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DIGITAL COMPETENCIES IN EU COUNTRIES – ADAPTABILITY TO THE "THE FUTURE OF WORK" PARADIGM

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Purpose: The main objective of this paper is to identify and compare the level of digital competences at the country level in the European Union (EU).
Design/methodology/approach: The data connected with digital competences of inhabitants were adopted from the Eurostat database. There were 19 selected variables, which refer to the last available official data for 2023. The grouping of the EU countries into clusters was provided by the K-Means method, and the ranking of EU countries by digital competence development was done using the TOPSIS method. ANOVA test was used to determine whether there are statistically significant differences in the averages of digital competency variables across the clusters, thereby validating the effectiveness of the clustering method.
Findings: The EU countries which can be treated as benchmarks for others in terms of digital competences are the Netherlands and the Nordic countries. At the same time, a very low level of digital competences is noticeable in Bulgaria and Romania.
Research limitations/implications: Beside the EU cross-country comparisons in terms of digital competences, another important issue is the change in the level of these competences over the years. This issue was not addressed due to the limited volume of the article, but it may be a direction for future research.
Practical implications: The analysis allowed for the identification of benchmark EU countries which can serve as samples for good practices analysis.
Social implications: Analyzing benchmarks can provide identification of the reasons (social and economic policy solutions) for the high level of digital competences in these countries.
Originality/value: There is a gap in scientific research concerning analyses of the level of digital competences at the macroeconomic level and cross-country comparisons.
Keywords: digital competencies, EU countries, future of work.
Category of the paper: Research paper.

1. Introduction

In the contemporary landscape, the trajectory of our careers and the success of our enterprises hinge upon our adeptness at comprehending and seamlessly integrating with technological advancements. A pivotal characteristic defining this transformative era is its intricate connection to the evolution of our skill sets, given that technology is not "skill neutral" (Stephany, Teutloff, 2024).

At the same time, in the 21st century, one of the biggest challenges in the workplace relate to digital transformation (Chen et al., 2022; Kraus et al., 2023). The rapid evolution of digital technologies has had an immeasurable impact on work and human resource management strategies (Dabić et al., 2023). Digital competencies were found to have a significant impact on employee readiness for the future of work (David et al., 2024).

The EU update in 2018 defines digital competence as follows:

"Digital competence involves the confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It includes information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and competences related to cybersecurity), intellectual property related questions, problem solving, critical thinking". (Council Recommendation on Key Competences for Lifelong Learning, 22 May 2018, ST 9009 2018 INIT).

Digital competences play a crucial role in the developing landscape of the future of work. The "future of work" paradigm refers to the evolving concepts, trends, and strategies shaping the nature of employment, careers, and workplaces in the coming years. Key aspects of the future of work include automation, artificial intelligence, remote work, gig economy, skills-based economy, and the need for continuous learning and adaptability (Dries et al., 2023). The paradigm emphasizes the necessity for individuals, businesses, and policymakers to navigate and respond to these transformative forces to ensure a resilient and sustainable future for the workforce.

Workforce readiness is a topic of major interest throughout society. Given the opportunities and threats created by globalization, developing and maintaining a skilled workforce is crucial. Workforce readiness is closely linked to the competencies required by the labor market and the complexity of new tasks (David et al., 2024). Digital competences enable employees to adapt to the paradigm of the future of work.

However, that process of adaptation varies in EU countries due to a combination of educational, economic, cultural, and policy-related factors that shape the overall readiness and willingness to embrace digital transformation.

The EU has set the ambitious policy target of reaching a minimum of 80% of the EU population with at least basic digital skills by 2030 (Vuorikari et al.,2022). However, the level of digital competences varies among EU member states (Ferrari, 2013).

The main objective of this paper is to identify and compare the level of digital competences at the country level in the EU. The practical implication of the paper is information for reskilling institutions at the EU level to assess the need for teaching digital competences to assure cohesion policy among member countries.

2. Literature review

In the last decade, information and communication technologies (ICTs) have expanded at unprecedented rates in both developed and developing economies (Dammert, Galdo, Galdo, 2013). The technologies and processes representing a manifestation of digitalization, and being of particular importance for the economy, primarily include the so-called big data, cloud computing, distributed ledger technology (DLT), artificial intelligence (AI), cyber-physical systems (CPS), Internet of Things (IoT), augmented reality, blockchain, FinTech, InsurTech, RegTech, cryptocurrencies and the so-called cashless economy (Marszałek, Ratajczak-Mrozek, 2022; Spötttl, Windelband, 2021). The resource necessary to assure digitalisation in the organisation is competent and highly qualified workforce (Tomczak et al., 2023). Today, companies are in high demand for digital skills of the staff (Cardenas-Navia, Fitzgerald, 2019; Beblavy, Fabo, Lenaerts, 2016; Plawgo, Ertman, 2021) and digital literacy has become one of the foundational literacies and skills in the twenty-first century (Chen, 2021; Wild, Schulze Heuling, 2020).

However, employers, workers and education providers seem uncertain about which new, often digital, skill is the first step towards a successful re-skilling trajectory (Stephany, Teutloff, 2024).

The future of work presents educators with a challenge: given the rapid rate of technological development, the fast-changing pace of social and environmental trends, and rapidly changing global socioeconomic positions the question appears: how does education empower graduates to succeed in the workplace (Figueiredo et al., 2022)? This question responds to the need to include 'future-ready' skills in learning experiences, equipping students with the ability to navigate future risks, complexities and opportunities (Holloway et al., 2019).

The reality dictates the need for critical changes in the education system based on total informatization, computer modelling, virtualization of the learning process, and artificial intelligence (Melnyk et al., 2021).

Moreover, there are crucial teaching techniques more oriented towards experiential learning, also known as learning by doing or experience based learning. Learning occurs there through experiential practice, emphasising experiences, and seeing education as a social process (Tuulos et al., 2016). Team-based learning can be more engaging (Balan et al., 2012), and multicultural teams can strengthen global competencies (Oda et al., 2017). Bailey et al. have also indicated the advantages of cognitive diversity within team-based learning activities (2021).

Skill requirements of occupations are dynamic, because technological innovations change the demand for specific skills and thereby the skill composition of occupations – a phenomenon known as skill-biased technological change (SBTC) (Acemoglu, Autor, 2011). In Industry 5.0, humans and robots collaborate and work together, and for this work, humans need to have certain core competences and skills. The significant implications are in matching human intelligence with machine intelligence and, correspondingly, in training people to adapt to robots while working together (Suciu et al., 2023). Industry 5.0 will require new skills in programming, intelligent systems control and emerging technologies (Matuszak et al., 2022).

If workers do not have demanded skills, they risk being pushed out of employment at the same time as companies struggle to find suitable employees to pursue new types of jobs (Stephany, Teutloff, 2024). Moreover, Stephany & Teutloff (2024) argue that complementarity is essential for estimating the value of a skill.

The level of technological development and implementation of industry 5.0 differ among countries and, as a result, the demand for digital competences among workforce is also diversified. In the dynamic landscape of the EU, the diversification of digital competences at the country level stands as a pivotal factor in shaping the future of work and socioeconomic progress.

Our study aims to identify and compare the level of digital competences at the country level in the EU. The paper addresses not only the academic environment and the business environment, but also the policymakers actively involved in developing long-term and inclusive national development policies and strategies. The study can provide valuable insights for policymakers at both national and EU levels. Understanding the current state of digital competences can inform the development of policies that support education, training, and workforce development in the digital age. At the same time, comparing the levels of digital competences allows for benchmarking among EU nations. Identifying countries with high levels of proficiency can provide insights into best practices and strategies that others can adopt to enhance their own digital readiness.

In the following empirical part of the article we present the selected methods and used variables to assure the study objective. Next, we provide the study results and their discussion that will include contributions and implications, both practical and theoretical. The paper is finished with conclusions, where future research directions are indicated.

3. Research method

The data connected with digital competences of inhabitants was adopted from Eurostat database. The selected variables refer to the latest available official data for 2023.

The variables included for analysis covered the different activities measured as proxies of digital competencies as well as the individuals' level of different digital skills.

The variables that have been selected for this analysis cover four areas of DigComp 2.0 (Vuorikari et al., 2016): Information and Data Literacy (IDL), Communication and Collaboration (CC), Digital Content Creation (DCC) and Problem Solving (PS) and they are the following:

X1 - Latest Internet use: within last 12 months.

X2 - Individuals with above basic overall digital skills.

X3 - Internet use: finding information about goods and services (IDL).

X4 - Internet use: reading online news sites/newspapers/news magazines (IDL).

X5 - Internet use: seeking health information (IDL).

X6 - Internet use: telephoning or video calls (CC).

X7 - Internet use: participating in social networks (creating user profile, posting messages or other contributions to facebook, twitter, etc.) (CC).

X8 - Individuals who have written code in a programming language (3 months) (DCC).

X9 - Individuals who have copied or moved files between folders, devices or on the cloud (3 months) (DCC).

X10 - Individuals who used word processing software (3 months) (DCC).

X11 - Individuals who have created files integrating elements such as text, pictures, tables, charts, animations or sound (3 months) (DCC).

X12 - Individuals who used spreadsheet software (3 months) (DCC).

X13 - Individuals who used advanced features of spreadsheet software to organise, analyse, structure or modify data (3 months) (DCC).

X14 - Individuals who edited photos, video or audio files (3 months) (DCC).

X15 - Internet use: doing an online course (of any subject) (PS).

X16 - Internet use: Internet banking (PS).

X17 - Internet use: selling goods or services (PS).

X18 - Individuals who downloaded or installed software or apps (3 months) (PS).

X19 - Individuals who changed the settings of software, app or device (3 months) (PS).

The result of statistics descriptive analysis for all 19 variables can be seen in table 1. Skewness and kurtosis – indicators of distribution – were calculated to analyse differences in selected variables. Kurtosis of all variables is less than 3 and it means that variables have a thin tail and stretch around the centre, and most variables have negative kurtosis value which means that the distribution of data doesn't have heavy tails and outliers, the tails are thinner and shorter. The higher the absolute value of kurtosis, the more likely it is that the level of the variable in a given country differs from the estimated average value of the variable (for example, variables X10, X12, X16). At the same time, the most of the variables have negative skewness which indicates that the most of the values are found on the right side of the mean when it comes to negative skewness, i.e. the most extreme values are found further to the left. Most of the variables are nearly symmetrical, with skewness between -0.5 and 0.5, but variables X3, X9, X12, X16 are significantly skewed with skewness between -1 and -0,5. The skewness and kurtosis show that the distribution of the data for this sample is close to Normal distribution.

Table 1.
Descriptive statistics of the selected variables

Variables	Minimum	Maximum	Mean	Median	Standard Deviation	Kurtosis	Skewness
X1	83.97	99.40	92.55	92.75	4.65	-0.87	-0.16
X2	7.73	54.53	28.78	28.13	11.19	0.54	0.42
X3	41.67	95.33	73.41	75.76	13.37	0.05	-0.63
X4	52.84	90.82	71.28	70.80	10.34	-0.82	-0.11
X5	43.14	82.62	59.79	55.58	10.53	-0.64	0.43
X6	56.07	87.03	71.12	71.52	7.85	-0.13	-0.12
X7	44.39	91.02	67.77	68.10	10.25	0.59	-0.12
X8	1.41	11.67	6.77	6.03	2.76	-0.59	0.05
X9	32.50	78.73	59.13	59.87	10.35	0.98	-0.72
X10	19.25	71.97	50.62	50.79	11.19	1.57	-0.54
X11	23.25	55.18	40.31	43.28	9.05	-0.84	-0.31
X12	16.99	55.95	39.37	38.85	8.92	1.17	-0.67
X13	5.06	33.40	21.52	21.78	7.34	-0.02	-0.33
X14	17.57	57.64	33.31	33.74	9.99	-0.12	0.28
X15	3.25	29.73	16.77	15.35	6.99	-0.59	0.20
X16	21.89	96.22	68.86	71.14	18.49	1.22	-0.91
X17	4.59	41.22	20.84	17.37	10.09	-0.82	0.33
X18	25.34	75.96	51.16	51.28	12.63	-0.12	-0.13
X19	18.30	65.15	39.90	41.29	11.29	0.37	-0.05

Source: own study based on MS Excel.

Maximum and minimum values of the selected variables and the countries corresponding to these values are illustrated in figures 1 and 2.

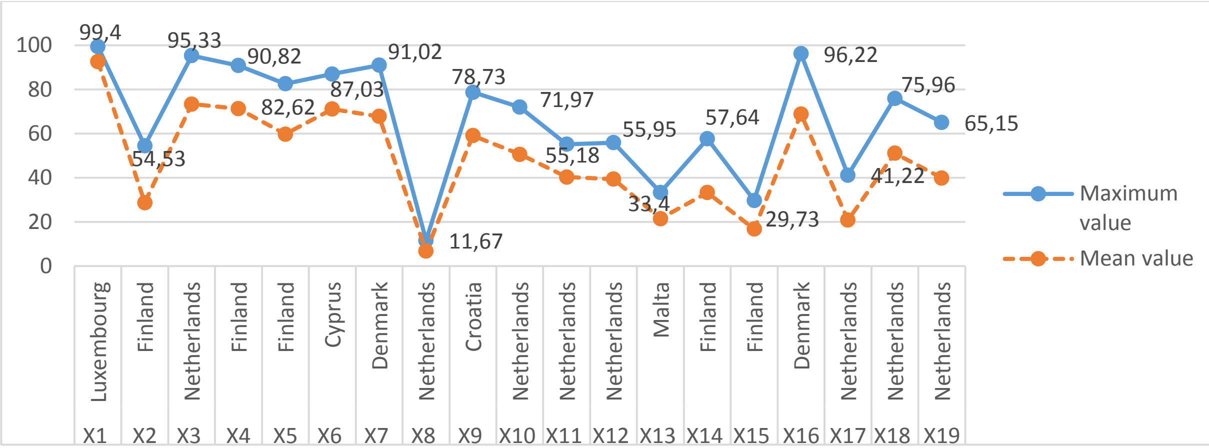

Figure 1. Maximum values of the selected variables.

Source: own study based on MS Excel.

The maximum values of the majority of variables were reached in the Netherlands, Finland and Denmark. However, the highest value of X1: *Latest Internet use: within last 12 months* was reached in Luxemburg, X6: *Internet use: telephoning or video calls* was reached in Cyprus, X9: *Individuals who have copied or moved files between folders, devices or on the cloud* was reached in Croatia and X13: *Individuals who used advanced features of spreadsheet software to organise, analyse, structure or modify data* - in Malta.

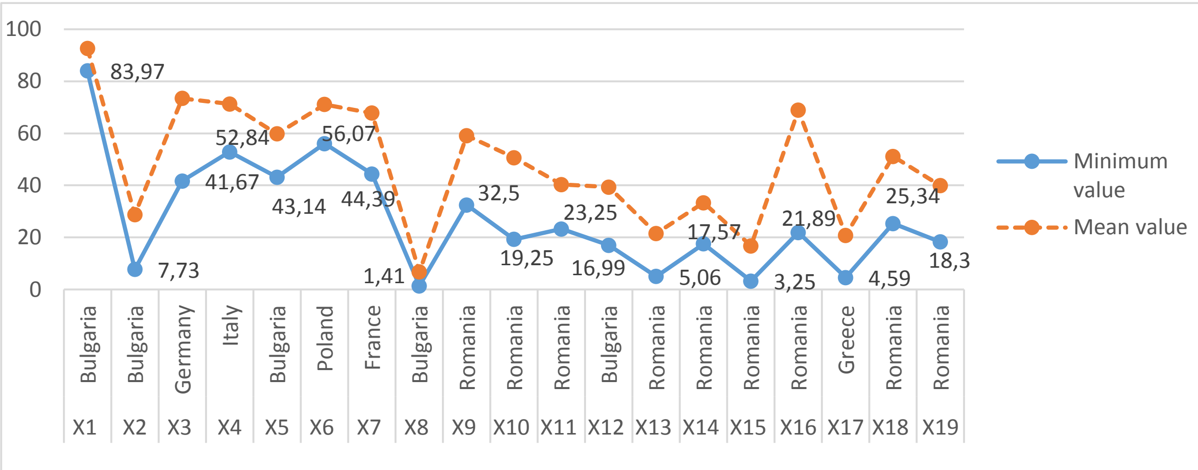

Figure 2. Minimum values of the selected variables.

Source: own study based on MS Excel.

On the other hand, the minimum values of the majority of variables were reached in Romania and Bulgaria. Surprisingly, the lowest values of one of Information and Data Literacy variable X3: *Internet use: finding information about goods and services* was reached in Germany and one Communication and Collaboration variable X7: *Internet use: participating in social networks* - in France.

As the purpose of the paper is to identify and compare the level of digital competences at the country level in the EU, there was a need for processing of databases containing large and varied elements and the breakdown of data into homogeneous groups (Herman et al., 2022).

Based on the data series, the grouping of the EU countries into clusters was determined. For that purpose, we implemented the K-Mean method, which is a well-known and frequently used clustering method (Soni, Petel, 2017). The K-Mean method uses the group mean (centroid) for data grouping. Each cluster is composed based on average values, and the values/elements attached to a cluster are the closest to this average (Kaur et al., 2014).

Moreover, for the implementation of the ranking of EU countries by the digital competences development, TOPSIS method was used as a popular strategy for Multi Attribute Decision Making. It is a technique which allows to build the ranking of alternatives based on the shortest distance from the positive ideal solution and the farthest from the negative ideal solution and it was already used for EU countries ratings (Masca, 2017; Rollnik-Sadowska, Jarocka, 2021).

The data analysis was performed by Tableau software and MS Excel.

4. Research results

The number of clusters was identified by the Elbow method. It is a technique used in clustering analysis to determine the optimal number of clusters K. The sum of the squared distance between each point and the centroid in a cluster WSS (Within-Cluster Sum of Square) was calculated for each value of K. The scree plot (figure 3) is a plot of the total within-cluster sum of squared distances as a function of K. The sum of squares always decreases as K increases, but at a declining rate. The optimal K is at the "elbow" in the curve - the point at which the curve flattens. In the scree plot below, the elbow may be K = 3. Based on the data series, the grouping of the EU countries into three performance clusters was determined – figure 3.

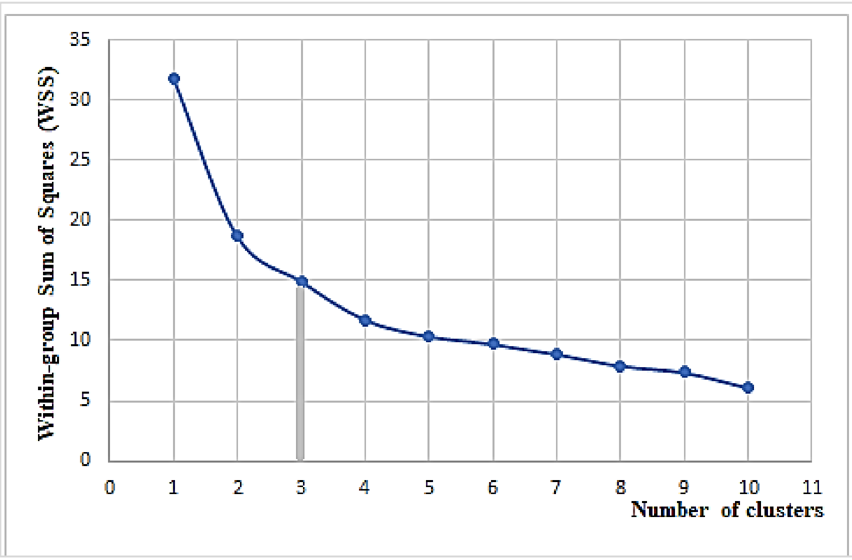

Figure 3. Number of clusters by the Elbow method.

Source: own study based on MS Excel.

The 1st cluster characterizes the average performing EU countries, the 2nd cluster - the best performing countries and the 3rd cluster - the least performing countries. The results are detailed in figure 4.

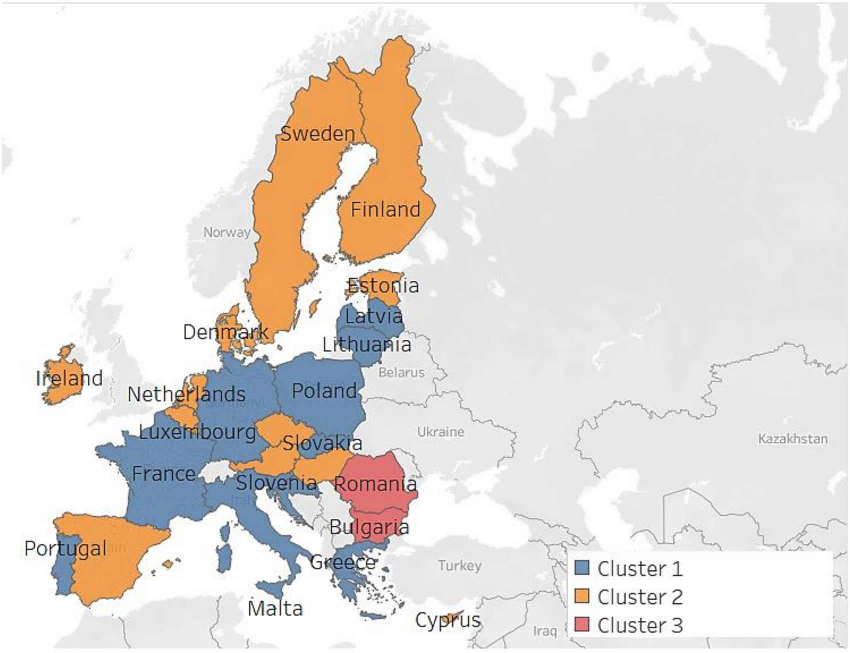

Figure 4. Cluster membership of EU Member Countries.

Source: own study based on Tableau software.

The results presented in figure 4 are represented in a more detailed form in table 2, so that the links established between states can be captured more properly, depending on the variables used in the analysis. The grouping of states in performance clusters shows that, currently, the most developed countries in terms of the digital skills and capabilities of individuals are Austria, Belgium, Cyprus, Czechia, Denmark, Estonia, Finland, Hungary, Ireland, Luxembourg, Malta, Netherlands, Spain and Sweden. At the same time the least developed ones in these terms are Bulgaria and Romania.

Table 2 presents the ANOVA test results including the centroids of each cluster for the selected variables, the F-statistic, and the p-value. F-statistic, which was calculated to estimate the difference between clusters, and significance level (p-value) of F-statistic are two important characteristics for cluster analysis. It is evident that Communication and Collaboration variable X7: *Internet use: participating in social networks (creating user profile, posting messages or other contributions to facebook, twitter. etc.)* has the least impact on the formation of clusters (p-value is 0.03229) while Digital Content Creation variable X12: *Individuals who used spreadsheet software* has the highest impact (p-value is 0.001142). All of the selected variables are statistically significant at 5%, indicating that the decision on grouping EU countries according to all 19 variables into three clusters is valid. The centroids appear in Table 2 as part of the K-Means clustering process. They are not a direct element of the ANOVA analysis but they are essential for understanding the composition of each cluster. The inclusion of centroids helps to illustrate the central values of the clusters which ANOVA then tests for significant differences. The ANOVA results in Table 2 confirm that the clustering method effectively groups countries into statistically distinct clusters based on their digital competencies. All variables included in the analysis were found to be statistically significant at the 5% level, validating the decision to use them for clustering.

Table 2.
ANOVA test result of cluster analysis

	Cluster 1	**Cluster 2**	**Cluster 3**	**ANOVA Test Statistics**	
Number of Items	11	14	2	**F-statistic**	**p-value***
Variables	**Centroids**				
X1	89.245	95.839	87.765	6.786	0.004615
X2	22.786	36.407	8.35	7.533	0.002891
X3	67.008	81.804	49.82	6.588	0.005241
X4	66.612	76.949	57.32	4.662	0.01948
X5	53.796	66.659	44.635	6.301	0.006316
X6	65.779	75.516	69.69	4.402	0.02352
X7	60.854	72.916	69.72	3.974	0.03229
X8	5.5636	8.47	1.53	6.752	0.004717
X9	57.209	63.79	37.01	5.705	0.009399
X10	47.043	57.114	24.825	7.598	0.002778
X11	35.506	46.507	23.3	7.717	0.002582
X12	35.733	45.304	17.78	9.104	0.001142
X13	18.602	25.932	6.7	6.892	0.004313
X14	29.112	38.655	19.005	4.643	0.01975
X15	13.319	21.1	5.48	6.125	0.007091
X16	62.811	80.216	22.66	8.741	0.001406
X17	16.293	26.348	7.3	4.623	0.02003
X18	45.248	59.406	25.925	7.554	0.002853
X19	35.433	46.254	20.015	5.706	0.00939

Note: *statistically significant at 5%.

Source: own study based on Tableau software.

The TOPSIS method was used for ranking the EU countries by digital competencies level (table 3). The first ranks were obtained by the Netherlands and the Nordic countries – Finland, Denmark and Sweden, which were included in the second cluster of the best performing EU countries. So it is worth analysing those countries' best practices and strategies that others can adopt to enhance their own digital readiness. In the second cluster there were also identified CEE countries such as Estonia, Czechia and Hungary (6th, 10th and 13th ranks by TOPSIS method) so those countries can be treated as benchmark for other CEE countries.

Table 3.
Ranking of EU countries in terms of digital competencies

	The overall preference score	**Rank**
Netherlands	0.908003904	**1**
Finland	0.885411579	**2**
Denmark	0.718553202	**3**
Sweden	0.706671874	**4**
Malta	0.700815181	**5**

Cont. table 3.

Estonia	0.681419186	**6**
Spain	0.660719193	**7**
Austria	0.657663265	**8**
Ireland	0.648822750	**9**
Czechia	0.605228174	**10**
Luxembourg	0.590998610	**11**
Belgium	0.589930458	**12**
Hungary	0.574327459	**13**
France	0.571300183	**14**
Cyprus	0.541851026	**15**
Lithuania	0.527466358	**16**
Portugal	0.506316800	**17**
Italy	0.501494349	**18**
Slovenia	0.501050340	**19**
Slovakia	0.479856279	**20**
Croatia	0.479276672	**21**
Germany	0.476801614	**22**
Poland	0.448005221	**23**
Latvia	0.441263405	**24**
Greece	0.432626955	**25**
Bulgaria	0.245681340	**26**
Romania	0.192602196	**27**

Source: own study based on MS Excel.

5. Discussion and conclusions

As the digital revolution continues to redefine industries and reshape traditional job roles, the imperative for individuals and nations to cultivate a versatile set of digital skills becomes increasingly evident. Digital competencies are now fundamental for both personal and professional domains. Presently, over 90% of occupations in Europe necessitate foundational digital proficiency in addition to conventional skills such as literacy and numeracy. Nonetheless, approximately 32% of Europeans remain deficient in basic digital competences (European data, 2023). Varying trajectories are observed across EU countries in their pursuit of digital competences diversification.

The study compares the level of digital competences at the country level in the EU. The countries which can be treated as benchmarks for others, such as the Netherlands and the Nordic countries, were identified. At the same time, a very low level of digital competences is noticeable in Bulgaria and Romania. Therefore, to stay in employment, workers need to learn new skills and combine them with existing skills in novel ways. To stay competitive, employers need to invest in reskilling their workforce and talent acquisition in those countries.

Following European data (2023), the digital competences differ depending on the demographic structure of the population of EU countries. Age seems to be a significant factor with a clear trend showing higher digital competences in younger age groups and a decline as age increases. There is a slight gender gap, as there are slightly more men with basic digital competences than women in the 16 to 74 age range. Education level is a strong determinant, where among individuals with higher formal education, there is a much higher percentage with digital competences compared to those with no or low formal education. Place of residence also plays a role: more individuals living in cities have at least basic digital competences than those in rural areas.

Findings from that study confirmed the research of Ragnedda & Kreitem (2018), who analyzed the levels of digital divide in Eastern EU countries during the period of 2008-2017. They noticed significant differences between Northern and Eastern EU countries, and even within Eastern Europe itself. Particularly significant differences were identified between the Baltic countries and Romania and Bulgaria, which were at the very bottom of the European ranking in terms of Internet penetration. Furthermore, access to the Internet was only one of the criteria for examining digital inequalities. Other forms of digital inequalities persist and grow, related to digital skills, the use of digital services, the integration of digital technology, and digital public services to improve the quality of life (Ragnedda, Kreitem, 2018).

Considering the diversification of digital competences among EU countries, it is of crucial importance to identify possible alternative viable solutions for developing the digital skills and competences of individuals belonging to emergent countries with a lower level of development, as well as in more vulnerable population groups, which can be treated as future research direction. It is also worth studying the change in the level of digital competences over the years to identify trends in that area and determine whether there has been progress in countries facing more difficult situations. Banholzer (2022) highlights the very important role played by universities in the new industrial revolution supported by the Industry 5.0 model by shaping the new skills, core competences and abilities important in the “the future of work” paradigm.

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