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Research article

THE IMPACT OF SOCIO-ECONOMIC FACTORS ON DIGITAL SKILLS IN THE POPULATION OF THE EU 27 COUNTRIES

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Abstract. This research investigates digital skills across the 27 EU countries, examining how incentive and disincentive factors shape these competencies, particularly under varying socio-economic conditions. Using a quantitative methodology, the study applies cluster analysis and linear ordering methods to classify countries by digital skills indicators, utilising data from the Eurostat Digital Economy and Society database. Key analytical methods—including Hellwig's method, order counting, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)—are employed to pinpoint crucial factors that stimulate digital competencies, such as investment in research, training programmes, and innovation. Findings indicate that countries within clusters featuring higher values in these stimulative factors tend to adopt a proactive approach to digital development. These clusters frequently correlate with substantial investments in skills training and comprehensive educational policies. Conversely, clusters characterised by high disincentive variables, such as limited funding and socio-economic disparities, show slower progress in digital skills development, highlighting barriers in educational and social inclusion systems. The results reveal marked spatial disparities across the EU. Leading countries typically have robust education systems promoting lifelong learning and inclusivity, while lagging countries face structural challenges, including centralised education systems and urban-rural divides. This disparity underscores the need for sustained investment in education, training, and policy support to enhance workforce digital skills. The study highlights that digital competencies are closely intertwined with each country's educational and socio-economic frameworks, recommending targeted interventions to foster lifelong digital literacy and reduce skills gaps. As the digital landscape continues to evolve, interdisciplinary research is essential for addressing both quantitative and qualitative aspects of digital skill development. Future studies should aim to bridge the digital divide through comprehensive strategies for upskilling populations, ensuring inclusive digital integration across all EU countries.

Keywords: digital skills; socio-economic factors; education and training programs

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1. Introduction

Digital competitiveness of a nation refers to its ability to efficiently leverage digital technologies to enhance economic growth, productivity, innovation, and overall welfare compared to other nations. A high level of digital competitiveness indicates that a country possesses robust digital infrastructure, fosters technological innovation, promotes digital literacy among its population, maintains a supportive regulatory framework for digital initiatives, and demonstrates widespread integration of digital technologies across both business operations and public services. A nation with a well-established digital sector capitalises on the opportunities presented by the digital economy, thereby securing a competitive advantage in the global marketplace.

The measurement of digital competitiveness thus becomes a crucial aspect for understanding a country's position in the global digital landscape. Metrics used for assessing digital competitiveness are based on a comprehensive set of indicators, methodologies, and data sources aimed at evaluating various dimensions of a country's digital ecosystem. These indicators can be categorised into three groups: (I.) Technical Indicators: These include aspects of the digital infrastructure, such as quality and availability, internet penetration rate, broadband connection speed, mobile connectivity, and the presence of advanced technologies like 5G networks and cloud computing services. (II.) Economic Indicators: This category pertains to a country's capacity for technological innovation and digital entrepreneurship. It includes indicators such as research and development (R&D) spending, patents granted, the strength of the startup ecosystem, and the availability of venture capital funding for digital initiatives. (III.) Social Indicators: These relate to the level of digital skills among the population, reflecting the extent of digital literacy and proficiency among citizens, which significantly influences national digital competitiveness.

The benchmarking system is complemented by comparative assessments of digital competitiveness, mediated by international benchmarks and indices such as the Digital Competitiveness Index (DCI), the Digital Economy and Society Index (DESI), and the Global Innovation Index (GII). An important part of the broader DCI and DESI indices is the more specific Digital Skills Indicator (DSI), which is designed to assess individuals' expertise and abilities in digital technology usage. The DSI composite index evaluates the digital skills of individuals aged 16–74 based on selected activities related to internet or software usage in five specific areas proposed by Ferrari [1]: (1) Information and data literacy; (2) Communication and collaboration; (3) Creation of digital content; (4) Security; and (5) Troubleshooting. Classifications are based on an individual's overall level of digital skills, determined by evaluating their proficiency in all five specific areas. The resulting classification provides an overview of the digital skills level of individuals within the population, categorised as follows:

- Individuals with basic or higher basic digital skills (all five component indicators are at the basic or higher level) [I_DSK2_BAB];
- Individuals with above-standard overall digital skills (all five component indicators are above baseline) [I_DSK2_AB];
- Individuals with basic overall digital skills (all five component indicators are at the basic level or above, without all being above the basic level) [I_DSK2_B];

- Individuals with low overall digital skills (four out of five component indicators are at the basic level or above) [I_DSK2_LW];
- Individuals with narrow overall digital skills (three of the five component indicators are at a basic level or above) [I_DSK2_N];
- Individuals with limited overall digital skills (two of the five component indicators are at a basic level or above) [I_DSK2_LM];
- Individuals without overall digital skills [I_DSK2_X];
- Digital skills could not be assessed because the individual had not used the internet in the last 3 months [I_DSK2_NA].

By assessing the dimensions of digital skills, the DSI provides valuable insights into the population's level of digital competence. However, the value of the resulting indicator presents a new research challenge: what factors can influence the overall measured score of this indicator? One significant influence on the indicator's value is the socio-economic conditions of a given country, as skills are inherently linked to individuals. From this perspective, considering the socio-economic conditions of a country is crucial, as these factors largely shape the development and utilisation of skills, including digital skills, which are closely tied to human resources.

Two aspects of digital skills are vital for fostering social cohesion and prosperity in European countries. One aspect relates to the ability to function effectively within the economy and society, given the pervasive use of digital technologies. The other aspect pertains to specialised digital skills that European firms require to keep pace with digital innovation and ongoing transformations in work and organisational processes [2]. The importance of these aspects is underscored by the ambitious goals outlined in the Digital Compass for 2030 concerning digital skills [3]. Progress in this area should be reflected not only in indicators measuring the population's digital skills but also in the proportion of digital specialists. However, achieving these goals relies on the environment—specifically, the conditions established by a country to support the development of digital skills. Within socio-economic conditions, we encounter a phenomenon highlighted by Van Dijk's research [4], which argues that individuals must first desire access to a digital tool before physically accessing it. This finding encourages further exploration of the relationship between the socio-economic environment and digital skills.

Establishing suitable conditions for acquiring digital skills within the population requires examining not only the improvement in the population's digital skills but also the factors that influence these skill levels. This multifaceted approach enables us to identify key drivers and barriers that shape digital proficiency, including socio-economic conditions, educational policies, and access to technology. By understanding these dynamics, we can better evaluate how different EU countries perform in terms of digital skills and which specific strategies might be needed to enhance these competencies.

2. Literature Review

In shaping the EU's key agenda on digitisation [5], it was assumed that digitisation would serve as an effective means of combating poverty and social exclusion. These documents outlined specific initiatives, funding programmes, and policy measures aimed, among other objectives, at supporting the development of digital skills. It quickly became apparent that socioeconomically disadvantaged groups—such as the unemployed, individuals with low levels of education, ethnic minorities, and citizens with disabilities—generally have limited access to ICT and basic digital competencies [6]. Given financial constraints at both individual and state levels, the first level of the digital divide emerged, primarily associated with household income levels. It is worth noting, however, that despite the logical assumption that economic factors significantly influence the acquisition, development, and use of digital skills—given that income levels and wealth play a pivotal role in determining access to digital devices and internet connections—there are studies indicating that there is no correlation between economic growth (both globally and at the national level) and the processes of ICT technology development or the willingness of governments to adopt AI [7].

Another problem arises from the widening digital divide driven by social factors. The literature on the second level of the digital divide [8] considers both differences in the skills of internet users and the motivation to use digital technologies to enhance well-being, representing the third level of the digital divide. These issues are not confined solely to EU member states but have global implications. According to Lloyds [9], 11.7 million people in the UK (22%), despite having internet access, lack the digital skills necessary for everyday life. Key axes of social inequality—such as socio-economic status, gender, age, and level of education [10,11,12]—thus influence how individuals utilise the internet and their digital skills. Socio-economic factors have a direct relationship with the adoption of digital technologies, and their impact varies across different regions. The primary factor affecting digitalisation in almost all contexts is the financial situation of the country and the economic status of households [13,14].

Education plays a critical role in developing the human capital necessary for digital transformation and innovation. The primary aim of the education system is to bridge the digital divide across economic backgrounds. Fox [15] highlighted that students from lower economic backgrounds have limited opportunities to learn digital literacy concepts. Key factors, including educational attainment levels, the quality of education systems, investment in STEM (science, technology, engineering, and mathematics) education, and access to lifelong learning opportunities, can be used to assess the education area. Countries with robust education systems that prioritise digital literacy and STEM education are likely to rank higher in this area, as they are better positioned to develop a skilled workforce capable of supporting digital innovation and economic growth. The composition of the workforce—such as the proportion of workers employed in STEM fields and the diversity of talent with complementary skills—can significantly impact a country's digital competitiveness. Countries with a higher concentration of STEM professionals and a diverse workforce with multidisciplinary skills are likely to rank higher in this regard.

The composition of the workforce reflects a country's ability to innovate, adapt to technological change, and seize new opportunities in the digital sector. The synergistic effect of favourable socio-economic factors and the educational system lies in their interconnectedness, collectively enhancing individuals' digital skills. This integration fosters a dynamic environment conducive to continuous learning and skill development, which is essential for navigating the complexities of the digital era and supporting sustainable economic growth. Nonetheless, the complexity of this issue highlights the need for further research and in-depth studies to achieve a comprehensive understanding.

The objective of our study was to theoretically contribute to elucidating the disparities in digital skills among populations of European Union countries. In the practical component, our research aimed to create a ranking of countries using three different techniques to construct a composite indicator. A secondary objective was to identify countries with similar characteristics within this multi-criteria framework, representing the digital proficiency of the population in relation to various socio-economic and educational indicators.

The article is structured as follows: after providing an overview of digital skills as a key driver of socio-economic development in the EU, we outline the theoretical background and discuss relevant literature on disparities in digital competencies across member states. The methodology section describes the data sources and the three techniques used to construct composite indicators, including cluster analysis and Hellwig's method. We then present our findings, highlighting significant groupings of countries based on common strengths and weaknesses in digital skills, as well as insights into the socio-economic factors influencing these clusters. The final section discusses the implications of our results for policymakers, emphasising the need for targeted strategies that address challenges unique to each country to promote more equitable digital skills development across the EU.

3. Methodology

The study employs a quantitative correlational research design, focused on analysing a multidimensional phenomenon. This approach utilises a range of techniques for constructing multivariate synthetic indicators, along with factor and cluster analysis methodologies.

3.1. Database

The empirical basis of our study is grounded in robust data from Eurostat's Digital Economy and Society database, a primary source providing comprehensive statistics on various aspects of the digital economy and society across Europe. Our analysis uses authoritative and standardised datasets sourced directly from Eurostat, covering a sample of the 27 European Union countries.

Digital skills are broadly defined by reputable organisations. According to the UNESCO Institute for Statistics [16], digital skills encompass "the range of abilities to use digital devices, communication applications, and networks to access and manage information." Similarly, the International Telecommunication Union describes digital skills as "the ability to use ICT in ways that help individuals achieve beneficial, high-quality outcomes in everyday life for themselves and others," while also minimising potential negative impacts associated with digital engagement [17].

The data used in this study spans 2021 and 2022, providing a comprehensive review of trends and developments in the digital environment during this period. This timeframe highlights the relevance and timeliness of Eurostat data, emphasising its reliability for empirical research. Unlike traditional sampling methods, Eurostat data is collected from administrative records, censuses, and extensive surveys, thereby representing the entire population and generally eliminating sampling error.

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The Digital Skills Indicator (DSI) is a crucial tool for assessing individuals' proficiency in digital technologies within specific countries, offering insights into their readiness for the digital age. Our analysis of the digital landscape across EU27 countries focused on various levels of the DSI indicator (see Table 1). Additionally, variables such as X4 (TRAINING), X5 (POVERTY), X6 (SCIENCE), and X7 (ENGINEERS) were included as socio-economic or demographic indicators. Their inclusion broadens our analysis, enabling a deeper exploration of the relationship between digital skills levels and socio-economic dynamics within these countries.

Table 1. Digital Skills Variables

Variables	Source
X1: Individuals with basic or higher basic overall digital skills (percentage of individuals aged 25 to 64) (DS_BASIC) X2: Individuals with no overall digital skills (percentage of individuals aged 25 to 64) (DS_NO) X3: Individuals whose digital skills could not be assessed due to lack of Internet usage in the last 3 months (percentage of individuals aged 25 to 64) (DS_UNDETECTED)	These variables related to digital skills could have been collected through surveys or studies conducted by national statistical offices or research organizations. Surveys may have included questions about individuals' digital skills and internet usage habits.
X4: Individuals who received training paid for or provided by an employer to enhance skills related to the use of computers, software, or applications (percentage of individuals aged 25 to 64) (TRAINING)	Data on individuals who received training related to computer skills or applications could have been obtained from surveys conducted by labour or employment agencies, as well as from employer records or administrative data on training programs.
X5: Persons at risk of poverty or social exclusion (percentage of the total population) (POVERTY)	Information on persons at risk of poverty or social exclusion is typically collected through surveys conducted by national statistical offices or international organizations such as Eurostat. These surveys often include questions about income, employment status, and other socioeconomic factors.
X6: Percentage of the labour force aged 25 to 64 employed in science and technology (SCIENCE) X7: Scientists and engineers (percentage of the labour force aged 25 to 64) (ENGINEERS)	Data on persons employed in science and technology, as well as scientists and engineers, may come from labour force surveys, industry reports, or administrative records from government agencies responsible for tracking employment statistics.
X8: Graduates of tertiary education in natural sciences, mathematics, informatics, engineering, production, and construction (per 1000 inhabitants aged 20-29) (EDU_TERT)	Information on graduates of tertiary education in specific fields such as natural sciences, mathematics, informatics, engineering, production, and construction, may be obtained from educational institutions' records or from national databases on higher education graduates.

Source: Authors' own data.

3.2. Research Methods

The research employed three distinct procedures—an order counting approach, TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution), and Hellwig's method—to construct a synthetic variable that reflects digital proficiency across countries. These methods were deliberately selected based on their individual strengths in addressing the complexities of multi-criteria decision-making and their combined ability to provide a comprehensive analysis of digital skills disparities across the European Union.

The order counting method was chosen for its simplicity and effectiveness in linear ranking. This technique systematically arranges countries based on their digital proficiency levels, providing a clear visual representation of disparities. Its straightforward approach enables stakeholders to quickly understand how countries compare to one another, facilitating targeted interventions. By creating a hierarchy of countries, leaders and laggards in digital skill development can be identified, making it easier for policymakers to prioritise areas requiring immediate attention.

TOPSIS was selected for its robust ability to handle multiple criteria and its focus on relative performance. This method is particularly valuable as it not only ranks alternatives but also provides insight into their proximity to ideal and non-ideal solutions. By utilising TOPSIS, it is possible to assess how each country's digital proficiency aligns with optimal conditions, taking into account both positive and negative factors. This dual perspective is crucial for understanding the dynamics of digital skill development, as it highlights not only the current standing of each country but also the potential for improvement. The incorporation of this method allows for a nuanced understanding of performance, empowering policymakers to design interventions that address specific gaps.

Hellwig's method was included for its comprehensive aggregation of indicators into a single composite measure, which is essential when analysing complex phenomena like digital proficiency. This method allows for the weighting of indicators based on their relative importance, ensuring that more influential factors have a greater impact on the final assessment. By applying Hellwig’s method, a more nuanced and precise synthetic variable is created, capturing the multifaceted nature of digital skills. Additionally, its reliance on Euclidean distance calculations facilitates a straightforward interpretation of how countries measure up against an ideal standard, thereby supporting the identification of best practices.

The distinction between stimulants, destimulants, and nonstimulants is fundamental to this analysis. Stimulants—such as increased investment in education, training programmes, and research initiatives—are critical for fostering digital skills. Destimulants, by contrast, include factors like socio-economic inequalities and lack of resources, which hinder progress and impede the development of digital proficiency. Lastly, nonstimulants refer to variables that neither promote nor hinder the assessment of digital skills; these factors have a neutral impact on the overall analysis.

In the initial phase of the analysis, selected methods were employed for linearly ordering objects. Overall, linear ordering techniques provide a structured approach for ranking countries and identifying similarities in digital proficiency levels. They offer a clear and interpretable means to summarise complex multi-criteria data, supporting decision-making processes in assessing and addressing digital disparities among countries. Linear ordering of objects (countries) involves creating a ranking of multidimensional objects, arranging them from best to worst or vice versa. This process entails projecting points in multidimensional space onto a straight line [20–22], with these points representing values of synthetic variables created by aggregating object descriptors [21].

TOPSIS, a multi-criteria decision-making method, identifies the best alternative from a set of options by evaluating their proximity to the ideal solution and their distance from the negative ideal solution. In this study, TOPSIS was applied to create the synthetic variable, determining the relative performance of countries in terms of digital proficiency based on predefined criteria. TOPSIS operates on the premise that the best solution is the one with the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution [23,24]. It calculates the distance of each object (country) from both the ideal and non-ideal solutions [22], identifying the best object as the one closest to the ideal solution and farthest from the non-ideal solution [22].

Hellwig's method [19] is a mathematical approach for aggregating multiple indicators into a composite measure. This method typically involves assigning weights to each indicator based on its relative importance, followed by summing or averaging the standardised scores. In this study, Hellwig's method was applied to construct a synthetic variable, incorporating the weighted contributions of various criteria. Unlike TOPSIS, Hellwig's method estimates only the distance from an ideal solution (fictitious object), using the Euclidean metric, which is utilised in both Hellwig's method and TOPSIS. For these methods, it is assumed that the values of the variables X1, X2, ..., Xk were measured across the objects (countries) O1, O2, ..., Om.

Based on how variables influence the analysed phenomenon, variables are categorised as stimulants, destimulants, or nominants. The concept of stimulants and destimulants was introduced by Hellwig [19]. Stimulants are variables where an increasing value enhances the assessment of an object's features, whereas destimulants are variables where an increasing value reduces this assessment [26]. In this study, X1, X4, X6, X7, and X8 were classified as stimulants, while X2, X3, and X5 were classified as destimulants. The next step involves determining the values of the synthetic feature.

When applying these methods, it is assumed that the values of variables X1, X2, ..., Xk were measured across the objects (countries) O1, O2, ..., Om. Based on how these variables influence the analysed phenomenon, they are categorised as stimulants, destimulants, or nominants. The concept of stimulants and destimulants was introduced by Hellwig [19]. Stimulants are variables where an increase in value enhances the assessment of an object's features, whereas destimulants are variables where an increase in value reduces this assessment [25]. In this analysis, X1, X4, X6, X7, and X8 were classified as stimulants, while X2, X3, and X5 were classified as destimulants. The next step involves calculating the values of the synthetic feature.

The formulas for calculating the synthetic variable order counting method $d_i^{(1)}$, Hellwig's method $d_i^{(2)}$, and the TOPSIS method $d_i^{(3)}$ are presented in Table 2.

Table 2. The Formulas for Calculating the Synthetic Variable

Transformation	Formula
$z_{ij} = \begin{cases} 1 \quad pre \quad \min\limits_{i} \{x_{ij}\} \; (j = 1.\ 2. \ldots\ k) \\ \ldots\ldots\ldots \\ m \quad pre \quad \max\limits_{i} \{x_{ij}\} \end{cases}$ for stimulant $z_{ij} = \begin{cases} 1 \quad pre \quad \max\limits_{i} \{x_{ij}\} \; (j = 1.\ 2. \ldots\ k) \\ \ldots\ldots\ldots \\ m \quad pre \quad \min\limits_{i} \{x_{ij}\} \end{cases}$ for destimulant	$d_i^{(1)} = \sum_{j=1}^{k} z_{ij}$ (i =1. 2.... m)
$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}$ for stimulant $z_{ij} = \frac{\bar{x}_j - x_{ij}}{s_j}$ for destimulant where $\bar{x}_j$ is the mean and s_j standard deviation of the variable Xj.	$d_i^{(2)} = \left[\frac{1}{k}\sum_{j=1}^{k}(z_{ij} - z_{0j})^2\right]^{\frac{1}{2}}$ $z_{0j} = \max\limits_{i} \{z_{ij}\}$ for stimulant $z_{0j} = \min\limits_{i} \{z_{ij}\}$ for destimulant zij – normalized value
$d_i^{+} = \sqrt{\sum_{j}(z_{ij} - z_j^{+})^2}$ $d_i^{-} = \sqrt{\sum_{j}(z_{ij} - z_j^{-})^2}$ $z_j^{+} := \max\limits_{i} \{z_{ij}\} \quad z_j^{-} := \min\limits_{i} \{z_{ij}\}$ zij – normalized value	$d_i^{(3)} = \frac{d_i^{-}}{d_i^{-} + d_i^{+}}$

Source: Created by the author based on sources [18,19,24].

By employing these three procedures, the study aimed to construct a comprehensive synthetic variable that captures the multidimensional nature of digital proficiency across countries. Each method offers unique insights and considerations in aggregating the criteria, contributing to a nuanced understanding of digital proficiency levels and enabling meaningful comparisons among countries. Data processing was conducted using SAS Enterprise Guide software and Excel.

In this research, both positive and negative methodological experiences were encountered, providing valuable insights into the effectiveness of the selected methodologies.

Positive methodological experience: Testing methodological tools, such as TOPSIS, Hellwig's method, and the Order Counting Method, proved valuable for assessing their applicability and performance in constructing a synthetic variable for digital proficiency.

Negative methodological experience: Challenges in implementation arose, particularly in aligning the chosen methodologies with the research objectives. These difficulties were primarily due to the complexity of the multidimensional nature of digital proficiency and the need to ensure that the methodological approach sufficiently captured its diverse aspects.

4. Results and Discussion

This section presents the findings of the study, which aimed to explore the association between various socio-economic factors and digital skills among individuals aged 25 to 64 across EU countries. The analysis involved examining aggregated data at the country level, focusing on variables such as digital skill proficiency, participation in educational programmes, and employment rates in science and technology fields within each country's population.

Table 3. Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum	Coefficient of Variation (%)
DS_BASIC	59.60	12.48	29.35	83.92	20.95
DS_LOW	17.50	3.46	10.47	22.72	19.76
DS_NO	2.32	2.09	0.13	10.10	90.16
DS_ UNDETECTED	6.90	4.47	0.44	17.55	64.70
TRAINING	8.05	5.76	1.88	26.75	71.57
POVERTY	20.69	5.28	11.80	34.40	25.52
EDU_TERT	37.37	9.24	19.70	53.50	24.72
EDU_LOW	16.56	9.65	5.40	39.70	58.26
SCIENCE	37.38	8.58	24.90	59.20	22.96
ENGINEERS	9.42	2,66	4.60	15.40	28.21

Source: Authors' own processing.

Table 3 provides a summary of key descriptive statistics for the analysed study variables, including the mean, standard deviation, minimum, maximum, and coefficient of variation (CV). Variables such as "Individuals with no overall digital skills" and "Digital skills could not be assessed because the individual has not used the internet in the last 3 months" exhibit relatively high values of the coefficient of variation, indicating greater spatial variability. The wide range of values (from R = 54.57 for "Individuals with basic or above basic overall digital skills" to R = 9.97 for "Individuals with no overall digital skills") highlights the heterogeneity of digital literacy levels within the EU population.

The relatively low average percentage of individuals participating in digital skills training programmes suggests significant potential for expanding access to digital literacy initiatives. Given the diversity in training participation rates and the critical role of continuous skills development in the digital age, targeted efforts to support training and upskilling programmes could prove beneficial.

Socio-economic factors, such as the risk of poverty or social exclusion, level of education, and employment in science and technology, demonstrate different associations with digital skills levels. For instance, higher levels of tertiary education correlate positively with digital skills, as shown by the higher average percentage of individuals with tertiary education in fields related to science, mathematics, computing, engineering, manufacturing, and construction. In contrast, a higher risk of poverty or social exclusion correlates with lower digital skill levels, underscoring the need for targeted interventions to address these disparities.

The distribution of digital skills levels among individuals represents the variation in digital skill proficiency within a given country's population, categorising individuals based on their level of digital knowledge.

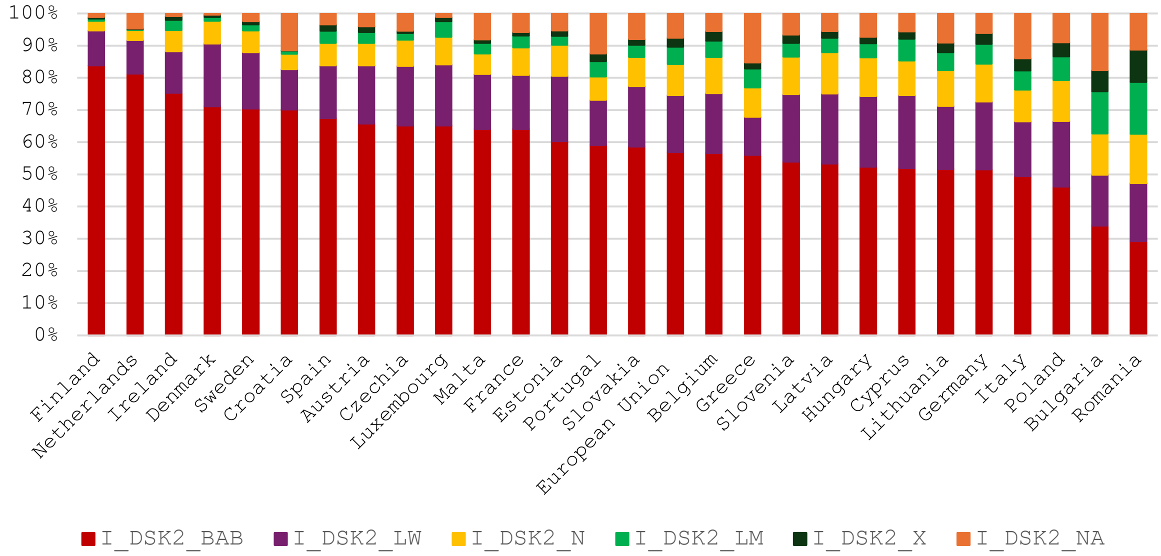

Figure 1. Distribution of Digital Skill Levels among the Population of EU Member States
Note: *[I_DSK2_BAB]* Individuals with basic or above-basic information and data literacy skills; *[I_DSK2_LW]* Individuals with low overall digital skills; *[I_DSK2_N]* Individuals with narrow overall digital skills; *[I_DSK2_LM]* Individuals with limited overall digital skills; *[I_DSK2_X]* Individuals with no overall digital skills; *[I_DSK2_NA]* Digital skills could not be assessed because the individual has not used the internet in the last 3 months.
Source: Authors' own processing.

Figure 1 illustrates the distribution of digital skill levels within the populations of individual EU countries. Finland (83.92%), the Netherlands (81.32%), Ireland (75.32%), Denmark (71.12%), Sweden (70.44%), and Croatia (70.20%) exhibit the highest proportions of individuals with basic or higher digital skills. Additionally, Croatia, Spain, Austria, the Czech Republic, Luxembourg, Malta, France, Estonia, Portugal, and Slovakia surpass the EU27 average in this regard. Conversely, Bulgaria (34.09%) and Romania (29.35%) have the lowest shares of individuals with basic or higher digital skills. Notably, Bulgaria and Romania also report the highest percentages of individuals without any digital skills, at 6.64% and 10.10%, respectively.

Bulgaria further stands out with the highest proportion of individuals who have not used the Internet in the last 3 months, reaching 17.55%. Greece reports 15.2% in this category, followed by Portugal at 12.38% and Croatia at 11.43%. The higher education sector plays a pivotal role in fostering advanced digital skills. The correlation between tertiary graduates in fields such as science, mathematics, computing, engineering, manufacturing, and construction and individuals with basic or above-average digital skills is depicted in Figure 2, with a correlation coefficient of r = 0.49547.

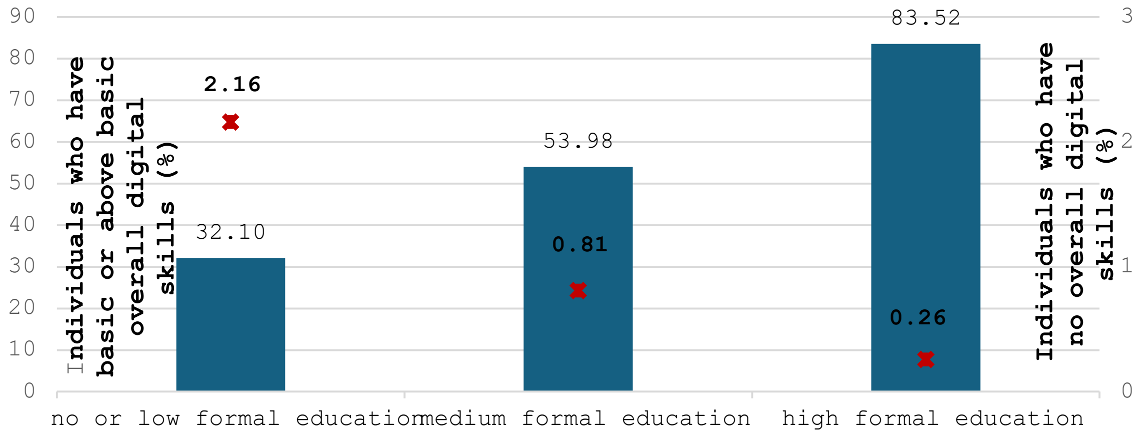

Figure 2. Percentage of Individuals with Above-Basic Digital Skills and Percentage of Individuals with No Digital Skills among the Population Aged 16–74
Source: Authors' own processing.

The research findings indicate a correlation between digital skills and educational attainment (Figure 2). Among individuals with high levels of formal education, up to 84% possess basic or higher digital skills, with only 0.26% lacking any digital skills. In contrast, 53.98% of individuals with medium levels of formal education have basic or higher digital skills, while 0.81% lack overall digital skills. For individuals with no or minimal formal education, only 32% demonstrate basic or higher digital skills, and 2.16% lack overall digital skills entirely.

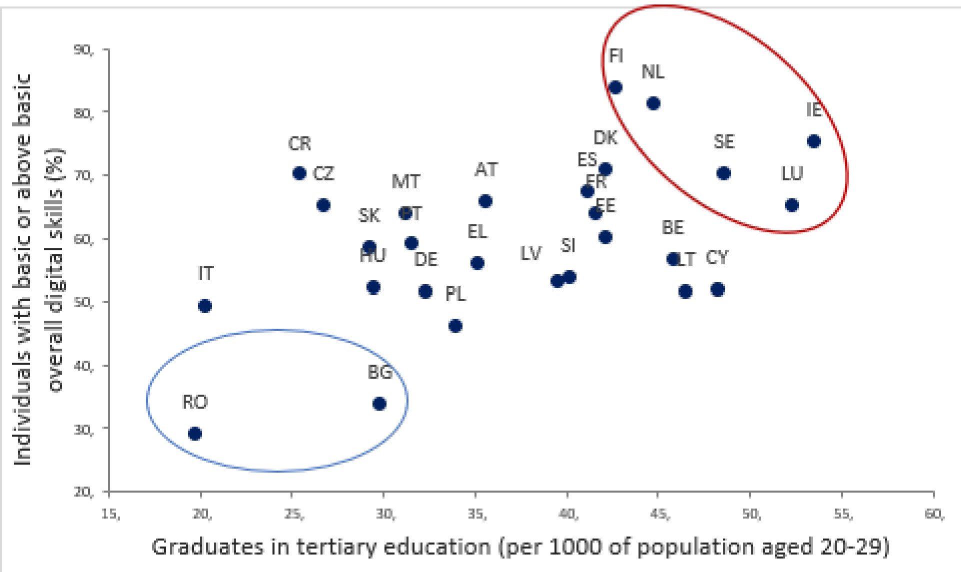

Figure 3. Relationship between Tertiary Education Graduates (%) and Individuals with Basic or Above-Basic Digital Skills (%)
Source: Authors' own processing.

The previously noted correlation is particularly evident in countries with a higher proportion of the population having completed tertiary education, such as Ireland, Luxembourg, Sweden, the Netherlands, Finland, and Denmark, as well as in countries with a lower proportion, such as Bulgaria and Romania. Figure 3 illustrates the impact of socio-demographic factors—such as

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the proportion of individuals at risk of poverty or social exclusion and the overall low educational level of the population—on the prevalence of individuals lacking digital skills.

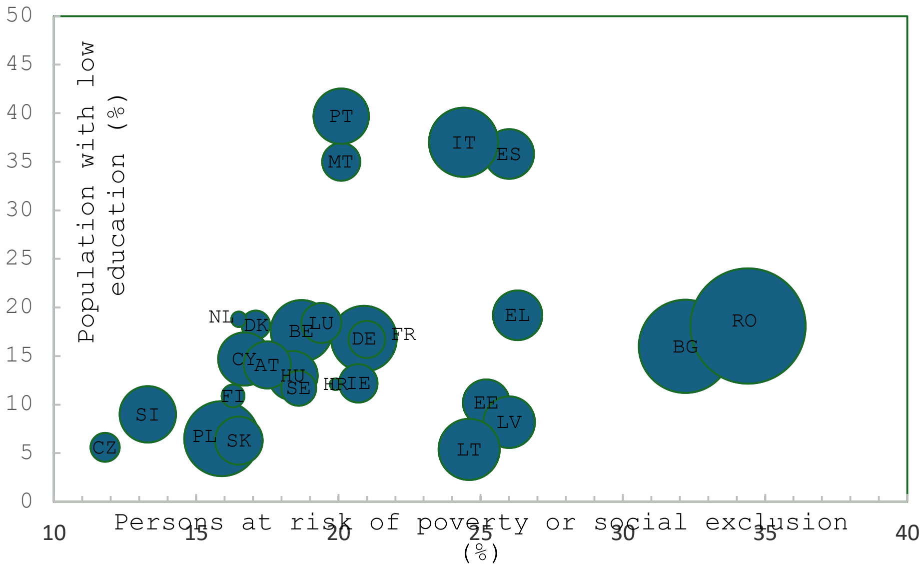

Figure 4. Proportion of Individuals with No Digital Skills in Relation to Poverty and Low Education Levels
Source: Authors' own processing.

The highest proportions of the population lacking digital skills (Figure 4) are observed in Romania (10.1%) and Bulgaria (6.64%). Notably, these countries also report the largest shares of the population at risk of poverty. The impact of the poverty risk variable on the prevalence of individuals with no digital skills is further supported by the Pearson correlation coefficient (r = 0.67219) (Table 4).

Table 4. Pearson's Correlation Coefficient (Correlation Values and p-Values)

	DS_BASIC	DS_LOW	DS_NO	TRAINING	POVERTY	EDU_LOW	EDU_TERT	SCIENCE	ENGINEERS	DS_UNDET
DS_BASIC	1.000	-0.499	-0.876	-0.464	-0.571	0.048	-0.048	-0.554	-0.549	-0.670
		0.009	0.001	0.015	0.003	0.822	0.822	0.005	0.006	0.000
DS_LOW	-0.499	1.000	0.281	0.490	0.342	-0.638	0.487	0.220	-0.465	0.521
	0.009		0.335	0.011	0.225	0.002	0.014	0.434	0.014	0.008
DS_NO	-0.876	0.281	1.000	0.346	0.232	-0.416	0.383	0.214	-0.641	0.482
	0.001	0.335		0.221	0.412	0.119	0.140	0.436	0.002	0.016
TRAINING	-0.464	0.490	0.346	1.000	0.465	-0.383	0.515	0.502	-0.472	0.510
	0.015	0.011	0.221		0.016	0.141	0.008	0.011	0.015	0.009
POVERTY	-0.571	0.342	0.232	0.465	1.000	-0.487	0.488	0.487	-0.451	0.511
	0.003	0.225	0.412	0.016		0.014	0.016	0.015	0.005	0.006
EDU_LOW	0.048	-0.638	-0.416	-0.383	-0.487	1.000	-0.321	-0.425	-0.512	-0.226
	0.822	0.002	0.119	0.141	0.014		0.244	0.102	0.006	0.109
EDU_TERT	-0.048	0.487	0.383	0.515	0.488	-0.321	1.000	0.432	-0.512	0.481
	0.822	0.014	0.140	0.008	0.016	0.244		0.098	0.004	0.007
SCIENCE	-0.554	0.220	0.214	0.502	0.487	-0.425	0.432	1.000	-0.451	0.222
	0.005	0.434	0.436	0.011	0.015	0.102	0.098		0.010	0.084
ENGINEERS	-0.549	-0.465	-0.641	-0.472	-0.451	-0.512	-0.512	-0.451	1.000	-0.571
	0.006	0.014	0.002	0.015	0.005	0.006	0.004	0.010		0.000
DS_UNDET	-0.670	0.521	0.482	0.510	0.511	-0.226	0.481	0.222	-0.571	1.000
	0.000	0.008	0.016	0.009	0.006	0.109	0.007	0.084	0.000	

Source: Authors' own processing.

Based on the calculated Pearson correlation coefficients, it can be concluded that the share of the population with a low level of education does not exhibit a statistically significant relationship with any indicator of digital skills proficiency. Additionally, no significant correlation was found between the share of the population with low overall digital skills and any of the other factors examined. Consequently, individuals with low overall digital skills, as well as populations with less than primary, primary, or lower secondary education, were excluded from further analysis due to the lack of significant associations with the variables under consideration.

Table 5. The nature of the variables

Variable	DS_BASIC	DS_NO	TRAINING	POVERTY	EDU_TERT	SCIENCE	INGINEERS	DS_UNDETECTED
Nature of Variables	stimulant	destimulant	stimulant	destimulant	stimulant	stimulant	stimulant	destimulant

Source: Authors' own processing.

Table 6 presents the ranking of countries derived from selected linear ordering techniques. This ranking is based on categorising the variables (stimulant, destimulant, nominant) in relation to the analysed phenomenon (see Table 5). The categorisation was informed by the correlation matrix (Table 4), particularly the values of the Pearson correlation coefficients between digital skills indicators and other socioeconomic variables. Based on this analysis, variables with stimulating or destimulating effects were identified, while nominants were excluded from further analysis, as previously discussed.

Table 6. Positions of Countries Obtained Using Selected Methods of Linear Arrangement

Method	$d_i^{(1)}$	$d_i^{(2)}$	$d_i^{(3)}$	$r_i^{(1)} + r_i^{(2)} + r_i^{(3)}$	PRIN1	Method	$d_i^{(1)}$	$d_i^{(2)}$	$d_i^{(3)}$	$r_i^{(1)} + r_i^{(2)} + r_i^{(3)}$	PRIN1
Country	**The arrangement of countries**					**Country**	**The arrangement of countries**				
Austria	7	7	11	7	7	Italy	25	25	25	25	25
Belgium	8	8	13	8	9	Latvia	23	21	21	23	20
Bulgaria	27	26	27	27	26	Lithuania	19	17	18	19	17
Croatia	21	23	8	18	22	Luxembourg	5	4	4	4	4
Cyprus	14	14	9	12	14	Malta	13	13	16	14	15
Czechia	11	15	7	10	12	Netherlands	2	2	3	2	2
Denmark	4	5	6	6	5	Poland	20	22	20	22	23
Estonia	10	11	17	13	11	Portugal	18	16	22	20	18
Finland	1	1	1	1	1	Romania	26	27	26	26	27
France	12	12	12	11	10	Slovakia	17	19	15	17	19
Germany	15	10	23	16	13	Slovenia	9	9	14	9	8
Greece	24	24	24	24	24	Spain	16	18	10	15	16
Hungary	22	20	19	21	21	Sweden	3	3	5	3	3
Ireland	6	6	2	5	6						

Source: Authors' own processing.

The results were compared with the outcomes of the cluster analysis. Using Eigen scores derived from principal component analysis (PCA), a cluster analysis was conducted. PCA is a linear dimensionality reduction technique that transforms a set of correlated input variables in a high-dimensional space into a series of uncorrelated variables in a lower-dimensional space. The optimal number of components was determined based on explained variance or eigenvalues. Following the Kaiser rule, only two principal components were considered, as these were the only components with eigenvalues greater than 1 (eigenvalues: 5.0691, 1.1552). The first component was correlated with DS_BASIC, TRAINING, and EDU_TERT, while the second component was correlated with POVERTY, DS_NO, and DS_UNDETECTED. Additionally, the values of the first principal component were used to arrange the countries (Table 6).

Table 7. Eigenvectors

Eigenvectors	PRIN1	PRIN2
DS_BASIC	0.376826	-0.322880
DS_NO	-0.331219	0.534643
TRAINING	0.341877	0.132796
POVERTY	-0.294386	0.485398
EDU_TERT	0.328785	0.346312
SCIENCE	0.394379	0.238190
INGINEERS	0.368144	0.413499
DS_UNDETECTED	-0.381560	-0.094931

Source: Authors' own processing in SAS Enterprise Guide.

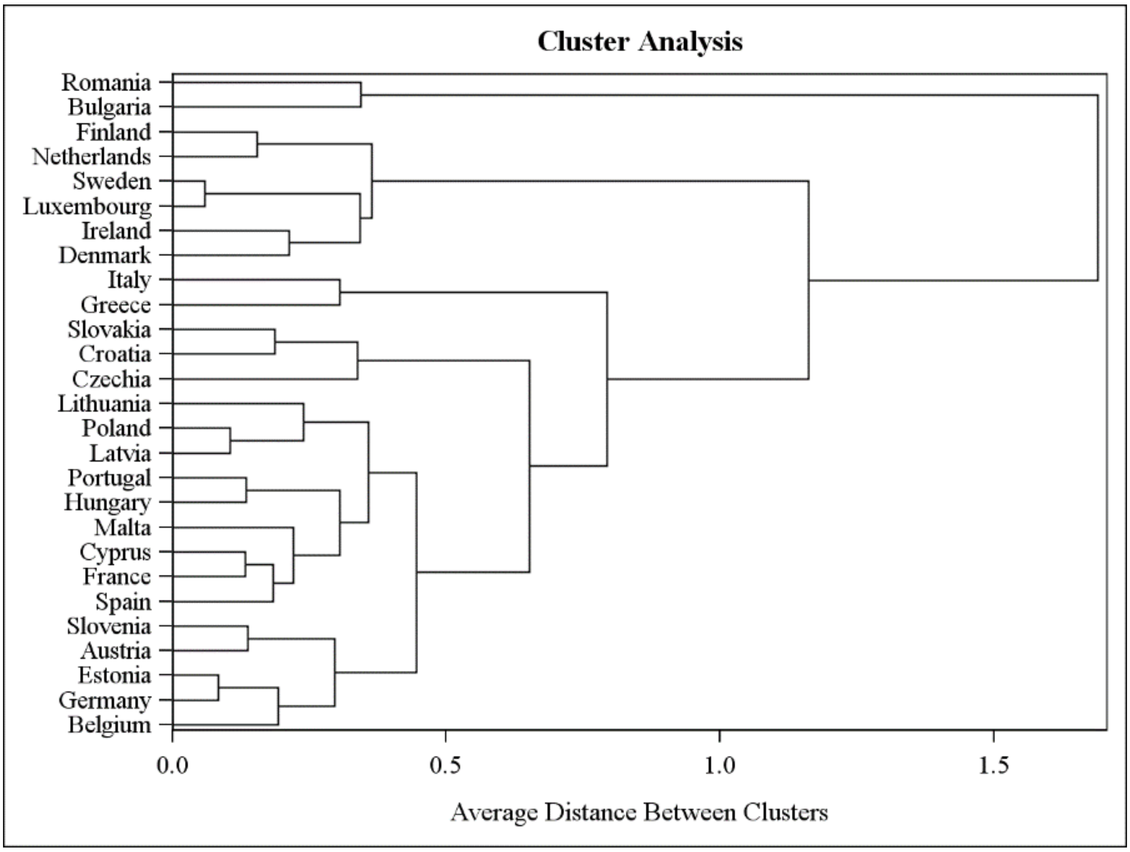

Figure 5. Cluster Analysis Dendrogram
Source: Authors' own processing in SAS Enterprise Guide.

Table 7 presents the eigenvectors derived from Principal Component Analysis (PCA), illustrating the relationships between various variables and the principal components, PRIN1 and PRIN2. For example, the variable SCIENCE has a high positive eigenvector value of 0.3944 for PRIN1, indicating a strong contribution to this component, while DS_NO has a negative value of -0.3312, suggesting an inverse relationship. In PRIN2, POVERTY shows a positive value of 0.4854, underscoring its significance in this dimension, whereas DS_UNDETECTED has a small negative contribution of -0.0949. These eigenvectors demonstrate the influence of each variable on the overall variance in the dataset, offering insights into the underlying factors at work.

For clustering, Ward's method was employed, with the number of clusters determined based on the Semi-Partial R-Squared (SPRSQ) criterion. Ward's minimum variance criterion aims to minimise the total variance within each cluster. At each iteration, the algorithm identifies the pair of clusters that, when merged, results in the smallest increase in total within-cluster variance. This increase is measured as the weighted squared distance between the cluster centres [20]. The resulting cluster analysis dendrogram is displayed in Figure 5.

The dendrogram in Figure 5 illustrates the hierarchical relationships among data points, highlighting their similarities and differences. It visually represents the formation and joining of clusters based on the proximity of data points in the multidimensional space defined by the analysed variables.

Table 8. Centroid of clusters showing characteristics of the cluster

	Cluster	**1**	**2**	**3**	**4**	**5**	**6**
Variable	**Nature of Variables**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
DS_BASIC	stimulant	74.55	57.68	56.71	64.68	52.78	31.72
DS_NO	destimulant	0.81	2.47	2.25	0.88	2.84	8.37
TRAINING	stimulant	15.32	9.99	5.48	5.17	2.98	2.28
POVERTY	destimulant	18.10	19.12	20.98	16.07	25.35	33.30
EDU_TERT	stimulant	47.32	39.18	38.10	27.10	27.70	24.75
SCIENCE	stimulant	49.75	40.42	33.84	32.07	28.20	25.70
INGINEERS	stimulant	13.30	10.42	8.36	6.60	6.20	7.50
DS_UNDETECTED	destimulant	1.74	5.47	7.32	8.25	14.58	14.38
		Luxembourg Sweden Netherlands Finland Denmark Ireland	Germany Estonia Austria Slovenia Belgium	Latvia Poland France Cyprus Hungary Portugal Spain Malta Lithuania	Croatia Slovakia Czechia	Greece Italy	Bulgaria Romania

Source: Authors' own processing in SAS Enterprise Guide.

Table 8, titled Centroid of Clusters, summarises the characteristics of each cluster. Analysis of these characteristics offers insights into the approaches or priorities of countries regarding the variables under consideration. Clusters are numbered 1 through 6, each presenting mean values for variables such as DS_BASIC, DS_NO, TRAINING, POVERTY, EDU_TERT, SCIENCE, and ENGINEERS.

Cluster 1: Luxembourg, Sweden, the Netherlands, Finland, Denmark, and Ireland form a distinct cluster characterised by the highest proportion of individuals with basic or higher digital skills. This cluster also includes a significant number of individuals who have received employer-funded or employer-provided training to enhance computer skills.

Cluster 2: Germany, Estonia, Austria, Slovenia, and Belgium share similarities with Cluster 1, showing higher values for incentive variables and lower values for disincentive variables. However, the mean values of the variables in this cluster are generally lower than those in Cluster 1.

Cluster 3: Latvia, Poland, France, Cyprus, Hungary, Portugal, Spain, Malta, and Lithuania display average values across most variables and do not exhibit extreme tendencies toward stimulation or destimulation. These countries demonstrate a balanced approach to the analysed variables and have the lowest proportion of individuals lacking digital skills, as well as those whose digital skills could not be assessed.

Cluster 4: Croatia, Slovakia, and Czechia form a cluster with lower values for stimulating variables and slightly higher values for destimulating variables compared to previous clusters. This cluster also has the lowest poverty risk, suggesting a limited emphasis on stimulation and research-related activities.

Cluster 5: Greece and Italy show the lowest mean values for incentive variables and relatively higher values for disincentive variables compared to other clusters. They also have the lowest proportion of scientists and engineers and the highest proportion of individuals whose digital skills could not be assessed.

Cluster 6: Bulgaria and Romania demonstrate the lowest average values across most variables, indicating a generally lower level of activity in all considered areas compared to other clusters. This cluster has the highest share of individuals without digital skills and persons at risk of poverty or social exclusion. Additionally, it has the lowest proportion of individuals with basic or higher digital skills, individuals who have received employer-supported training, tertiary education graduates, and persons employed in science and technology.

The cluster analysis identified distinct groupings of countries based on their characteristics related to incentive and disincentive variables. Stimulus variables—such as investment in research, training programmes, and innovation initiatives—were associated with clusters that demonstrated higher average values in these areas. In contrast, disincentive variables, representing factors that hinder the development of digital skills among the population, showed higher mean values in clusters with less emphasis on such activities. Clusters with higher mean values for incentive variables reflected a proactive approach to development and innovation, while clusters with higher mean values for disincentive variables highlighted potential challenges or areas of weakness. Understanding these clusters offers valuable insights into the varying strategies and priorities among countries, which can inform targeted interventions and support overall progress in key areas such as education, research, and innovation.

5. Conclusion

The pace of technological development and the advancement of digital skills in human resources [25,26] are closely linked, though not directly proportional. Currently, technological advancements are progressing rapidly [27], driven by factors such as increased research and development efforts, heightened investment in innovation, and the emergence of disruptive technologies. Breakthroughs in fields like artificial intelligence, robotics, and biotechnology frequently occur at a swift pace, propelled by competition, market demand, and scientific progress. However, the development of digital skills within the workforce requires educating and training individuals to effectively use digital technologies in both personal and professional contexts. While technological progress provides a foundation for digital skill development, the process of acquiring and enhancing these skills in the workforce is time-intensive and resource-dependent, necessitating substantial investment in education, training programmes, infrastructure, and supportive policies.

Across European countries, significant differences exist not only in socio-economic conditions but also in the strategies they employ to implement policies aimed at developing the digital skills of the population [28]. The central issue lies less in the physical availability of devices and more in the education system, as incentives for digital skills development primarily originate from the broader education sector. Countries ranked at the forefront are distinguished by high-quality, inclusive education systems that provide educational opportunities regardless of socio-economic background, with a strong emphasis on lifelong learning. In these environments, acquiring new knowledge is perceived as a natural part of life, continuing through both active and post-active periods. In contrast, countries positioned lower in the rankings often contend with not only low funding but also with urban-rural disparities, socio-economic inequalities, and challenges faced by marginalised communities. Additionally, rigid centralisation within school systems limits flexibility and innovation at the local level [29].

The rapidly evolving digital landscape necessitates continuous upskilling across the entire population, as digital integration involves a convergence of complementary physical, intangible, and computational technologies [30]. This integration demands a diverse skill set, encompassing STEM competencies [31,32] as well as interpersonal and social skills. The need for ongoing skill development highlights a key direction for future research, emphasizing the importance of interdisciplinary exploration that incorporates both quantitative and qualitative methodologies. While the digital divide driven by disparities in household income [33] is gradually narrowing, a new priority emerges: encouraging the population to continuously enhance and innovate their digital skills [34,35]. Addressing these issues calls for the expansion of interdisciplinary research that embraces a variety of methodological approaches [36].

However, this study has certain limitations. The reliance on secondary data from Eurostat may introduce biases, as the data may not fully capture the range of digital skills across all demographics or regions within the analysed countries. Furthermore, the selected indicators for cluster analysis could overlook significant contextual factors influencing digital skills, such as cultural attitudes towards technology or specific national policies. Additionally, the study's cross-sectional design restricts the ability to draw causal inferences about the relationship between incentive and disincentive variables and digital skill development. Despite these limitations, the insights gained from understanding these clusters offer valuable perspectives on the varied strategies and priorities across countries, which can guide targeted interventions and promote progress in key areas, including education, research, and innovation.

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