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Clustering of countries according to programme for international student assessment (PISA) scores

Uluslararası Öğrenci Değerlendirme Programı skorlarına göre ülkelerin kümelenmesi

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Abstract

This study aims to cluster 65 countries based on PISA results. In the study, PISA results (Science-Mathematics-Reading) published by OECD in 2015 and 2018 were used. The main purpose of the analysis is to apply cluster analysis using a multivariate data structure to identify similarities and differences in education systems between countries. In this analysis, the k-means method and the hierarchical clustering algorithm were used to group countries into specific groups, so that countries with similar educational performance were included in the same cluster. In addition, Dunn, Connectivity and Silhouette indexes were used to increase the reliability of the analysis and to determine the optimal number of clusters. According to the validation indexes, k-means method with k = 2 was used for 2015 PISA scores while hierarchical clustering algorithm with k = 2 was used for 2018 PISA scores. In 2015, Turkey was the only country that changed clusters between the countries clustered according to their PISA scores and the countries clustered according to their PISA scores in 2018, and the reasons for this change were discussed. It is also observed that Turkey was in Cluster-1 in 2015, which includes countries with lower performance, and in Cluster-2 in 2018, which includes countries with higher performance. The clustering methods and indexes used provide a more robust and informed interpretation of the results obtained and make an important contribution to understanding the education systems of countries based on PISA results and grouping countries with similar performance.

Keywords: Cluster analysis, Education performance, PISA scores

Öz

Bu çalışma PISA sonuçlarına dayanarak 65 ülkeyi kümelemeyi amaçlamaktadır. Çalışmada OECD tarafından 2015 ve 2018 yıllarında yayımlanan PISA sonuçları (Fen-Mathematik-Okuma) kullanılmıştır. Analizin temel amacı, ülkeler arasındaki eğitim sistemlerindeki benzerlikleri ve farklılıkları belirlemek üzere çok değişkenli bir veri yapısı kullanılarak kümeleme analizi uygulamaktır. Bu analizde, k ortalamalar yöntemi ve hiyerarşik kümeleme algoritması kullanılarak ülkeler belirli gruplara ayrılmış ve bu sayede benzer eğitim performansına sahip ülkeler aynı kümeye dahil edilmiştir. Ayrıca, analizin güvenilirliğini artırmak ve en uygun küme sayısını belirlemek amacıyla Dunn, Connectivity ve Silhouette İndeksleri kullanılmıştır. Küme geçerlilik endekslerine göre, 2015 PISA puanları için k=2 ile k-ortalamalar yöntemi kullanılırken, 2018 PISA puanları için k=2 ile hiyerarşik kümeleme algoritması kullanılmıştır. 2015 yılında PISA puanlarına göre kümelenen ülkeler ile 2018 yılında PISA puanlarına göre kümelenen ülkeler arasında küme değiştiren tek ülkenin Türkiye olduğu görülmüş ve bunun nedenleri tartışılmıştır. Ayrıca Türkiye'nin 2015 yılında daha düşük performanslı ülkelerin yer aldığı Küme-1'de olduğu 2018 yılında ise daha yüksek performanslı ülkelerin yer aldığı Küme-2'de yer aldığı görülmektedir. Kullanılan kümeleme yöntemleri ve indeksler, elde edilen sonuçların daha sağlam ve bilinçli bir şekilde yorumlanmasını sağlayarak, PISA sonuçlarına dayalı olarak ülkelerin eğitim sistemlerini anlama ve benzer performansa sahip ülkeleri gruplama konusunda önemli bir katkı sunmaktadır.

***Anahtar kelimeler**: Kümeleme analizi, Eğitim performansı, PISA skorları*

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1. Introduction

PISA (Programme for International Student Assessment) is an international student assessment program that measures the abilities and knowledge levels of 15-year-old students in mathematics, reading, and science. The program compares the performance of education systems in different countries worldwide and provides recommendations for improvement. PISA also plays an important role in determining global education trends and shaping education policies. The study, conducted every three years, allows for the examination of various factors, such as the effectiveness of education systems, student motivation, student experiences, investments in education systems and schools, and economic factors. PISA is considered a leading tool in education and is carried out to contribute to developing countries' education systems and create new policies (Soh, 2012).

Cluster analysis is a data analysis method that aims to group observations based on similar characteristics. This method allows a better understanding of observations, emphasizing different features and identifying similarities. Cluster analysis is applied to different data types and allows for the quick analysis of large amounts of data. As a result, cluster analysis enables a more effective interpretation of data and facilitates the comparison of different data sets (Everitt et al., 2001).

PISA data can be classified by cluster analysis method. Accordingly, it aims to cluster countries by considering the students' mathematics, science, and reading skill levels. Cluster analysis allows a better understanding of PISA data and a comparison of the education systems of different countries. In addition, this analysis can be used in determining countries' education policies. Cluster analysis allows for a more detailed examination of PISA data, highlighting distinctive features that can contribute to the effectiveness of countries' education systems and enhance education for students.

Although there are many studies on PISA in the literature, it has been observed that the number of studies using cluster analysis is not very high. Linnakylä & Malin (2008) tried to determine the profiles of Finnish students by performing cluster analysis using PISA 2003 data. Kjærnsli & Lie (2011) clustered countries according to their similarities using PISA 2006 data. Akın & Eren (2012) examined the education indicators of OECD countries with cluster analysis. Acar (2012) investigated Turkey's position among OECD member and candidate countries according to PISA 2009 results by using the cluster analysis method. Aksu et al. (2017) used a hierarchical clustering approach to determine how the OECD member and other participating countries clustered according to the average scores of self-efficacy, interest and attitude in the PISA 2012 student questionnaire. Mazurek & Mielcová (2019) examined the relationship between 2015 PISA scores and socioeconomic indicators such as GDP, education expenditures, and the democracy index using the k-means method. Ötken & Süslü (2020) examined Turkey's position among OECD member and candidate countries according to PISA 2012 results in terms of mathematics achievement scores by clustering and discriminant analysis. Güler & Veysikarani (2022) clustered 37 countries in the OECD community by taking into account their socio-economic and 2018 PISA scores.

The aim of this study is to classify countries into homogeneous groups based on their PISA scores obtained in 2015 and 2018. For clustering, the k-means method and the hierarchical clustering algorithm were used, while Dunn, Silholutte and Connectivity indexes were used to determine the optimum number of clusters.

2. Cluster analysis

In this study, countries were categorized into homogeneous groups according to their PISA scores using k-means and hierarchical clustering algorithms.

Clustering Analysis is a multivariate statistical analysis that aims to group units according to their similarities. Homogeneity within the cluster and heterogeneity between clusters is desired. In other words, cluster analysis divides similar groups into any data set into clusters that are homogeneous and different from other groups. In addition, it is aimed to have a lot of dissimilarity between groups (Çilgin & Kurt, 2021).

Clustering algorithms play an important role in the context of data analytics and mining. Hierarchical clustering algorithms can aggregate data points without the need for an initial number of clusters. This method functions by creating clusters based on similarities and ranking these clusters in a hierarchical structure. The results obtained through dendrograms offer a valuable perspective to understand the overall organization of the dataset. On the other hand, non-hierarchical clustering algorithms work with an initial set number of clusters and group data points based on this parameter, which is usually set by the user (Bulut, 2023).

2.1. k-means algorithm

The k-means algorithm's first step is determining the number of clusters. The aim is to divide the data set of n units into k clusters given as input parameters. This method aims to minimize the sum of squares of the intra-cluster distances from the cluster center of the observations in the clusters or groups obtained from the data set. Within the clusters, similarity will be high, and similarity between clusters will be low (Linnakylä & Malin, 2008).

The k-means algorithm is expressed as follows (Bulut, 2019).

I. Random selection of starting centroids: The algorithm chooses k centroids to split the data.
II. Assigning data to centroids: Each data point is assigned to the nearest centroid.
III. Recalculation of centroids: Each centroid is recalculated as the average vector of data points in the same cluster.
IV. Steps 2 and 3 are repeated until the k centroids are stable and the data are correctly distributed over their clusters.

2.2. Hierarchical clustering algorithm

The hierarchical method evaluates the similarity of all data objects in a cluster with the cluster center. This center is called $\mathrm{Sim}(C)$ and is the sum of the cosine similarities for each data object d with the center c in cluster C. The process of selecting pairs of clusters to be merged is performed by identifying pairs of clusters that show small differences in similarity.

The hierarchical algorithm is expressed as follows (Begum et al., 2016).

I. In the first step, N clusters are created for N items, initializing each item as a cluster. The distance between items in each cluster is called the distance between clusters.
II. Clusters close to each other are identified and merged into a single cluster, reducing the number of clusters by one.
III. The distances between the newly created cluster and the old clusters are calculated.
IV. Steps 2 and 3 are repeated so that all items are merged into a single cluster and the final cluster is of size N.

2.3. Cluster validity indexes

Cluster validity indexes are used to evaluate the number of clusters and to decide whether the number of clusters is optimal. The correct determination of the number of clusters suitable for the data shows the success of the index used in determining the number of clusters.

2.3.1. Dunn index

The Dunn index is calculated by dividing the smallest distance of the units from the units in other groups with the largest distance between the units in the group (Bulut, 2019; Bulut, 2023).

$$D(C) = \frac{\min d(x_i, x_j)}{\max d(x_i, x_j)}, \frac{x_i \epsilon C_{m_1}, x_j \epsilon C_{m_2}, m_1 \neq m_2 = 1,2,\ldots,k}{x_i, x_j \epsilon C_m, m = 1,2,\ldots,k} \tag{1}$$

The Dunn index takes values from zero to infinity. A larger value of the Dunn index indicates that the clustering result is optimum (Brock et al., 2008; Bulut et al., 2017).

2.3.2. Connectivity index

The value of the Connectivity index provides an approximation that shows an increase when the closest observations to a given point are in a different cluster. We can define $nni(j)$ as the jth closest neighbor to the ith observation. Connectivity index is defined as in Equation 2.

$$\mathrm{Conn}(C) = \sum_{i=1}^{n} \sum_{j=1}^{L} x_{i,nn_{i(j)}} \quad (2)$$

Here, L is a parameter determining how many neighbors to consider. $x_{i,nn_{i(j)}}$ is defined as {0 , if i and $nn_{i(j)}$ are in the same cluster; 1, if i and $nn_{i(j)}$ are in different clusters}, and it is calculated for each observation. Therefore, the connectivity index varies from zero to infinity for each observation, and it is desired to be minimized (Bulut, 2023).

2.3.3. Silhouette width index

Silhouette width index is the average of the silhouette values for each observation. The silhouette value of the ith observation is given in Equation 3.

$$S(i) = (b_i - a_i) / \max(a_i, b_i) \quad (3)$$

Where a_i is the average of the distances between observations in the same cluster as the ith observation. The distances $d(x_i, C_j)$ are calculated for all clusters. The smallest of the distances is taken as b_i. Silhouette index takes values in the range $[-1,1]$ and is desired to be maximum (Bulut, 2023).

3. Application

The data set used in this study consists of the PISA results published by the OECD in 2015 and 2018 for 65 countries (OECD, 2021), and it is aimed to cluster the countries in line with these results. Countries that applied for PISA in both years were included in the study. The R programming language was used in the study. In clustering analysis, k-means algorithm, which is one of the non-hierarchical clustering methods, and hierarchical clustering algorithm were used. Dunn, Silhoulette and Connectivity indexes were used to decide the optimum number of clusters.

According to Table 1 and Figure 1, Connectivity and Silhouette indexes selected k-means method as the optimum clustering method with $k = 2$. Dunn index, on the other hand, determined the hierarchical clustering algorithm as $k = 11$ as the optimum clustering method. Accordingly, considering the majority rule, k-means method was used for 2015 PISA scores with $k = 2$. Similarly, according to Table 2 and Figure 2, Connectivity and Silhouette indexes selected the hierarchical clustering algorithm as that the optimum clustering method with $k = 2$. Dunn index, on the other hand, determined the hierarchical clustering algorithm as $k = 4$ as the optimum clustering method. Accordingly, considering the majority rule, hierarchical clustering algorithm was used for 2018 PISA scores with $k = 2$. The optimum values are shown in bold in Table 1 and Table 2.

Table 1. Determining the number of clusters for PISA 2015 scores

Cluster number	Hierarchical clustering			k-means clustering		
	Connectivity	Dunn	Silhouette	Connectivity	Dunn	Silhouette
k=2	5.5718	0.1052	0.6326	**1.8944**	0.1464	**0.6514**
k=3	10.496	0.164	0.5912	14.0623	0.1062	0.5395
k=4	13.5917	0.1826	0.4811	12.9996	0.0797	0.4778
k=5	17.4413	0.1838	0.3644	26.752	0.1426	0.4332
k=6	19.7329	0.1838	0.3512	29.0437	0.1798	0.4249
k=7	28.8627	0.1445	0.3365	32.6119	0.1623	0.4116
k=8	37.5321	0.1857	0.3362	40.4048	0.0908	0.3679
k=9	43.998	0.2037	0.3494	47.3488	0.1826	0.3656
k=10	50.0901	0.2229	0.345	49.919	0.2168	0.3767
k=11	52.152	**0.2384**	0.3327	53.4611	0.131	0.3531
k=12	53.3365	0.2384	0.319	57.4258	0.131	0.3494
k=13	56.7194	0.2384	0.3097	67.5524	0.1778	0.3209
k=14	59.5028	0.2384	0.3037	70.1357	0.1919	0.3188
k=15	62.0028	0.2384	0.2954	72.6357	0.1941	0.3106

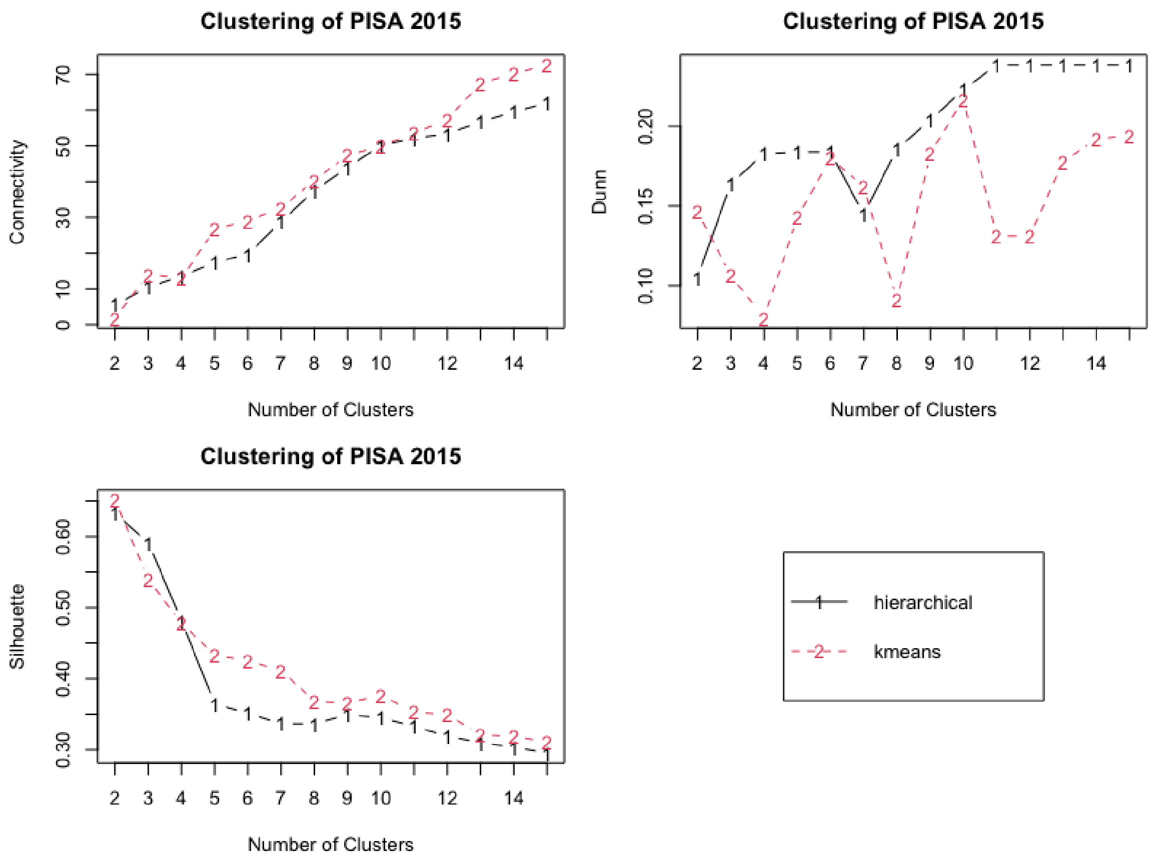

Figure 1. Determining the optimum cluster number for PISA 2015 scores

Table 2. Determining the number of clusters for PISA 2018 scores

Cluster number	Hierarchical clustering			k-means clustering		
	Connectivity	**Dunn**	**Silhouette**	**Connectivity**	**Dunn**	**Silhouette**
k=2	**1.0595**	0.1598	**0.6522**	3.9111	0.0902	0.6499
k=3	4.2385	0.1598	0.5997	15.5377	0.0609	0.5492
k=4	8.2214	**0.2572**	0.5625	13.7159	0.0947	0.4644
k=5	13.973	0.2175	0.5184	22.9619	0.0947	0.4155
k=6	18.294	0.1495	0.464	23.3762	0.0901	0.456
k=7	21.148	0.1495	0.374	41.0544	0.0901	0.3765
k=8	23.148	0.1495	0.343	35.05	0.1995	0.3958
k=9	26.2476	0.1495	0.2924	39.9218	0.2188	0.3854
k=10	34.6722	0.1611	0.354	45.2103	0.1201	0.3679
k=11	40.5313	0.2188	0.3356	47.2103	0.1201	0.3511
k=12	42.9758	0.2188	0.3304	51.9155	0.1507	0.3482
k=13	45.9655	0.2188	0.3157	54.9052	0.1507	0.3367
k=14	52.4754	0.2455	0.3058	57.3246	0.1507	0.3319
k=15	57.5964	0.2504	0.3072	58.6357	0.1507	0.3144

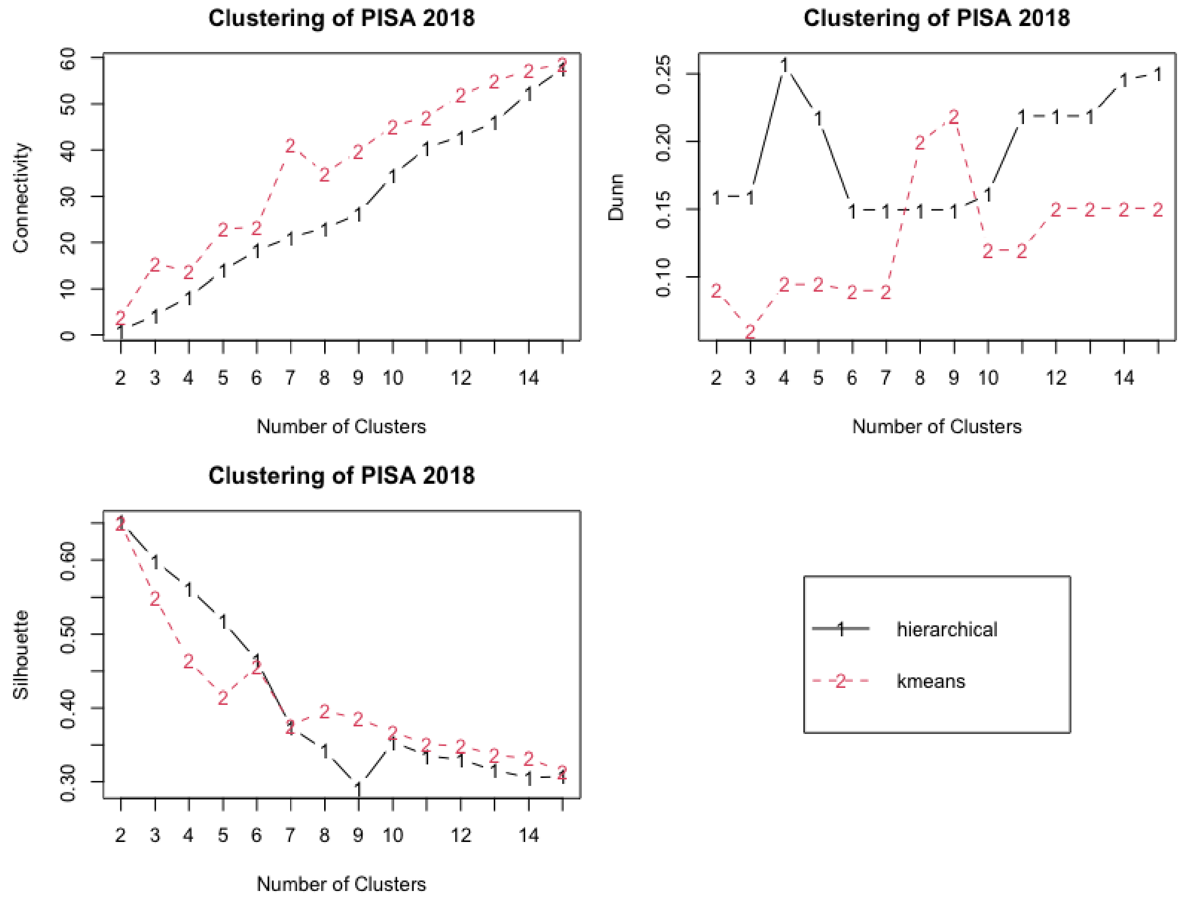

Figure 2. Determining the optimum cluster number for PISA 2018 scores

Accordingly, Table 3 shows the countries in the clusters formed according to the clustering analyses conducted for 2015 and 2018. According to Table 3, Turkey is the only country that changed clusters among all countries with regard to PISA performance from 2015 to 2018. Fort his reason, we can say that all countries except Turkey maintained their current position and performance. Therefore, how should Turkey's relocation be evaluated in terms of PISA performance? To answer this question, comparing the 2015 and 2018 PISA Reading, Science, and Mathematics scores of these clusters is necessary.

Table 3. Clustering of countries according to optimum methods

Cluster no	PISA 2015	PISA 2018
1	Albania, Argentina, Brazil, Bulgaria, Chile, Colombia, Costa Rica, Cyprus, Dominican Republic, Georgia, Indonesia, Jordan, Kazakhstan, Kosovo, Lebanon, Malaysia, Mexico, Moldova, Montenegro, North Macedonia, Peru, Qatar, Romania, Thailand, **Turkey**, United Arab Emirates, Uruguay	Albania, Argentina, Brazil, Bulgaria, Chile, Colombia, Costa Rica, Cyprus, Dominican Republic, Georgia, Indonesia, Jordan, Kazakhstan, Kosovo, Lebanon, Malaysia, Mexico, Moldova, Montenegro, North Macedonia, Peru, Qatar, Romania, Thailand, United Arab Emirates, Uruguay
2	Australia, Austria, Belgium, Canada, China, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Singapore, Slovak Republic, Slovenia, Sweden, Switzerland, United Kingdom, United States	Australia, Austria, Belgium, Canada, China, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Singapore, Slovak Republic, Slovenia, Sweden, Switzerland, **Turkey**, United Kingdom, United States

For this comparison, boxplot graphs were drawn for Reading, Science and Mathematics scores in 2015 and 2018 PISA exams. The graphs for 2015 are given in Figure 3 and the results for 2018 are given in Figure 4. Accordingly, in both graphs, the Reading, Science and Mathematics performances of the countries in Cluster-

2 are by far higher than those of the countries in Cluster-1. As a result, while Turkey was in Cluster-1, which included countries with lower performance in 2015, in 2018 when Turkey moved to Cluster-2, which included countries with higher performance, and showed that it was more successful.

Table 4 summarises the averages of each cluster for PISA 2015 and 2018 scores and Turkey's scores in the respective years.

Table 4. Mean of clusters' PISA scores

Cluster no	PISA 2015			PISA 2018		
	Reading	**Mathematics**	**Science**	**Reading**	**Mathematics**	**Science**
1	411.0356	406.7407	416.5362	404.6183	407.3462	411.4323
2	497.4189	499.8158	499.8256	494.7528	501.1795	497.3504
Türkiye	428.3351	420	425.4895	465.6317	454	468.2996

According to Table 4, in 2015, Turkey scored slightly above the average of Cluster-1, but it was still quite close to the center of Cluster-1. Looking at the 2018 PISA scores, Turkey's scores are now significantly higher than the average of Cluster-1 in all tests and closer to the average performance of Cluster-2 than in 2015. Therefore, Turkey is now in Cluster-2, although it still has lower scores than the average performance of Cluster-2. It is possible to say that innovations in education policies, improvements in student preparation, and improvements in educational infrastructure have influenced this remarkable change in Turkey's PISA performance.

Despite the rise in 2018, we believe that this rise is not sufficient considering Turkey's young potential. This is thought to be due to Turkey's frequently changing examination systems. Therefore, Turkey's education policies need to be based on a more sustainable, stable and long-term foundation. Consistency in education can help young generations realize their full potential and contribute to the creation of a nationally competitive educational environment.

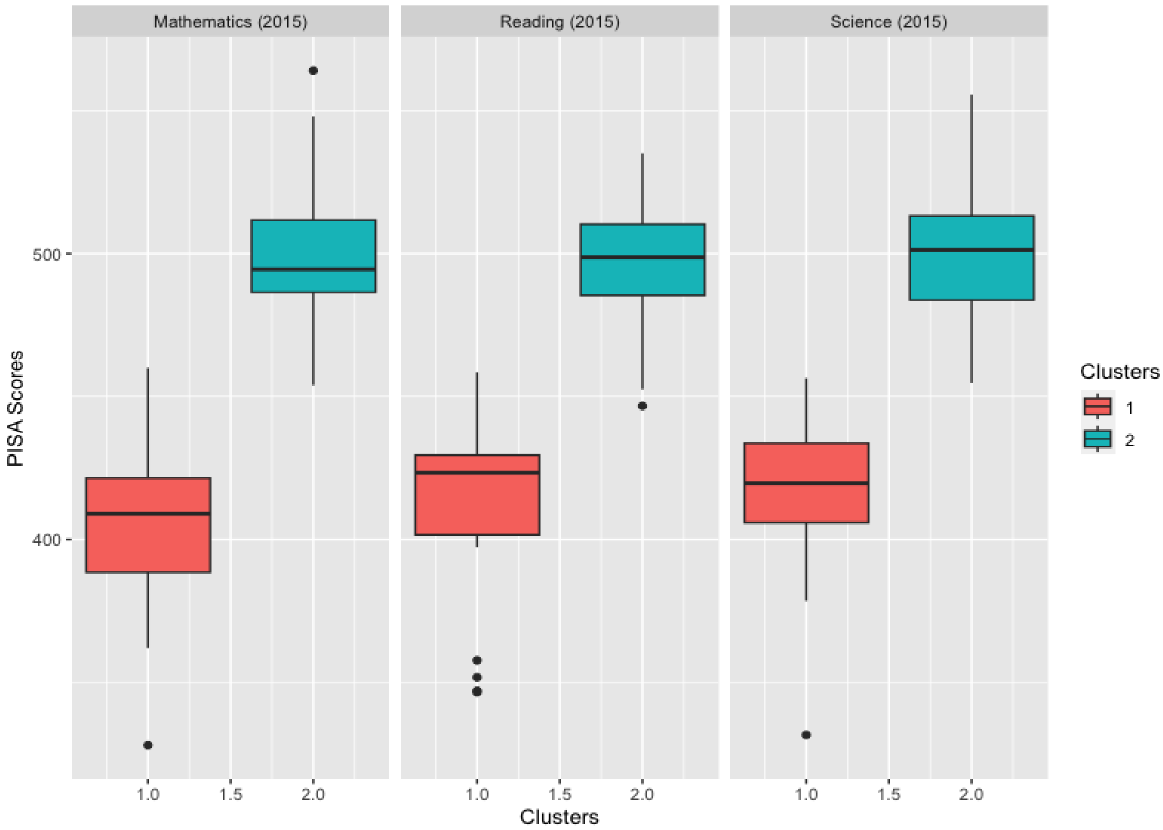

Figure 3. Boxplot graphics of countries' scores according to clustering results based on PISA 2015

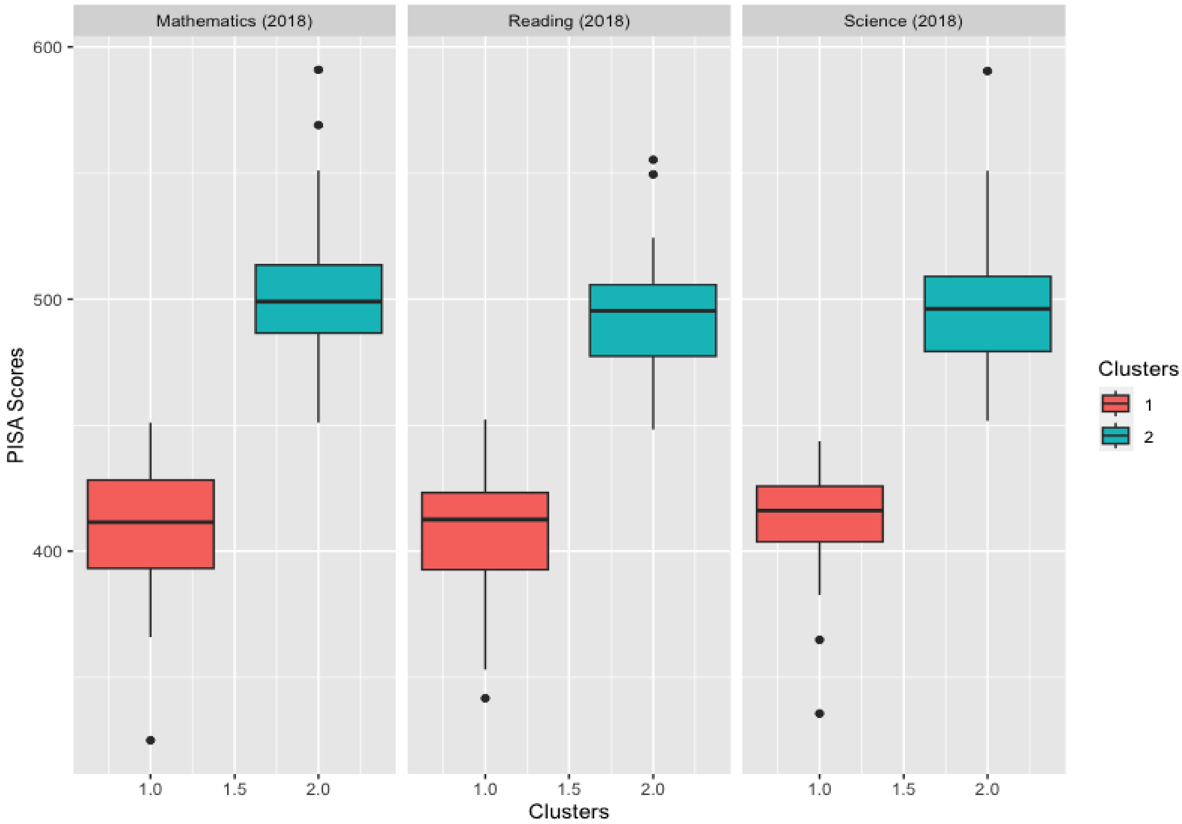

Figure 4. Boxplot graphics of countries' scores according to clustering results based on PISA 2018

At this stage of the study, the clustering results of the countries in PISA 2015 and 2018 were reflected on the world map. When the map is analyzed, it is seen that all countries except Turkey are in the same clusters. The clustering results for PISA 2015 are given in Figure 5 and the clustering results for PISA 2018 are given in Figure 6. In the relevant graphs, burgundy colors are used for Cluster-1 and blue colors are used for Cluster-2, and countries that did not participate in the PISA exam are highlighted in gray. When Figure 5 and Figure 6 are compared, it is easily seen that Turkey is the only country that changed cluster and color.

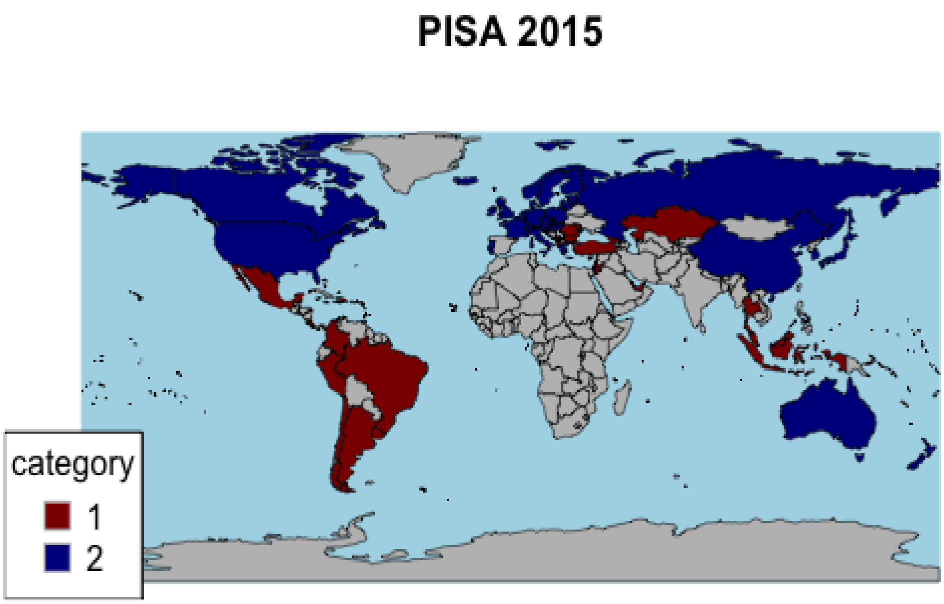

Figure 5. The clustering maps of countries according to 2015 PISA scores

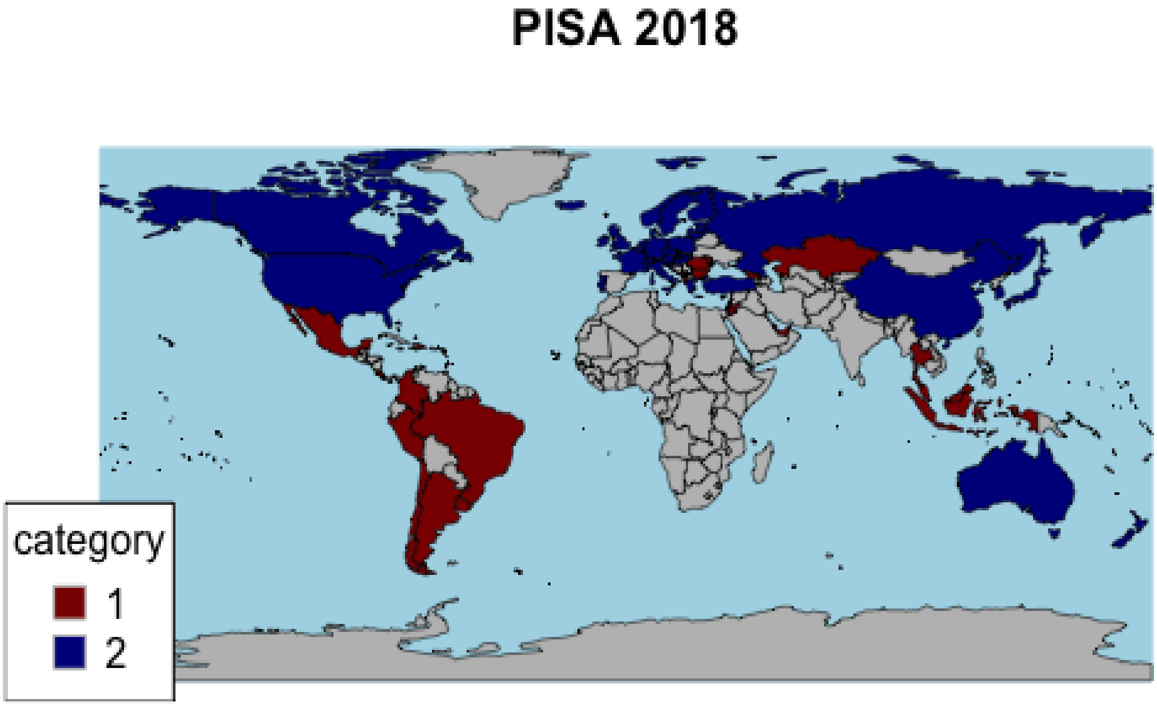

Figure 6. The clustering maps of countries according to 2018 PISA scores

Analyzing geographical patterns in combination with aggregated PISA scores provides insights into the regional dynamics shaping educational achievements and offers further opportunities to explore common challenges or successful strategies among neighboring countries.

4. Discussion and conclusions

PISA is a survey to measure the performance of education systems and can be used to compare students' reading, mathematics and science skills across countries. It is also possible to use the results to analyze the performance of education systems and guide countries' educational reforms.

This study aims to cluster countries into homogeneous groups according to their PISA scores (math-reading-science) in 2015 and 2018. The k-means clustering method, which is one of the most preferred non-hierarchical clustering methods in terms of easy of application, and the hierarchical clustering algorithm were used to classify the countries. In addition, Dunn, Silhoulette and Connectivity Indexes were used to determine the optimal number of clusters.

Between 2015 PISA scores and 2018 PISA scores, Turkey was the only country that changed its cluster. All countries except Turkey maintained their current positions. Turkey scored slightly above the Cluster-1 average in 2015, although it was still located quite close to the center of Cluster-1. When 2018 PISA scores are analyzed, Turkey's scores are well above the Cluster-1 average in mathematics, science and reading and closer to the average performance of Cluster-2 than in 2015. Therefore, Turkey is among the successful countries despite having lower scores than the average performance of Cluster-2. The increase in Turkey's PISA performance can be attributed to innovations and improvements in education policies. Despite the rise in 2018, given Turkey's potential, Turkey's education policies need to be based on a stable and long-term foundation in order for this rise to continue.

Like in our study, Akın & Eren (2012) divided OECD countries into 3 basic clusters according to the results of Cluster Analysis and found Turkey as a cluster member alone. According to this result, they found that Turkey is separated from other OECD countries. Their study supports our findings. As we show in our study, they showed that Turkey had a different performance from other countries.

As a result, the cluster analysis of countries based on PISA results is a detailed reflection of a country's education system performance. The analysis clearly identifies countries with successful education systems and can serve as a model for other countries. This research is expected to contribute significantly to improving the performance of education systems implemented by countries. Identifying successful examples may enable other countries to learn from these successes and improve their own systems. Moreover, determining the optimal number of clusters by using different clustering methods and cluster validity indexes is expected to add depth to education systems research and make a significant contribution to the related literature.

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Author contribution

The authors contributed equally to the study. Çağlar Sözen undertook the data collection, literature research, and writing of the study, and Hasan Bulut performed the data analysis.

Declaration of ethical code

The authors of this article declare that the materials and methods used in this study do not require ethical committee approval and/or legal-specific permission.

Conflicts of interest

The authors declare that there is no conflict of interest.

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