Universidad Pública de Navarra
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Facultad de Ciencias Económicas y Empresariales

TRABAJO FIN DE GRADO EN
ADE Y ECONOMÍA INTERNACIONAL

ANALYSIS OF EDUCATION PERFORMANCE IN THE EUROPEAN UNION. A STUDY BASED ON PISA REPORT AND ET2020.

Módulo:
Economía Española, Internacional y Sectorial

Pamplona-Iruña, 18 de diciembre de 2020

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Abstract
Education is considered a key domain of the welfare state and nations are legally bounded to offer equal opportunities and universal access to their populations. International assessment programs like the PISA exam provide a solid ground for cross-country comparisons to be driven. This paper focuses on the European Union and proposes a composite indicator able to identify the best and worst performers in terms of educational performance and achievement. The analysis detects the weak points of each country, also classifying them into clusters. Already established frameworks as the ET2020 launched by the European Commission in 2009 confirm the role that a convergence in educational systems would play in the consolidation of a strong EU. Results conclude that significant differences in results lie between clusters and that in fact dimensions as the social progress, truancy levels and home conditions contribute to performance levels.
Key words
Education systems, composite indicator, clustering, PISA, ET2020.

Resumen
La educación se considera un pilar fundamental del estado de bienestar y las naciones están legalmente obligadas a ofrecer igualdad de oportunidades y acceso universal a sus poblaciones. Los programas de evaluación internacionales como el examen PISA proporcionan una base sólida para las comparaciones de países. Este documento se centra en la Unión Europea y propone un indicador compuesto capaz de identificar los mejores y peores países en términos de rendimientos y logros educativos. El análisis pretende detectar los puntos débiles de cada país, también clasificándolos en grupos homogéneos. Planes estratégicos ya establecidos como el ET2020 lanzado por la Comisión Europea en 2009 confirman el importante papel que la educación tiene en la consolidación de una UE fuerte. En conclusión, los resultados muestran diferencias entre los grupos. En esta línea, dimensiones como el progreso social, los niveles de absentismo escolar y las condiciones del hogar afectan a los niveles de rendimiento
Palabras clave
Sistema educativo, índice compuesto, clustering, PISA, ET2020.

Laburpena
Hezkuntza giza eskubidea ta ongizate estatuaren funtsezko arloa izanik, estatuak legez lotuak daude aukera berdintasuna eta hezkuntza sarbide unibertsala sustatzera. Hezkuntza sistemak ebaluatzeko nazioarteko programek, hots, PISA azterketak, oinarri sendoa eskaintzen dute herrialdeen arteko konparaketak egiterako orduan. Honako ikerketa hau Europa mailan oinarritzen da eta hezkuntza arloko emaitzen arabera, herrialde onenak ta okerrenak nabarmentzen ditu, proposatutako indize konposatuaren bitartez. Ikerketak estatu bakoitzaren puntu ahulak antzematen ditu, aldi berean, talde homogeneoetan sailkatuz. Europako Kontseiluak 2009an bultzatutako ET2020 plan estrategikoak, Europa indartsu baten finkatzean hezkuntzak duen garrantzia azpimarratzen du. Ondorioz, emaitzek dibergentziak erakusten dituzte taldeen artean. Horrela, gizarte bilakaera mailak, eskola absentismoak edo eta etxeko kondizioek ikasleen errendimendu akademikoa baldintzatzen dute.
Hitz gakoak
Hezkuntza sistema, indize konposatua, clustering, PISA, ET2020.

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1. INTRODUCTION

Education is constituted as a human right, a basic right corresponding to every person across the world. Even more, it has been defined as an "empowering right" that provides people everywhere, the necessary tools to lift out of the poverty trap and be active in society (UNESCO, 2019). For this purpose, it is fundamental to provide equality of opportunity and universal access, which are backed up by legal obligations in all nations.

Indeed, education plays an important role in the Sustainable Development Goals (SDG), being the fourth of the seventeen demands approved by the international community in 2015 at the United Nations General Assembly (United Nations, 2020). Precisely, this objective goes in line with the previous idea, since it addresses the assurance of an inclusive and equitable quality education and it is aimed at the provision of lifelong learning chances for all people.

The Right of Education Initiative (RTE), organization supporting human rights worldwide and established in 2000, defined education as a crucial powerful tool to "*develop the full potential of everyone and ensuring human dignity*" (Right to Education Initiative, 2020). Stumbriene et al. (2020) also shared this view, adding to this statement that it provided well-being in the long-run, competitiveness and prosperity.

Within the academic literature, education has been a widely researched and discussed area throughout history. Many articles have been published for many decades and still the number is increasing (Hopfenbeck et al., 2018). Levstik & Barton (2008) stated that although some might view educational research as something not systematic, noncumulative and some even doubt the usefulness of it when improving school conditions, the truth is that it is far from being a reality. Researchers lean on previous works, building conclusions that can be after contrasted with other similar findings. In this way, it can be understood as a continuous improvement process.

However, that same process still nowadays faces some challenges, since the evaluation of education itself is not an easy task. This paper will comment on the uniqueness of educational systems, providing a tool to evaluate their performance. Precisely, this paper will aim at the elaboration of a composite index, to obtain a synthetic measure of the educational system performance in the European Union, accounting for the 27 countries that form the union at the present day. The creation of a composite indicator facilitates the understanding of the educational efficiency to the general public, due to its aggregated nature. An additional contribution will be the proposal of a classification of countries accordingly with their educational results.

As a whole, this paper, being inspired by the current policies of the European Union in the educational field, will aim at the pursuit of differences in educational performance within the Member States (MS). Even more, one of the interests of this paper lies in the finding of those attributes which are related with the position of a country in terms of education. For this purpose, the research will grasp a large set of educational, institutional, economic and social factors, looking for underlying factors that could be related to the position of a country. At the end of the day, this methodology could guide policy makers in the European Union to find out which factors contribute to explain the differences within MS and therefore, improve them.

The structure of the brief is organized as follows. The next section comments on the academic literature related to this research topic and which is available at the present day, together with the main contribution of this paper. Secondly, Initiatives and Programmes on Education presents the overall picture of the efforts made at the supranational level to promote the education, particularly focusing on the European environment. Later on, Methodology and Information Sources provides the technical perspective and the description of the analytical tools and the data that is going to be used throughout this work. Results section will present the main findings of the empirical analysis and clustering. The last section, Conclusions, will interpret the results and give an end to this paper.

2. RELATED LITERATURE AND PAPER'S CONTRIBUTION

As mentioned in the introductory part of this paper, education has been a very discussed topic in the scientific arena. Zurawski (2019) argued that many of the authors have dug in the relationship of this field with other institutional areas, such as the labor market. However, some others have also focused on the area itself and highlighted the importance of the educational domain. When it comes to the contribution of education in the development of human capital, Becker (1964) underlined the importance of the investment in human capital for the economy, giving a special focus to education. In fact, he stated that a sustained period of growth was positively correlated with substantial investment in human capital. Giambona et al. (2011) also gathered the researches of other human capital theorists saying that when a population is well-educated, productivity will be high, due to a group of workers with higher cognitive, leading to a higher income population that will adopt new technologies before. Eventually, this ends up in larger economic growth and social progress.

Some authors have tried to analyze education output in the classical frame of economic theory of production. At the end of the day, the production of education works as an industrial firm, which employs and combines many factors in a way to obtain an outcome (Lassibille & Navarro Gómez, 2004). These writers, following the theorical frame, suggested that an educational center (E.g. School, University) would be technically efficient, when it produces the maximum product quantity with the number of inputs available to them. But, unfortunately, the estimation of the production function of education is not straightforward. On the one hand, the product itself is not easily identifiable and measurable, meaning that the result of a learning process is more than just a score in the final exam. On the other hand, the definition of the production factors employed in the process is not crystal clear and there is always a risk of not including important qualitative points to the analysis. As a consequence, the production function would not be capable of reflecting the truth.

Moreover, Lassibille & Navarro-Gómez (2004) also made a point about the special nature of the public education as a production process. Not only it must be taken into account that the education provided by public schools do not aim at getting profits or minimize their costs, but there is also a lack of competition within the "educational market". This all makes the estimation of the educational production function quite hard.

Furthermore, researches about the diversity of educational performance, as the one presented in this paper, have been very relevant in the recent years, both at the regional and international level.

At the regional level, for example, Hippe et al. (2018) came up with a research based on the regional differences of Italy and Spain in the area of education, concluding with "*significant regional inequalities within Spain and Italy*" (Hippe et al, 2018, p. 25).

In the international level, analyses have been driven in the European framework, as a way to address the diversity of educational systems and the performance across countries. Two key researches of this nature, which at the same time have profoundly inspired the methodology of this research, are the papers by Zurawski (2019) and Stumbriene et al. (2020). The latter one proposed a composite indicator based on variables thought as inputs of the educational production process such as expenditures, quantity and quality of resources, enrolment, school features and socio-economic and cultural characteristics across countries in the European Union. On the other hand, Zurawski (2019) proposed a classification of European countries in clusters based on similar institutional features.

The contribution of this paper lies on the combination of the two methodologies, this is, the proposal of a composite indicator, together with a cluster classification. Not only that, this paper builds the composite indicator based on the performance of different educational factors, henceforth described as output variables, instead of focusing on the factors that focus on the inputs or the context of the production of education. At the same time, these last dimensions will not go unnoticed, since they will be used to eventually explain the composite indicator itself.

Finally, it is also important to point out that this research uses the last available PISA database, corresponding to 2018 that as far as the author knows, has not been used yet in any paper with a proposal as the one presented in this paper. Very recently, however, this same database has been employed for a research consisting on a cluster analysis of schools in all participating countries in the PISA exam by Gamazo & Martínez-Abad (2020)[1].

3. INITIATIVES AND PROGRAMMES ON EDUCATION

3.1 Education in Europe.

The European Commission launched in 2009 the Education and Training 2020 (ET2020) framework, based on lifelong learning (Council of the European Union, 2009). The goal of this strategic initiative was to reach a collaboration between MS to build a common education policy, leaning on the exchange of knowledge and best practices as a way to improve education at national and regional levels (European Commission, 2020a). Quality and efficiency of education, equity, social cohesion, active citizenship, creativity, innovation and entrepreneurship are some of the objectives that were sought with this framework.

ET2020 also supposed the establishment of seven benchmarks at the European level for 2020, which are included below in Table 1.

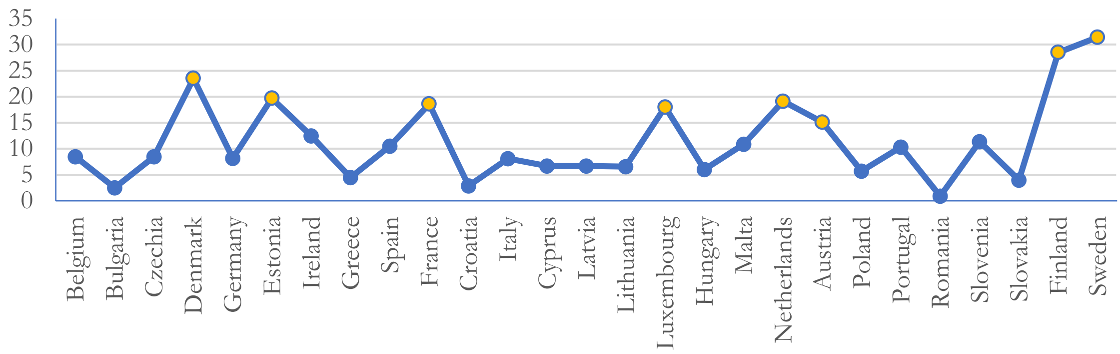
Table 1: Benchmarks at European level by 2020. Source: (Council of the European Union, 2009)

1.	At least 95% of children should participate in **early childhood education**
2.	Fewer than 15% of 15-year-olds should be **low-achievers** in reading, mathematics and science
3.	The rate of **early leavers** from education and training within 18-24 years should be below 10%
4.	At least 40% of people aged 30-34 should have completed some form of **higher education**
5.	At least 15% of **adults** should **participate in learning**
6.	At least 20% of higher education graduates and 6% of 18 to 34 years-old with an initial vocational qualification should have spent some time s**tudying or training abroad**
7.	The share of **employment graduates** should be at least 82%

[1] The paper uses Data Mining Techniques to reach a predictive model of school performance, based on process and outcome variables from PISA 2018 and socioeconomic dimensions. The analysis follows a Decision Tree Mining technique with acceptable levels of fit, in order to find out the determinants of school performance.

In 2018, this paper's target year of analysis, none of these requirements were fully satisfied. Taking benchmark number 5 as an example, Figure 1 shows that only eight countries out of all the MS passed the threshold of 15% of adults participating in learning.

Figure 1: Adult Participation Rate in Learning. Source: (Eurostat, 2020a)



Although it is true that from 2018 to 2020 there was still room for further improvement, and although progress has been made, still the EU has not been able to achieve the proposed targets (European Commission, 2020b). Results in Table 2 show that countries are closer to the targets in benchmarks 1, 3, 4 and 6, which suggests that these targets will soon be achieved, but not in 2020 as it was desired. Regarding the low-achievers and the adult participation in learning, there is still a lot to improve in the European Union.

Table 2: EU targets for 2020 in education and training. Source: (European Commission, 2020b)

	Latest available data	Value	Target
B1. Early childhood education	2018	94.8%	95%
B2. Underachievement	2018	Reading: 22,5% Maths: 22.9% Science: 22.3%	15%
B3. Early leavers	2019	10.2%	Below 10%
B4. Tertiary education	2019	40.3%	At least 40%
B5. Adult participation in learning	2019	10.8%	15%
B6. Employment graduates	2019	80.9%	82%

In 2017, the European Commission communicated the intention to create a European Education Area (EEA) as a way to combat imbalances across MS and to be up to the numerous challenges faced by the European Union. Digitalization, the need to adapt skills and competences to the new jobs of the future, demographic trends, ageing workforce and populism are examples of these developments.

In this way, the EEA and the subsequent investment in education will help with the creation of decent jobs, the adaptation to the skills' need and also, with Europe's resilience.

Resilience, a word that has been on a rise lately and that was originally introduced in 1973 as a concept to understand ecosystems, is nowadays understood as the capacity of social-ecological systems to constantly change and adapt within critical threshold (Folke et al., 2010). Capacity that although some people have taken the risk to call it the "21st Century Workplace Skill", there is still a recognized shortage of it (Executive Forum, 2019).

In September 2020 (European Commission, 2020c), the Commission agreed on the establishment of a new vision of the EEA for 2025. This vision underlines six dimensions, shown in Figure 2, in order to consolidate the efforts made until today and further improve. These dimensions are the quality of education, inclusion and gender equality, a green and digital transition, a focus on teachers and trainers and on higher education and lastly, the geopolitical dimension of education.

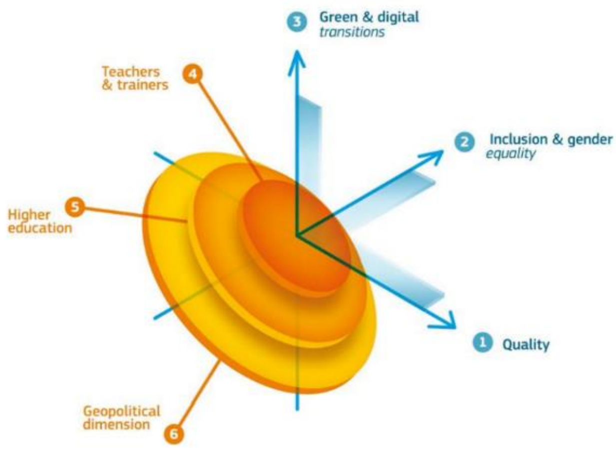


Figure 2: Six dimensions of the EEA 2025 (Source: (European Commission, 2020c)

In this context, the Commission also proposed a number of targets to be achieved by 2030, matching with the deadline of the previously mentioned SDGs. These objectives in the EEA framework are presented in Table 3.

Table 3: EEA targets by 2030. Source: (European Commission, 2020c, p. 27)

1.	The share of low-achieving 15-year-olds in reading, mathematics and science less than 15%.
2.	The share of low-achieving eight-graders in computer and information literacy less than 15%.
3.	At least 98% of children between 3 years old and the starting age for compulsory primary education should participate in early childhood education
4.	The share of people aged 20-24 with at least an upper secondary qualification should be 90%.
5.	The share of 30-34 years-old with tertiary educational attainment should be at least 50%.

Comparing this new horizon of targets set by the EEA framework with the previously explained ET2020, some amendments can be identified. Both early childhood and tertiary education attainment were identified to be close to the desired targets in 2019, which seems to have encouraged the European Commission to set stricter goals for 2030. However, due to the bad results in underachievement in 2018, the EEA did not contemplate to change the target and it continued betting for a 15% underachievement level in reading, mathematics and science categories within 15 years-old students. On the other hand, two new objectives are set by the new framework, which are related to the computer and information literacy of eight graders and the upper secondary qualification rate in the age range of 20-24 years.

After all, education seems to be crucial for the development of future generations in the European Union. Jean-Claude Juncker, president of the European Commission from 2014 to 2019, declared in 2017 in the European Commission's contribution to the Leaders' meeting in Gothenburg that:

Education and culture are the key to the future, both for the individual as well as for our Union as a whole. It is how we turn circumstance into opportunity, how we turn mirrors into windows and how we give roots to what it means to be "European", in all its diversity (European Commission, 2017, p. 1)

With this inspiring statement the former president stressed the importance of the social dimension of Europe. Although Europe is known as one of the most egalitarian and inclusive societies worldwide, still there are big differences from one country to another. Europe is not as homogeneous as desired. As an example, the differences in the youth unemployment rates across MS in Europe in 2018 are represented by Figure 3. Although the variable does not directly measure education, it is a good representation of the imbalances taking place in the union and in fact, the observed deviations are the ones seeking to be smoothed through education and other similar policies.

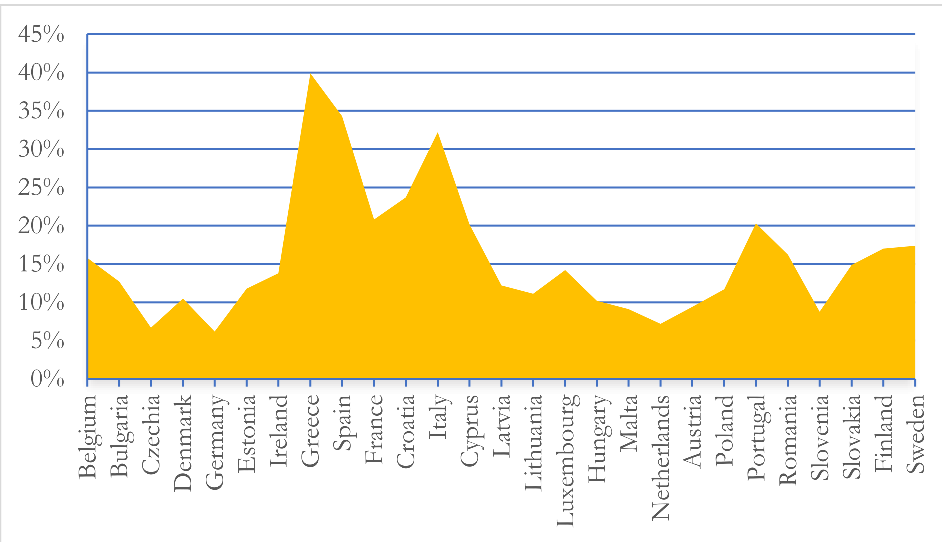


Figure 3: Youth Unemployment Rate from 15 to 24 years. Source: (Eurostat, 2020b)

The youth unemployment rate is defined as the percentage of young unemployed people, who are in the age range between 15 and 24 years old and participate actively in the search of a job. The graph clearly shows how rates differ from one country to the other. Following the theory, this should not happen in an Optimum Economic Area, since the free movement of people and therefore, workers, is the cornerstone of the union. However, Barslund et al. (2015) do admit that although numbers have substantially improved, still internal labour mobility is low. Otherwise, young people from Greece would decide to move to Germany and have a job there. One reason for the lack of movement within the EU could be that young people are not willing to face the psychological costs of migrating to another country, but there are other many factors influencing this fact, and educational differences are probably playing a role in this lack of mobility (Gros, 1996).

3.2 Programme for International Student Assessment (PISA)

Once explained the arguments and the background of this paper, an interesting question to be asked is the following: if the aim of this paper is to compare results across countries, how is that going to be measured? On the one hand, information about the general education levels was chosen through the ET2020 framework and data was collected by Eurostat on these six variables (excluding target number 6 in Table 1, which addresses the learning and studying degree abroad). On the other hand, additional information generated by a specific survey conducted directly to students and their environment was needed.

Through the last decades, there have been many surveys of this kind designed to consider and evaluate the knowledge and abilities of students from a number of countries. Giambona et al. (2011) named some of them, such as the International Adult Literacy Survey (IALS), the Trends in Maths and Science Study (TIMSS), the Progress in International Reading Literacy Study (PIRLS) and the Program for International Student Assessment (PISA). Eventually, the latter one was chosen for this study due to its capacity to analyze a target population of 15-year-old students in 79 countries (including all MS) and so, its capacity to compare disparities across them (Schleicher, 2019).

Since its very first days in 1999, the goal of this test has been to assess "*aspects of preparedness for adult life*" (OECD, 2000, p. 7). This is, it does not address a specific school curriculum, but in fact, seeks to make young students use the abilities and skills learned to "*meet real-life challenges*", (OECD, 2010, p. 3). These questionnaires are administered across countries following standardized procedures, with strong measurement properties and always emphasizing on their authenticity and validity (OECD, 2000). This standardization makes it possible to describe the impact of different cultures and economic backgrounds on school performance.

PISA is one of the most used large-scale assessments in the literature. PISA provides a rich dataset to the scientific community and many authors have based their researches in the information obtained by this program. Anderson et al. (2007, p. 591) underlined its relevance, due to the fact that it provides "*a window to the broadly defined concepts of literacy*", while it also gives information about complementary aspects, like for example, overall student background, school infrastructure, home characteristics, attitudes towards learning and other perceptions of the actors involved in the questionnaire. Hopfenbeck et al. (2018), while systematically reviewing the number of peer-reviewed articles on PISA, agreed on its strategic prominence in the evaluation of education.

Student results are based on three domains, which are reading, mathematical and science literacy. This paper will take the mean score of each country in each of the domains to properly compare mean values of the different countries in the European Union.

4. METHODOLOGY AND INFORMATION SOURCES

4.1 Methodology

As it was presented in the introduction of this paper, the purpose of this analysis is to obtain a classification of the European countries in relation with the results of their education system and to elaborate a composite index capable of measuring the education performance of countries in just a single number. For the proper elaboration of this measure, previous testing and the transformation of information was necessary. For that purpose, factorial analysis was selected. The results obtained in the factorial analysis were further exploited with the cluster analysis, which uses the transformed information in the previous step to derive a classification of the objects in the analysis. The following sub-section will explain the three specific methodologies employed in the development of this research.

4.1.1 Factorial Analysis

The purpose of this paper is to analyze the education outcomes in the frame of the European Union, this is, accounting for the 27 countries that form the union at the present day. Part of the analysis will be devoted to elaborating a classification of countries in relation to the performance of their education systems in terms of specific indicators. To reach that goal cluster analysis was chosen. This method groups objects or individuals in conglomerates based on the characteristics they possess (Hair et al., 1999). Hence, groups should be formed in a way that objects inside a conglomerate have a high degree of internal homogeneity, while showing a high inter-conglomerate heterogeneity. Therefore, the very first step should be to identify the variables on which to base the analysis, in order to derive this classification.

Once the variables have been identified and data is gathered, and once the representativeness of the variables have been validated, a study of multicollinearity needs to be driven. Multicollinearity is perceived across researchers as a problem, since it represents a lack of independence within the set of variables included in the study, expressed in the form of high intercorrelations among one another (Farrar & Glauber, 1967). Thus, it makes it hard to discern the "true" impact of those variables. In order to avoid this problem, the literature suggests using, as a previous step, factorial analysis.

This last technic is used to reduce the dimensionality of the data and to summarize the relationships of the variables in a group of factors, with no such multicollinearity among one another (Thompson, 2004). In other words, its goal is to find a minimum number of dimensions able to explain the maximum information gathered in the data (Marin Diazaraque, 2020).

The principal component analysis (PCA) method will be employed to collect the important information or components of the original variables, transforming them in new orthogonal variables (Abdi & Williams, 2010). Forina et al. (1989) added that these new variables formed would be linear combinations of the original variables, capable of describing a large amount of the total variance. The last step of the factor analysis is to rotate the factors. For this, varimax rotation method will be used and only factors with an eigenvalue greater than one will be recognized. The number of factors obtained will be interpreted through the rotation of the factors, which tries to minimize the set of variables with high loadings and therefore, the set of variables that explain a specific factor (Nicoletti et al., 2000).

A very important aspect in the analysis is to pay attention to the measures of sampling adequacy, this is, the Kaiser-Meyer-Olkin (KMO) suggested by Kaiser (1970) and Bartlett's test of sphericity. The KMO measures how large the correlations among the variables involved are (Lloret Segura et al., 2014). In a sense, the higher the value of this measure, the more appropriate the computation of the factorial analysis will be. It is a measure ranging from 0 to 1 and depending on the value it gets, the adequacy will be higher or lower. Lloret Segura et al. (2014) explained that the factorial analysis would not be supported with a KMO value below 0.5. Between 0.6-0.69 sampling adequacy will be mediocre and from 0.8 on the analysis would make sense, it will be useful.

Bartlett's test, on the other hand, comes up with a null hypothesis that the correlation matrix is an identity, in other words, that the variables are not correlated among one another (Ferrando & Anguiano-Carrasco, 2010). Following the previous logic that in order to use factor analysis, there must be a hidden relation between variables, the analysis should reject this null hypothesis. Therefore, p-value of the Bartlett's test of sphericity should be lower than 0.05.

Eventually, the anti-image correlation matrix can be used to identify the variables that should be removed from the analysis. This matrix represents the outlying pairwise correlations after having cancelled the relation between the variables (Hauben et al., 2016). Thus, the lower the values in the off-diagonal, the better. This will translate into no multicollinearity among the variables. The diagonal of the matrix shows the measures of sampling adequacy for the individual variables (Marin Diazaraque, 2020). In this way, the criteria to follow is the same as the one used when evaluating the KMO measure. The closer they are to 1 the values in the diagonal, the better and the more useful it will be to use the factorial analysis (Lloret Segura et al., 2014). Consequently, following Hair et al. (1999) a limit will be put in 0.5 and variables whose value is lower than 0.5 will be excluded from the factorial analysis.

At this point, once the factorial analysis is validated, the components identified will be used as input for the cluster analysis and the construction of the composite index.

4.1.2 Cluster analysis

There exist two procedures to obtain the conglomerates of objects or units of analysis (countries in this case): the hierarchical and the non-hierarchical methods. This paper will deal with both of them, since the clustering will be a combination of both, as suggested by Hair et al. (1999) as the best option.

In this way, the number of clusters to be defined will be established with the help of the hierarchical technic. This method will firstly calculate the distance between objects with the Euclidean distance method. After, clusters will be formed, based on the agglomeration schedules obtained by Ward's method, also known as method of minimum variance (Hervada-Sala & Jarauta-Bragulat, 2004). The answer to the question of how many clusters to select will be found in the agglomeration schedule, precisely in the agglomeration coefficients, which represent the homogeneity within the clusters. Hair et al. (1999) explained that low coefficients lead to very homogeneous groups of objects. Although one goal is to obtain clusters with low heterogeneity within the group, another goal is also to come up with a classification, in order to facilitate the interpretation of results. Therefore, researchers need to take a decision in regards of this trade-off. A general rule that is used in the literature is to look for the highest sudden increase in the agglomeration coefficient and stay with the previous situation to this increase. This is the logic that this paper will follow.

Once this decision has been made and a specific number of clusters has been chosen, observations will be grouped together through the non-hierarchical method or K-Means method. The number of clusters to form determine the number of starting centroids. Objects are allocated randomly based on the distance to the centroids (Galiano & García, 2017). These centroids constantly update taking the position of the average of the objects belonging to the group, until the optimal position has been reached.

The cluster methodology has been widely used in the scientific community, grouping countries in the European Union, in the same way as in this research. Some examples of these are the cluster analysis in terms of the country's level of greenhouse emission (Kijewska & Bluszcz, 2016), in reference to their association regarding non-pharmaceutical measures taken to prevent the spread of the COVID-19 (Tallon et al., 2020) or in terms of the agricultural sustainability of countries (Dos Santos & Ahmad, 2020).

4.1.3 Composite Index (CI)

The next part of this paper will be to create a Composite Index (CI) that will evaluate the performance of the education systems of the European countries using the same set of variables included in the factorial analysis. A CI aims at "*aggregating multi-dimensional processes into simplified, stylized concepts*", providing the summarized picture of complex systems (Saltelli, 2007, p. 65).

This methodology has gained a lot importance in the last years due to its capacity and usefulness to guide policy discussions and public interest. OECD (2008) stressed that the composite indicators are particularly useful when translating results to the general public, since it is easier to interpret a number rather than to identify common trends among a battery of indicators. Moreover, it enables cross-country comparisons, which can be particularly interesting for benchmarking, performance and policy analysis. Some well-known examples of these indicators are the Human Development Index by Sudhir & Sen (1994), the Technology Achievement Index by Desai et al. (2002) or the Index of Social Progress by Porter et al. (2014). Stumbriene et al. (2020) support the idea that CIs can also monitor the effect of national policies and encourage continuous improvement.

The very first step of the building of the CI is the understanding of the variables to be measured through the new indicator. Once this criterion is decided, data should be compiled, always checking for quality and reliability. When evaluating a set of variables, it is crucial to pay attention to the measurement units, since the chances are that the comparison of two indicators is unreasonable and incommensurate. Nardo et al. (2005, p.44) stated that in order to "*avoid adding up apples and pears*", normalization of the variables was necessary to convert all indicators into the same standard. This normalization of the variables, consequently, improves the comparability and suitability of the analysis.

Eventually, the weighting and aggregation logic should be defined. This is an important step, since weights represent the relative importance that each indicator has on the output willing to explain by the aggregated index (Nardo et al., 2005). One of the weighting methods discussed in the literature, in order to obtain an objective building of weights, is the one based on factor analysis. In this way, since factor analysis seeks to gather the maximum variability of the data, through the minimum number of factors possible, the CI will depend on the "*statistical dimensions of the data*" (OECD, 2008, p. 89).

In the output of the factorial analysis, as previously explained, each factor reveals its degree of association to each of the variables. This can be identified in the rotation of factors and only indicators scoring high loadings in each factor will be chosen (Nicoletti et al., 2000). This is done in order to minimize the set of indicators that a factor explains.

Once variables with high loadings have been recognized and have been related to a specific factor, the distribution of weights is conducted. The interpretation behind is that the higher the loading of a variable in a factor, the more it will explain it. In this line, as a previous step to the construction of the final CI, Nicoletti et al. (2000) proposed the building of intermediate composites. These intermediate indexes are formed by the variables explaining a specific factor and the weights assigned to them. It follows the logic below.

$$INTI_{ij} = \sum_{K=1}^{n} w_{jk} I_{ik} \qquad (1)$$

Being I_{ik} the value of country i (i=1,2…27) in variable *k,* and w_{jk} the weight corresponding to that variable in the factor j. These weights are calculated following the subsequent formula:

$$w_{jk} = \frac{\left(factor\ loading_{jk}\right)^2 / total\ unit\ variance_j}{\sum_j \frac{\left(factor\ loading_{jk}\right)^2}{total\ unit\ variance_j}} \qquad (2)$$

These intermediate indicators will need to be grouped through a weighted sum, this is, taking into account the percentage of the model's variability they explain. The more a factor explains the model, the higher its weight in the final composite indicator it will be. It follows the logic below:

$$CI_i = \sum_{j=1}^{m} \delta_j INTI_{ij} \qquad (3)$$

Being *m* the number of factors selected and δ_j the weight of each of the intermediate indicators, computed as:

$$\delta_j = \frac{total\ unit\ variance_j}{\sum_{j=1}^{m} total\ unit\ variance_j} \qquad (4)$$

Eventually, a composite index will be obtained that will evaluate countries' education performance.

Further analysis will be possible once obtained the scores of each country in the composite index through a linear regression. Taking the CI as the dependent variable, the regression will reproduce the impact that some variables identified by the literature as possibly related with the education performance, which will be explained in the next section.

Regarding the linear regression, the very first step will be to correlate the CI variable with the selected variables. This allows to identify and select for the next step only those variables that have a significant correlation with the indicator. Those selected variables will be introduced in a linear regression. Due to the fact that the number of observations analyzed is low when comparing it to the number of variables included in the analysis, the estimation will be computed following the stepwise method. This procedure, widely used in educational and psychological research fields, evaluate the relevance of each variable in the model and order them, ending up only with the subset of variables statistically significant (Thompson, 1995).

4.2 Information Sources

Information sources used for this paper can be divided into two parts. On the one hand, variables for the factorial and cluster analysis, also called as "output variables" throughout this paper. On the other hand, a set of "input and contextual variables", representing circumstances that could be related with the output variables. These "input and contextual variables" will be included in the regression at the end of the analysis.

Regarding the former, outcome variables were included due to the fact that the paper focuses on results of students across MS. These variables can be divided into two sets of variables. Firstly, measures or results obtained from PISA 2018 exam. Namely these are the mean scores in the three parts of the test (*Read*, *Math* and *Science*), together with two indexes calculated by the OECD, one addressing the capacity of students to understand and remember, and other one considering the capacity to summary (*UnderRemem* and *Summ*). Secondly, indicators of the previously mentioned ET2020 program were also included as output variables. Also, a variable accounting for the percentage of young people neither employed nor studying and training (*Young*) was included in the first group. Table 4 gathers the whole set of variables explained above.

Table 4: List of variables in factorial analysis

Variables	Explanation	Source	Year
Read	PISA reading scale: overall reading score[2]	OECD	2018
Math	PISA mathematics scale: overall mathematics score	OECD	2018
Science	PISA science scale: overall science score	OECD	2018
UnderRemem	Index meta-cognition: understanding and remembering. Awareness of effective strategies to understand and remember information	OECD	2018
Summ	Index meta-cognition: summarizing. Awareness of effective strategies to summarize information.	OECD	2018
Young	Young people neither in employment nor in education and training (15-24 years) - % of the total population in the same age group	Eurostat	2018
Early_child	Participation in early childhood education (%). Education and care for children from birth to compulsory primary school age, (European Commission, 2019a)	Eurostat	2018
Employ	Employment rates of young people within the age 20-34 (graduated 1-3 years ago)	Eurostat	2018
Tertiary	Percentage of the population aged 30-34 who have successfully completed tertiary studies (e.g. university, higher technical institution, etc.) (European Commission, 2020a)	Eurostat	2018
Particip	Participation rate in education and training (in the last 4 weeks) (as % of people from 25 to 64 years). "Range of formal and informal learning activities, both general and vocational, undertaken by adults after leaving initial education and training", (European Commission, 2019b)	Eurostat	2018
Underachieve	Rate of underachievers in reading, mathematics and science among 15-year-olds. Pupils who fail to reach the minimum proficiency level necessary to participate successfully in society[3]	OECD, Ministerio de Educación y Formación Profesional	2018
Early_leave	Early leavers from education and training (as % of people within the age 18-24 years)	Eurostat	2018

For analytical purposes, the variables *Early_leave*, *Underachieve* and *Young* will be converted using the complement to 100%. In this way, the three new variables will be used instead of the previous. These are: *No_Early_leave*; *Achieve* and *No_Young*. This is a crucial step in the construction of the composite indicator, since higher values of sub-indicators

[2] Spanish results in PISA 2018 reading test showed an implausible response behavior across respondents. Therefore, specific results for Spain were not published in the PISA 2018 Results Report. The data of the Spanish reading questionnaire was extracted from Ministerio de Educación y Formación Profesional (2020).

[3] Due to the missing values of the reading part for Spain, underachievement statistics did not account for this country. Therefore, a mean value was calculated with the underachievement values reported by Ministerio de Educación y Formación Profesional (2019) and Ministerio de Educación y Formación Profesional (2020) for the three different categories of the PISA test, in order to build the overall underachievement rate of Spain.

must be linked to better performance (Stumbriene et al., 2020). As a consequence, all indicators included in the factorial analysis will follow this logic.

Table 5 represents the minimum, maximum, considered mean values and the standard deviation of the output variables. Altogether minimum and maximum values differ quite a lot, meaning that differences do exist across MS in Europe. While 31.4% of adults participate actively in learning and training (*Particip*) in Sweden, not even 1% of adults do so in Romania. Furthermore, when looking at the table, it is quite shocking to see that in Bulgaria 47.1% of the students completing the PISA questionnaire do not achieve the minimum efficiency level (*Achieve*). In the same way, Greece scores the lowest employment rate of recent graduates (*Employ*) of the whole European Union. This goes in line with Figure 1, in which the youth unemployment rate was represented. Moreover, the high average values in the variables related to the early childhood education (*Early_child*) and the rate of early leavers (*No_Early_leave*) show signs of hope in the sense that children are starting soon with education and in fact, only few of them leave school earlier.

Regarding the three variables representing the scores of the reading, mathematics and science parts, values in the data are between 420 (minimum in reading) and 530 (maximum in science). OECD (2019) explained that PISA scores are not a specific sum of points obtained by students in the conducted questionnaire, but instead, scores are assigned based on the variation in results observed by the countries participating in the survey. Scores are set following a normal distribution, having a total mean value around 500 points and a standard deviation of 100 points. Table 5 shows mean values between 480 and 488 for the three parts, which leads to the conclusion that the mean value of the European MS in the PISA test of 2018 is below the mean value of the 79 countries that completed the questionnaire in that year.

Table 5: Descriptive statistics of the output variables included in factorial analysis

Variable	Minimum	Maximum	Mean	Std. Deviation
Read	420	523	481	27,62
Math	430	523	488	24,25
Science	424	530	483	26,43
UnderRemem	-0.399	0.31	0.001	0,17
Summ	-0.421	0.29	0.01	0,18
No_Young	80.8	95.8	90.37	3,57
Early_child	75.2	100.0	92.82	6,32
Employ	55.3	94.8	81.77	9,17
Tertiary	24.6	57.6	42.55	9,055
Particip	0.9	31.4	11.46	7,87
Achieve	52.9	88.9	75.79	9,155
No_Early_leave	82.1	96.7	90.86	4,067

Regarding the second part of the analysis, the purpose was to identify variables that could be related to the performance of education systems, measured by the CI. The goal of the previous step of the analysis was to collect information about the students' conditions, which at the end of the day influence the learning environment of a 15 years-old student. Table A1 in the appendix gathers the variables tested for significance in this model. The variables are categorized according to the following criteria: family environment, school characteristics and infrastructure, individual characteristics of students and lastly, general socio-economic factors.

Farooq et al. (2011) underlined the importance of the inside and outside school factors contributing to this performance, meaning that performance is not only measure through a specific score in one exam or test. In fact, their research concluded with the relevance of variables such as the socio-economic status, the education of the parents and the achievement rate in the specific subjects of mathematics and English. They found out that parents' education influences more the school performance of their children rather than the actual occupation they have. Also, results showed that overall girls perform better than boys at school, which suggests that the gender variable can be something interesting to include in the data analyzed.

In this line, Hanushek and Woessmann (2011) also came up with an educational production function, which included a broad set of factors like the quantity and quality of school inputs, own abilities of students and family resources and background among others. Precisely, an interesting conclusion these authors reached was that the input quality of schools was in fact more significant than the input quantity. This means that, overall, when increasing the performance of schools, a reduction in the class size or an increase in the expenditure levels is not as effective as improving the quality of the instructional material and the teaching force.

As part of the general socio-economic factors' variables a specific index was used. This is the Social Progress Index (Social Progress Imperative, 2020), which gathers a battery of indicators related to the general environment that eventually could have an impact on educational results. The index, measured for 163 countries, is composed of three dimensions (Basic Human Needs, Foundations of Wellbeing and Opportunity), which at the same time are formed by four components each. Some of these components, indeed, are related to education as for example the ones representing the access to basic knowledge, or the access to advanced education. Hence, since education itself is what it is measured through the CI, these components needed to be excluded. In other words, the Social Progress Index had to be modified in order not to include the components related to the object of the analysis, education. That is why this variable was called "*Mod_SPI*".

5. RESULTS

5.1 Factorial analysis

Before starting the analysis, the variables were normalized following the standardization or z-score technique proposed by OECD (2008). This technique is applied in order to facilitate comparability of the data and to reduce the impact of extreme values in the formation of the composite index.

The next step of the factorial analysis is to test for multicollinearity of the variables subject to the analysis. For this, the correlation matrix of all variables was computed. Results, presented in Table A2 in the appendix, showed that there were high inter-correlation values among some of the variables. For example, the variable *Read* showed a correlation of 0.886 with *Math*, 0.954 with *Science* and 0.984 with *Achieve*. In a sense, this would mean that the variables *Read* and *Achieve* were closely linked. In fact, it means that those countries scoring high in the reading part were most likely to have a high achievement rate in the test. High inter-correlations meant that there were some common dimensions incorporated in the variables, having an impact in the result. Therefore, factor analysis was implemented as a previous step.

The very first time data was introduced in SPSS[4] the factor analysis gave an output, whose KMO value was 0.645. Furthermore, following Hair et al. (1999), variables whose measure of sampling adequacy was lower than 0.5 needed to be removed. As a whole, the process led to the removal of four variables in four different stages starting from "*UnderRemem*", and subsequently, "*Summ*", "*No_early_leave*" and "*Employ*".

This all introduced improvements to the analysis, with a final result of the selection of two factors or components with an eigenvalue bigger than one, that jointly explain 77% of the model's variability (Table 6). Table 7 shows both the final KMO sampling adequacy, which is 0.818 and the significance level of the Bartlett's test of sphericity. This last clearly shows a p-value lower than the 0.05. In this way, we reject the null hypothesis that the correlation matrix involving all variables included in the analysis is an identity and therefore, conclude that statistically speaking, the factorial analysis is acceptable. Furthermore, all values

[4] This SPSS software by IBM Corp. (2017) will be used throughout the whole set of analyses in this paper.

in the diagonal of the anti-image correlation matrix close to one, as it can be seen in Table A3 in the appendix. All three measures agree on the sampling adequacy of the analysis.

Table 6: Total variance explained in factorial analysis

Component	Eigenvalue	% of Variance	Cumulative
1	5.082	63.52	63.52
2	1.106	13.83	77.35

Table 7: KMO & Bartlett measures

Kaiser-Meyer-Olkin sampling adequacy measure		0.818
Bartlett's test of sphericity	Aprox. Chi-square	236.528
	gl	28
	Sig.	0.000

The two factors obtained can be interpreted by the rotation of factors and its factor loadigns or "salient loadings". Table 8 shows represents the end eight variables introduced in the factorial analysis. The outcome led the analysis to four variables explaining mostly factor 1 (*Achieve*, *Read*, *Math*, *Science*) and four variables explaining mostly factor 2 (*Particip*, *Tertiary*, *Early_child*, *No_Young*). Factor 1 accounts for a very large part of the explanation of the first four variables in the table. Precisely, it explains around 86% and 95% of the behaviour of the variables *Math* and *Achieve*, respectively. Regarding factor 2, the loadings are smaller, but still 84% of *Particip* is represented by this factor.

Table 8: Component rotation matrix in factor analysis

Variables	Component	
	1	2
Read	0.949	0.252
Math	0.863	0.415
Science	0.922	0.341
Achieve	0.954	0.173
No_young	0.385	0.643
Early_child	0.322	0.642
Tertiary	0.017	0.835
Partici	0.445	0.654

As a whole, it could be said that Factor 1 represents the variables measured by the PISA 2018 exam, since the three variables measuring the reading, mathematics and science performance are rated through the questionnaire, since it is the mean scored obtained by each country participating in the test. At the same time, achievement is quantified as the number of students who are over the minimum proficiency level in the PISA questionnaire. As a consequence, since PISA test is distributed to 15-year-old students, Factor 1 will deal with the secondary education level.

On the contrary, Factor 2 focuses more on the rest of the education levels, starting from the early childhood education (encompassing children from birth till compulsory primary education), after the education and training levels of people between 15 and 24 years old, the tertiary education attainment (30-34 years) and lastly, the general adult participation in learning (24-65 years).

5.2 Cluster analysis

Following the analysis, the two components from the factorial analysis were introduced in the hierarchical clustering. After analyzing at which step the increase in the coefficient of similarity measure took place, the final decision was to establish 3 different clusters. Having Table A4 as guidance in the appendix, this was because when going from 3 clusters to 2 clusters, the coefficient rose in 66%. In other words, when going from 3 to 2 clusters variability within the clusters increased a lot, translating into a reduction in similarity of the clusters.

Combining the three clusters obtained in the hierarchical method with the non-hierarchical one, the following cluster membership was obtained, as represented in Figure 4. Looking at the map, a geographical distribution can be approached, mostly when speaking about Cluster 3. In fact, the six countries forming this cluster, represented by the dark reddish colour, lie to the south east of Europe. Regarding the six countries included in Cluster 1, the distribution is not straightforward. Half of the countries lie more to the north, as it is the case of Sweden, Lithuania or Netherlands, but it also includes a few countries in the south, precisely, Malta and Cyprus. Cluster 2 is the most numerous cluster, composed by fifteen countries. Due to its large nature, countries do not follow a specific geographical distribution, having thus, countries located more to the south (i.e. Spain) and other more to the north (i.e. Finland).

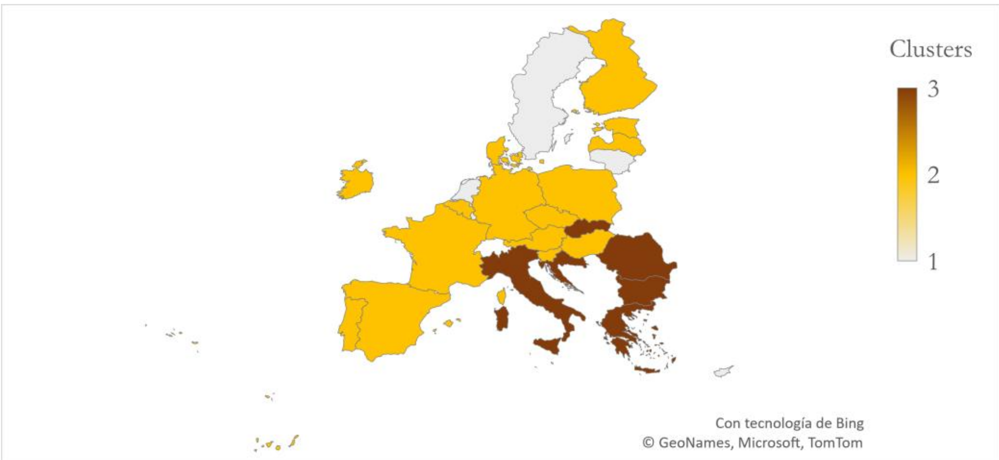


Figure 4: Cluster Membership

Table 9 gathers the mean values regarding the eight output variables, with each cluster accounting for an average value of the countries inside the group.

When analyzing the variability, as a way to find out whether there exist significant differences across clusters in terms of the eight variables, ANOVA test was driven. The table analyzed shows that all variables have a p-value lower than 0.05, and therefore, the null hypothesis of "no differences in the mean values of the variables" can be rejected. In fact, there do exist significant differences across clusters and that is indeed why the factorial analysis was conducted.

Table 9: Mean values in clusters and ANOVA test for output variables

Variable	Cluster 1	Cluster 2	Cluster 3	Total	F	Sig.
Number of countries	6	15	6	27		
Read	468.17	496.73	453.00	480.67	10.82	0.000
Math	484.67	501.00	459.00	488.04	12.02	0.000
Science	476.17	498.93	451.00	483.22	15.48	0.000
Achieve	70.70	81.13	67.55	75.79	9.99	0.001
No_young	92.67	91.38	85.57	90.37	15.18	0.000
Tertiary	51.13	42.66	33.70	42.55	8.98	0.001
Particip	15.45	12.91	3.82	11.46	5.06	0.015
Early_child	95.08	95.57	83.67	92.82	19.86	0.000

Regarding the interpretation of the clusters, it is straightforward to say that Cluster 3 accounts for the lowest scores in all the variables, being as a consequence, the worst cluster in terms of performance. An interesting insight out of Table 9 is that countries in Cluster 1 are the best ones in the variables addressing education levels of people from 24 years on. This is, people in the six countries forming Cluster 1 participate actively in learning and training, and it might be so, because in fact, a largest share of people have studied more years and have achieved a tertiary education. However, Cluster 2 is the best performer in terms of the PISA 2018 results, accounting for the best scores in the reading, mathematics and science tests and having also more people achieving the minimum level of efficiency in the test. An interpretation offered by the table would be that Cluster 1 scores best in the variables included in the Factor 2 and Cluster 2 in the variables explained by Factor 1.

5.3 Composite index

Regarding the Component Index (CI), the very first step was to check on the factorial analysis' output, precisely Table 8. The eight variables were divided into two groups in terms of their association to the two factors. As it has already been mentioned, the outcome led the analysis to four variables explaining mostly factor 1 and four variables explaining mostly factor 2. Table 10 recalls the set of variables that belong to each one of the factors.

Table 10: Linking of variables to the factors

Variables A (included in factor 1)	*Achieve*, *Read*, *Math*, *Science*
Variables B (included in factor 2)	*Particip*, *Tertiary*, *Early_child*, *No_Young*

Table 11 represents the weights of each variable on the factor on which they score a high loading. They have been computed according to expression (2) in the methodology section.

Table 11: Weights of the variables

Variables	Factor 1	Factor 2
Achieve	0.267	-
Read	0.264	-
Math	0.219	-
Science	0.250	-
No_Young	-	0.212
Particip	-	0.219
Tertiary	-	0.358
Early_child	-	0.211

For example, following Table 8, being 0.954 the factor loading of the variable Achievement in factor 1 meant that its weight in the intermediate indicator 1 is 0.267. Following this distribution of weights, two intermediate composites, in the form of $INTI_{i1}$ and $INTI_{i2}$, were formed.

$$INTI_{i1} = \sum_{A=1}^{n} w_A I_{iA} \qquad (5)$$

$$INTI_{i2} = \sum_{B=1}^{n} w_B I_{iB}$$

Being $INTI_{i1}$ and $INTI_{i2}$ the values of intermediate indicators 1 and 2 respectively for country i (i=1,2,3…27); w_A the weight of the variable A (A= *achieve*, *read*, *math*, *science*) and w_B, the weight of the variable B (B= *Particip*, *Tertiary*, *Early_child*, *No_Young*) and I_{iA} and I_{iB} the values of the variables A and B in country *i*.

The results of the factorial analysis in Table 6 and expression (3) are used for assigning weights to the two intermediate indicators for elaborating the composite indicators. In this way, intermediate indicator 1 was accountable of explaining 82% of the variance, while intermediate indicator 2 explained the rest. Eventually, the CI was composed, and it was represented in the following way:

$$CI_i = INTI_{i1} * w_{INTI_{i1}} + INTI_{i2} * w_{INTI_{i2}} \qquad (6)$$

Being CI_i, the value of the composite index for country *i*; $INTI_{i1}$ and $INTI_{i2}$ the value of intermediate indicator 1 and 2 respectively, for country *i*; and lastly, $w_{INTI_{i1}}$ and $w_{INTI_{i2}}$ the weights of intermediate indicator 1 and 2 respectively.

Table 12 gathers the CI results of the twenty-seven countries that form the European Union. With a maximum of 1.341, Estonia is in the lead of the twenty-seven countries, followed by Finland and Ireland. These countries have the best scores not only in the PISA test, but also in the variables measured by the ET2020. When it comes to the countries that perform worse in the CI, Bulgaria is presented as the worst, scoring a minimum value of the indicator (-2.097) and followed by Romania. Since the two countries were part of Cluster 3, it can be said that results of the CI were coherent with the interpretation made in section 5.2.

Table 12: Results of country specific Composite Index

Countries	CI	Ranking	Countries	CI	Ranking
Austria	0.229	14	Italy	-0,351	20
Belgium	0.496	9	Latvia	0,134	15
Bulgaria	-2.097	27	Lithuania	-0,014	16
Croatia	-0.431	21	Luxembourg	-0,097	18
Cyprus	-1.474	25	Malta	-0,878	23
Czechia	0.303	12	Netherlands	0,588	8
Denmark	0.752	6	Poland	0,901	4
Estonia	1.341	1	Portugal	0,231	13
Finland	1.095	2	Romania	-1,956	26
France	0.392	11	Slovakia	-0,656	22
Germany	0.451	10	Slovenia	0,638	7
Greece	-1.029	24	Spain	-0,058	17
Hungary	-0.216	19	Sweden	0,786	5
Ireland	0.919	3			

Table 13: Descriptive statistics of the CI

	Min.	Max.	Media	Variance
CI	-2.097	1.341	0,000	0,786

At this point all the necessary information was obtained, in order to do a regression with the composite index as dependent variable. The very first step was mentioned to be the correlation matrix. As it is shown in Table A5, only eleven variables concluded to be significant at the 5% significance level. Table A6 gathers the descriptive statistics for these relevant dimensions. Results showed that CI was strongly positive correlated mainly with the social progress level (*Mod_SPI*), with the government expenditure on education as a percentage of GDP (*Govern_exp*), the level of help provided by schools regarding homeworks (*Staff_homework*) and the percentage of students that did not skipped a whole day of school in the prior days to the PISA exam (*No_Truancy*). This would mean that in the general socio-economic sphere, countries having a higher social progress and a greater government expenditure on education as percentage of the GDP were the ones scoring best in the CI. Another clear relation was shown by the number of teachers willing to provide help with homework and the share of students not skipping classes. This suggests that the more a student attends classes and the more help he or she is offered, not only the better the performance of the student it will be, but also the performance of the whole education system. Furthermore, a smaller positive correlation was also found between the CI and real GDP per capita (*Real_GDP*), the female response rate (*Female*) and the index of economic social and cultural status in 2018 (*ESCS*[5]). The logic behind would be to say that an increase in the number of girls completing the PISA questionnaire in a country, in its real GDP per capita and in its score of the index of economic, social and cultural status, will lead to a better performance of the CI.

Results also showed that the indicator had a significant negative relation with some other dimensions. The most remarkable ones were between the CI and the percentage of students being victims of bullying acts at least few times a month (*Bullying*) and the share of students not having a quiet place to study (*Place*). In a sense, the larger the share of students having suffered from bullying acts at school and the more students recognizing not having a proper place to study in at home, the worse the score in the CI was. Apart from these, competitiveness across students (*Competitiveness*) and a lower value in the GINI coefficient (*GINI*), which measures the inequality level in the distribution of disposable incomes across countries, were negatively correlated with the CI. This means that a competitive atmosphere at school is counterproductive for the overall performance. At the same time, the lower the value of the GINI coefficient, this is, the closer the index is to zero and so, the more egalitarian the distribution of the income in a country is, the better it scores in the CI.

As a next step, once introduced the previous dimensions as independent variables in the model and following the stepwise procedure, a model explaining 65% of the variability was obtained.

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[5] Regarding the interpretation of the index of economic, social and cultural status (*ESCS*) it must be understood that it is a composite indicator carried out by the OECD, based on the PISA questionnaires. Lagravinese et al. (2017, p. 5) described this index as a measure capable of describing the family background, through the inclusion of dimensions such as "*the occupation and education level of parents and indicators of cultural and educational resources at home*". This is a largely used indicator in the academic sphere, due to its all in one nature, since it addresses the financial, social and cultural resources.

Table 14: Output of the regression

	Coefficient	Significance
(Constant)	-8.261	0.003
Mod_SPI	0.082	0.009
No_Truancy	0.023	0.021
Place	-0.074	0.059
R^2	0.651	
Adjusted R^2	0.605	

Eventually only three variables were identified as relevant and Table 14 gathers the coefficients and their significance. The output obtained in the previous table is represented through the following expression:

$$CI_n = -\ 8.261 + 0.082\ Mod\_SPI_n + 0.023\ No\_Truancy_n -\ 0.074\ Place_n \qquad (7)$$

The logic behind is that the higher the social progress of a country and the people attending the whole day to class, the higher it will be its score in the composite indicator. On the opposite, the greater the number the students not having a quiet place to study, the lower its score will be in this measure. This result leads us to confirm how important was to address the overall environment of the students, accounting to its surrounding conditions as the socio-economic factors, the family environment and home conditions. Indeed, the three explanatory variables of the CI model belong to these categories. This is, "*Mod_SPI*" would be a measure of the socio-economic factors, "*No_Truancy*" related to the individual characteristic of students and lastly, "*Place*" relates to the family environment.

Linking these results with the previous cluster analysis, an interesting contribution would be to relate the set of clusters and their performance both in the relevant variables of the model explaining the CI and the CI itself. Table 15 shows the average values of the three clusters in each of the relevant variables, while also showing the average CI performance by clusters.

An interpretation of this table would be to say that as a whole, and in terms of the CI built in this paper, Cluster 2 is the best performer and the cluster whose education system is the best. This cluster is described as the one with lower truancy levels and so, with more people attending lectures. At the same time, it is the cluster with the lowest share of people not having a proper place to study in at home. In terms of social progress there are not significant differences between Cluster 1 and Cluster 2, which suggests that the real difference between the two clusters rely on the other two variables previously explained. Again, there is no question that Cluster 3 is the worst performer. In fact, around 35% of students have recognized that have someday skipped lessons for the whole day, 11% of students do not have a silent place to study at home and lastly, the social progress level of the countries in Cluster 3 is lower.

Table 15: Mean values in clusters and ANOVA test for CI and relevant input variables

Variable	Cluster 1	Cluster 2	Cluster 3	Total	F	Sig.
Number of countries	6	15	6	27		
CI	-0.18	0.51	-1.09	0	14.389	0.000
SPI	87.93	87.41	81.61	86.24	6.121	0.007
NoTruancy	76.20%	79.87%	64.55%	75.65%	3.216	0.058
Place	7.28%	6.17%	10.95%	7.48%	5.893	0.008

At the same time, when analyzing the variability across clusters in these categories, ANOVA test was once again driven. Through the significance levels in Table 15, the null hypothesis of "no differences in the mean values of the variables" can be rejected at the 10% significance level for all four dimensions. As a consequence, it could be stated that differences across clusters in the relevant variables traduce into different CI scores for the three clusters constructed in this paper.

6. CONCLUSIONS

The main interest of this paper was to assess the performance of educational systems in the European framework, based on the PISA 2018 exam conducted across students in the twenty-seven countries forming the union at the current date. As complementary, data on the ET2020 framework launched by the European Union was also used. For this purpose, this paper proposed a combination of two tools widely used in the research arena, which are the building of a composite indicator and a cluster classification.

The classification of European countries in terms of the performance or output variables concluded with three clusters with a high degree of internal homogeneity within the group, while, at the same time, having a high inter-cluster heterogeneity. The cluster accounting for the worst values in the dimensions previously mentioned was the one formed by the countries in the south-east of Europe, namely Bulgaria, Croatia, Greece, Italy, Romania and Slovakia (cluster 3). The group formed by Cyprus, Lithuania, Luxembourg, Malta, Netherlands and Sweden (cluster 1) was highlighted as the one addressing best education levels of people from 24 years on, based on the measures of participation rates in learning and training or the tertiary education attainment levels among others. The last group gathered the rest of the European countries (cluster 2), whose combination generated the group with the best performance in terms of the PISA 2018 results and achievement levels.

These previous results were confirmed by the composite index constructed, which identified Estonia, Finland and Ireland (from cluster 2) as the best performers, while pointing out Bulgaria and Romania (from cluster 3) as the worst performers. In fact, the CI showed that the fifteen countries in cluster 2 were on average the best ones, followed by cluster 1 and eventually cluster 3. Indeed, differences in the CI score across clusters were statistically significant, showing very different educational system efficiencies across Europe.

The creation of the CI also helped in the finding of some attributes related to the position of a country in comparison to the rest of member states. For this purpose, a large set of input and contextual variables regarding the family, school and a more general socio-economic environment, together with individual attributes of students was collected, from which three dimensions were identified as relevant, when explaining the CI. These were related with the social progress level of the countries, the truancy levels and the home conditions of the students.

As a consequence, the research confirms that Europe is not homogeneous in terms of educational performance. Although EU policies and initiatives as the ones mentioned and used throughout the research, such as the ET2020 and the EEA, have made efforts to orientate towards a convergence, still there is a lot to improve and in fact, a new horizon has been set for 2025-2030.

At the end of the day, this paper contributes to the job of policy makers in the European Union to find out which factors contribute to explain the differences within member states and therefore, improve them as a way to achieve the convergence and cohesion desired in a strong and optimum union.

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8. APPENDIX

Table A 1: List of input variables

Criteria	Variables	Explanation	Source	Year
Family Environment	*Place*	Students who do not have a quiet place to study	OECD	2018
	ESCS	Index of economic, social and cultural status 2018	OECD	2018
School Characteristics and Infrastructure	*Teachers_bachel*	Index proportion of all teachers with level ISCED 5a Bachelor	OECD	2018
	Teachers_master	Index proportion of all teachers with level ISCED 5a Master	OECD	2018
	Staff_homework	School staff help with homework (out of 100%)	OECD	2018
	Math _time	Learning time per week (regular mathematic lessons)	OECD	2018
	Science _time	Learning time per week (regular science lessons)	OECD	2018
	Learning_time	Total learning time in regular lessons (hours)	OECD	2018
	Size_ class	Index size of [test language] class 2015	OECD	2015
	Stud_teacher_ratio	Student-teacher ratio	OECD	2018
Individual Characteristics of Students	*Female*	Female respondents	OECD	2018
	No_Truancy	Student Truancy (Percentage of students that never skipped a whole day of school)	OECD	2018
	Bullying	% of students who reported being victims of any type of bullying act at least a few times a month	OECD	2018
	ISEI	Index students' expected occupational status (ISEI)	OECD	2015
	Sense_belonging	Index sense of belonging	OECD	2015
	Competitiveness	Index measuring the co-operative or competitive environment in the class	OECD	2018
Socio-Economic Factors	*Govern_exp*	Government expenditure in the EU on education (% of GDP)	Eurostat	2018
	Pub_expend_second	Public Expenditure on secondary education (as % of GDP)	Eurostat	2018
	Real_GDP_pc	Real GDP per capita	Eurostat	2018
	GINI	Gini coefficient of equivalized disposable income (scale from 0 to 100)	Eurostat	2018
	Stud_pub_upp_sec	% of pupils in public institutions (upper secondary)	Eurostat	2018
	Stud_pub_tertiary	% of students in public institutions out of total students in tertiary level 2017	Eurostat	2017
	Mod_SPI	Modified Social Progress Index, after excluding indicators related to education (access to knowledge, access to advanced education)	Social Progress Imperative	2018

Table A 2: Correlation Matrix of output variables

Variables	*Particip*	*Achieve*	*Tertiary*	*No_Early_ leave*	*Early_child*	*Employ*	*Read*	*Math*	*Science*	*UnderRemem*	*Summ*	*No_Young*
Particip	1.000	0.518	0.459	0.087	0.467	0.313	0.596	0.592	0.599	0.092	0.015	0.491
Achieve	0.518	1.000	0.254	0.345	0.402	0.131	0.984	0.855	0.925	0.005	0.005	0.397
Tertiary	0.459	0.254	1.000	0.533	0.355	0.221	0.297	0.339	0.326	-0.033	-0.182	0.386
No_Early _leave	0.087	0.345	0.533	1.000	-0.170	0.039	0.345	0.291	0.333	0.063	-0.129	0.340
Early_child	0.467	0.402	0.355	-0.170	1.000	0.491	0.432	0.574	0.474	-0.144	-0.154	0.418
Employ	0.313	0.131	0.221	0.039	0.491	1.000	0.222	0.417	0.359	-0.138	-0.083	0.837
Read	0.596	0.984	0.297	0.345	0.432	0.222	1.000	0.886	0.954	-0.011	-0.001	0.466
Math	0.592	0.855	0.339	0.291	0.574	0.417	0.886	1.000	0.945	0.015	-0.019	0.630
Science	0.599	0.925	0.326	0.333	0.474	0.359	0.954	0.945	1.000	-0.016	0.003	0.602
UnderRemem	0.092	0.005	-0.033	0.063	-0.144	-0.138	-0.011	0.015	-0.016	1.000	0.854	-0.069
Summ	0.015	0.005	-0.182	-0.129	-0.154	-0.083	-0.001	-0.019	0.003	0.854	1.000	-0.086
No_Young	0.491	0.397	0.386	0.340	0.418	0.837	0.466	0.630	0.602	-0.069	-0.086	1.000

Table A 3: Anti-Image Correlation Matrix in factorial analysis

	Particip	*Achieve*	*Tertiary*	*Early_child*	*Read*	*Math*	*Science*	*No_Young*
Particip	.817[a]	0.393	-0.245	-0.176	-0.437	-4.904E-05	0.072	-0.085
Achieve	0.393	.764[a]	0.007	-0.036	-0.883	-0.053	0.079	0.217
Tertiary	-0.245	0.007	.889[a]	-0.142	-0.012	0.028	0.008	-0.160
Early_child	-0.176	-0.036	-0.142	.851[a]	0.038	-0.407	0.167	-0.028
Read	-0.437	-0.883	-0.012	0.038	.750[a]	0.075	-0.436	0.017
Math	-4.904E-05	-0.053	0.028	-0.407	0.075	.865[a]	-0.607	-0.139
Science	0.072	0.079	0.008	0.167	-0.436	-0.607	.839[a]	-0.338
No_Young	-0.085	0.217	-0.160	-0.028	0.017	-0.139	-0.338	.888[a]

Table A 4: Agglomeration Schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	6	22	0.005	0	0	8
2	4	15	0.023	0	0	20
3	1	2	0.041	0	0	5
4	16	26	0.068	0	0	14
5	1	10	0.100	3	0	14
6	20	27	0.134	0	0	16
7	8	9	0.185	0	0	18
8	6	11	0.238	1	0	12
9	7	14	0.299	0	0	16
10	21	25	0.445	0	0	12
11	12	24	0.596	0	0	17
12	6	21	0.804	8	10	18
13	17	19	1.066	0	0	19
14	1	16	1.345	5	4	21
15	3	23	1.630	0	0	23
16	7	20	1.990	9	6	21
17	12	13	2.458	11	0	20
18	6	8	3.326	12	7	24
19	17	18	4.420	13	0	22
20	4	12	6.004	2	17	23
21	1	7	7.906	14	16	24
22	5	17	10.151	0	19	25
23	3	4	14.456	15	20	26
24	1	6	19.892	21	18	25
25	1	5	33.092	24	22	26
26	1	3	52.000	25	23	0

Table A 5: Correlation between input variables and CI and significance level

FAMILY ENVIRONMENT	
Place	-.600***
	.001
ESCS	.478**
	.012
SCHOOL CHARACTERISTICS	
Staff_homework	.497***
	.008
INDIVIDUAL CHARACTERISTICS OF STUDENTS	
Female	.392**
	.043
No_Truancy	.618***
	.001
Bullying	-.610***
	.001
Competitiveness	-.422**
	0.028
SOCIO-ECONOMIC FACTORS	
Govern_exp	.535***
	.004
Real_GDP_pc	.396**
	.041
GINI	-.458**
	.016
Mod_SPI	.660***
	.000

***, ** statistically significant at 1% and 5%, respectively.

Table A 6: Descriptive statistics for significant input variables

Variable	Minimum	Maximum	Mean	Standard Deviation
Place	3.30	18.15	7.48	3.38
ESCS	-0.47	0.52	-0.015	0.23
Staff_homework	19.01	90.23	56.00	17.36
Female	46.22	50.78	49.27	1.06
No_Truancy	43.19	92.76	75.65	13.54
Bullying	12.00	35.00	23.85	6.24
Competitiveness	-0.28	0.31	-0.022	0.14
Govern_exp	3.20	6.90	4.87	0.95
Real_GDP_pc	6550	83470	27150	17420
GINI	20.9	39.6	29.76	4.3
Mod_SPI	77.17	91.91	86.24	4.35