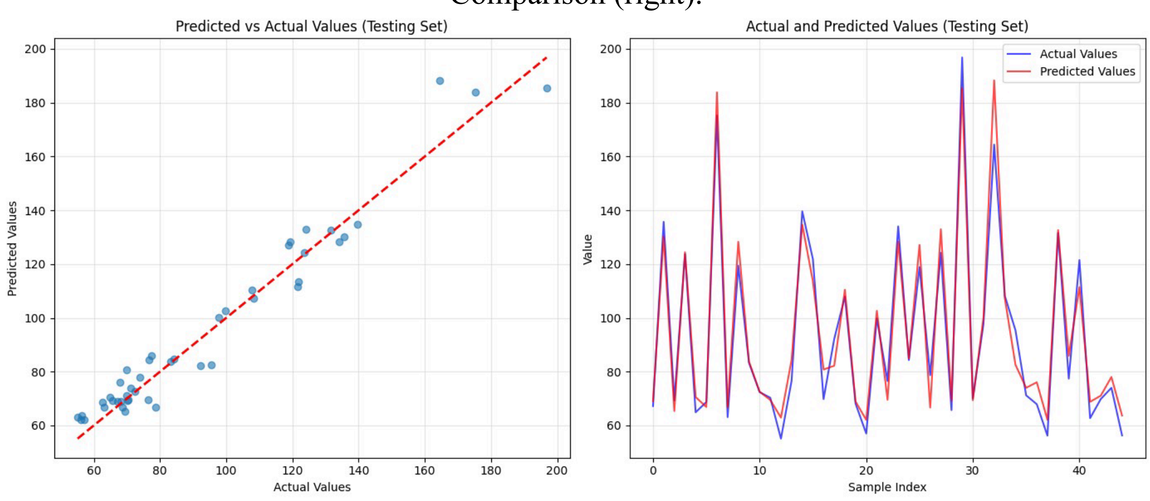


**Figure 3. Predicted vs. Actual (Scatter and Time-Series Comparison on Testing Set)**

Source: Authors' own elaboration based on model estimates.

In above scatter plot, most points are extremely near the diagonal red line, indicating high correlation between actual and predicted values, with minimal deviations, namely at high values where predictions slightly overestimate or underestimate actual results. This is also validated by comparing over time as the predicted values (red) closely follow actual values (blue), which well reflect fluctuations, peaks, and troughs over time. Even though there are small differences, the general consistency suggests that the model is generalizing and providing good predictions. Having small differences, especially for big values, suggests possible improvements such as fine-tuning the model, adding more features, or mitigating possible overfitting. However, the extremely high predictive performance in both graphs suggests that the model is well-calibrated and can be useful in predicting the provided dataset.



## Conclusion

The paper adopts a cumulative analytical method to examine worker productivity and digitalization's relationship among European Union countries from 2012 through 2023 based on EUROSTAT datasets and through utilizing state-of-the-art machine learning methods. It appears that there was immense and diversely shaped effect from worker productivity by digitalization. The strongest variable identified was GDP per capita measured in purchasing power standards (PPS) and accounted for 93.37% of model effectiveness. However, indicators related to digitalization like use of online banking, internet penetration, and digital exclusion had statistically significant but relatively weaker explanatory power regarding productivity outcomes.

This work is also prone to some methodological and data-linked challenges. The presence of missing values determined the applicability of complete case analysis that could reduce the sample and induce bias. The transience of some digital indicators also hampered historical study of their effect. The aggregations at national level suppress industry-level impacts and can provide finer details on relationships between labour productivity and digitalization. The study is constrained by potential endogeneity between GDP and indicators of digitalization that can muddy causality interpretation. The time-series nature of the data necessitates advanced methods for dealing with temporal interdependence effectively. The use of only GDP per capita as a control variable constrains any consideration of additional contextual factors informing observed relationships.

The findings from this study provide evidence for Hypothesis 1 (H1) that digital transformation has a large effect on EU economies' labour productivity. Hypothesis 2 (H2) also finds support since feature selection reduced eight variables including broadband coverage measurements. The full set of indicators for digitalization found digital exclusion (importance: 0.0238), use of online banking (0.0222), and internet access by household (0.0204) most related. The indicators revealed substantially reduced contribution compared to GDP per capita (0.9337) highlighting economic factors' leading role. Hypothesis 3 (H3) stands because GDP per capita was discovered to moderate between digitalization and labour productivity such that prosperous countries reap larger benefits from digital adoption.

Future research can extend this work's model by adding a broader set of socio-economic and technological considerations and overcoming current methodological hurdles. Analysis of the impacts of digital literacy, economic gaps, and infrastructure provides further insights into environments surrounding digital transformation and its role in improving labour productivity. These factors apply uniformly to all economic agents: governments must prioritize investment in education and infrastructure, companies must provide for digital upskilling, and employees must adapt to new technologies. Understanding these interactions enables policymakers and stakeholders to craft particular initiatives geared toward reducing digital gaps, equalizing access to digital resources, and realizing inclusive productivity growth among all sectors of society.

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