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THE ROLE OF DIGITAL SKILLS AND DIGITALISATION IN ENHANCING LABOUR PRODUCTIVITY IN THE EU

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ABSTRACT
Digitalisation and digital skills are often considered key factors shaping labour productivity and international competitiveness. The paper aims to examine the potential relationship between the level of digital skills and labour productivity. It explores the interdependence between the level of digital skills and labour productivity while considering the possible effects of business digitalisation. Using the Granger causality tests and panel data regression, we get several novel results. The results indicate a bidirectional causal relationship between productivity and digital skills, albeit with a two-year lag for e-commerce. Panel fixed-effects regressions and Generalised methods of moments (GMM) have been further used to get more detailed and robust results. Panel regression analysis confirms the positive effect of general digital skills on labour productivity, while this effect was not found in the case of advanced digital skills and R&D expenditure. This research brought new knowledge regarding the economic impact of using digital technology. Our findings highlight the importance of general digital skills in the population. The relationship between digital transformation and labour productivity depends on the type of skills and ability of employees to adapt to new technologies. From the perspective of increasing the country's international competitiveness, programs to improve digital skills across the population and different socio-economic groups are the key issue

Keywords: *digital skills, digitalisation, labour productivity, digital economy, international competitiveness*

1. INTRODUCTION

Digitalisation is one of the key drivers of economic growth. Investments in digital infrastructure and technological innovation play a crucial role in boosting economic growth, as found, for example, by Mura & Donath (2023) and Arsic (2020). Despite the potential of digital technology to substitute some jobs, it also helps to gain new skills and enhance the productivity of organisations (Daher & Ziade, 2024). The successful adoption of digital technology often requires the development of transferable human skills (Daher & Ziade, 2024). Several previous studies have shown that the lack of available skills appears to be one of the key problems when adopting new technology in a company (Bello et al., 2021; Kamble et al., 2018). Especially advanced digital technologies require trained professionals with adequate digital skills to thrive in the new digital environment (Hernandez-de-Mendez et al., 2020). The availability of digital skills is, therefore, significantly affecting the adoption of advanced digital technologies, such as artificial intelligence systems (Kinkel et al., 2022). Digital skills, therefore, play a crucial role in the adoption and utilisation of digital technology within companies. The lack of digital skills can reduce productivity due to the limited adoption of new digital technology (Priambodo et al., 2025). Moreover, there could also be direct effects of digital skills on productivity. The relative scarcity of skilled employees increases the natural rate of unemployment and reduces productivity (Abbritti & Consolo, 2024). Despite several studies focused on the adoption of digital technology and the potential effect of digital skills, there is currently a limited number of studies examining the relationship between digital skills and labour productivity.

This paper aims to bridge the research gap by examining the potential relationship, while also considering the potential effects of digital technology and e-commerce. Our study makes several contributions to the literature. First, our approach distinguishes between the direct effect of digital skills and the possible indirect effects through the adoption of digital technologies and e-commerce. Second, we also used two different variables of digital skills. While the first variable captures the set of general digital skills, the second variable represents ICT specialists. This approach allows us to distinguish between general and advanced skills and their potential effects on labour productivity. Third, our approach is combining three different methods to ensure robust results. Fourth, our data is not limited to one specific country or region. Hence, the results can be applied generally to EU countries, and they also allow us to make recommendations for EU policies. This paper aims to examine the potential relationship between variables capturing digital transformation and labour productivity. The research is based on the qualitative analysis of available secondary data for EU countries. The next section outlines the theoretical background and presents a comprehensive literature review. The methodology section discusses the formulation of the research questions and describes the methodological approaches and data used in the analysis. The main methods include Granger causality, which enables us to determine how digital skills (both general and advanced) impact work productivity and whether there is a bidirectional causal relationship between them. Moreover, it also uses the panel regression analysis (fixed effects and GMM models), through which we identify the potential causal effect of digital skills on labour productivity. The results are described and discussed, with a focus on their relevance to the stated research questions. The results provide important insights for more effective policymaking to support innovation and growth in labour productivity. The final section summarises the main research findings, suggests measures to improve innovation policies, and highlights the limitations of the data and methods analysed.

2. LITERATURE REVIEW AND SPECIFICATION OF RESEARCH QUESTIONS

Regional differences in digitalisation among EU countries are one of the relatively well-researched research problems. Hunady et al. (2022) found significant differences in digital readiness between northern and southern EU countries. Grichchenko (2024) found robust geographical heterogeneity and consistent spatial patterns in digital skills in the EU. Hurduzeu et al. (2022) identified differential impacts of digitalisation on the competitiveness between Central and Eastern Europe and Western Europe. Considering their findings, some authors advocate for diversity in digital skills policy within the EU (Grichchenko, 2024), while others argue in favour of harmonised digital strategies across the EU (Mura & Donath, 2023).

Digital development, as measured by the DESI, is growing along with GDP per capita, with a widening gap between digitally advanced and less advanced EU countries (Török, 2024). The positive correlation between economic growth and digital technology has also been empirically confirmed by Olczyk & Kuc-Czarnecka (2022). They identified a positive and statistically significant impact of DESI on GDP per capita and emphasised the importance of investing in digital infrastructure and education in EU countries.

Differences in digitalisation levels related to variations in economic performance (Kakizhanova et al., 2025). Moreover, the digital economy contributes not only to economic growth but also to social inclusion (Sahi, 2022). Skare et al. (2020) showed that digital transformation promotes countries' competitiveness through productivity and efficiency gains. Enhancing digital capabilities and infrastructure enables countries to respond more quickly to shifting economic conditions and promote innovation.

On the other hand, Chiemeke & Imafidor (2020) found mixed evidence and argued that the effect of digital technology on economic growth and productivity is adverse in the short term. In line with the results of previous studies, we also use digital technology in firms as one of the independent variables, which allows us to explain the mentioned contradictions in the existing literature.

While most previous studies have found that higher levels of digitalisation can lead to better economic outcomes, the exact cause is not often explained. Several studies suggest that improvements in skills and infrastructure are two potential ways in which digitalisation affects economic performance. As reported by Boikova et al. (2021) and Kleszcz & Nowak (2020), investments in digital skills and digital infrastructure are playing a crucial role. Miethlich et al. (2020) also emphasised the importance of developing digital literacy as well as enhancing cybersecurity to improve digital competitiveness. Since digital transformation promotes e-commerce mentioned findings can also be applied to e-commerce and e-business (Criveanu, 2023; Anastasiei & Georgescu, 2021). Since e-commerce activities have the potential to increase labour productivity (Kiani & Ahmed, 2013), our analysis also considers variables related to e-commerce activities.

Although the direct effect of digital skills on labour productivity has been out of focus in previous studies, some of them have examined similar effects of digitalisation. Basol & Yalcin (2021) identified the positive impact of DESI on employment and personal income, and Balashova (2023) highlighted the impact of digitalisation on productivity growth.

Several previous studies have also looked at the impact of specific digital technologies. Magoutas et al. (2024) found that information and communication technology (ICT) has a positive impact on GDP, with human capital being a key driver of economic growth. Morou (2024) found that the increasing role of technologies such as cloud computing and big data is evident in developed European countries. Overall, research confirms that digitalisation plays a crucial role in driving economic growth and enhancing international competitiveness. Its success depends on targeted support for infrastructure, skills, and technological innovation.

Despite the lack of empirical evidence regarding the productivity effects of digitalisation, there is a consensus in the literature that research and development (R&D) and innovation enhance productivity at the national level (Blanco et al., 2015; Nekrep et al., 2018). As well as at the firm level (Hunady et al., 2020; Pieri et al., 2018). Hall et al. (2013) argue that R&D and investment in ICT are both associated with changes in productivity. However, ICT expenditure is even more important for productivity compared to R&D. Since R&D expenditure is considered one of the main drivers of labour productivity, we used this indicator as a control variable in our regression models.

Two previous studies conducted at the country level yielded contradictory results. Varlamova & Larion (2020) demonstrate that the digitalisation of business processes and an increase in organisations utilising the Internet result in a rise in labour productivity, as shown in data from Russia. On the contrary, Chiemeke & Imafidor (2020) argue that there is an adverse effect of digital technology on labour productivity in the short term, which turns out to be positive in the long term. Due to a lack of studies directly examining the effect of digital skills on labour productivity on larger datasets, the problem remains unclear. Our paper aims to fill this gap with the result of empirical analysis. Based on the results of previous studies, the following four research questions (RQ) have been formulated:

1. Are there any relationships between general digital skills, advanced digital skills, usage of digital technology in firms, and e-commerce?
2. Does the usage of digital technology in firms significantly affect labour productivity?
3. Do general digital skills directly affect labour productivity (while considering the potential effect of digital technology and e-commerce)?
4. Do advances directly affect labour productivity (while considering the potential effect of digital technology and e-commerce)?

All research questions relate to the relationship between digitalisation and labour productivity, with a focus on digital skills. Answering these research questions allows for a deeper understanding of the potential effects of digital skills, digital technology, and e-commerce in the EU.

3. METHODOLOGY

The empirical research is based on panel data for EU countries. Since our main aim is to examine the potential effect of digital skills on labour productivity, labour productivity represents our primary dependent variable. This variable is calculated as labour productivity per person employed and number of hours worked. Labour productivity is expressed in relative terms as a percentage of the EU27 average in 2020. This approach enables us to compare the efficiency with which countries utilise labour, considering differences in the number of hours worked.

Labour productivity per person employed and hours worked is an essential indicator of economic activity. It is defined as the value of all goods and services produced less than the value of inputs used in their production. This indicator is shown as an index, where a value above 100 indicates that the GDP per person employed in each country exceeds the EU27 average for 2020, and a value below 100 indicates a lower level.

Input data are calculated in the Purchasing Power Standard (PPS), which eliminates price level differences between countries. The measurement of labour productivity per hour worked eliminates differences due to the structure of the labour force, specifically the split between full-time and part-time work, and considers changes within a given year. This approach provides a more accurate and reliable picture of productivity developments in the economy. We have chosen this indicator based on the assumption that a competitive country can produce output efficiently in terms of both time and labour. Combined with the selected variables of DESI, this indicator offers insight into how digitalisation impacts economic performance and contributes to economic growth. At the same time, countries with higher levels of labour productivity show a greater ability to compete in global markets.

Four main dependent variables captured the digital skills and digitalisation. These variables were constructed based on the Digital Economy and Society Index (DESI) methodology. DESI represents a composite indicator established by the European Commission to measure the digital performance of European Union member states (Konc, 2025). Since 2023, DESI has also served as a monitoring tool for progress towards the targets set in the Digital Decade Policy Program 2030 (European Commission, 2024).

Considering our primary aim and the results of previous studies, the values of four DESI subindices have been used as independent variables in our analysis. These variables capture four different areas of digitalisation: General digital skills, advanced digital skills, digital technology and e-commerce. The general digital skills subindex/variable assesses the overall level of basic and advanced digital skills and internet usage. The advanced digital skills subindex is calculated based on the share of ICT specialists, ICT graduates, and the share of enterprises providing ICT training. The digital technology subindex encompasses a diverse range of indicators related to the utilisation of digital technology in businesses. It includes the share of enterprises using AI, big data analytics, cloud computing, electronic information sharing, social media, and e-invoices. Finally, the e-commerce subindex comprises the share of SMEs selling online, the share of businesses having turnover from E-commerce and those selling their products online cross-border. All variables have equal weights for the calculation of subindices.

The paper examines the period between 2016 and 2023; however, due to rapid changes in digital technologies, not all the variables, such as cloud, AI, or e-invoices, were consistently applicable throughout the entire timeframe. A comprehensive description of variables is provided in Appendix 1.

Using the mentioned variables, we analysed the potential causality between different areas of digitalisation and labour productivity. In the first part, we used the panel Granger causality tests, which require testing for stationarity. This fundamental assumption of the Granger causality test was tested by the panel unit-root tests (Levin-Lin-Chu test: LLC test).

The second part of the analysis focuses on examining the potential effects of digital skills on labour productivity by using panel regression analysis. This approach enables us to provide more in-depth insights into the problem and capture the possible causal effects, along with their statistical significance. Two different regression techniques (fixed effects panel regression and GMM panel regression) have been used to analyse the research problem. Fixed effects regression is commonly used in previous studies. The Generalised Method of Moments (GMM) is also popular in economic research due to its several advantages. The combination of both methods was primarily used to compare results and enhance their robustness. A similar approach has been previously used, for example, by Hunady et al. (2023). The initial GMM model was first introduced in finance by Hansen and Hodrick (1980), and a system GMM estimator was proposed by Arellano and Bover (1995) as well as by Blundell and Bond (1998). The GMM usually produces less biased and more consistent results compared to standard OLS (such as fixed-effects regression). It also eliminates problems with endogeneity (Nickell, 1981). The GMM estimator is consistent if the condition of no serial correlation between error terms and instruments is met. This condition is, in our case, tested using Arellano & Bond (1991) approach.

4.RESULTS

Firstly, the analysis summarises the descriptive statistics of the main independent variables and dependent variables, which are presented in Table 1. The results are shown for both cross-sectional and panel data. While the correlation analysis utilises cross-sectional data, other methods used in the study are based on panel data for 25 EU countries (Malta and France were excluded due to data unavailability) during the period between 2016 and 2023.

Table 1. Overview of descriptive statistics for cross-sectional data and panel data

Cross-sectional data/ Panel data	Observations (Cross-sectional data / Panel data)	Mean (Cross-sectional data / Panel data)	Standard deviation (Cross-sectional data / Panel data)	Median (Cross-sectional data / Panel data)
General digital skills	25 / 200	51.03 / 50.83	8.81 / 11.53	50.28 / 51.2
Advanced digital skills	25 / 200	12.53 / 12.50	2.34 / 2.52	12.20 / 12.3
Digital technology	25 / 200	26.53 / 26.45	7.86 / 9.78	26.04 / 25.7
e-Commerce	25 / 200	13.36 / 13.36	5.17 / 5.63	13.57 / 12.7
Labour productivity	25 / 200	93.56 / 94.69	36.93	77.17 / 78.5

Source: Authors

The standard deviation is higher in the case of variables capturing general digital skills, digital technology and labour productivity. This fact implies that these variables vary more across EU countries. There is also a slight rightward skew in variables capturing digital skills and digital technology, suggesting that some countries have significantly higher levels of digital skills and adoption of digital technology compared to others. For the general digital skills indicator, the highest average value was recorded in the Netherlands. At the same time, other Western and Northern European countries such as Finland, Denmark, and Luxembourg also achieved high values.

On the other hand, the lowest level of general digital skills was found in Bulgaria. Finland scored best for the advanced digital skills and digitalisation of business. Italy and Bulgaria were at the other end of the ranking. Ireland dominated in e-commerce usage and labour productivity, with Bulgaria again coming last on both indicators.

The correlation matrix in Table 2 reveals a strong positive correlation between digital skills and business digitisation, suggesting that countries with higher general digital skills in their population also tend to have more digitised businesses. Advanced digital skills and enterprise digitisation exhibit a positive linear correlation, indicating that advanced digital skills are associated with higher levels of enterprise digitisation. Based on the positive linear correlation, countries with higher levels of digital skills tend to have higher labour productivity. The correlation between advanced skills and labour productivity is slightly lower. We also observe a moderate correlation between the level of digitalisation of enterprises and labour productivity. E-commerce has lower correlations with the other variables. Results suggest that the use of e-commerce may not be directly related to the level of digital skills or labour productivity.

Table 2. Correlation analysis based on the cross-sectional data for EU countries

	General digital skills	Advanced digital skills	Digital technology	e-Commerce	Labour productivity
General digital skills	1.00	0.71	0.77	0.49	0.67
Advanced digital skills	0.71	1.00	0.74	0.45	0.63
Digital technology	0.77	0.74	1.00	0.47	0.58
E-commerce	0.49	0.45	0.47	1.00	0.47
Labour productivity	0.67	0.63	0.58	0.47	1.00

Source: Authors

The previous results of the correlation analysis provided the foundation for applying the panel Granger causality test, which requires time series to be stationary. Failure to ensure stationarity can lead to incorrect results and misinterpretations of causal relationships. We employed the Levin-Lin-Chu (LLC) test to test stationarity, with the results presented in Table 3.

Table 3. Results of LLC unit-root tests

	Lag 0		Lag 1	
	z-score	p-value	z-score	p-value
Labour productivity	-3.17678	0.0007	-4.83845	0.0000
General digital skills	-76297	0.0000	-6.26622	0.0000
Advanced digital skills	-10.2135	0.0000	-14.3188	0.0000
Digital technology	-5.21218	0.0000	-12.1504	0.0000
E-commerce	-8.56288	0.0000	-6.68193	0.0000

Source: Authors` processing based on Eurostat and DESI

The results of unit-root tests indicate that all the examined time series are stationary with lag 0, indicating that no transformation to the first difference is necessary. To enhance the accuracy, the test was also conducted for a lag of 1. The results are consistent with those obtained for a lag of 0. In the next step, the Granger causality tests were applied to the panel data, and the results are presented in Table 4.

Table 4. Results of panel Granger causality test

Variable	H0:	Variable	Lag 1	Lag 2
Labour productivity	≠>	General digital skills	2.2e-16	2.2e-16
General digital skills	≠>	Labour productivity	2.2e-16	2.2e-16
Labour productivity	≠>	Advanced digital skills	0.002835	2.2e-16
Advanced digital skills	≠>	Labour productivity	2.836e-16	2.2e-16
Labour productivity	≠>	Digital technology	0.001824	2.2e-16
Digital technology	≠>	Labour productivity	2.2e-16	2.2e-16
Labour productivity	≠>	E-commerce	0.282	2.2e-16
E-commerce	≠>	Labour productivity	0.1326	2.2e-16

Source: Authors

The primary goal of the Granger causality test was to analyse the potential relationship between labour productivity per employee hours worked and other variables. Based on the low p-value, we can reject the null hypothesis H0 at all common statistical levels of significance for most time series. This result confirms that digital skills affect both labour productivity (at both the user and specialist levels) and the use of digital technologies in enterprises. At the same time, labour is also linked to other examined variables. Revealed bidirectional causality between labour productivity and digital skills highlights the importance of continuous training to improve the digital skills of employees. Moreover, the usage of digital technologies is also related to changes in labour productivity.

Regarding e-commerce variables, the number of lags plays a significant role. A one-year lag (lag 1), there is no statistically substantial Granger causality in either direction. However, when using a two-year lag, the relationship becomes significant in both directions. This result may suggest that changes in e-commerce have some impact on labour productivity, but this effect is noticeable with a longer time lag.

The results of Granger causality further supported the creation of regression models.

The results of the Husman test help us to decide between the usage of fixed-effects and random-effects models. This test is commonly used to compare the fixed and random effects models for their consistency and efficiency. The result of the Hausman test is depicted in Table 5. The very low p-value suggests that the random effects model is not consistent. The test shows that the fixed effects model is a more suitable alternative, and the random effects model could lead to incorrect or inconsistent estimates.

Table 5. Results of Hausman test

Hausman test		
Chi-squared = 21.521	df = 4	p-value = 0.00025

Source: Own processing

The fixed-effects panel regression takes the following form:

$$LP_{it}=\beta 0+\beta 1*GDS_{it}+\beta 2*ADS_{it}+\beta 3*DBT_{it}+ \beta 4*EC_{it}+\beta 4*RDexpc_{it}+\mu_i+\lambda t+\varepsilon_{it} \quad (1)$$

Where:

LPit – Labour Productivity per person per hour (Labour productivity) in country i and year t

IUSit – General Digital Skills

ADSit – Advanced Digital Skills

DBTit – Digital Technology of Businesses

ECit – E-commerce

RDexpit – R&D expenditure - control variable, countries that invest more in innovation tend to have higher labour productivity

μi– Country fixed effects (economic differences between countries)

λt – Time effects (controls for the impact of specific events over time)

εit– Standard error.

R-studio and Stata software were used to calculate panel regression. The panel fixed-effects regressions have been further completed with GMM regression models. GMM models enable the elimination of potential endogeneity problems and allow for a comparison of the results. A robustness check has been performed by modifying regression specifications and by adding or removing some of the regressors. The results of the regression are summarized in Table 6. Some of the robustness checks are shown in the table.

Table 6. Results of panel regression analysis using fixed effects and GMM models

	Fixed-effects 1.	Fixed-effects 2.	Fixed-effects 3.	GMM 4.	GMM 5.
General digital skills	0.325*** (0.11)	0.375*** (0.110)	0.392*** (0.115)	0.172** (0.069)	0.098*** (0.017)
Advanced digital skills		-0.752 (0.497)	-0.661 (0.465)	-1.237 (0.983)	
Digital technology		-0.122 (0.079)	-0.119 (0.079)	-0.071 (0.169)	
E-commerce	-4.733 (3.11)	-0.121 (0.297)	-0.107 (0.292)	-0.072 (0.170)	-0.019 (0.059)
R&D exp.	-0.260 (0.277)		-3.245 (2.768)	-0.829 (3.761)	1.724 (2.97)
Labour productivity(-1) (lag= 1 year)				0.382*** (0.069)	0.284*** (0.035)
C (Fixed effects)	89.57*** (2.863)	89.82*** (3.42)	93.05*** (4.365)		
Observations	200	200	200	150	150
R2	0.988	0.988	0.989		
F-stat	525.9***	521.4***	50.93***		
J-statistic				11.935	13.26

Source: Authors

Lagged dependent variables were used in GMM models as required. Moreover, we also used independent variables lagged by one and two years to capture potential effects. However, the results were still very similar, and we lost a significant number of observations by this procedure. The results obtained by all models are identical, suggesting they are robust and interpretable. The general digital skills variables emerged as a positive and statistically significant factor in labour productivity. This result indicates that general digital skills enhance employee efficiency and overall productivity in digitised work environments. Advanced digital skills, closely linked to ICT specialists, do not have a statistically significant effect, which may indicate that advanced technical skills are not the primary factors influencing productivity. The results might indicate some adverse impacts of digital technologies in the short term, but this potential effect is again statistically non-significant. However, this may suggest that the introduction of digital technologies requires an adaptation period to have any positive impact on labour productivity or that not all enterprises use them effectively. R&D expenditure does not have a significant impact on labour productivity, which may indicate that the effect of R&D is more evident in the long run. It also implies that R&D requires additional factors, such as the availability of digital technology and digital skills, to be translated into significant productivity gains.

5. DISCUSSION

This section discusses the findings obtained within the context of the main aim and research questions. As reported in the literature review, all research questions have been created in line with the results of previous studies and to examine the critical research gap. Based on the literature review, we found that digitalisation is one of the essential factors determining economic growth and competitiveness. However, there is currently only a minimal number of studies focused on the relationship between digital technology, digital skills, and labour productivity. This study aims to clarify these relationships. The insights are provided by an empirical analysis based on Granger causality tests and panel regression analysis conducted using data from EU countries. We successfully addressed individual research questions.

Interconnectedness of digital factors (RQ1): We found a significant positive relationship between general and advanced digital skills and enterprise digitalisation. This finding aligns strongly with previous research, which indicates that skill availability is a crucial factor in technology adoption. Bello et al. (2021) and Kamble et al. (2018) argue that the skill gap is one of the main obstacles to the digital transformation of businesses. Hernandez-de-Mendez et al. (2020) noted the need for trained professionals, and Kinkel et al. (2022) linked the level of employees' skills to the success of AI adoption. This evidence is also supported by our results, which suggest that countries with higher skills tend to have more digitised businesses. Bidirectional Granger causality between skills, technology, and productivity further expands the current knowledge of the problem and suggests the existence of more complex relationships. The finding that e-commerce exhibits a significant Granger causality link to productivity, albeit with a two-year lag, aligns with the results of Kiani and Ahmed (2013), who found that the relationship may be more complex. Only some e-commerce activities, such as e-selling, have a positive impact on productivity, while others do not have a similar effect.

Digital technology used in firms and labour productivity (RQ2): Our research also brings some interesting results regarding the impact of business digitalisation on labour productivity. While Granger causality suggested a potential link, the panel regressions did not find statistically significant short-term causal effects. This result partly contrasts with a study by Varlamova & Larionova (2020), who found a positive relationship between two similar indicators in Russia, as well as the general theoretical expectation that digitalisation enhances efficiency. However, the results align with those of Chiemeke & Imafidor (2020), who found an adverse short-term effect between digital technology and productivity, implying that the adoption of new technology does not immediately lead to productivity gains in the short run. The adaptation period of digital technology may depend on the availability of skills, as well as other complementary factors, such as effective management and processes.

General digital skills and labour productivity (RQ3): This part of the analysis provides some of the key findings. The results suggest statistically significant positive effects of general digital skills on labour productivity. These results are robust across all models. It supports the idea that general digital literacy, especially, has the potential to enhance labour efficiency in the economy. It also, to some extent, aligns with the previous studies despite their limited scope and depth. This fact further supports and enhances the arguments by Daher & Ziade (2024). They highlighted the importance of transferable skills for successful technology adoption in companies. It also complements the findings of Magoutas et al. (2024), who argue for the role of human capital in digital transformation and the use of ICT in business.

Advanced digital skills and labour productivity (RQ4): Our results are somewhat unexpected in this case. Interestingly, advanced digital skills, which are typically associated with ICT specialists, did not show a significant direct effect on labour productivity in the regression models. Despite some positive correlations and Granger causality results, we fail to find significant causal effects in the short term. This fact requires careful interpretation and discussion. Firstly, our findings do not necessarily contradict the importance of ICT specialists. However, this may not be notable in the short term, or the effect may not be detectable in isolation, but it is present through other factors.

Furthermore, while general digital skills are required across a broader range of activities, more specialised and advanced digital skills are usually needed in selected areas and professions. The impact could be more indirect, enabling the effective use of digital technologies and improving the general digital skills level in the population, with a certain time lag. The results of Granger causality also suggest this potential effect.

In general, our results strongly affirm the direct, positive impact of general digital skills on labour productivity. This fact emphasises the role of human capital and digitalisation. It especially highlights the crucial role of digital literacy despite the importance of advanced digital skills and up-to-date digital technology. Investments in emerging digital technology or training in advanced digital skills often fail to have an impact when a sufficient level of general digital skills is not available within the firm. The ability of employees to use technologies effectively is a crucial problem, as reported, for example, by Miethlich et al. (2020). General digital literacy across the workforce is a more immediate booster of labour productivity. Our results support the previous findings of Skare et al. (2020) and Balashova (2023) on the impact of digitalisation on the productivity and international competitiveness of countries. Hence, public support for digital training is crucial, especially given the signs of declining digital literacy among young people, as reported by Stofova et al. (2022).

Despite our efforts to utilise relevant data and methodology to achieve robust results, our approach still has some limitations. The research was conducted based on data from the Eurostat database and the DESI index. However, due to the differences in metrics, the results may exhibit certain inaccuracies. The analysis focused only on selected EU countries based on data availability, with France and Malta excluded from the study. Additionally, in the case of the regression model, Ireland was excluded. Despite these exclusions, the analysis includes 24 countries, which means the results may not be fully applicable to all EU Member States. The use of GMM models enables us to address the problem of endogeneity. However, we used only models capturing short-run causal relationships. To identify potential long-run causalities, it would be necessary to apply cointegration analysis and use panel cointegrated regressions, such as FMOLS or DOLS. Moreover, limited data availability did not allow us to include some variables that could have been significant in the models. The overall level of skills, management practices, capital allocation, infrastructure, and labour market policies are some of the main potential omitted variables.

In future research, it would be beneficial to consider other factors that influence labour productivity. Future research should also focus on a deeper analysis of firm data and regional comparisons. Firm data will allow us to obtain detailed information on firm-specific and sector-specific factors, which could further complement our results.

6.CONCLUSION

The main aim of this paper was to examine the potential relationship between the level of digital skills and labour productivity. Based on the results, we can observe significant geographical differences within the EU in all areas examined. The Netherlands achieved the highest level of digital skills, while Bulgaria was identified as the country with the most underdeveloped digital skills. Similarly, Bulgaria also faces an unfavourable situation in terms of labour productivity. Given the strong positive relationship between the mentioned, the lack of digital skills may be one of the key reasons for low labour productivity.

The results of the Granger causality confirm the significant impact of general digital skills on productivity. A similarly significant Granger-causal relationship exists between labour productivity and the integration of digital technologies in enterprises. On the other hand, the area of e-commerce affects productivity only in the long term. Regression analysis also confirmed the statistically significant impact of general digital skills on labour productivity. We fail to find any empirical evidence on the causal effects of advanced digital skills. Identified relationships highlight the need for additional investments in digital education to enhance labour productivity in EU countries.

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Appendix 1. Description of variables

Indicator	Description	Metric	Source
Internet use	Individuals accessing the internet at least once a week	% of individuals	Eurostat
At least basic digital skills	Individuals with at least basic digital skills	% of individuals	Eurostat
Above basic digital skills	Individuals who have above basic overall digital skills	% of individuals	Eurostat
At least basic digital content-creating skills	Individuals with basic or above basic digital content-creation skills	DESI weighted score (2016-2019) % of individuals (2020-2023)	Eurostat DESI
ICT specialists	ICT specialists as percentage of total employment	% of total employment	Eurostat
Female ICT specialists	Employed female ICT specialists	% of ICT specialists	Eurostat
ICT graduates	Graduates of tertiary education in the field of Information and Communication technology	% of graduates	Eurostat
Enterprises providing ICT training	Enterprises providing training to their personnel to develop their ICT skills in all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat
Electronic information sharing	Enterprises who have ERP software package to share information between different functional areas, including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat
Social media	Enterprises who use two or more social media including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat
Big Data / Data Analytics	Enterprises analysing big data from any data source including all manufacturing and service sectors except financial sectors (10 or more persons employed) Data analytics for the enterprises is performed by the enterprise's own employees or by an external provider including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat DESI
e-Invoices	Enterprises sending e-Invoices, suitable for automated processing, including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat
SMEs with at least basic digital intensity	Enterprises with at least basic level of digital intensity (DII Version 3) including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (from 10 to 249 persons employed)	% of enterprises	Eurostat
Cloud	Enterprises buying sophisticated or intermediate Cloud Computing services including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat
AI	Enterprises that use at least one of the AI technologies, including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (10 or more persons employed)	% of enterprises	Eurostat
SMEs selling online	Enterprises with E-commerce sales of at least 1 % turnover including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (from 10 to 249 persons employed)	% of enterprises	Eurostat
E-commerce turnover	Enterprises´ total turnover from E-commerce sales including all sectors except agriculture, forestry and fishing, mining and quarrying and financial sector (from 10 to 249 persons employed)	% of turnover	Eurostat
Selling online cross-boarder	Enterprises that carried out electronic sales to other EU countries, including all manufacturing and service sectors except the financial sector	% of enterprises	DESI