Marija Bečić, PhD

Associate Professor
University of Dubrovnik
Faculty of Economics and Business
E-mail: marija.becic@unidu.hr
Orcid: https://orcid.org/0000-0001-8361-2675

Perica Vojinić, PhD

Full Professor
University of Dubrovnik
Faculty of Economics and Business
E-mail: perica.vojinic@unidu.hr
Orcid: https://orcid.org/0000-0001-8027-4711

Ante Zdilar, PhD

Senior Assistant
University of Dubrovnik
Faculty of Economics and Business
E-mail: ante.zdilar@unidu.hr
Orcid: https://orcid.org/0000-0001-9411-3409

DETERMINANTS OF DIGITAL SKILLS USE: EVIDENCE FROM CENTRAL AND EASTERN EUROPE

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Abstract

Digital transformation is reshaping labour market structures and increasing the importance of digital skills as a key component of human capital. This paper examines the determinants of digital skills use in eight Central and Eastern European countries (Croatia, Poland, Czechia, Slovakia, Hungary, Estonia, Lithuania, and Latvia). It uses data from the PIAAC survey released in December 2024 and applies a GSEM model. The findings show that countries such as Czechia and Estonia significantly outperform Croatia in employees' digital skill levels. Higher education and employment in larger firms are associated with a greater likelihood of using more advanced digital skills. Gender differences remain evident, particularly in more demanding digital tasks.

Keywords: digital skills, human capital, PIAAC, Central and Eastern Europe

1. INTRODUCTION

Digital transformation has been a key driver of economic growth, innovation, and changes in the structure of the labour market in recent years. Although digital technologies are widely available, significant differences in digital skills levels between countries persist, with European countries displaying heterogeneity in education policies, investment in human capital, and institutional capacity, which determine the pace and success of adaptation to the digital environment. Research shows that a higher level of digital skills is not only a result of technology availability, but above all a consequence of the quality of the education system, lifelong learning opportunities, and the broader socioeconomic situation (Labudova & Fodranova, 2024). Countries with better indicators of digital skills in the population have inclusive, high-quality education systems that emphasise lifelong learning, while countries with lower rankings face a lack of funding, social inequalities, and centralised management of schools, which limits innovation.

Skills, and adaptability to technological change are important factors for modern economic development (Becker, 1934; Rogers & Shoemaker, 1971; Aghion & Howitt, 1992; Romer, 1990). In the current rapidly digitalising environment, digital skills are becoming a central component of human capital and a key factor in individual productivity, labour mobility, and overall economic performance. As noted in the literature, understanding how digital skills and competencies are developed and applied is crucial for designing effective public policies and labour market strategies.

Over several decades, countries in Central and Eastern Europe (CEE) have experienced overall economic progress, but they still face specific challenges. Historical differences in economic structures, education systems, and uneven investment in digital infrastructure have resulted in significant variations in digital skills within the workforce. Labudova and Fodranova (2024) indicate that these differences, together with the use of digital technologies, affect opportunities for regional development, innovation processes, and long-term growth. Therefore, it is important for the professional and scientific community to understand patterns of digital skills across countries, which is why CEE countries were chosen for analysis in this paper. Another reason for selecting these countries for the analysis of digital skills is the gap in the literature, specifically the lack of comparative and methodologically rigorous analyses in the CEECs. Due to data availability from PIAAC, only eight out of eleven CEE countries in the EU were considered (Croatia, Poland, Czechia, Slovakia, Hungary, Estonia, Lithuania, and Latvia).

The aim of this paper is to provide a deeper understanding of the determinants of digital skills use and to offer empirical insights into this topic, particularly in countries seeking to accelerate digital transition, enhance competitiveness, and achieve rapid technological progress. The findings in the paper extend the existing literature by using the latest PIAAC data set (from 2024), providing the most up-to-date insight into the structure and use of digital skills

among adults in eight CEE countries. The research combines the theories of human capital, innovation diffusion, and endogenous growth with empirical analysis, enabling a better understanding of how digital competences develop in institutionally and economically heterogeneous contexts. The results reveal clear geographical, socio-demographic, and organisational patterns in the use of digital skills, with particular emphasis on the relative position of Croatia compared to the other countries analysed.

2. CONCEPTUAL FRAMEWORK

2.1. Theoretical Background

Investments in education, knowledge, and skills increase individuals' productivity and earnings, thereby enhancing overall economic efficiency (Becker, 1934; Schultz, 1972). In the context of human capital theory in the digitalisation era, digital skills are becoming a key form of human capital, as they enable workers to use new technologies effectively and create added value. This highlights the need for continued investment in education systems, reskilling programmes, and lifelong learning. Technological advances are causing polarisation in the labour market, with the value of digital skills rising as routine jobs decline in importance. The diffusion of innovation theory (Rogers & Shoemaker, 1971) explains how new technologies and knowledge spread within society, from pioneers and early adopters to late users. This theory is particularly useful for understanding how digital skills develop and spread among different population groups, and how institutions, cultures and education policies can accelerate or slow this process. Building on previous concepts, endogenous growth theories (Aghion & Howitt, 1992; Aghion, Howitt, Brant-Collett & García-Peñalosa, 1998.; Romer, 1990; Lucas, 1988) emphasise that knowledge, innovation and human capital are internal drivers of economic growth. In this context, digital skills foster innovation, enable adaptation to technological change and stimulate the creation of new ideas, products and markets, making digitalisation a self-sustaining source of growth.

More recently, digital technologies have changed the structure of the labour market by increasing demand for highly skilled workers who can use, develop, and supervise new technologies (Acemoglu, 2002). The common denominator of these theories is the emphasis on knowledge and skills as key factors in economic development in the digital age, with digital skills serving as a bridge between technological progress and social well-being. Digital transformation is fundamentally changing skill demand and the structure of the labour market, with the success of its implementation largely depending on workers' digital skills and the role of information and communication technology (ICT) experts. Technology and skills form an interdependent system: technological innovations redefine competency requirements, while the level of available skills determines the speed and efficiency of new technology adoption in companies. Although digitalisation leads to the disappearance of certain professions, it also

transforms existing jobs and creates new ones (Frey & Osborne, 2017). Therefore, in the context of the digital environment, workers must continuously develop and combine new competencies to remain competitive, while employers must invest in training and human resource development to stay competitive in dynamic industrial environments.

There are various classifications of digital skills in the scientific and professional literature, but most authors agree on dividing them into three basic levels: basic, intermediate, and advanced digital skills (Zimba, Nyirenda & Khonje, 2021). This three-level division provides a clearer understanding of the progression from basic digital literacy to complex and strategic competencies essential for the digital transformation of society and the economy. Basic digital skills are most often defined as a set of fundamental abilities required to use digital devices, communication applications, and networks to access, manage, and exchange information. According to UNESCO (2018), these include the ability to use computers, smartphones, and the internet, search for information, engage in basic online communication, and manage digital content. In the European context, the European Commission, through the DigComp framework, further defines these skills in the areas of information and data literacy, communication and collaboration, digital content creation, security, and problem solving. Basic digital skills are considered a prerequisite for active participation in modern society and are closely linked to the concept of digital inclusion. Intermediate digital skills are the competencies required to independently and effectively use digital technologies in professional and organisational contexts. They include implementing and managing applications developed by experts with advanced knowledge, as well as adapting existing solutions to the specific needs of users or organisations. Individuals at this level may participate in developing digital content, providing technical support, administering systems, and maintaining digital infrastructure (OECD, 2019). Advanced digital skills encompass competencies in the creation, development, and strategic use of new digital technologies and applications. These include advanced programming, software development, database management, artificial intelligence, cybersecurity, and information systems architecture (European Commission, 2020).

2.2. Empirical Review

The economics of skills is a concept increasingly highlighted in recent literature. According to this concept, the value of individual skills is determined by their complementarity. Stephany and Teutloff (2024) show that skills related to artificial intelligence are among the most valuable due to their comprehensive potential for combination with other competencies and the growing demand across different sectors. This finding implies that the economic relevance of skills depends not only on their independent usability but also on their role in complementing other competencies. Additionally, digital skills can be considered within the broader framework of 21st-century skills. Van Laar, Van Deursen, Van Dijk, and

De Haan (2020) integrate the digital component into seven core skills: technical skills, information management, communication, collaboration, creativity, critical thinking, and problem solving, emphasising that all are prerequisites for the successful use of ICT in modern organisations.

Digitalisation also has a strong impact on education systems, with many countries noting the slow adaptation of education policies to technological and market changes (Collins & Halverson, 2018). Štaffenová and Kucharčíková (2021) warn that human capital is often measured solely by the formal level of education, which can be problematic due to heterogeneity within the same qualification levels and the insufficient recognition of non-formal and informal learning. Deming (2017) highlights the distinction between education as formally acquired qualifications and skills as practical competences developed through experience and training, emphasising that the growth of the digital economy has increased the need for continuous learning, flexibility, and the development of social skills. In line with this, Moncada, Carbonero, Geuna and Riso (2025) argue that public policies must support both the strengthening of formal education and the development of short, targeted training programmes that enable workers to adapt quickly to the demands of the transforming labour market.

Regional differences in human capital also influence the intensity of digital technology use and innovation dynamics. Ramos-Poyatos, Barrientos-Marín, Millán, Millán, and Van Stel (2025) show that both regional general human capital and regional digital human capital have significant spillover effects on the frequency of ICT use among the self-employed, contributing to convergence between regions. Similar findings are reported by Buyukyazici (2024), who notes that digital skills promote industrial diversification and the development of new regional comparative advantages. Mikulić and Barbić (2025) examine how different economic structures contribute to variations in the short-term economic effects of investments in broadband Internet across the six countries of the Western Balkans (Croatia, Albania, Bosnia and Herzegovina, Serbia, Montenegro, and North Macedonia). The results reveal significant economic benefits, including increased production, job creation, and state revenues, emphasising the importance of supportive government policies and regulatory frameworks.

At the macroeconomic level, technological progress and automation pose potential risks of labour market polarisation. Afonso, Sequeira and Almeida (2023) show that automation shocks increase technological knowledge but also wage polarisation, while Tran, Herdon, Phan and Nguyen (2023) find that almost all digital skills indicators are positively correlated with economic performance in EU27 countries. At the micro level, Đorđević, Milanović Zbiljić and Radosavljević (2025) show that advanced dimensions of digital competence, such as communication and collaboration, digital content creation, and digital security, have a strong positive impact on employability.

In addition, the literature identifies gender differences as a significant factor in the analysis of digital competences. Martínez-Cantos (2023) shows that

the gender gap does not automatically close with increased ICT penetration, and that the underrepresentation of women in advanced technological fields persists despite generational changes. Data from Campos and Scherer (2024) indicate that girls in many countries have better digital skills than boys, but differences in attitudes towards technology partly explain the subsequent shortage of women in certain technological fields.

Digital transformation does not occur exclusively as a result of individual capabilities, but develops through interaction with organisational capacities, infrastructure, and the regulatory environment. According to theories of technological diffusion (Brynjolfsson & McElheran, 2016) the adoption of new technologies in firms varies depending on size, industry, management practices, and organisational readiness. Smaller firms often have lower absorptive capacity, which can limit their ability to exploit workers' digital skills, while larger organisational structures and greater resource availability facilitate the integration of advanced technologies.

2.3. Research Question and Hypothesis

The theoretical and literature review outlined above shows that the determinants of digital skills can be observed in three dimensions: the sociodemographic characteristics of individuals, the organisational context, and the geographical and institutional characteristics of countries. Accordingly, the following research question and hypotheses were formulated:

RQ: Which geographic, sociodemographic, and organisational factors determine the likelihood of employees using digital skills in Central and Eastern European countries?

H1: A higher level of education significantly increases the likelihood of using digital skills in the workplace.

Education is a fundamental component of human capital, and digital skills are increasingly considered a key part of it. According to the skills economy (Stephany & Teutloff, 2024), highly educated workers are more likely to possess complementary competencies that enable more effective use of digital technologies.

H2: Employees in larger companies and the private sector are more likely to use advanced digital skills.

Organisational resources, investments in digitalisation, and the presence of specialised IT structures are greater in private, especially large, companies (Brynjolfsson & McElheran, 2016), which increases the demand for more complex digital competencies.

H3: Employees in more technologically advanced CEE countries are more likely to use digital skills than employees in Croatia.

Regional differences in digital human capital and institutions influence the dynamics of technology adoption and the use of digital skills (Ramos-Poyatos et al., 2025; Buyukyazici, 2024).

3. DATA DESCRIPTION AND METHODOLOGY

In this study, we use data from the most recent international PIAAC survey (Programme for the International Assessment of Adult Competencies) for eight Central and Eastern European (CEE) countries: Croatia, Poland, Czechia, Slovakia, Hungary, Estonia, Lithuania, and Latvia. The latest database was released in December 2024, while the data were collected during 2022–2023. Although the PIAAC database is one of the most widely used international data sources for analysing adult skills, its reliance on self-reported competences is a methodological limitation. Self-reported digital skills may be affected by social desirability bias, over- or under-reporting of abilities, and differences in question interpretation among respondents and countries. Consequently, measuring digital competences through subjective assessment may result in measurement errors and potential overestimation of variability in the relationships between variables. Nevertheless, PIAAC remains a relevant data source as it enables comparative analysis at the international level while controlling for a range of respondents' socio-economic characteristics of respondents.

PIAAC is a research programme conducted by the Organisation for Economic Co-operation and Development (OECD) to measure and compare the key skills of the adult population across different countries. The research covers adults aged 16 to 65 and uses a standardised methodological approach to ensure international comparability of results. The PIAAC survey generally includes at least 4000 respondents per country; in this paper, the average number of respondents per country is 5450. The analysis uses official PIAAC weights to account for the stratified and multi-tiered structure of the sample and to ensure that the results are representative of the adult population, with weighting correcting for differences in the likelihood of selecting subjects and adjusting estimates for non-response.

Table 1 Descriptive statistics

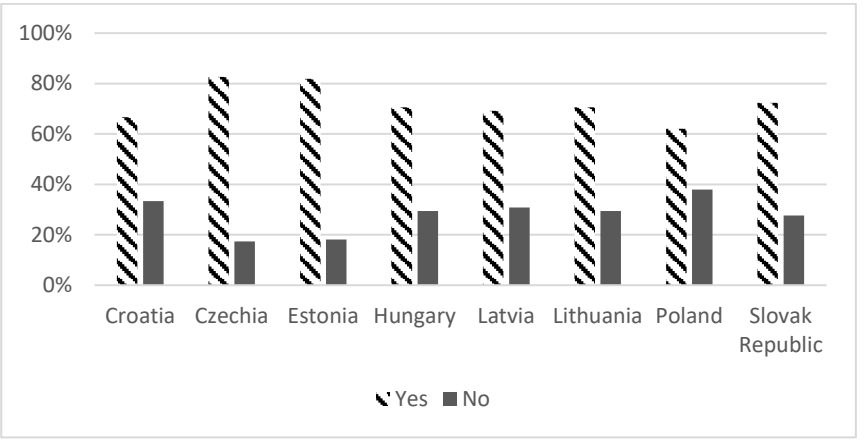
		Percentage
Gender	Male	44,4
	Female	55,6
Education level	Low	13,6
	Medium	54,6
	High	31,7
Sector of the economy	Public	27,4
	Private	72,6
Firm size	1 to 10 people	30,9
	11 to 49 people	33,2
	50 to 249 people	23,0
	250 to 499 people	5,6
	500 to 999 people	3,3
	1000 and more people	4,0
Type of employment	Full-time employed (self-employed, employee)	90,7
	Part-time employed (self-employed, employee)	9,3
Type of contract	An indefinite contract	89,8
	A fixed term contract, including seasonal contract	10,2

Source: Authors' calculation

The previous table presents the average values of the basic characteristics of the sample. The majority are women (55.6%), with men comprising 44.4%. Most respondents have completed secondary education (54.6%), followed by higher education (31.7%), while 13.6% have a lower level of education. Most work in the private sector (72.6%), while 27.4% are employed in the public sector. Most companies are small or medium-sized: 30.9% of respondents work in companies with up to 10 employees, and 33.2% in those with 11–49 employees. Large companies represent a smaller proportion of the sample. Most respondents work full-time (90.7%) and have a permanent contract (89.8%), while only 10.2% are employed on a temporary basis.

The data collected by PIAAC provide various aspects related to the development of digital skills in each country, such as experience with computers at work, frequency of communication and access to information via the Internet, creating electronic documents, using specialised software, and more advanced skills such as the use of programming languages (Figure 1 – Figure 6).

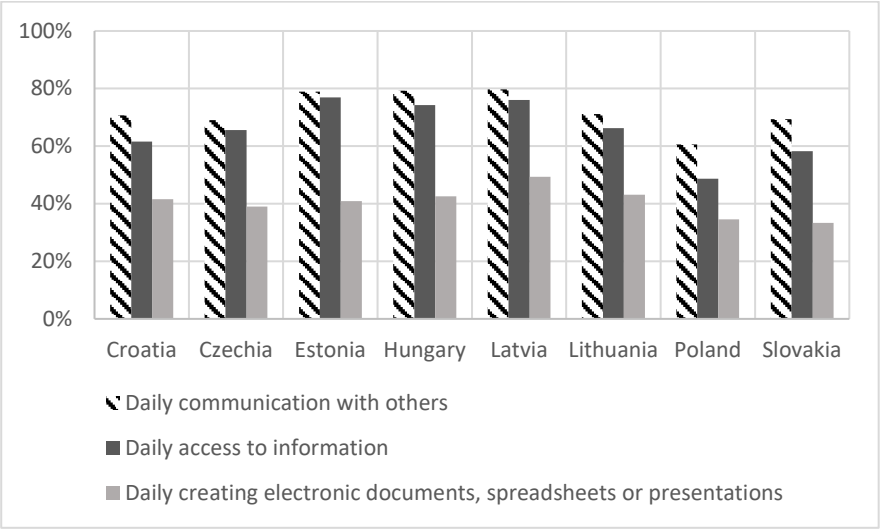
Figure 1 Experience with computer in the job



Source: Authors' calculation

Figure 1 shows that most respondents in all countries have experience using a computer at work. The highest percentage is recorded in the Czech Republic and Estonia (over 80%). The lowest percentage is in Poland (about 62%). In Croatia, Hungary, Latvia, Lithuania, and the Slovak Republic, the proportion with experience is around 70%. Conversely, the proportion without experience ranges from about 17% in the Czech Republic and Estonia to almost 38% in Poland.

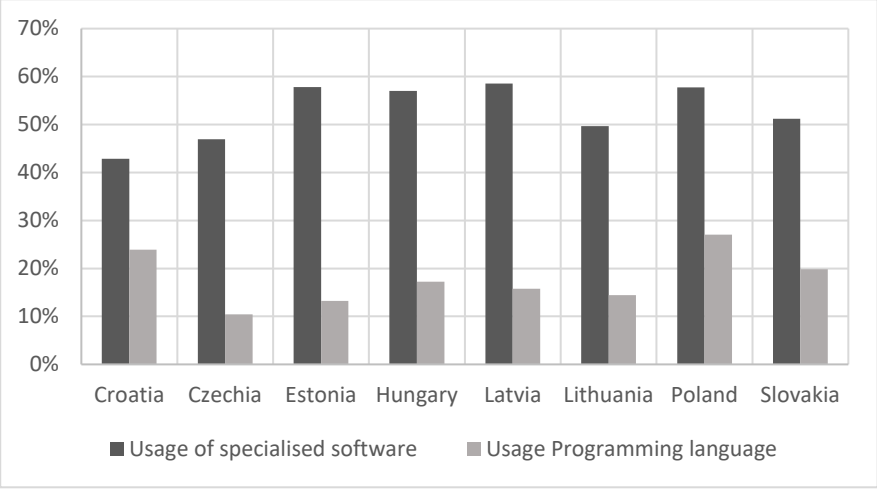
Figure 2 Daily use of digital skills in the workplace



Source: Authors' calculation

Figure 2 shows that in most of the analysed Central and Eastern European countries, everyday online communication is widespread, especially in the Baltic States (Estonia and Latvia), while it is slightly lower in Poland. In Croatia, about 70% of respondents communicate via the Internet daily, indicating that the Internet has become an important tool for daily communication, although a portion of the sample still uses it less frequently, possibly due to age, habits, or access to technology. Based on this, Croatia demonstrates a solid level of digital connectivity; the Internet is a regular communication channel, but there is room to encourage more frequent and diverse use of digital tools across all age groups. Furthermore, most respondents use the Internet daily to access information, with the Baltic countries again being the most active users. In Croatia, about 62% of respondents access information via the Internet daily, indicating that the majority use the Internet as their main source of information, though not to the same extent as in the Baltic countries, such as Estonia or Latvia, where this share is higher. In Croatia, only 40% of respondents create electronic documents, which is similar to the figures for Czechia, Estonia, and Hungary.

Figure 3 Advanced digital skills use in the workplace



Source: Authors' calculation

Figure 3 shows that in all observed countries the proportion of specialised software users is significantly higher than that of programming language users. Croatia records a lower level of specialised software use, but a relatively higher proportion of programming language users compared to most other countries, while Poland has the highest proportion of programming language users. This can be explained by the fact that Croatia has many small and medium-sized companies in the ICT sector working for the foreign market (Galić, 2025), which increases the proportion of people using programming languages in their daily work, although

the overall level of digital activities (e.g. e-mail, communication) is not the highest. The descriptive analysis clearly shows that Croatia lags behind other Central and Eastern European countries. Except for the use of programming languages, where Croatia ranks second, it is not among the top three countries in the other five categories. In contrast, countries such as Estonia and Latvia occupy the top two positions in five out of six analysed categories, clearly demonstrating a higher level of digital skills compared to Croatia.

To analyse the key factors influencing the likelihood of using digital skills, the analysis employs a generalised structural equation model (GSEM). As the use of digital skills at work is observed only among employed individuals, GSEM provides a flexible framework for modelling both selection into employment and the likelihood of performing digital tasks within a single system of equations. The selection equation includes variables that plausibly influence the likelihood of employment but should not directly affect digital skills use once individuals are employed, such as the partner's employment status and the presence of children in the household. These variables serve as exclusion restrictions and help distinguish the determinants of employment from those related to digital skills use. Other demographic variables, including gender and education level, appear in both equations because they are theoretically linked to both labour market participation and skill use:

Selection equation is defined as:

$$employed_i^* = Z_i\gamma + u_i$$

where:
dependent variable* – Tendency for examinee to be the sample of employed,
Z_i - Vector of explanatory variables that affect the selection (independent variables listed in the Table 1 – gender, education level, spouse/partner's employment status, presence of children in the household),
γ – vector of coefficients next to independent variables,
u_i – error

Main equation is done only for employed:

$$Y_i^* = X_i\beta + \varepsilon_i$$

dependent variable* – Tendency for examinee to have digital skill,
X_i - Vector of explanatory variables that affect the selection (independent variables listed in the Table 1 – country, gender, education, sector of employment (public/private), firm size, type of employment (full-time/part-time), contract type (permanent/fixed-term)),
β – vector of coefficients,
ε_i – error

A key element of the model is the correlation between the errors of both equations (u_i and ε_i), which indicates the presence of selection bias. If this correlation is significant, using a standard probit model would yield inaccurate results. The variables included in the two equations are listed in Table 2.

Table 2 Variables in the model

Dependent variables		
ICT_exp	Experience with computer in job	0 – No 1 – Yes
comm_oth	Internet - Communicate with others every day	0 – No 1 – Yes
access_inf	Internet - Access information every day	0 – No 1 – Yes
create_doc	Create electronic documents, spreadsheets or presentations every day	0 – No 1 – Yes
spec_softw	Use specialised software	0 – No (the examinee never uses specialised software) 1 – Yes
prog_lang	Use programming language	0 – No (the examinee never uses a programming language) 1 – Yes
Dependent variable – selection equation		
employed	Status of employment	0 – otherwise 1 – employed
Independent variables		
cntry_ID	Country	Croatia Czechia Estonia Hungary Latvia Lithuania Poland Slovakia
gender	Gender	0 – male 1 – female
education	The level of education	1 – low 2 – medium 3 – high
sector	Economic sector in which individual works	0 – Public sector 1 – The private sector (for example a company)
firm_size	Number of people working in a firm	1 – from 0 to 9 2 – from 10 to 49 3 – from 50 to 249 4 – from 250 to 499 5 – from 500 to 999 6 – 1000 and more
part_time	Type of the employment	0 – full time 1 – part time
fixed_term	Type of the employment contract	0 – permanent contract 1 – fixed term contract, including seasonal
Independent variables – selection equation		
gender	Gender	1 – male 2 – female
education	Level of education	1 – low 2 – medium 3 – high
spouse_employ	Spouse/partner's employment status	1 – full time 2 – part time 3 – unemployed 4 – other
children	Examinees having children living with them in the household	0 – No 1 – Yes

Source: Authors' calculation

The first selection equation, which examines the likelihood of employment, includes variables for gender, level of education, and household data: whether the respondent lives with a spouse or partner, and whether he or she has children. According to Becker's allocation of time model (Becker, 1989), the partner's employment status and the presence of children influence the decision to participate in the labour market through the allocation of time and income within the household. However, there is no direct theoretical mechanism suggesting that these variables directly determine an individual's level of digital skills, which are primarily a function of education, work experience, and professional specialisation. Therefore, these variables are used as excluded restrictions in the selection part of the model. The second equation, which examines the determinants of digital skills use, includes the following variables: the respondent's country, gender, education, the sector in which the company operates, company size, and whether the respondent is employed full-time or part-time, as well as whether the employment is permanent or temporary, including seasonal employment (Andrews, Égert, & de La Maisonneuve, 2025; Hecker, Spaulding & Kuehn, 2021; Maehler, Hernández-Torrano, Courtney, Fischer, Hollricher & Gorges, 2025; Miyamoto, Gauly & Zabal, 2024; Pichler & Stehrer, 2021). All analyses were conducted using the appropriate sampling weights and accounted for the complex survey design in SPSS and Stata statistical software.

4. RESULTS

This part of the paper presents the results of the analysis. The results are reported separately for each stage: first, the factors affecting the use of digital skills, and then the coefficients of the selection equation. At the end of the table, the relationships between the errors of the two equations are shown. If the covariance of the residuals is statistically significant, it indicates that the latent errors in the two equations are interrelated; that is, unobserved factors affecting one decision or outcome also partially affect the other. Such significance suggests the presence of selection bias, meaning the equations cannot be considered independent. In practice, this justifies the use of the joint model, as simple modelling without correction for selection could produce biased estimates.

Table 3 Results of the GSEM

Main equation						
	(1) ICT_exp	(2) Comm_oth	(3) access_inf	(4) create_doc	(5) spec_soft	(6) prog_lang
Country – reference category: Croatia						
Czechia	0.582*** (9.99)	0.120 (1.90)	0.256*** (4.18)	0.0467 (0.80)	0.232*** (4.02)	-0.513*** (-7.05)
Estonia	0.379*** (8.28)	0.273*** (4.99)	0.460*** (8.69)	-0.0707 (-1.42)	0.345*** (7.04)	-0.431*** (-7.46)
Hungary	0.125** (2.63)	0.197** (3.27)	0.380*** (6.49)	0.0261 (0.48)	0.347*** (6.39)	-0.326*** (-5.13)
Latvia	0.0311 (0.68)	0.267*** (4.53)	0.378*** (6.68)	0.107* (2.02)	0.409*** (7.80)	-0.311*** (-5.11)
Lithuania	-0.0149 (-0.30)	-0.231*** (-3.75)	-0.0372 (-0.62)	-0.137* (-2.33)	0.143* (2.50)	-0.378*** (-5.53)

Poland	-0.151** (-3.28)	-0.350*** (-5.92)	-0.472*** (-8.19)	-0.266*** (-4.66)	0.317*** (5.67)	0.116 (1.87)
Slovakia	0.198*** (3.81)	-0.0116 (-0.18)	0.00539 (0.09)	-0.134* (-2.24)	0.314*** (5.39)	-0.138* (-2.04)
Gender – Male						
Female	0.152*** (5.58)	-0.00339 (-0.10)	-0.0187 (-0.54)	0.133*** (4.18)	-0.143*** (-4.40)	-0.328*** (-8.34)
Education – low						
Medium	0.417*** (7.45)	0.147 (1.63)	0.260** (2.89)	0.167 (1.76)	0.108 (1.23)	0.0747 (0.63)
High	1.518*** (21.14)	0.747*** (6.78)	0.899*** (8.16)	0.762*** (6.71)	0.646*** (5.98)	0.473*** (3.42)
Sector – public						
Private	-0.162*** (-5.55)	0.136*** (4.22)	0.002 (0.06)	0.152*** (5.23)	0.157*** (5.46)	0.167*** (4.81)
Firm size 1 -10						
10 - 49	-0.097** (-3.28)	-0.0216 (-0.58)	-0.0171 (-0.48)	0.0392 (1.14)	0.0505 (1.51)	0.0420 (1.01)
50 - 249	-0.0266 (-0.77)	0.0688 (1.66)	0.0746 (1.86)	0.220*** (5.90)	0.180*** (4.90)	0.135** (3.01
250 - 499	0.0572 (0.99)	-0.0846 (-1.32)	0.0088 (0.14)	0.202*** (3.40)	0.163** (2.78)	0.0973 (1.38)
500 – 999	0.0773 (1.04)	0.197* (2.33)	0.185* (2.29)	0.342*** (4.77)	0.309*** (4.28)	0.238** (2.95)
1000 -	0.248*** (3.36)	0.136 (1.82)	0.179* (2.45)	0.338*** (5.23)	0.413*** (6.22)	0.452*** (6.42)
Part time: No						
Part time Yes	-0.268*** (-5.44)	-0.300*** (-4.98)	-0.234*** (-3.92)	-0.336*** (-5.76)	-0.162** (-2.90)	-0.123 (-1.62)
Permanent contract						
Fixed term	-0.304*** (-6.67)	-0.0495 (-0.82)	0.019 (0.32)	0.0068 (0.12)	-0.104 (-1.89)	0.0011 (0.02)
Const.	0.0264 (0.33)	0.231 (1.86)	-0.0919 (-0.74)	-0.852*** (-6.67)	-0.309* (-2.57)	-0.655*** (-4.27)
Selection equation - Dependent variable: employed						
Gender – Male						
Female	-0.559*** (-24.5)	-0.570*** (-22.53)	-0.570*** (-22.51)	-0.570*** (-22.51)	-0.568*** (-22.43)	-0.571*** (-22.48)
Education – low						
Medium	0.476*** (13.47)	0.828*** (18.16)	0.828*** (18.16)	0.830*** (18.20)	0.832*** (18.24)	0.828*** (18.16)
High	0.953*** (24.80)	1.552*** (32.56)	1.553*** (32.57)	1.554*** (32.58)	1.555*** (32.61)	1.554*** (32.59)
Spouse/partner's employment status: full time						
part time	-0.132* (-2.40)	-0.123* (-2002)	-0.114 (-1.86)	-0.124* (-2.02)	-0.108 (-1.78)	-0.116 (-1.89)
unemployed	-0.612*** (-12.95)	-0.685*** (-12.01)	-0.678*** (-11.89)	-0.677*** (-11.89)	-0.678*** (-12.01)	-0.677*** (-11.85)
Other	-0.673*** (-26.66)	-0.745*** (-26.22)	-0.746*** (-26.23)	-0.746*** (-26.25)	-0.743*** (-26.21)	-0.745 (-26.17)
Children						
children	-0.215*** (-6.59)	-0.274*** (-7.51)	-0.274*** (-7.52)	-0.277*** (-7.61)	-0.291*** (-8.05)	-0.274*** (-7.42)
const	1.374*** (23.76)	0.835*** (12.34)	0.834*** (12.33)	0.834*** (12.33)	0.840*** (12.47)	0.834*** (12.33)
Cov(main*selection)	0.164***	0.197***	-0.005	0.219***	0.221***	0.156***

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Source: Authors' calculation

Czechia, Estonia, Hungary, and Latvia generally have positive and statistically significant coefficients in most models, indicating that employees in these countries, on average, have higher levels of ICT use and digital skills than those in Croatia. Lithuania and Poland show mixed results compared to Croatia: employees in Poland use computers at work less, but coefficients for more advanced digital skills are positive. Slovakia also differs across individual domains but overall stands slightly above Croatia in more complex digital tasks. Croatia, as the reference country, has lower average levels of digital skills among employees compared to most other Central and Eastern European countries. These findings correspond to the Theory of Diffusion of Innovation (Rogers & Shoemaker, 1971), which emphasises that the spread of technologies depends on individual characteristics, the social environment, and institutional support (Mokyr, 2016).

Considering the gender aspect in the analysis, the coefficient indicates that, on average, females use computers slightly more in the workplace. However, for more complex tasks, such as using specialised software and programming languages, they have statistically significant negative coefficients. This finding suggests that women are more active in basic digital activities, such as using computers in the workplace or document processing, but are less often engaged in more technically demanding roles, such as programming. Another individual characteristic that is statistically significant is the level of education. As expected, highly educated individuals have higher endowments of digital skills across all categories. These findings are consistent with the theories of endogenous growth and human capital (Becker, 1934; Schultz, 1972), which suggest that a higher level of education increases the ability to acquire new knowledge and technologies.

An interesting pattern emerges when comparing the private and public sectors of the economy. The negative coefficient in the first equation indicates that employees in the public sector use computers more frequently at work. However, for more complex tasks requiring advanced digital skills, the private sector displays positive and statistically significant coefficients, suggesting that advanced digital skills are more developed and in greater demand in private companies. This can be explained by the relatively high level of formalisation of work processes and standardisation of administrative procedures in the public sector of these countries. The digitalisation of public administration primarily focuses on implementing e-government, digital registers, and standard information systems, which increases the need for basic digital competencies (European Commission, 2023). The private sector in post-transition economies faces stronger market pressures, international competition, and integration into global value chains, which increases demand for advanced digital skills, particularly in information and communication technologies, data analytics, and automation (Autor, Levy & Murnane, 2003). Additionally, in Central and Eastern European countries, the public sector often has limited flexibility in salary and promotion systems, making it difficult to attract and retain highly specialised ICT professionals. EU labour market analyses (European Commission, 2023) indicate a pronounced shortage of advanced digital

professionals in public administrations and their concentration in the private sector, especially in ICT and financial services.

Company size correlates positively with the level of digital skills. In larger companies, employees are more likely to use complex digital tools and programmes, while in the smallest companies, digital sophistication is lower. The positive effects in the fourth, fifth, and sixth equations are statistically significant in the largest companies, which aligns with expectations that larger companies have more resources, structured IT departments, and a greater need for specialised knowledge.

Part-time work has a significant negative impact across models, indicating that part-time workers use digital skills less and are less involved in digital processes. Temporary contracts also have negative effects, although these are not always statistically significant. This suggests that job instability can limit access to advanced digital tasks and training. The analysis reveals geographical differences. Croatia lags behind most Central European countries in employees' digital skills, particularly compared to the Czech Republic and Estonia. Higher education has a strong influence on all forms of digital skills. The results also indicate that gender differences are present, with women showing higher activity in basic digital tasks but lower activity in advanced technical domains. Furthermore, the analysis shows that digital competences in the labour market depend strongly on structural and socio-demographic factors, not solely on individual motivation. Therefore, education policy, gender equality in technical professions, and the digital transformation of the public sector are key instruments for reducing the digital divide between countries and groups of employees.

The results also confirm the polarisation of the labour market and the increasing value of complementary skills (Acemoglu, 2002; Stephany & Teutloff, 2024), as employment in large companies and the private sector is associated with the use of more advanced digital tools. Women are under-represented in more technically demanding digital tasks, which is consistent with research on the gender gap in digital skills and competences.

5. DISCUSSION AND POLICY IMPLICATIONS

Based on the results, the hypotheses were evaluated as follows:

The first hypothesis (H1), which states that a higher level of education statistically significantly increases the likelihood of using digital skills, was fully confirmed. The results show that education is the most consistent and strongest predictor in all estimated models, which aligns with human capital theory and previous literature. The second hypothesis (H2), which assumes that employees in larger companies and in the private sector use advanced digital skills more intensively, was partially confirmed. Although employees in larger companies use more complex digital tools and specialised software significantly more often, the results for the sector show a two-way dynamic: the public sector leads in basic

computer use, while advanced digital competences are more common in the private sector. The third hypothesis (H3), which states that employees in countries with more developed digital ecosystems have a higher likelihood of using digital skills compared to Croatia, was confirmed in most models. Estonia, Latvia, Hungary, and the Czech Republic stand out, as their employees statistically rely significantly more on digital tools and advanced ICT tasks. These findings support diffusion of innovation theory and the concept of skill complementarity, highlighting the importance of the institutional and technological environment.

The research findings underscore the importance of education policies that foster digital skill development through both formal education and flexible lifelong learning opportunities. Priority should be given to short, modular, practice-oriented programmes that facilitate rapid adaptation to technological change. Support should be provided for developing digital competence in small and medium-sized enterprises, which often have limited capacity to adopt new technologies. Disparities in technological maturity across enterprises can be reduced through incentives for digital transformation, co-financing of specialised training, and support for implementing digital solutions. Policy design should specifically address gender gaps and the situation of part-time workers, who are identified in the results as being more exposed to lower levels of advanced digital competencies. These measures can be differentiated into short-term interventions aimed at rapidly upgrading skills, such as training vouchers, flexible online programmes, and employer incentives to train part-time workers, and long-term structural reforms that integrate digital competencies into education systems and organisational practices, including institutional support for the career development of part-time employees and other vulnerable groups.

6. CONCLUSION

As the structure of the labour market changes with digital transformation, digital skills are becoming a key component of human capital in modern economies. This paper analyses the determinants of digital skills use in eight Central and Eastern European countries: Croatia, Poland, Czech Republic, Slovakia, Hungary, Estonia, Lithuania, and Latvia. The most recent PIAAC data are used for this purpose. The analysis confirms that individual (gender, education), organisational (company size, sector), and structural factors (country) have a strong and differentiated influence on the use of digital skills. Gender affects advanced digital skills, with women using them less frequently, while higher education positively influences both basic and advanced digital skills. Digital skills are also more commonly used in the private sector than in the public sector. Company size has a positive impact on the use of advanced digital skills in particular. The results align with the main theoretical approaches presented in the theoretical framework and provide empirical confirmation of the expected patterns of adoption of digital competences in the context of CEE countries.

The main limitation of the research is that PIAAC data are based on self-assessments and reported frequency of digital skills use, which can result in subjective evaluations or underestimation or overestimation of actual competences. In addition to data limitations, the research is geographically restricted, as it was conducted on a sample from eight CEE countries, limiting the generalisability of the results to the wider European population. Based on these limitations, recommendations for future research are proposed. Qualitative research, or a combination of quantitative and qualitative methods, could provide deeper insights into the role of organisational culture, managerial practices, and individual strategies in developing digital competences. Expanding the analysis to additional European regions would allow comparison of the observed countries with Western and Northern European countries, which are considered digital leaders in the European context.

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Dr. sc. Marija Bečić
Izvanredna profesorica
Sveučilište u Dubrovniku
Ekonomski fakultet, Dubrovnik
E-mail: marija.becic@unidu.hr
Orcid: https://orcid.org/0000-0001-8361-2675

Dr. sc. Perica Vojinić
Redovita profesorica
Sveučilište u Dubrovniku
Ekonomski fakultet, Dubrovnik
E-mail: perica.vojinic@unidu.hr
Orcid: https://orcid.org/0000-0001-8027-4711

Dr. sc. Ante Zdilar
Viši asistent
Sveučilište u Dubrovniku
Ekonomski fakultet, Dubrovnik
E-mail: ante.zdilar@unidu.hr
Orcid: https://orcid.org/0000-0001-9411-3409

DETERMINANTE KORIŠTENJA DIGITALNIH VJEŠTINA: ANALIZA SREDNJE I ISTOČNE EUROPE

Sažetak

Digitalna transformacija mijenja strukturu tržišta rada i povećava važnost digitalnih vještina kao ključne sastavnice ljudskog kapitala. Cilj rada jest analizirati čimbenike koji utječu na vjerojatnost korištenja digitalnih vještina u osam zemalja srednje i istočne Europe (Hrvatska, Poljska, Češka, Slovačka, Mađarska, Estonija, Litva i Latvija). U tu su svrhu korišteni podaci iz istraživanja PIAAC, objavljeni u prosincu 2024., a primijenjen je GSEM model. Rezultati pokazuju da zemlje poput Češke i Estonije znatno nadmašuju Hrvatsku u razini digitalnih vještina zaposlenika, dok viša razina obrazovanja i zaposlenost u većim poduzećima povećavaju vjerojatnost korištenja složenijih digitalnih vještina. Uočene su i razlike među spolovima, osobito u zahtjevnijim digitalnim zadacima.

Ključne riječi: digitalne vještine, ljudski kapital, PIAAC, Srednja i Istočna Europa.

JEL klasifikacija: J24, O33, M53, I25.