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DEVELOPMENT OF LIFELONG LEARNING IN THE COUNTRIES OF THE EUROPEAN UNION: K-MEANS CLUSTER ANALYSIS EVALUATION

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ABSTRACT

The article analyses lifelong learning development across EU countries, focusing on disparities in doctoral education. A cluster analysis methodology is used to identify homogeneous groups of countries based on various indicators, such as the number of doctoral graduates divided by age and gender and GDP per capita. The analysis categorises countries into clusters based on similarities, applying the K-means clustering technique. This method groups countries to highlight differences in lifelong learning, particularly emphasising economic development. Cluster analysis reveals significant differences between economically advanced European countries and less developed regions, particularly in Eastern Europe. The results underline that Western European countries show a higher number of doctoral graduates, both in total and within the 25-34 age group, compared to Eastern European nations, where these figures are considerably lower. The study concludes that fostering lifelong learning is crucial for socio-economic development, and countries must implement strategies to enhance participation in higher education.

KEY WORDS

lifelong learning, cluster analysis, doctoral education, European Union, k-means clustering

CLASSIFICATION

JEL: C38, I23, O15

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INTRODUCTION

Lifelong learning has become a central component of modern education systems and a key factor in economic development, especially within the European Union (EU). As labour markets and technological advancements evolve rapidly, the ability of individuals to continuously update their skills and knowledge is crucial for maintaining employability, fostering personal development, and promoting social inclusion. European countries have made significant efforts to promote adult education, but participation levels and outcomes remain heterogeneous across the region [1]. The strategic framework for European cooperation in education and training, particularly through initiatives like the Europe 2020 strategy, underscores the importance of enhancing lifelong learning toss achieve sustainable economic growth and social cohesion [2].

This article aims to explore the development and participation in lifelong learning across selected EU member states and associated countries. The study focuses on key indicators of formal and non-formal education, trends in doctoral education, and the relationship between educational attainment and economic performance. Specifically, the paper investigates how different countries cluster based on their educational outcomes, using advanced statistical methods like cluster analysis, and assesses the socio-economic factors that influence participation rates in lifelong learning and higher education.

Through the use of Eurostat data from 2013 to 2019, this study presents a comparative analysis of lifelong learning indicators, PhD graduation rates, and GDP per capita across 35 European countries. The findings will shed light on the disparities between countries in terms of educational achievements, highlight the economic implications of lifelong learning, and suggest policy recommendations to enhance participation in adult education. By understanding the factors that contribute to successful lifelong learning frameworks, this paper aims to provide insights that can inform policymakers and educators in their efforts to improve educational systems across Europe.

LITERATURE REVIEW

The strategic framework for European cooperation in education and training, approved in May 2009, included a number of requirements for adult participation in learning, including the need for at least 15 % of people aged 25-64 to participate in lifelong learning [3]. In 2020, 9,2 % of EU citizens aged 25-64 were enrolled in some form of education or training, which is 0,9 percentage points less than in 2015 and 1,6 percentage points less than in 2015. Part of the decline in 2019 can be linked to the COVID-19 pandemic, which is why training programs have been suspended [4].

The adult learning indicator in the Labour Force Survey refers to participation in formal and non-formal education and training [5].

Results presented in [3] indicate that Denmark, Finland, and Sweden were the only EU member states that reported a significantly higher percentage of their adult population engaged in lifelong learning in the four weeks prior to the survey, ranging from 20.0 to 28.6%. Estonia, the Netherlands, and Luxembourg were the only other EU countries to have a participation percentage of over 15 % in 2020. Adult learning rates were less than 4% in Romania, Bulgaria, Slovakia, Croatia, and Poland, on the other hand. The reference period for participation is four weeks before the interview.

In addition, as reported in [3], women (10,0 % in 2020) are more likely than men (8,3 %) to participate in adult learning in the EU. Both men and women had lower participation rates in 2020 than five years earlier. Participation rates for women and men gradually increased until 2019 but decreased in 2020, coinciding with the onset of the COVID-19 outbreak. In all EU

Member States in 2020, women had higher participation rates than men, except for the Czech Republic, Germany, Greece and Cyprus (where men had higher rates), while Romania had the same rate for both sexes.

The Adult Education Survey, together with the data from the Labour Force Survey, which provides data on participation in education and training in the four weeks preceding the survey interview, also includes data on education and training [6]. Because the survey assesses engagement in learning activities over a longer period (12 months before the survey interview), it is more likely to cover more learning activities, resulting in higher rates of involvement in formal and non-formal education and training. However, this is not done as often as it should (every six years since 2016). The last wave of the survey was carried out in 2022, and before that in 2016.

In the 12 months preceding the EU-wide Labour Force Survey [6], men and women had almost similar rates of participation in education and training. In Cyprus, the Czech Republic, Hungary and Italy, men were much more likely than women to participate in education and training. In contrast, the opposite is true in Estonia, Finland, Latvia, Sweden and Lithuania. Younger individuals (aged 25-34) had more than 20 percentage points higher than those who said they would participate in the EU in 2016. The participation of older people in education and training was extremely low in Romania and Greece. Educational achievement is linked to the likelihood of inclusion in education and training: those with higher education reported the highest participation rates, while those with lower secondary education reported the lowest participation rates.

In the reference period of 2022, 55 % of persons aged 25-64 reported engaging in lifelong learning (formal and/or non-formal education), an increase from 54 % in 2017. In 2022, little more than 11 % of persons aged 25-64 engaged in formal education, reflecting a 2 % rise from 2017. In 2022, 50 % of persons aged 25-64 engaged in non-formal education, maintaining the same participation percentage as in 2017. In 2022, over half (54 %) of adults aged 25-64 reported participating in informal learning, a decrease from 62 % in 2017 [7].

It is also common knowledge that the European Commission has emphasised for many years the importance of lifelong learning in achieving Lisbon's goals, especially in terms of personal growth and fulfilment. As a result, since 2005, a public debate on the future of social policy has developed in the European Union. In this context, lifelong learning plays a key role in building a common European socio-economic paradigm [8].

EU-SILC statistics show a high level of reliability in the literature on adult education and training [9]. The formal phenomenon of lifelong learning is significantly higher among younger and more educated employees and significantly lower among workers who have changed jobs in the last year and work in small enterprises or low-skilled occupations, statistics show for both men and women. According to estimates for both genders in the full sample, employees are far more likely to engage in formal lifelong learning for a fixed and fixed-term period. These two explanatory factors also had the greatest impact on the likelihood of adult subsequent learning. In fact, lifelong learning remains a key goal for European countries, as people need to update their skills throughout their working lives to improve employment prospects and contribute to personal fulfilment, social inclusion, and active citizenship in an era of rapidly changing technologies. Many countries are changing their institutional frameworks to ensure that everyone has access to high-quality lifelong learning opportunities (European Commission, 2010). However, empirical research on the factors of lifelong learning in European countries is insufficient [9].

METHODOLOGY

The research presented in the paper consists of two parts. First, the trends in the number of completed PhDs in selected European countries are explored. Data on the number of completed PhDs per 1000 inhabitants and the number of men and women who received PhDs per 1000 inhabitants are analysed, with special emphasis on the age group from 25 to 34. Data was collected from the Eurostat database. Second, the homogeneity of lifelong learning in selected European countries is analysed.

Cluster analysis is a useful approach for detecting homogeneous groups of units, objects, instances, or observations. As a result, units in the same cluster share many similarities. Units belonging to different clusters, on the other hand, have a wide range of features. The choice of the most acceptable variables for grouping must be determined at the initial stage of the cluster analysis. The variables used are determined by the theory used and the preferences of the researchers. However, the ratio of the number of variables to the sample size should be considered when selecting variables.

The grouping technique determines how clusters are generated. Clustering strategies vary depending on the optimisation goal, such as minimising variation between units in clusters or increasing the distance between units in different clusters [10]. Other techniques for grouping procedures exist, but they can be categorised into hierarchical and non-hierarchical methods [11].

Different distance measurements are used to generate clusters of units in hierarchical cluster analysis [12]. Clusters are generated by using variations within clusters in non-hierarchical cluster analysis. Additionally, in hierarchical cluster analysis, the total number of clusters is determined after the study is completed. However, in non-hierarchical cluster analysis, the final number of clusters is determined before the cluster analysis begins [12]. Units in hierarchical cluster analysis do not change their cluster affiliation, but this is a possibility in non-hierarchical cluster analysis. The stability and validity of the cluster solution are tested at the end [13]. If multiple clustering algorithms produce comparable results, the cluster solution can be considered stable. A cluster analysis was carried out with regard to the above factors.

The first phase involves undertaking a descriptive statistical study on the characteristics of 35 European countries. This study aims to understand better the differences between the countries studied. The analysis of descriptive statistics also serves as a foundation for cluster analysis.

The number of alternate partitions of n units in a k cluster is described by [14] as:

$$N(n,k) = \frac{1}{k!}\sum_{m=1}^{k}(-1)^{k-m}\binom{k}{m}m^{n} \tag{1}$$

where *n* is the number of units, *k* is the number of clusters. The problem is that even with a small *n* and *k*, the number of alternate partitions is still large. There are 35 European countries in the analysis, which implies that there are many different divisions. As a result, a non-hierarchical (partition) clustering technique was chosen to perform cluster analysis. The k-means approach is also used here because it is efficient in computer science and the most popular among scientists [15]. As its name implies, the k-mean grouping process deals with observing the means of clusters. An iterative process of simultaneously moving units to the cluster with the nearest mean is included in the k-mean grouping algorithm. A new cluster mean is then determined [13]. Obviously, there are several stages in the technique of grouping k-mean values.

In the first stage, the initial solution is determined by taking into account the specified number of clusters and starting centres or by observing the p-dimensional vector for each set:

$$x^{\sim m} = \left(x_1^{\sim m}, x_2^{\sim m}, \ldots, x_p^{\sim m}\right) \tag{2}$$

where $x_k^{\sim m}$ describes the k-th characteristic of the initial seed of cluster m [13]. Euclidean square distances can be used to calculate the distance between the ith unit and the initial seed of the cluster m as stated:

$$d_{ix^{\sim m}}^{2} = \sum_{k=1}^{p}\left(x_{ik} - x_k^{\sim m}\right)^2 \tag{3}$$

These distances are calculated for all clusters, and the ith unit is assigned to the cluster with the shortest distance. This allows all units to be assigned to specific clusters. The cluster mean is performed in the next step by flashing all units associated with a particular cluster. To achieve this, each of the dimensions of the p attribute is examined:

$$\bar{x}^m = \left(\bar{x}_1^m, \bar{x}_2^m, \dots, \bar{x}_p^m\right) \tag{4}$$

Subsequently, the cluster mean $\bar{x}^m$ replaces the initial seeds $x^{\sim m}$, and the distances between each unit and each cluster centre are recalculated using equation 3 [13].

As a result, units can "travel" from one cluster to another. This process continues until no units change their membership in the cluster. The cluster solution is then declared stable, and a final solution is reached. The contents of the cluster are then discussed and understood in the next stage.

This research uses the statistical program Statistica (version 13.1) to perform cluster analysis. The final cluster solution is performed by observing the average values of the six variables used in cluster analysis for units within the cluster. This explains the main properties of the units in clusters.

The v-fold cross-check strategy was chosen to identify a finite number of clusters in order to select the optimal number of clusters [16]. The data is initially split into v strata or subsamples of approximately similar size in a v-fold cross-validation procedure. In the following stages, each subsample is removed, and the remaining subsamples are used to estimate the value of the removed subsample. The estimated errors for all summed subsamples are compared with the errors from previous iterations. Finally, [17] select the solution with the lowest projected error rate. It has been shown that, in most cases, it is sufficient to extract 10 ($v = 10$) random subsamples from the data [16]. As a result, it was placed at the same number in our analysis.

Further restriction is imposed in order to obtain meaningful and interpretive clusters. As a result, the final cluster count should be somewhere between 2 and 25. If the relevant error function for a solution with a $k + 1$ cluster is not at least 5 % better than the solution with a k cluster, the solution with a k cluster is considered final [18].

Cluster analysis has emerged as a valuable tool in educational research, enabling the identification of distinct student profiles based on various learning behaviours and motivational factors. For example, cluster analysis has been used to explore how physical education students regulate their motivation, identifying unique combinations of intrinsic and extrinsic motivations that influence performance and engagement [19]. The method has been applied to categorise student behaviours in educational settings, highlighting how unsupervised techniques can reveal patterns in student engagement and academic performance [20]. Similarly, cluster analysis has been proven useful in examining the impact of external factors, such as the COVID-19 pandemic, on e-learning, identifying variations in response across different countries based on development levels [21]. Further research used cluster analysis to investigate employment trends in knowledge-intensive fields, emphasising gender disparities in European countries [22].

RESULTS

TREND OF LIFELONG LEARNING DEVELOPMENT IN SELECTED EUROPEAN COUNTRIES

Total number of completed PhDs per 1000 inhabitants

Table 1 shows the total number of completed PhDs per 1000 inhabitants. From 2013 to 2019, statistics for 35 European countries (EU member states plus Iceland, Norway, Montenegro, Macedonia, Serbia and Turkey) were collected from the European Commission's statistical database – Eurostat. The highest number of PhD graduates per 1000 inhabitants in 2019 was

Table 1. Completed PhDs, number per 1000 inhabitants (n.d. – no data).

Country / Year	2013	2014	2015	2016	2017	2018	2019
EU – 27 countries (as of 2020)	1.8	1.8	1.9	1.9	1.9	1.9	1.7
EU – 28 countries (2013-2020)	1.9	1.9	2.0	2.1	2.1	2.1	1.9
Belgium	1.7	1.8	1.9	2.0	2.0	2.1	2.0
Bulgaria	1.2	1.4	1.5	1.5	1.5	1.5	1.4
Czech Republic	1.6	1.7	1.7	1.7	1.7	1.7	1.7
Danish	2.9	3.2	3.3	3.2	3.2	2.9	2.8
Germany	2.7	2.8	2.9	2.8	2.7	2.6	2.7
Estonia	1.2	1.1	1.1	1.2	1.3	1.3	1.3
Ireland	2.1	2.5	2.1	2.4	2.2	2.3	2.5
Greece	1.0	1.1	1.3	1.5	1.5	1.3	1.5
Spain	1.6	1.8	1.9	2.6	3.7	3.2	1.8
France	1.7	1.7	1.8	1.7	1.7	1.7	1.7
Croatia	1.4	1.5	1.6	1.2	1.3	1.3	1.4
Italy	1.5	1.5	1.5	1.4	1.4	1.2	1.2
Cyprus	0.4	0.4	0.6	0.7	0.7	0.8	0.9
Latvia	1.1	0.9	0.9	0.7	0.5	0.5	0.5
Lithuania	1.2	1.1	1.1	0.9	0.9	0.9	0.9
Luxembourg	0.8	1.0	1.3	1.2	1.7	1.5	1.1
Hungary	0.8	0.9	1.0	1.0	1.0	1.0	1.0
Malta	0.4	0.3	0.5	0.5	0.7	0.7	0.5
Netherlands	2.1	2.2	2.3	2.4	2.2	2.2	n.d.
Austria	2.0	2.0	1.9	1.9	2.2	2.3	1.8
Poland	0.6	0.6	0.6	0.6	0.5	0.6	0.7
Portugal	1.9	2.0	1.9	2.0	1.8	2.0	1.9
Romania	1.9	1.4	1.5	0.8	0.7	0.7	0.8
Slovenia	4.0	3.5	3.5	3.8	1.9	1.8	1.9
Slovakia	2.4	2.5	2.2	2.1	2.0	1.7	1.8
Finnish	2.8	2.9	2.9	2.9	2.6	2.6	2.5
Sweden	2.8	2.9	2.9	2.7	2.7	2.3	2.3
Island	1.2	1.9	1.4	1.5	1.3	1.2	1.7
Liechtenstein	2.6	3.7	2.8	5.7	5.6	3.5	5.7
Norway	2.3	2.1	2.0	1.9	2.1	2.1	2.2
Switzerland	3.3	3.5	3.4	3.4	3.6	3.6	3.7
United Kingdom	3.0	2.9	3.0	3.1	3.1	3.3	3.3
North Macedonia	0.7	0.6	0.8	0.6	0.6	0.8	0.6
Serbia	n.d.	0.8	1.1	1.1	1.7	1.0	0.9
Turkey	n.d.	0.4	0.4	0.5	0.5	0.6	0.6

observed in economically advanced Western European countries, with Liechtenstein leading at 5,7, followed by Switzerland (3,7), the United Kingdom (3,3), Denmark (2,8), Germany (2,7), Ireland (2,5), and Finland (2,5). These figures remained stable between 2013 and 2019. In contrast, countries such as Cyprus (0.9), Latvia (0,5), Poland (0,5), and Turkey (0,6) recorded significantly lower rates, lagging the EU average of 1,9 PhDs per 1000 inhabitants during the same period. The data suggests that PhD attainment is more concentrated in economically and socially developed nations, with expectations of growth in developing countries as their education systems improve.

Total number of completed PhDs per 1000 population aged 25 to 34

To extend the analysis, Table 2 shows the total number of PhD graduates aged 25 to 34 per 1000 population for the period from 2013 to 2019. Data are not available for the European Union average in 2013 and 2014, the Netherlands in 2019, Romania for the period 2014-2017, and Serbia and Turkey for 2013. It can be noted that Germany (2,1 per 1000 inhabitants aged 25 to 34), Liechtenstein (2,1 per 1000 inhabitants aged 25 to 34), Switzerland (2,9 per 1000 inhabitants aged 25 to 34) and the United Kingdom (2,0 per 1000 inhabitants aged 25 to 34) achieved a significantly higher number of PhDs in 2019 compared to other countries and the European Union average for the period 2013 to 2019 which was 1,4 per 1000 residents from 25 to 34 years old. Indeed, doctoral studies are vital for determining the future career of scientists in the labour market, and Eastern European researchers are in a somewhat worse situation than their counterparts from Western Europe and the Nordic countries.

Table 2. Completed PhDs aged 25-34, number per 1000 population (n.d. – no data)**.** Source: Eurostat.

Country / Year	2013	2014	2015	2016	2017	2018	2019
EU – 27 countries (as of 2020)	n.d.	n.d.	1.3	1.3	1.3	1.3	1.2
EU – 28 countries (2013-2020)	1.4	1.3	1.4	1.4	1.4	1.4	1.4
Belgium	1.3	1.4	1.4	1.5	1.5	1.6	1.6
Bulgaria	0.4	0.5	0.5	0.6	0.6	0.6	0.5
Czech Republic	1.1	1.2	1.2	1.1	1.2	1.2	1.1
Danish	2.0	2.3	2.3	2.2	2.2	2.0	2.0
Germany	2.2	2.3	2.3	2.2	2.1	2.1	2.1
Estonia	0.8	0.7	0.6	0.8	0.8	0.8	0.8
Ireland	1.5	1.8	1.4	1.6	1.4	1.4	1.5
Greece	0.5	0.4	0.5	0.7	0.6	0.5	0.6
Spain	0.9	1.0	1.1	1.2	1.2	1.5	1.1
France	1.2	1.2	1.2	1.2	1.4	1.4	1.4
Croatia	0.8	0.8	0.8	0.5	0.6	0.5	0.5
Italy	1.2	1.1	1.2	1.1	1.1	1.0	1.0
Cyprus	0.3	0.3	0.3	0.5	0.4	0.6	0.6
Latvia	0.5	0.5	0.5	0.4	0.2	0.2	0.3
Lithuania	0.8	0.8	0.8	0.6	0.7	0.7	0.6
Luxembourg	0.7	0.8	1.1	1.0	1.3	1.2	1.1
Hungary	0.5	0.6	0.6	0.6	0.6	0.7	0.6
Malta	0.2	0.2	0.2	0.2	0.4	0.3	0.2
Netherlands	1.8	1.9	1.9	2.0	1.9	1.8	n.d.
Austria	1.5	1.5	1.4	1.4	1.4	1.3	1.3
Poland	0.5	0.4	0.5	0.5	0.4	0.5	0.5
Portugal	0.8	0.8	0.7	0.8	0.8	0.8	0.8
Romania	1.1	n.d.	n.d.	n.d.	n.d.	0.4	0.4
Slovenia	2.7	2.0	2.0	4.0	1.2	1.1	1.0
Slovakia	1.8	1.8	1.7	1.6	1.5	1.3	1.3
Finnish	1.2	1.3	1.3	1.3	1.1	1.2	1.1
Sweden	1.6	1.7	1.7	1.6	1.5	1.3	1.3
Island	0.6	0.9	0.6	0.8	0.6	0.5	0.9
Liechtenstein	1.5	1.5	1.5	2.6	2.6	1.5	2.1
Norway	1.2	1.1	0.9	1.0	1.0	1.0	1.1
Switzerland	2.6	2.7	2.6	2.7	2.8	2.8	2.9
United Kingdom	1.9	1.8	1.9	1.9	2.0	2.0	2.0
North Macedonia	0.2	0.2	0.2	0.2	0.2	0.2	0.3
Serbia	n.d.	0.3	0.4	0.5	0.5	0.5	0.4
Turkey	n.d.	0.2	0.3	0.3	0.3	0.3	0.3

Total number of male PhDs per 1000 inhabitants

Table 3 shows the number of male graduates per 1000 inhabitants. As for the number of male graduates per 1000 inhabitants in the period from 2013 to 2019, it can be noted that Cyprus is recording an increasing trend in the number of male PhDs, in contrast to Italy, Latvia, Lithuania, Slovenia, Slovakia, Romania which has been recording a decline over the years. The average of the 28 countries in the European Union for the period 2013-2020 seems to maintain a stable trend in terms of male graduates at doctoral level over the years (≈ 1,1 men per 1000 inhabitants). The highest number of PhD graduates was recorded in Belgium (1,2 men per 1000 population), Denmark (1,4 men per 1000 population), Germany (1,5 men per 1000 population),

Table 3. Completed PhDs**,** number of men per 1000 inhabitants (n.d. – no data). Source: Eurostat.

Country / Year	2013	2014	2015	2016	2017	2018	2019
EU – 27 countries (as of 2020)	0.9	0.9	1.0	1.0	1.0	1.0	0.9
EU – 28 countries (2013-2020)	1.0	1.0	1.1	1.1	1.1	1.1	1.0
Belgium	1.0	1.0	1.1	1.1	1.1	1.2	1.2
Bulgaria	0.6	0.7	0.7	0.7	0.7	0.7	0.6
Czech Republic	0.9	1.0	0.9	1.0	1.0	1.0	1.0
Danish	1.6	1.7	1.7	1.7	1.6	1.5	1.4
Germany	1.5	1.5	1.6	1.5	1.5	1.4	1.5
Estonia	0.5	0.5	0.5	0.6	0.6	0.7	0.6
Ireland	1.1	1.3	1.1	1.2	1.1	1.1	1.2
Greece	0.6	0.6	0.7	0.8	0.8	0.7	0.8
Spain	0.8	0.9	1.0	1.3	1.8	1.5	0.9
France	1.0	0.9	1.1	1.0	0.9	1.0	1.0
Croatia	0.7	0.7	0.7	0.5	0.6	0.6	0.6
Italy	0.7	0.7	0.7	0.7	0.7	0.6	0.6
Cyprus	0.2	0.2	0.3	0.3	0.3	0.4	0.4
Latvia	0.5	0.4	0.4	0.3	0.2	0.2	0.2
Lithuania	0.5	0.5	0.5	0.4	0.4	0.4	0.4
Luxembourg	0.5	0.6	0.7	0.7	0.9	1.0	0.7
Hungary	0.4	0.5	0.5	0.5	0.5	0.6	0.5
Malta	0.2	0.3	0.2	0.3	0.4	0.3	0.3
Netherlands	1.1	1.2	1.2	1.2	1.2	1.1	n.d.
Austria	1.1	1.1	1.1	1.1	1.2	1.3	1.1
Poland	0.3	0.3	0.3	0.3	0.2	0.3	0.3
Portugal	0.8	0.9	0.9	0.9	0.8	0.9	0.9
Romania	0.9	0.7	0.7	0.4	0.3	0.3	0.4
Slovenia	1.8	1.5	1.5	5.3	1.0	0.8	0.9
Slovakia	1.2	1.3	1.1	1.0	1.0	0.9	0.9
Finnish	1.4	1.4	1.4	1.4	1.2	1.3	1.2
Sweden	1.5	1.6	1.6	1.5	1.5	1.2	1.3
Island	0.6	0.8	0.7	0.5	0.4	0.5	0.8
Liechtenstein	1.1	2.8	1.5	3.5	3.5	1.9	4.2
Norway	1.2	1.1	1.0	1.0	1.0	1.0	1.1
Switzerland	1.9	2.0	1.9	1.9	2.0	2.0	2.0
United Kingdom	1.6	1.5	1.6	1.7	1.7	1.7	1.7
North Macedonia	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Serbia	n.d.	0.4	0.5	0.5	0.7	0.4	0.5
Turkey	n.d.	0.2	0.2	0.3	0.2	0.3	0.3

Ireland (1,2 men per 1000 population), Austria (1,1 men per 1000 population), Finland (1,2 men per 1000 population), Sweden (1,3 men per 1000 population), Norway (1,1 men per 1000 population), Switzerland (2,0 men per 1000 inhabitants), the United Kingdom (1,7 men per 1000 inhabitants) with a significantly higher number in Liechtenstein (4,2 men per 1000 inhabitants). The data show that there is a significantly lower number of male graduates in doctoral studies in Cyprus (0,4 men per 1000 population), Latvia (0,2 men per 1000 population), Lithuania (0,4 men per 1000 population), Malta (0,3 men per 1000 population), Poland (0,3 men per 1000 population), Romania (0,4 men per 1000 population), North Macedonia (0,3 men per 1000 population), Serbia (0,5 men per 1000 inhabitants) and Turkey (0,3 men per 1000 inhabitants).

Total number of completed male PhDs per 1000 inhabitants aged 25 to 34

Furthermore, Table 4 presents data on the total number of male doctoral students aged 25 to 34 per 1000 population. It can be noted that the average of the European Union for the 28 countries for the period 2013 and 2020 is stable, as well as in the Netherlands, Poland, and North Macedonia. In addition, an increasing trend in the number of PhD holders over the years can be observed in Belgium, France, and Switzerland, while the opposite is true for Lithuania and Sweden.

Table 4. Completed male PhDs, age 25-34 per 1000 inhabitants (n.d. – no data). Source: Eurostat (continued on p.772).

Country / Year	2013	2014	2015	2016	2017	2018	2019
EU – 27 countries (as of 2020)	n.d.	n.d.	0.7	0.7	0.7	0.7	0.7
EU – 28 countries (2013-2020)	0.7	0.7	0.7	0.7	0.7	0.7	0.7
Belgium	0.7	0.7	0.8	0.8	0.8	0.9	0.9
Bulgaria	0.2	0.2	0.3	0.3	0.3	0.2	0.2
Czech Republic	0.6	0.7	0.7	0.6	0.7	0.7	0.6
Danish	1.2	1.3	1.3	1.3	1.2	1.1	1.1
Germany	1.2	1.2	1.2	1.2	1.1	1.1	1.1
Estonia	0.3	0.4	0.4	0.4	0.4	0.4	0.4
Ireland	0.8	0.9	0.7	0.8	0.7	0.7	0.8
Greece	0.3	0.2	0.3	0.3	0.3	0.3	0.3
Spain	0.4	0.4	0.5	0.5	0.5	0.7	0.5
France	0.7	0.7	0.7	0.7	0.8	0.8	0.8
Croatia	0.3	0.4	0.3	0.2	0.3	0.2	0.3
Italy	0.6	0.5	0.6	0.5	0.6	0.5	0.5
Cyprus	0.1	0.1	0.1	0.2	0.2	0.3	0.2
Latvia	0.3	0.2	0.2	0.2	0.1	0.1	0.1
Lithuania	0.4	0.4	0.4	0.3	0.3	0.3	0.3
Luxembourg	0.4	0.5	0.6	0.6	0.7	0.7	0.6
Hungary	0.3	0.3	0.3	0.3	0.3	0.4	0.3
Malta	0.1	0.2	0.1	0.1	0.2	0.2	0.1
Netherlands	1.0	1.0	1.0	1.0	1.0	1.0	n.d.
Austria	0.8	0.9	0.8	0.8	0.8	0.8	0.8
Poland	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Portugal	0.4	0.4	0.3	0.3	0.3	0.4	0.4
Romania	0.5	n.d.	n.d.	n.d.	n.d.	0.2	0.2
Slovenia	1.3	0.9	0.9	1.6	0.7	0.5	0.5
Slovakia	0.8	0.9	0.8	0.7	0.7	0.6	0.6
Finnish	0.7	0.7	0.7	0.7	0.6	0.7	0.6
Sweden	1.0	1.0	1.0	1.0	0.9	0.8	0.8

Table 4. Completed male PhDs, age 25-34 per 1000 inhabitants (n.d. – no data). Source: Eurostat (continuation from p.771).

Country / Year	2013	2014	2015	2016	2017	2018	2019
Island	0.3	0.4	0.4	0.3	0.2	0.2	0.5
Liechtenstein	0.4	0.9	0.9	1.3	1.3	0.6	1.5
Norway	0.7	0.6	0.5	0.5	0.6	0.6	0.6
Switzerland	1.4	1.5	1.5	1.5	1.5	1.6	1.6
United Kingdom	1.0	1.0	1.0	1.1	1.1	1.1	1.1
North Macedonia	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Serbia	n.d.	0.1	0.2	0.2	0.2	0.2	0.2
Turkey	n.d.	0.1	0.1	0.1	0.1	0.2	0.1

Total number of completed female PhDs per 1000 population

Table 5 represents the total number of female PhD graduates aged 25 to 34 per 1000 population. It is worth noting that the European Union average for the 27 countries as of 2020 has been quite stable over time. In addition, the number of individuals with PhDs increased over the years in Belgium, France, and Switzerland). A positive trend in the analysed period can be observed in Belgium, Bulgaria, Poland, Switzerland, and Turkey, while Italy, Lithuania, and Romania recorded the opposite trend.

Table 5. Completed PhDs, number of women per 1000 inhabitants (n.d. – no data). Source: Eurostat (continued on p.773).

Country / Year	2013	2014	2015	2016	2017	2018	2019
EU - 27 countries (as of 2020)	0.9	0.9	0.9	0.9	0.9	0.9	0.8
EU - 28 countries (2013-2020)	0.9	0.9	1.0	1.0	1.0	1.0	0.9
Belgium	0.7	0.8	0.8	0.9	0.9	0.9	0.9
Bulgaria	0.6	0.7	0.7	0.8	0.8	0.8	0.8
Czech Republic	0.7	0.7	0.7	0.7	0.7	0.8	0.7
Danish	1.3	1.5	1.6	1.6	1.5	1.4	1.4
Germany	1.2	1.3	1.3	1.3	1.2	1.2	1.2
Estonia	0.7	0.6	0.6	0.7	0.8	0.6	0.7
Ireland	1.0	1.2	1.0	1.2	1.1	1.2	1.3
Greece	0.5	0.6	0.6	0.8	0.7	0.6	0.7
Spain	0.8	0.9	1.0	1.3	1.8	1.7	0.9
France	0.8	0.7	0.7	0.7	0.8	0.8	0.8
Croatia	0.8	0.8	0.9	0.6	0.7	0.7	0.8
Italy	0.8	0.8	0.8	0.7	0.7	0.6	0.6
Cyprus	0.2	0.2	0.3	0.4	0.3	0.4	0.5
Latvia	0.6	0.6	0.5	0.4	0.3	0.2	0.3
Lithuania	0.7	0.7	0.7	0.5	0.5	0.5	0.5
Luxembourg	0.3	0.4	0.6	0.5	0.8	0.5	0.5
Hungary	0.4	0.4	0.4	0.5	0.4	0.5	0.5
Malta	0.2	0.1	0.2	0.2	0.4	0.3	0.2
Netherlands	1.0	1.0	1.1	1.2	1.1	1.1	n.d.
Austria	0.9	0.8	0.8	0.8	1.0	1.0	0.8
Poland	0.3	0.3	0.3	0.3	0.3	0.4	0.4
Portugal	1.0	1.1	1.0	1.1	1.0	1.1	1.0
Romania	1.0	0.7	0.8	0.5	0.4	0.4	0.4
Slovenia	2.1	1.9	2.0	8.4	0.9	1.0	1.0
Slovakia	1.2	1.2	1.1	1.1	1.0	0.8	0.9

Table 5. Completed PhDs, number of women per 1000 inhabitants (n.d. – no data). Source: Eurostat (continuation from p.772).

Country / Year	2013	2014	2015	2016	2017	2018	2019
Finnish	1.4	1.5	1.5	1.5	1.4	1.4	1.3
Sweden	1.3	1.4	1.3	1.2	1.2	1.1	1.0
Island	0.6	1.1	0.8	1.0	0.9	0.7	0.9
Liechtenstein	1.5	0.9	1.3	2.2	2.2	1.5	1.5
Norway	1.1	1.0	1.0	1.0	1.0	1.0	1.1
Switzerland	1.5	1.5	1.5	1.5	1.6	1.6	1.7
United Kingdom	1.4	1.3	1.4	1.4	1.5	1.5	1.6
North Macedonia	0.4	0.3	0.4	0.3	0.4	0.4	0.4
Serbia	n.d.	0.4	0.6	0.6	1.0	0.6	0.5
Turkey	n.d.	0.2	0.2	0.2	0.2	0.3	0.3

Total number of completed female PhDs per 1000 population from 25 to 34 years

From 2013 to 2019, the number of women's PhDs increased in Bulgaria, Greece, France, Hungary, Switzerland, and Turkey, while in Italy and Sweden, the number of women earning PhDs decreased over time. Between 2013 and 2020, the European Union average of 28 countries seems to have maintained a steady trend in terms of the number of women with doctorates, as well as in the Czech Republic, Austria and North Macedonia. According to the data, there are significantly fewer female PhD students in Bulgaria (0,3 women aged 25-34 per 1000 population), Greece (0,3 women aged 25-34 per 1000 population), Croatia (0,3 women aged 25-34 per 1000 population), Latvia (0,1 women aged 25-34 per 1000 population), Lithuania (0,3 women aged 25-34 per 1000 population), Hungary (0,3 women aged 25-34 per 1000 population), Malta (0,1 women aged 25-34 per 1000 population), Poland (0,3 women aged 25-34 per 1000 population), Romania (0,2 women aged 25-34 per 1000 population), North Macedonia (0,1 women aged 25-34 per 1000 population), Serbia (0,2 women aged 25-34 per 1000 population) and Turkey (0,2 women aged 25-34 per 1000 inhabitants) compared to Germany (1,1 women aged 25-34 per 1000 inhabitants) and Switzerland (1,3 women aged 25-34 per 1000 inhabitants).

Table 6. Completed PhDs, number of women aged 25-34 per 1000 population (n.d. – no data). Source: Eurostat (continued on p.774).

Country / Year	2013	2014	2015	2016	2017	2018	2019
EU - 27 countries (as of 2020)	n.d.	n.d.	0.6	0.7	0.6	0.6	0.6
EU - 28 countries (2013-2020)	0.6	0.6	0.7	0.7	0.7	0.7	0.6
Belgium	0.6	0.6	0.6	0.8	0.7	0.7	0.7
Bulgaria	0.2	0.2	0.3	0.3	0.3	0.3	0.3
Czech Republic	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Danish	0.8	1.0	1.0	0.9	0.9	0.9	0.9
Germany	1.0	1.1	1.0	1.0	1.0	1.0	1.0
Estonia	0.5	0.3	0.3	0.4	0.5	0.4	0.4
Ireland	0.7	0.9	0.6	0.8	0.7	0.7	0.8
Greece	0.2	0.2	0.2	0.3	0.3	0.3	0.3
Spain	0.5	0.5	0.6	0.7	0.7	0.9	0.6
France	0.5	0.5	0.5	0.5	0.6	0.6	0.6
Croatia	0.4	0.4	0.5	0.3	0.3	0.3	0.3
Italy	0.6	0.6	0.6	0.6	0.6	0.5	0.5
Cyprus	0.2	0.2	0.2	0.3	0.2	0.3	0.3
Latvia	0.2	0.3	0.3	0.2	0.1	0.1	0.1

Table 6. Completed PhDs, number of women aged 25-34 per 1000 population (n.d. – no data). Source: Eurostat (continuation from p.773).

Country / Year	2013	2014	2015	2016	2017	2018	2019
Lithuania	0.5	0.4	0.4	0.3	0.4	0.4	0.3
Luxembourg	0.3	0.3	0.5	0.4	0.7	0.5	0.4
Hungary	0.2	0.3	0.3	0.3	0.3	0.3	0.3
Malta	0.1	0.0	0.1	0.1	0.2	0.2	0.1
Netherlands	0.8	0.9	0.9	1.0	0.9	0.9	n.d.
Austria	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Poland	0.3	0.2	0.3	0.3	0.2	0.3	0.3
Portugal	0.4	0.4	0.4	0.5	0.4	0.4	0.4
Romania	0.6	n.d.	n.d.	n.d.	n.d.	0.2	0.2
Slovenia	1.4	1.1	1.1	2.5	0.6	0.6	0.5
Slovakia	1.0	1.0	0.9	0.9	0.7	0.7	0.6
Finnish	0.5	0.6	0.6	0.6	0.5	0.5	0.5
Sweden	0.7	0.7	0.6	0.6	0.6	0.5	0.5
Island	0.3	0.5	0.2	0.4	0.3	0.3	0.4
Liechtenstein	1.1	0.6	0.6	1.3	1.3	0.9	0.6
Norway	0.5	0.5	0.4	0.4	0.4	0.4	0.5
Switzerland	1.1	1.2	1.2	1.2	1.2	1.2	1.3
United Kingdom	0.9	0.8	0.9	0.9	0.9	0.9	0.9
North Macedonia	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Serbia	n.d.	0.1	0.2	0.3	0.3	0.3	0.2
Turkey	n.d.	0.1	0.1	0.2	0.2	0.2	0.2

ANALYSIS OF THE HOMOGENEITY OF LIFELONG LEARNING IN SELECTED EUROPEAN COUNTRIES

Description of data

Table 7 provides an overview of the variables used in the analysis, along with their abbreviations, descriptions, and their measurements. A total of seven variables were used to determine the number of units with homogeneous characteristics. Data were collected from the Eurostat database for 2019 for 35 European countries, including the Czech Republic, Ireland, Spain, France, the Netherlands, Austria, Portugal, Slovenia, Slovakia, Finland, Sweden, Iceland, Norway, Estonia, Greece, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Poland, Romania, North Macedonia, Serbia, Turkey, Denmark, Germany (former FRG territory until 1990), Liechtenstein, Switzerland and the United Kingdom.

Table 7. Variable names.

Abbreviation	Description of the variable	Measurement
ALL	Number of PhD graduates	Per 1000 inhabitants
25_34	Number of PhD graduates aged 25 to 34	Per 1000 inhabitants
M_ALL	Number of male PhD graduates	Per 1000 inhabitants
M_25_34	Number of male PhD graduates from 25 to 34 years	Per 1000 inhabitants
F_ALL	Number of female PhD graduates	Per 1000 inhabitants
F_25_34	Number of female PhD graduates aged 25 to 34	Per 1000 inhabitants
GDP_pc	GDP per capita	Per 1000 inhabitants

Table 8 presents the variables included in the analysis and their descriptions. Based on these variables, K-means was used for the grouping procedure.

Table 8. Variable descriptions.

Abbreviation	Variable	Description
ALL	PhD Graduates (per 1000 inhabitants)	The number of individuals who have completed a PhD normalised per 1000 people in the total population.
25_34	PhD Graduates (per 1000 population, aged 25-34 years)	The number of PhD graduates among people aged 25 to 34 is normalised per 1000 individuals in that age group.
M_ALL	PhD Graduates (per 1000 inhabitants, men)	The number of men who have completed a PhD normalised per 1000 men in the total population.
M_25_34	PhD Graduates (per 1000 population, aged 25-34 years, men)	The number of male PhD graduates aged 25 to 34 normalised per 1000 men in that age range.
F_ALL	PhD Graduates (per 1000 population, women)	The number of women who have completed a PhD normalised per 1000 women in the total population.
F_25_34	PhD Graduates (per 1000 population, aged 25-34 years, women)	The number of female PhD graduates aged 25 to 34 normalised per 1000 women in that age group.
GDP_pc	GDP per capita	GDP per capita in 2019 in EUR

Descriptive analysis

A total of seven variables were used for the analysis, Table 9. It contains the results of descriptive statistics of variables. It should be noted that the analysis used data from 2019 for 35 European countries. The median and mean were used as measures for the central tendency. The mean value of the variables ranges from 0,49 for PhD students in the age group from 25 to 34 years is 1,76 for the total number of PhD graduates for 2019 and the average GDP per capita of 40 775,47.

Furthermore, it can be observed that the mean values for all variables are lower than the mean values, suggesting that the data is skewed to the right. The coefficient of variation for the dataset includes a high value of 84,45 for GDP per capita and a lowest value of 46,51 for the total number of female doctors. Furthermore, the standard deviation ranges for the dataset range from 0,28 for female PhD graduates within the 25-34 age group and 1,05 for the total number of PhD students.

The minimum value of data for the observed variable ranges from 0,10 for male doctoral students in the age group 25-34 years and 1,30 for the total number of female graduates in the age group 25-34 years, while the minimum value of data for GDP per capita is 6 070,40.

On the other hand, it can be noted that the maximum value of the data ranges from 1,30 for female graduates aged from 25 to 34 and 5,70 for the total number of graduates in 2019. The maximum value for GDP per capita is 175814,00. The values for the lower and upper quartiles are also shown in Table 9.

The Pearson correlation matrix for the six observed variables is shown in Table 10. Scattering diagrams of the research variables are shown in Figure 1.

Table 9. Results of descriptive statistics for seven observed variables, n = 35, data from 2019.

Indicator	Variable						
	ALL	25_34	M_ALL	M_25_34	F_ALL	F_25_34	GDP_PC
Average	1.76	1.06	0.94	0.57	0.83	0.49	40775.47
Median	1.70	1.00	0.90	0.50	0.80	0.50	29555.30
Standard deviation	1.05	0.64	0.71	0.39	0.39	0.28	34435.42
Coefficient of variation	59.77	60.42	75.85	68.88	46.51	56.77	84.45
Skewness	1.71	0.88	2.96	0.92	0.46	0.91	2.14
Kurtosis	4.71	0.52	12.48	0.43	-0.46	0.86	6.11
Minimum	0.50	0.20	0.20	0.10	0.20	1.30	6070.40
Maximum	5.70	2.90	4.20	1.60	1.70	1.30	175814.00
Lower quartile	0.90	0.50	0.50	0.20	0.50	0.30	17926.80
Upper quartile	2.20	1.40	1.20	0.80	1.10	0.60	51939.00

Table 10. Pearson correlation matrix, h = 6 variables, n = 35 European countries.

	ALL	25_34	M_ALL	M_25_34	F_ALL	F_25_34
ALL	1					
25_34	0.8474***	1				
M_ALL	0.9701***	0.7708***	1			
M_25_34	0.8997***	0.9834***	0.8525***	1		
F_ALL	0.9066***	0.8745***	0.7795***	0.8685***	1	
F_25_34	0.7343***	0.9627***	0.6122***	0.9091***	0.8537***	1

***statistically significant correlations at the significance level of 1 %

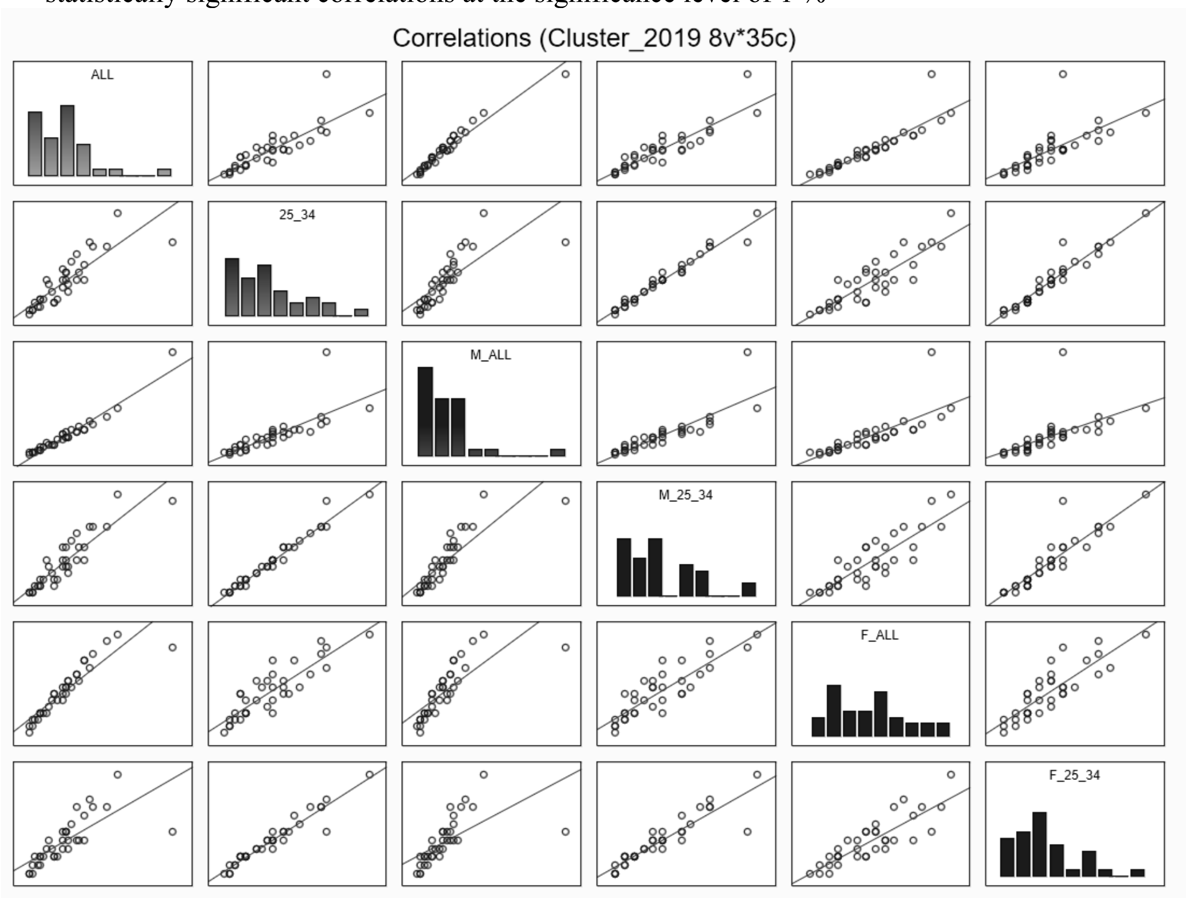

Figure 1. Scattering diagram of observed variables.

The correlation matrix presents significant associations between PhD graduation rates across different demographic groups. Notably, the correlation between PhD graduates in the total population and those aged 25-34 (r = 0,8474***) suggests a strong alignment between overall PhD trends and the younger age cohort. A similar pattern is observed between male and female PhD graduates, with high correlations both in the total population (r = 0,9066***) and within the 25-34 age group (r = 0,8537***). However, the relatively lower correlation between male PhD graduates (M_ALL) and female graduates aged 25-34 (r = 0,6122***) hints at potential gender-specific dynamics in the younger cohort, warranting further investigation into gender disparities. Additionally, the strong correlation between PhD graduates among younger men and women (r = 0,9091***) reflects consistent patterns of educational attainment in the 25-34 age group, suggesting that trends in male and female PhD graduation rates within this cohort are closely related. Overall, these findings highlight both the similarities and nuanced differences across demographic segments in PhD attainment.

k-Means cluster analysis

Statistical non-hierarchical cluster analysis was used to group the observed countries. A k-mean grouping algorithm was used. The greatest average distance technique was used to obtain the first centroids or estimates. The new centroids were calculated using all the analysed countries assigned to them after all countries were assigned to the nearest centroid. Euclidean square distances were used as a measure of distance to give more weight to countries that were farther away from the centroid [23].

This grouping technique has been carried out 50 times. However, it should be noted that before any calculations, the variables are normalised individually using the built-in data normalisation feature in the computer software. The minimum and maximum values of the observed variables, as well as the data, are translated into a predefined range during the normalisation process. As a result, the accuracy of clustering algorithms increases, thereby improving the ability to establish high-quality clusters [24].

The rule of thumb [25], cross-checking, the elbow technique, access to information criteria [26], and kernel matrix [27] are just a few of the ways to find the exact number of clusters. Due to the limitations of the computer program used (Statistica), the final number of clusters will be determined using the v-fold cross-check procedure.

The cost sequence graph, shown in Figure 2, reveals that the three-cluster solution is the best. The cost sequence graph shows the error function for different cluster solutions, which is defined as the average observation distance in subsamples to the cluster's assigned hubs [28]. Variations in cluster costs or errors between solutions with two to three clusters are considered significant. In other words, as the number of clusters increases, the error decreases by more than 5 % compared to a cluster solution with one cluster less. On the other hand, the error difference between solutions with two and three clusters is less than 5 %. As a result, a three-cluster solution was chosen as the best option.

The ANOVA analysis for 3 clusters shows that the null hypothesis is rejected at the 1 % level, showing that the solution of using 3 groups is appropriate, Table 11.

Table 12 shows the mean values of clusters of research variables, while Figure 3. It shows the distribution of research variables among clusters.

The mean values of the studied variables in clusters are shown in Figure 3.

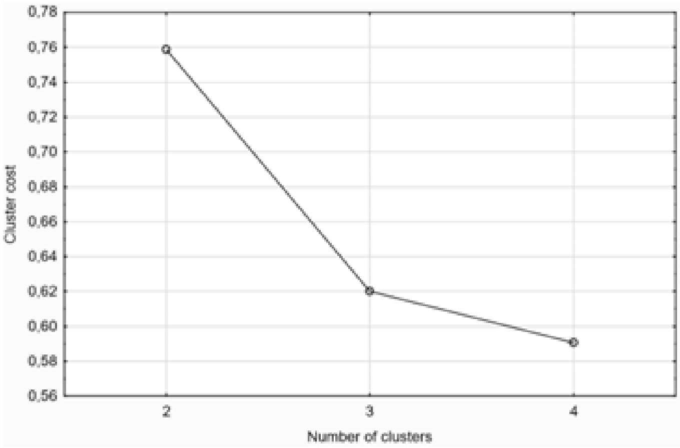

Figure 2. Cost sequence chart.

Table 11. ANOVA analysis, k-mean grouping, h = 6 variables, k = 3 clusters, n = 35 European countries.

	Between SS	Df	Within SS	Df	F	p-value
ALL	28.814	2.000	8.691	32.000	53.044	0.000
25_34	11.424	2.000	2.520	32.000	72.550	0.000
M_ALL	11.143	2.000	6.141	32.000	29.035	0.000
M_25_34	4.239	2.000	0.976	32.000	69.504	0.000
F_ALL	4.098	2.000	1.021	32.000	64.221	0.000
F_25_34	1.905	2.000	0.710	32.000	42.944	0.000

Table 12. Average values by cluster, cluster analysis of k-mean values, h = 6 variables, n = 35 European countries, 2019.

	Cluster 1	Cluster 2	Cluster 3
ALL	2.00	0.96	3.64
25_34	1.24	0.54	2.22
M_ALL	1.04	0.47	2.16
M_25_34	0.67	0.26	1.28
F_ALL	0.98	0.51	1.48
F_25_34	0.58	0.27	0.94
Number of cases	14	16	5
age, %	40.00	45.71	14.29

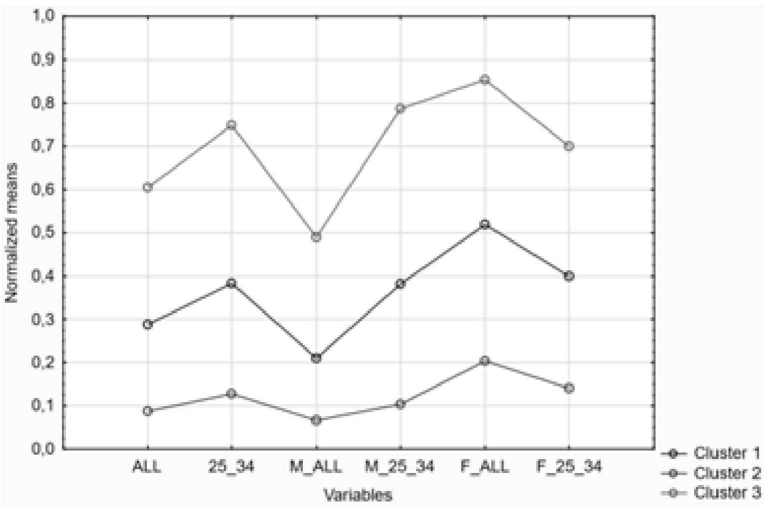

Figure 3. Average values of research variables by cluster.

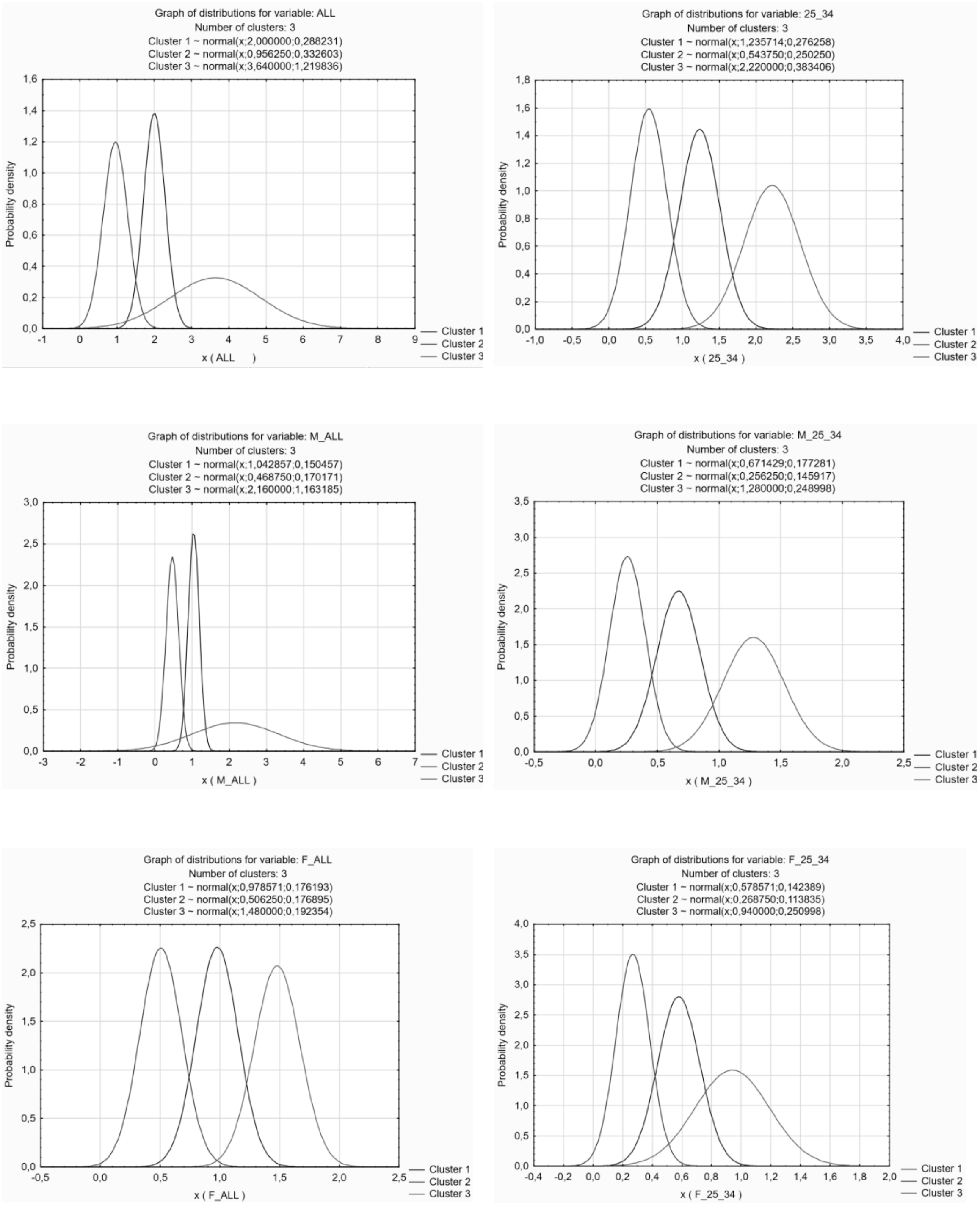

Figure 4. Distribution of research variables by cluster.

Figure 3 shows the distributions of all six observed research variables for the analysed countries. Distributions can be used to observe the degree to which countries differ in a cluster based on the observed variable. The smaller the gap between countries, the narrower the distribution. Knowing the probability density function for a sample of data can help us determine whether a particular observation is plausible or so unlikely that it can be labelled extraordinary or anomalous and should be ruled out. It is quite useful for selecting acceptable learning methods that require certain probability distributions in the input data.

This study uses data from 2019 for cluster analysis for 35 European countries. According to the factors studied, we found three groups with significant differences: the total number of doctoral graduates per thousand inhabitants, the total number of doctoral graduates aged 25 to

34 per thousand inhabitants, the total number of male graduates at the doctoral level per thousand inhabitants, the total number of male graduates at the doctoral level aged 25 to 34 per thousand inhabitants, the total number of female graduates at the doctoral level per thousand inhabitants and the total number of female graduates aged 25 to 34 per thousand inhabitants.

Table 13 lists the countries by cluster, and the Western Balkan countries fall into groups C1 and C2. Cluster 1 consists of 13 countries, including the Czech Republic, Ireland, Spain, France, Netherlands, Austria, Portugal, Slovenia, Slovakia, Finland, Sweden, Iceland, and Norway. The countries belong to different geographical regions such as Scandinavia (Iceland, Norway, Sweden, and Finland), Central Europe (Austria, Czech Republic, Slovakia), Southeastern Europe (Slovenia), Southern Europe (Portugal, Spain), Western Europe (France, Netherlands), and Northwestern Europe (Ireland). This cluster is the most diverse with regard to the geographical position of the countries. All countries are members of the EU. To improve the quality and openness of EU Member States' education and training systems, the European Union has two types of instruments: a set of policy instruments that encourage EU countries to develop their education systems and learn from each other's successes and a significant programme to support exchanges, networks and mutual learning between schools, universities or training centres, as well as between political authorities.

Cluster 2 consists of 15 European countries: Estonia, Greece, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Poland, Romania, North Macedonia, Serbia, and Turkey. Six countries belong to the Western Balkans (Greece, Croatia, Cyprus, Romania, North Macedonia, Serbia and Turkey). The levels of educational achievement in the countries of this region are different. Despite the fact that the Balkans have experienced multiple conflicts in recent years, they have made progress towards democratic societies and improved their economic infrastructure. However, there are still countries with flawed democracies and those with thriving economies where gains in terms of basic freedoms, the rule of law and democratic governance are not yet durable or irreversible. The EU's capacity to convey democracy through its enlargement agenda is failing to deliver on its promise to give democracy to these countries in the EU accession process (North Macedonia, Serbia and Turkey), and the area is becoming increasingly vulnerable to authoritarian governments.

Furthermore, this cluster includes countries from the Baltic Sea region (Estonia, Latvia and Lithuania), known as the "Baltic states". The key goals of the three countries are to establish a free and open market economy, to open up globally within the EU, to reform science and research, and to increase innovation. The Baltic countries have significantly changed their economies and scientific systems in the years since independence, gaining full membership in the European Union. Other countries in this cluster belong to Central Europe (Hungary and Poland), South-Central Europe (Italy) and the Mediterranean region of Europe (Malta). All these countries are members of the EU. This cluster shares similar characteristics and the lowest level of educational achievement compared to Cluster 1 and Cluster 3.

Cluster 3 has the highest level of cluster mean, as shown in Figure 4. The most distinctive attribute of this cluster is the highest total number of PhD graduates in 2019 compared to other clusters. This cluster consists of five European countries: Denmark, Germany (until 1990, the former territory of the FRG), Liechtenstein, Switzerland, and the United Kingdom. These countries belong to the Northwest Europe region; that is, this cluster includes economies from Northern Europe (Denmark and the United Kingdom) and Western Europe (Germany and Switzerland), with the exception of Liechtenstein. Compared to other OECD countries, educational achievement in Northern and Western Europe is quite high. Most countries in the area are democratic welfare states with a government that provides a wide range of social services and benefits. This region is known for its high level of organisational flexibility and civic involvement, as well as its philanthropic political climate.

Table 13. Countries by Clusters**.** Source: author's research based on Eurostat data from 2019.

Cluster	Countries
C1	Czech Republic, Ireland, Spain, France, Netherlands, Austria, Portugal, Slovenia, Slovakia, Finland, Sweden, Iceland, Norway
C2	Estonia, Greece, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Poland, Romania, North Macedonia, Serbia, Turkey
C3	Denmark, Germany (former FRG territory until 1990), Liechtenstein, Switzerland, United Kingdom

Figure 5 shows a European map by country grouped into specific clusters based on PhD-level graduates by country: 2019.

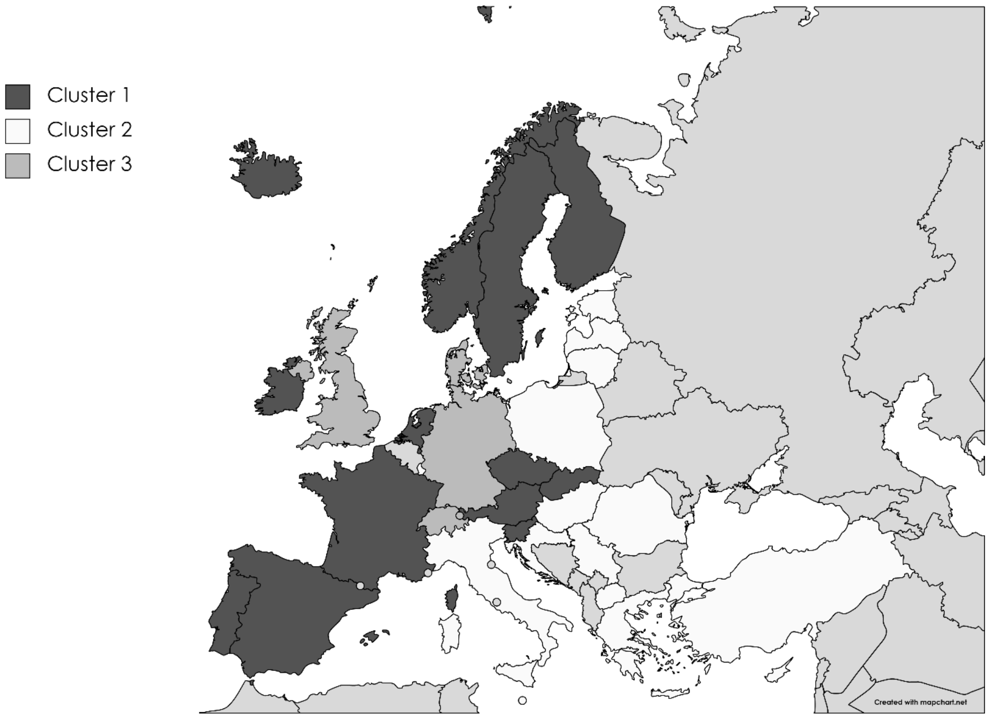

Figure 5. European map by country grouped in specific clusters based on PhD-level graduates by country; 2019.

This section presents the results of the ANOVA analysis and an indicative group-by-group diagram for GDP per capita by cluster, Table 14.

We estimated the average GDP per capita values for each cluster to examine the relationship between educational achievement and the level of economic growth of the selected European countries surveyed in 2019, Table 14. Cluster 3, which was the most developed in terms of educational indicators, was also the most developed in terms of average GDP per capita (USD 82 157,2) as a result of the grouping of the most developed European countries (Denmark, Germany (until 1990 the former territory of the FRG), Liechtenstein, Switzerland and the United Kingdom) into this cluster. On the other hand, Cluster 2 had the lowest average GDP per capita ($23 657,90), which was also the lowest in terms of lifetime educational metrics. A similar relationship exists for the percentage change in GDP. The Kruskal-Wallis test suggests that the variation in medians reported for the three clusters identified is not statistically significant, indicating a strong association between economic growth and educational achievement in the observed European countries.

The results of the ANOVA analysis, as well as the box-plot diagram by groups for GDP per capita by cluster, are shown in Table 14 and Figure 6.

Table 14. Average value of GDP per person by cluster; ANOVA analysis. Mean values and standard deviations (in parentheses) are given; bold letters indicate the highest average value.

	Projects	N	Std.Dev.	F-test	p-value
C1	45558,96	14	19922,35	8,118	0,001***
C2	23657,90	16	25199,86		
C3	82157,92	5	54911,03		
Total	40775,47	35	34435,42		

***significant at the level of 1 %

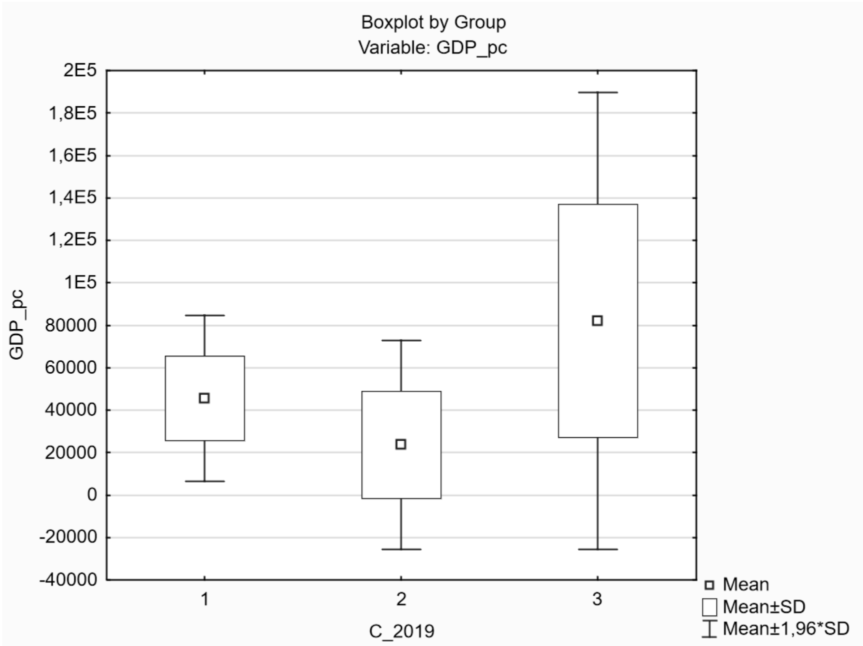

Figure 6. Box plot diagram of GDP per person by cluster.

Post hoc analysis was used to observe the levels of educational achievement in which groups of countries differ significantly in educational parameters, Table 15. For this purpose, the post hoc Fisher comparison of the least significant difference (LSD) is used. The primary principle of LSD is to calculate the lowest significant difference (i.e. LSD) between the two mean values as if they were the only means of comparison (i.e., use on the test) and declare any difference greater than LSD significant. Only certain pairs that are statistically significant at the 10 % level (six pairs) are given in the table. The table also shows the mean % difference between the groups. We can determine that the most significant difference occurs in most cases between cluster 2 and cluster 3 (2 pairs), followed by cluster 3 and cluster 1 (2 pairs). The same number of pairings is shown between Cluster 1 and Cluster 2. From here, we can reasonably conclude that cluster 3 (Denmark, Germany (former FRG area until 1990), Liechtenstein, Switzerland and the United Kingdom) has the highest levels of lifelong learning uptake, while the other countries analysed lag behind. This finding implies that the development gap between the European countries studied will remain unchanged, if not widened, unless serious efforts are made to improve educational achievement in the countries.

It can be concluded that the cluster analysis data confirmed that there are significant differences between European countries regarding the implementation of lifelong learning in 2019 and that these differences are related to economic development. Finally, the differences are statistically significant between individual clusters, as shown by the post-hoc analysis, confirming that there is a strong heterogeneity in European countries with regard to the implementation of lifelong learning. The limitation of this analysis arises from the fact that only one year has been analysed, and the analysis should be repeated for a longer period to confirm the results presented.

Table 15. Post-hoc LCD Cluster Difference Comparison Test.

	(I) C_2019	(J) C_2019	Mean Difference (I-J)	Std. Error	Mr.
LSD	C1	C2	21901.06	10580.15	0.047**
		C3	-36598.96	15062.01	0.021**
	C2	C1	-21901.06	10580.15	0.047**
		C3	-58500.02	14812.21	0.000***
	C3	C1	36598.96	15062.01	0.021**
		C2	58500.02	14812.21	0.000***

**significant at the level of 5 %
*** significant at the level of 1 %

DISCUSSION

Lifelong learning has become increasingly important in the fields of economics, business, and management, as highlighted in recent research. Laal and Salamati [29] support the notion that lifelong learning is essential for personal and professional development, arguing that it enables individuals to stay competitive in an ever-changing labour market. Lifelong learning has become increasingly important in the fields of economics, business, and management, as highlighted in recent research. Vrdoljak [30] further emphasises the growing need for continuous education to adapt to the evolving demands of the global economy, with a focus on the benefits of lifelong education for professionals in these fields. Lifelong learning has recently been supported by e-learning. In the context of e-learning, Głodowska et al. [31] discuss the pros and cons of digital education in economics and business, noting its increased relevance during the COVID-19 pandemic. Their cross-country study in Central and Eastern Europe reveals that while e-learning offers flexibility and accessibility, it also presents challenges, such as the digital divide and varying levels of engagement. Mališ Sever et al. [32] explore the landscape of e-learning during the pandemic in Croatia, focusing on economic disciplines. Their findings indicate that while the shift to online education provided a necessary solution, it also raised questions about the quality and effectiveness of learning in virtual environments. Both researches [31, 32] indicate that e-learning has a significant potential as a leverage for increasing lifelong learning.

This research is a continuation of the research conducted by Vrdoljak in 2023 [33]. Based on the conducted research on the development of lifelong learning in the countries of the European Union, a cluster analysis was conducted that identified significant differences in educational achievements, especially at the doctoral level. The results show that Western and Northern European countries, such as Denmark, Germany, Switzerland and the United Kingdom, achieved the highest number of PhDs per capita. In contrast, Eastern and Southern European countries, including Greece, Croatia, and Romania, had significantly lower rates of PhD studies. Also, there are significant differences in the gender representation of doctoral students, whereby women are generally less represented than men, especially in the younger population.

These differences in educational achievements are closely related to the economic development of countries, with more economically developed countries having a greater number of doctoral students and more developed lifelong learning systems. These results highlight the need to strengthen education and lifelong learning systems in less-developed European countries in order to reduce the educational achievement gap and promote economic and social inclusion. Therefore, strategic policies that encourage education, research and development, especially at the doctoral level, are key to achieving long-term economic growth and social cohesion throughout the European Union.

Based on the conducted research on the development of lifelong learning in the countries of the European Union, using K-means cluster analysis, significant differences in educational achievements among EU countries were identified, with a special emphasis on doctoral education. The analysis classified the countries into three clusters. The first cluster, which includes countries such as the Czech Republic, Ireland, Spain, and the Netherlands, is characterised by moderate educational achievements. The second cluster, which includes countries such as Croatia, Italy, Poland and Romania, shows significantly lower educational results and lower rates of doctorates per capita. The third cluster, which includes economically developed countries such as Denmark, Germany, Switzerland and the United Kingdom, shows the highest rates of doctorates and the most developed lifelong learning systems. These differences between clusters clearly indicate the connection between economic development and the success of educational systems, with an emphasis on doctoral studies.

Cluster analysis has proven to be a useful method for grouping countries based on educational and economic variables, allowing the identification of similar educational patterns within the European Union. The results of the cluster analysis clearly indicate that countries with higher GDP per capita also have higher rates of doctorates, which confirms the importance of economic factors in the development of educational systems. The analysis also highlights regional differences between Western and Eastern Europe, whereby Western European countries, despite their geographic and economic diversity, show greater homogeneity in educational achievement. In contrast, Eastern European countries lag, partly due to less developed educational institutions and lower investment in research and development.

One of the key limitations of this study is the limited amount of available data, as the data for the cluster analysis refer to only one year (2019), which does not allow insight into long-term trends. Another limitation is that the focus is only on selected variables, such as the number of PhDs per capita and GDP per capita. In contrast, other important factors that may influence lifelong learning, such as political or social indicators, are not included in the analysis. Additionally, cluster analysis, although useful for grouping countries according to similarities, has its limitations in terms of classification precision and the possibility of some countries being misplaced into clusters.

Recommendations for future research are based on this study's limitations but also the identified opportunities for a deeper understanding of the development of lifelong learning in Europe. First, future research should expand the time frame of analysis to allow monitoring of long-term trends. By analysing data over several years, it is possible to identify changes in educational systems, determine the factors that contributed to these changes, and observe how different economic and political situations affect the development of doctoral education and lifelong learning [34].

It is also recommended to include additional variables that can provide a broader picture of the factors that influence educational achievements. For example, variables such as political stability, investment in research and development, social equity, and social and cultural policies may play an important role in shaping education systems and should be further explored. These variables can provide deeper insights into how social and political contexts within individual countries affect educational outcomes.

Expanding the sample of countries is also an important recommendation. Although this study covered 35 European countries, the inclusion of countries outside of Europe could offer a wider international context and enable a comparison between European and non-European education systems. This would enable the understanding of global educational trends and could contribute to the development of better strategies for lifelong learning at the global level.

Finally, it is recommended that quantitative and qualitative research methods be combined. Although cluster analysis provides valuable statistical insights, qualitative methods, such as interviews with policymakers, experts and education workers, can provide a deeper understanding of specific challenges and opportunities within education systems. Such an approach would enable a holistic overview of the problem and could help in designing concrete and adapted solutions to encourage the development of doctoral education and lifelong learning.

CONCLUSION

In conclusion, this study underscores the critical importance of lifelong learning and doctoral education in fostering economic development and social inclusion across the European Union. The findings highlight significant disparities in educational achievements, particularly in doctoral education, between economically developed Western European countries and less-developed Eastern European counterparts. These disparities are closely linked to economic factors, with countries having higher GDP per capita demonstrating more advanced lifelong learning systems and higher doctoral completion rates. While considering these findings, it has to be considered that the progress of each doctoral student is based on sufficient funds, salaries, opportunities, scholarships, and other resources useful for research and the creation of a standard of living, as well as on the commitment and work invested in study and research. PhD students in Western Europe have greater opportunities to publish, participate in conferences and workshops, and improve their academic position than PhD students in Eastern Europe. From here, it is important to note that universities should address the social and economic needs of individuals who are technologically and informationally literate while enhancing students' language abilities to increase interest in pursuing a doctorate. In addition, universities should learn to adapt to an ever-changing environment where students must learn to adapt instead of studying solid and solid information.

The cluster analysis provides valuable insights into educational patterns within Europe, emphasising the need for tailored strategic policies to strengthen education systems in less-developed regions. Addressing these disparities requires increased investment in research, development, and support systems for doctoral students, alongside initiatives that enhance access, equity, and adaptability in education. Future research should focus on expanding the scope and depth of analysis, incorporating additional variables such as political, social, and cultural factors, and extending the geographic and temporal range of studies. Combining quantitative and qualitative approaches will offer a more comprehensive understanding of the challenges and opportunities in promoting lifelong learning and doctoral education globally.

REFERENCES

[1] Tuschling, A. and Engemann, C.: *From education to lifelong learning: The emerging regime of learning in the European Union*.
Educational Philosophy and Theory **38**(4), 451-469, 2006,
http://dx.doi.org/10.1111/j.1469-5812.2006.00204.x,

[2] Hervás Soriano, F. and Mulatero, F.: *Knowledge policy in the EU: From the Lisbon strategy to Europe 2020*.
Journal of the Knowledge Economy **1**, 289-302, 2010,
http://dx.doi.org/10.1007/s13132-010-0020-9,

[3] –: *Council Resolution on a strategic framework for European cooperation in education and training towards the European Education Area and beyond (2021-2030)*.
https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32021G0226(01)&from=EN,

[4] World Bank: *The COVID-19 pandemic: Shocks to education and policy responses*.
World Bank, 2020,

[5] Roosmaa, E.L. and Saar, E.: *Participation in non-formal learning in EU-15 and EU-8 countries: Demand and supply side factors*.
International Journal of Lifelong Education **31**(4), 477-501, 2012,
http://dx.doi.org/10.1080/02601370.2012.689376,

[6] Eurostat: *Adult education survey*.
https://ec.europa.eu/eurostat/web/microdata/adult-education-survey,

[7] Central Statistics Office: *Adult Education Survey 2022*.
https://www.cso.ie/en/releasesandpublications/ep/p-aes/adulteducationsurvey2022/aes2017comparison,

[8] Babić, Z. and Tomašević, M.: *Comparative analysis of policies and participation in lifelong learning of selected countries of the European Union and the Republic of Croatia*. In Croatian. Napredak: Časopis za interdisciplinarna istraživanja u odgoju i obrazovanju **162**(1-2), 137-166, 2021,

[9] Biagetti, M. and Scicchitano, S.: *The determinants of lifelong learning incidence across European countries (evidence from EU-SILC dataset)*.
Acta Oeconomica **63**(1), 77-97, 2013,
http://dx.doi.org/10.1556/aoecon.63.2013.1.5,

[10] Ullmann, T.; Hennig, C. and Boulesteix, A.L.: *Validation of cluster analysis results on validation data: A systematic framework*.
Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery **12**(3), No. e1444, 2022,
http://dx.doi.org/10.1002/widm.1444,

[11] Ikotun, A.M.; Ezugwu, A.E.; Abualigah, L.; Abuhaija, B. and Heming, J.: *K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data*.
Information Sciences **622**, 178-210, 2023,
http://dx.doi.org/10.1016/j.ins.2022.11.139,

[12] Gülagiz, F.K. and Sahin, S.: *Comparison of hierarchical and non-hierarchical clustering algorithms*.
International Journal of Computer Engineering and Information Technology **9**(1), No. 6, 2017,

[13] Hennig, C.: *Cluster-wise assessment of cluster stability*.
Computational Statistics Data Analysis **52**(1), 258-271, 2007,
http://dx.doi.org/10.1016/j.csda.2006.11.025,

[14] Li, P.S.; Li, L. and Zong, L.: *Postgraduate educational aspirations and policy implications: A case study of university students in western China*.
Journal of Higher Education Policy and Management **29**(2), 143-158, 2007,
http://dx.doi.org/10.1080/13600800701351736,

[15] Pejic-Bach, M.; Zoroja, J. and Ćurko, K.: *Internet and E-Learning Usage among European Individuals: Cluster Analysis Approach*.
In: ICERI2019 Proceedings. IATED, pp.2889-2897, 2019,
http://dx.doi.org/10.21125/iceri.2019.0737,

[16] Fushiki, T.: *Estimation of prediction error by using K-fold cross-validation*.
Statistics and Computing **21**, 137-146, 2019,
http://dx.doi.org/10.1007/s11222-009-9153-8,

[17] De'ath, G. and Fabricius, K.E.: *Classification and regression trees: a powerful yet simple technique for ecological data analysis*.
Ecology **81**(11), 3178-3192, 2000,
http://dx.doi.org/10.1890/0012-9658(2000)081[3178:CARTAP]2.0.CO;2,

[18] Statistica: *Generalised EM and k-Means Cluster Analysis Overview*.
https://docs.tibco.com/pub/stat/14.2.0/doc/html/UserGuide/_shared/generalized-em-and-k-means-cluster-analysis-overview.htm,

[19] Ullrich-French, S. and Cox, A.: *Using cluster analysis to examine the combinations of motivation regulations of physical education students*.
Journal of Sport and Exercise Psychology **31**(3), 358-379, 2009,
http://dx.doi.org/10.1123/jsep.31.3.358,

[20] Battaglia, O.R.; Di Paola, B. and Fazio, C.: *A new approach to investigate students' behavior by using cluster analysis as an unsupervised methodology in the field of education*.
Applied Mathematics **7**(15), 1649-1673, 2016,
http://dx.doi.org/10.4236/am.2016.715142,

[21] Pejić Bach, M.; Jaković, B.; Jajić, I. and Meško, M.: *Investigating the impact of COVID-19 on e-learning: Country development and COVID-19 response*.
Mathematics **11**(6), No. 1520, 2023,
http://dx.doi.org/10.3390/math11061520,

[22] Pejić Bach, M.; Zoroja, J. and Miloloža, I.: *Employment in Knowledge-Intensive Activities in European Countries: Gender Perspective*.
In: *44th International Convention on Information, Communication and Electronic Technology (MIPRO)*. IEEE, pp.1409-1413, 2021,
http://dx.doi.org/10.23919/MIPRO52101.2021.9596746,

[23] Bora, D.J. and Gupta, A.K.: *Influence of different distance measures on the performance of the K-Prosjeks algorithm: Experimental study in Matlab*.
International Journal of Computer Science and Information Technologies **5**(2), 2014, 2501-2506, 2014,

[24] Mohamad, I. and Usman, D.: *Standardization and its effects on the K-means grouping algorithm*.
Research Journal of Applied Sciences, Engineering and Technology **6**(17), 3299-3303, 2013,
http://dx.doi.org/10.19026/RJASET.6.3638,

[25] Mardia, K.V.; Kent, J.T. and Bibby, J.M. *Multivariate analysis*.
Academic Press, London, 1979,

[26] Sugar, C. and James, G.: *Finding the number of clusters in a data set: an information-theoretic approach*.
Journal of the American Statistical Association **98**, 750-763, 2003,
http://dx.doi.org/10.1198/016214503000000666,

[27] Honarkhah, M. and Caers, J.: *Stochastic simulation of patterns using distance-based pattern modeling*.
Mathematical Geosciences **42**(5), 487-517, 2010,
http://dx.doi.org/10.1007/s11004-010-9276-7,

[28] Tibshirani, R.; Walther, G. and Hastie, T.: *Estimation of the number of clusters in the data set through gap statistics*.
Journal of the Royal Statistical Society, Series B (Statistical Methodology) **63**(2), 411-423, 2001,
http://dx.doi.org/10.1111/1467-9868.00293,

[29] Laal, M. and Salamati, P.: *Lifelong learning; why do we need it?*
Procedia-Social and Behavioral Sciences **31**, 399-403, 2012,
http://dx.doi.org/10.1016/j.sbspro.2011.12.073,

[30] Vrdoljak, I.: *Lifelong Education in Economics, Business and Management Research: Literature Review*.
Business Systems Research **14**(1), 153-172, 2023,
http://dx.doi.org/10.2478/bsrj-2023-0008,

[31] Głodowska, A.; Wach, K. and Knežević, B.: *Pros and cons of e-learning in economics and business in Central and Eastern Europe: Cross-country empirical investigation*.
Business Systems Research **13**(2), 28-44, 2022,
http://dx.doi.org/10.2478/bsrj-2022-0014,

[32] Mališ Sever, S.; Sačer, I.M. and Žager, K.: *Landscape of e-learning during Covid-19: Case study of economic disciplines in Croatia*.
Business Systems Research **13**(2), 8-27, 2022,
http://dx.doi.org/10.2478/bsrj-2022-0013,

[33] Vrdoljak, I.: *Development of Lifelong Education in the Republic of Croatia: An Analysis of Trends in PhD Graduations*.
ENTRENOVA-ENTerprise REsearch InNOVAtion **9**(1), 148-158, 2023,
http://dx.doi.org/10.54820/entrenova-2023-0014,

[34] Guzikova, L.: *Forming Entrepreneurial Competences: Interaction of Universities and Business*.
ENTRENOVA-ENTerprise REsearch InNOVAtion **6**(1), 265-274, 2020.