Multidimensional Comparisons of Health Systems Functioning in OECD Countries

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Abstract—Objective of the article is comparison of health care status and functioning of health systems in OECD countries, depending on risk factors, health expenditures, and health care resources and activities using appropriate multidimensional statistical methods. There are significant differences in health and healthcare results between and within OECD countries and regions. Article aims to present the results of application of multivariate statistical methods, namely factor analysis, cluster analysis and multidimensional comparative methods which provide an overview of the health care status and public health systems expenditures, various causal relations and differences or similarities of the OECD countries. This information is essential to the development of national and international health policies for treatment and financial budget of public health systems.

Keywords—Comparison, health care, health expenditure, health systems, health status, multidimensional methods, risk factors.

I. Introduction

The mission of the Organization for Economic Co-operation and Development (OECD) is to promote policies that will improve the economic and social well-being of people around the world. Today this organization focuses on helping governments around the world to re-establish healthy public finances as a basis for future sustainable economic growth.

Good health is a key aspect of people's well-being and enhances opportunities to participate in the labor market and to benefit from economic and employment growth. Despite remarkable progress in health status and life expectancy in OECD countries over the past decades, there remain large inequalities not only across countries, but also across population groups within each country. These inequalities in health status are linked to many factors, including differences in exposure to risk factors to health and in access to health care. [7]

Most OECD countries have endorsed, as major policy objectives, the reduction of inequalities in health status and the principle of equal access to health care based on need. The OECD regularly monitors to what extent these policy objectives are achieved, as well as the potential benefits and costs of various policy interventions that might help reduce health inequalities. [8]

By [7] people in OECD countries are living longer than ever before, with life expectancy now exceeding 80 years on average, thanks to improvements in living conditions and educational attainments, but also to progress in health care. But these improvements have come at a cost. Health spending now accounts for about 9% of GDP on average in OECD countries, and exceeds 10% in many countries. Higher health spending is not a problem if the benefits exceed the costs, but there is sample evidence of inequities and inefficiencies in health systems which need to be addressed.

Despite these improvements, important questions about how successful countries are in achieving good results on different dimensions of health system performance remain. Answering these questions is by no mean an easy task. The aim of this article is to help shed light on how well countries do in promoting the health of their population and on several dimensions of health system performance. Application of some selected advanced multidimensional statistical method on a selected set of indicators of health and health system functioning in OECD countries could summarize some of the relative strengths and weaknesses and can be useful to identify possible priority areas for actions.

II. Data and Methods

A. Data

The OECD health database *OECD Health Statistics 2016* [9] offers the most comprehensive source of comparable statistics on health and health systems across OECD countries. It is an essential tool to carry out comparative analyses and draw lessons from international comparisons of diverse health systems. This online database was released on June 30 and all datasets have been updated on October 12.

List of variables in OECD health statistics is very broad.

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Their complete list can be found at [10]. The problem is a missing data for some OECD countries which it is possible partially supplement from the database of World Health Organization [17].

As the basis of multivariate statistical analysis will be these selected indicators from the database *OECD Health Statistics 2016* [9]:

Selected data variables:

X1 Current expenditure on health, % of gross domestic product
X2 Current expenditure on health, per capita, US$ purchasing power parities
X3 Public expenditure on health, % of current expenditure on health
X4 Public expenditure on health, per capita, US$ purchasing power parities
X5 Physicians, density per 1 000 population
X6 Hospital beds, density per 1 000 population
X7 ALOS, Average length of stay, all causes, days
X8 Life expectancy at birth, female population
X9 Life expectancy at birth, male population
X10 Life expectancy at birth, total population
X11 Life expectancy at 65 years old, female population
X12 Life expectancy at 65 years old, male population
X13 Infant mortality rate, deaths per 1 000 live births
X14 Causes of mortality: Suicides, deaths per 100 000 population
X15 Tobacco consumption, % of adult population who are daily smokers
X16 Alcohol consumption, litres per population aged 15+

B. Factor analysis

The goal of *Factor analysis* [1], [2], [14], [16] is to characterize the *p* variables in terms of a small number of common factors.

An important result of the above model is the relationship between the variances of the original variables and the variances of the derived factors. This variance is expressed as the sum of two quantities: the *communality* and the specific variance. The communality is the variance attributable to factors that all the origin variables have in common, while the specific variance is specific to a single factor.

An important concept in factor analysis is the rotation of factors. In practice, the objective of all methods of rotation is to simplify the rows and columns of the factor matrix to facilitate interpretation. The *Varimax criterion* centres on simplifying the columns of the factor matrix. With the Varimax rotation approach, the maximum possible simplification is reached if there are only 1's and 0's in a single column.

The correlation between the original variables and the factors show the factor loadings. They are the key to understanding the nature of a particular factor. Squared factor loadings indicate what percentage of the variance in an original variable is explained by a factor.

The *Factor Scores* in output of Factor analyse procedure display the values of the rotated factor scores for each of *n* cases, in our analysis in each of 28 countries of EU. Factor score show where each country falls with respect to the extracted factors.

C. Cluster Analysis

Cluster analysis [1], [2], [5], [16] is an analytical technique that can be used to develop meaningful subgroups of object, in our case of countries. The objective is to classify a sample of objects into a small number of mutually exclusive groups based on the similarities among the objects. The clusters are groups of observations with similar characteristics.

The Cluster Analysis procedure is designed to group observations (countries) into clusters based upon similarities between them. In order to create clusters of observations, it is important to have a measure of "similarity" so that like objects may be joined together. When observations are to be clustered, the closeness is typically measured by the distance between observations in the p dimensional space of the variables. We have used Euclidian distance for measuring the distance between two items (i.e. countries), represented by *x* and *y*

$$d(x,y)=\sqrt{\sum_{i=1}^{p}\left(x_i-y_i\right)^2} \tag{1}$$

A number of different algorithms are provided for generating clusters. Some of the algorithms are agglomerative, beginning with separate clusters for each observation and then joining clusters together based upon their similarity. To form the clusters, the procedure began with each observation in a separate group. It then combined the two observations which were closest together to form a new group. After re-computing the distance between the groups, the two groups then closest together are combined. This process is repeated until only one group remained.

Ward's method [11], [12], which has been used for clustering, defines the distance between two clusters in terms of the increase in the sum of squared deviations around the cluster means that would occur if the two clusters were joined. The results of the analysis are displayed in several ways, including a *dendrogram*. Working from the bottom up, the dendrogram shows the sequence of joins that were made between clusters. Lines are drawn connecting the clustered that are joined at each step, while the vertical axis displays the distance between the clusters when they were joined.

D. Multidimensional Comparative Methods

Multidimensional comparative analysis [3], [4], [6], [12], [16] deals with the methods and techniques of comparing multi-feature objects, in our case OECD countries. The objective is establishing a linear ordering among a set of objects in a multidimensional space of features, from the point of view of certain characteristics which cannot be measured in a direct way (the level of socio-economic development, the standard of living, product quality, economic performance, public health situation ...).

At the beginning of the analysis, the type of each variable should be defined. It is necessary to identify whether the "great" values of a variable positively influence the analysed processes (such variables are called stimulants) or whether their "small" values are favourable (these are called destimulants). The variables of the third type, nominants (which have an "optimal" level and deviations either upwards or downwards are undesirable) are not suitable for this analysis.

The initial variables employed in composing an aggregate measure are, usually, measured in different units. The aim of normalisation is to bring them to comparability. Normalisation is performed according to the formulas [12], [16]:

$$\text{for stimulants } \rightarrow b_{ij} = \frac{x_{ij}}{x_{\max, j}} \cdot 100 \tag{2}$$

$$\text{for destimulants } \rightarrow b_{ij} = \frac{x_{\min, j}}{x_{ij}} \cdot 100 \tag{3}$$

The aggregate measure of health care level for each country has been calculated as the average of the b_{ij}, $i = 1, 2, \dots 34$. According to the formulas (2), (3) obviously implies that the higher the value of the average score, the higher the level of the multidimensional object.

III. Results and Discussion

A. Results of Factor analysis

The purpose of factor analysis is to obtain a small number of factors which account for most of the variability in the selected 14 variables: $X1$ - current expenditure, % GDP, $X2$ - current expenditures, per capita US$ PPP, $X3$ - public expenditures, per capita US$ PPP, $X4$ - physicians, density per 1 000 populations, $X5$ - hospital beds, density per 1 000 populations, $X6$ - ALOS, all causes, $X7$ - LE females at birth, $X8$ - LE males at birth, $X9$ - LE total population at birth, $X10$ - LE females at 65, $X11$ - LE males at 65, $X12$ - tobacco consumption, total, $X13$ - alcohol consumption, $X14$ - obese population.

Factor is a linear combination of the original variables. In this case, four factors have been extracted (Figure 1), since four factors had eigenvalues greater than to 1,0. Together they account for 83,72 % of the variability in the original data. Since we have selected the principal components method, the initial communality estimates have been set to assume that all of the variability in the data is due to common factors.

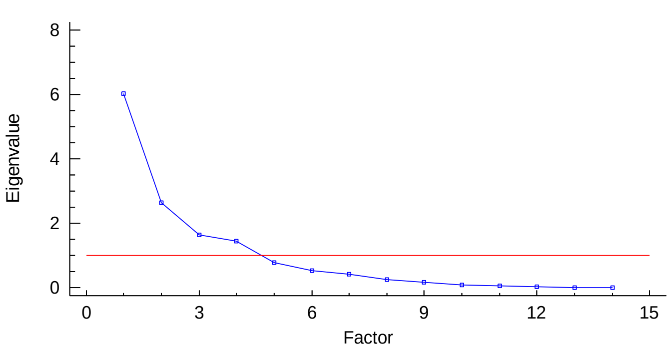

Fig.1 Scree plot

The *Scree Plot* [11], [12], [14], [16] can be very helpful in determining the number of factors to extract, because displays the eigenvalues associated with a component or factor in descending order versus the number of the components or factors. We use scree plots to visually assess which factors explain most of the variability in the data.

Factor loadings (Table 1) present the correlation between the original variables and the factors and they are the key to understanding the nature of a particular factor. Rotation is useful method used to rotate the factor loading matrix after it has been extracted. *Varimax rotation* [1], [2] maximizes the variance of the squared loadings in each column.

Table 1: Factor Loading Matrix After Varimax Rotation

Varia-ble	*Factor1*	*Factor2*	*Factor3*	*Factor4*
X1	0,268273	0,839641	-0,0588272	0,108291
X2	0,314018	0,910905	-0,0758203	-0,017325
X3	0,413872	0,834708	-0,0363578	-0,0258452
X4	0,406053	0,0835257	-0,218922	0,641637
X5	0,0253017	0,0137146	0,936172	0,13941
X6	0,184318	-0,0929827	0,911919	-0,0247764
X7	0,914325	0,144364	0,265438	0,135271
X8	0,924122	0,296987	-0,0421104	-0,0572955
X9	0,951922	0,239487	0,090297	0,0267102
X10	0,883684	0,179101	0,29724	0,0537621
X11	0,900871	0,311384	-0,0637482	-0,119745
X12	-0,0599572	-0,494635	0,0926103	0,718714
X13	-0,175303	0,366196	0,371789	0,627497
X14	-0,264301	0,280808	-0,504775	0,388812

Source: Own calculation, output from Statgraphics Centurion XV

Substantive interpretation of the four extracted factors is based on the significant higher loadings in Table 1. Factor 1 ($F1$), which explains 42,993 % variability of the total variability in the data, has 5 significant loadings with positive signs with variables $X7$-$X11$. Therefore, this factor can be interpreted as a *Factor of life expectancy*. The high values of this factor mean high level of life expectancy. Strong significant positive correlation with variables $X1$, $X2$ and $X3$ is the reason that we interpret Factor 2 ($F2$) as a *Factor of health expenditure*. This factor explains 18,749 % of the variability in the data. The higher the values of F2, the higher are the health expenditures in OECD countries and vice versa. Factor 3 ($F3$) explains 11,690 % of the variability in the data and correlates strongly with variables X5 and X6 so we can interpreted it's as a *Factor of health care activities*. Again, the higher the values of factor $F3$, the higher are health care activities in the country. The fourth factor $F4$ explains 10,288 % of the whole variability and its positive correlation with variables $X4$ and $X12$-$X14$ is reason that we have interpreted it's as a *Health risks factor*.

Table 2 shows the factor scores for each OECD country. In countries with low values of factor $F1$ is short life expectancy, in countries with low values of factor $F2$ is low level of health expenditure. Low values of factor $F3$ means low level of health care activities and low values of factor $F4$ means low level of health risks factors. For high values of factors interpretation is analogous.

Table 2: Factor Scores

Country	*Sign*	*Factor1*	*Factor2*	*Factor3*	*Factor4*
Australia	AU	3,32822	2,27443	-0,995323	-0,234179
Austria	AT	2,68197	2,37762	1,61454	2,59685
Belgium	BE	0,880969	1,74032	0,709422	-0,076370
Canada	CA	2,30198	2,36029	-0,924418	-1,19495
Chile	CL	-5,13699	-4,99837	-1,07168	-0,430208
Czech Repub.	CZ	-5,88518	-3,04573	0,88381	1,53104
Denmark	DK	0,140769	2,38839	-1,91121	-0,138136
Estonia	EE	-7,45816	-4,64653	0,167712	1,92167
Finland	FI	1,34048	0,587266	1,08586	-0,421567
France	FR	5,21371	2,82933	1,19389	1,4337
Germany	DE	1,93541	2,88874	1,73205	1,47602
Greece	EL	2,57314	-2,16755	-0,867592	4,23162
Hungary	HU	-10,8432	-5,04599	0,598363	1,77142
Iceland	IS	2,74515	1,81938	-2,10831	-1,20985
Ireland	IE	-0,297172	0,24318	-1,52082	0,861487
Israel	IL	2,53146	-1,56413	-1,83749	-2,03404
Italy	IT	4,99943	-0,0306766	0,187548	-0,488216
Japan	JP	7,65489	1,39811	8,30448	-1,30343
Korea	KR	2,53173	-2,79687	7,5354	-1,29515
Luxembourg	LU	2,98132	1,74021	1,08326	-0,495886
Mexico	MX	-10,6746	-6,48281	-2,45547	-4,04446
Netherlands	NL	2,57594	3,63984	-0,616842	-0,242653
New Zealand	NZ	1,70026	1,21249	-0,581673	-0,907659
Norway	NO	4,25192	3,53385	-1,44991	-1,09478
Poland	PL	-7,97788	-4,78783	0,81515	0,482587
Portugal	PT	0,554121	-0,390579	-0,741653	1,01937
Slovak Rep.	SK	-8,90422	-3,94842	-0,199494	0,388881
Slovenia	SI	-1,17588	-1,08571	-0,0238959	0,151678
Spain	ES	5,39396	0,571913	0,0985103	1,26356
Sweden	SE	4,10268	4,01199	-1,63695	-1,24468
Switzerland	SW	6,6617	4,67511	1,10404	0,539103
Turkey	TR	-10,3219	-7,52589	-3,61992	-2,47609
United King.	UK	0,484332	0,509966	-1,02714	-0,0580228
United States	US	-0,890323	7,71467	-3,52426	-0,278656

Graphical display of OECD countries in a two-dimensional coordinate system with axes of the selected factors allows us to assess quickly the health situation in each country and allows also compare situation in all OECD countries. Figure 2 present evident direct correlation of the factors $F1$ and $F2$. A higher level of life expectancy requires higher health care costs, and vice versa, with higher spending on health care is evident a higher level of life expectancy. In Figure 2 are evident two different groups of OECD countries. The first group of countries with relatively low value of the both factors consist the countries Czech Republic, Slovak republic, Estonia, Chile, Poland, Hungary, Mexico and Turkey. Other countries, except the United States, consists second group with a relatively high level of both factors. In the United States at current level of life expectancy it is too high level of health expenditure in comparison to other OECD countries.

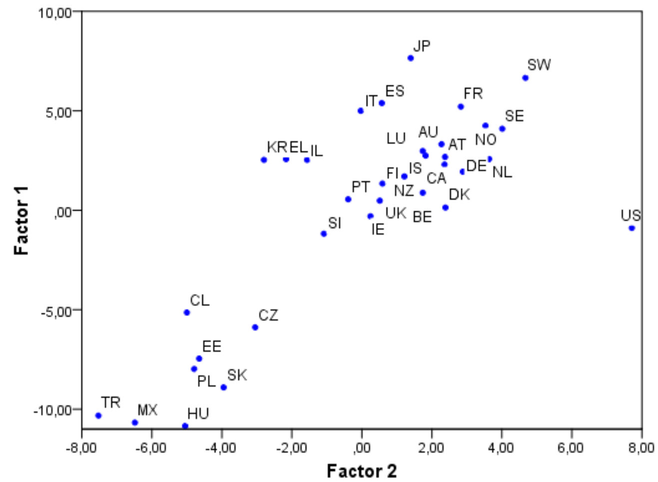

Fig. 2 Location OECD countries in the coordinate system of the factors F1 and F2

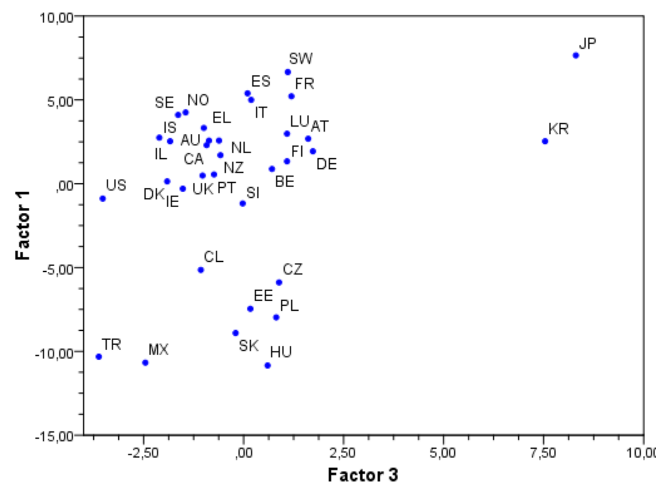

Fig. 3 Location OECD countries in the coordinate system of the factors F3 and F1

Figures 3 and 4 do not confirm an unequivocal direct dependence of $F1$ - factor of life expectancy from the factors $F3$ - factor of health care activities and factor $F4$ - health risk factor. This may be related to the efficiency of health systems, which is not the subject of this article.

A suitable method for measuring the effectiveness of health systems in OECD countries is for example Data Envelopment Analysis (DEA) method. DEA is thus a multicriteria decision making method for evaluating effectiveness, efficiency and productivity of homogenous group. Examples of its application for evaluation of the EU member states there are for example publications [14], [15]. To measure the effectiveness of treatment of certain diseases is an appropriate method a logistic regression [13], application however requires the use of individual data.

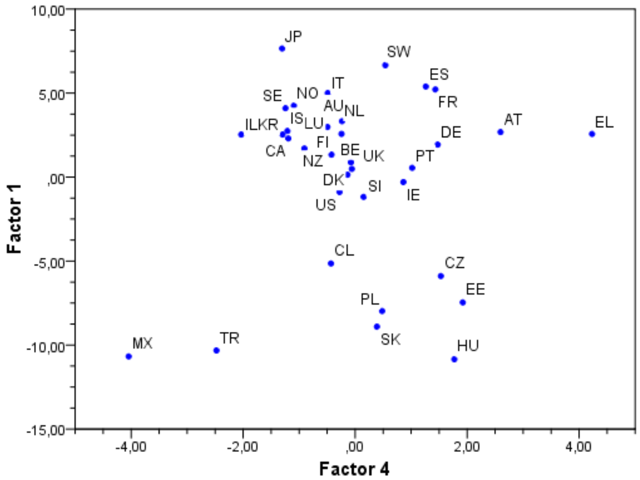

Fig.4 Location OECD countries in the coordinate system of the factors F4 and F1

B. *Results of Cluster analysis*

The results of cluster analysis by 14 variables, the same as in factor analysis, are consistent with the results of factor analysis, as we can see from dendrograms on Figure 5 and Figure 6, as a results of Ward's Method with Euclidian distance between two different countries.

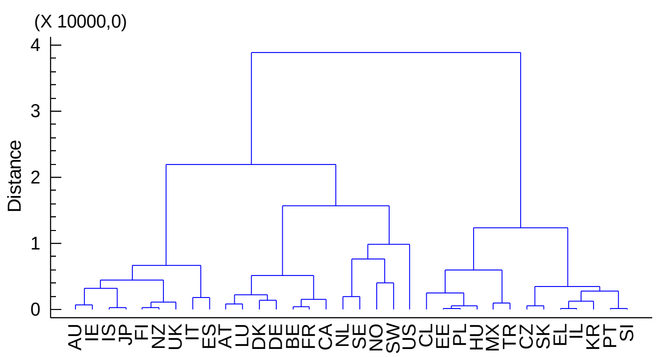

Figure 5 The dendrogram of Cluster Analysis, one cluster

Cluster, consisting of the all OECD countries, has been joined with the cluster of countries Chile, Estonia, Poland, Hungary, Mexico, Turkey, Czech Republic, Slovak Republic, Greece, Israel, Korea, Portugal and Slovenia and with cluster of other countries OECD on a large distance. It means that the health situation in these two groups of countries noticeably different.

Neither of these two main clusters are not homogeneous, as we can see at Figure 6. The cluster of developed countries is composed of three distinct clusters and cluster of less developed countries consist from two distinct clusters. In cluster of less developed countries first from two different clusters consists of the countries Chile, Estonia, Poland, Hungary, Mexico and Turkey, second one is composed of countries Czech Republic, Slovak Republic, Greece, Israel, Korea, Portugal and Slovenia.

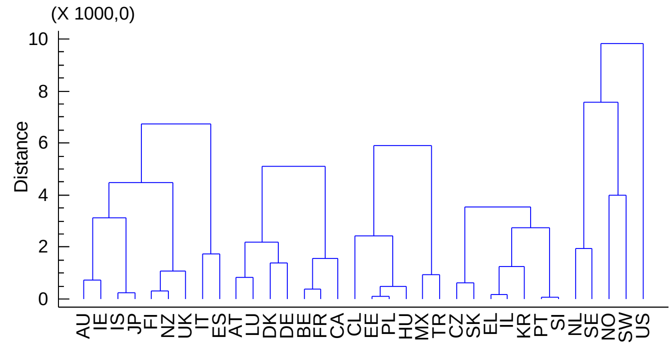

Fig. 6 The dendrogram of Cluster Analysis, five clusters

Cluster of developed countries contains two rather similar clusters, first one consists of countries Austria, Luxembourg, Denmark, Germany, Belgium, France and Canada, and second one consists of countries Netherlands, Sweden, Norway, Switzerland and United States. To the joint cluster of the last two clusters at a quite large distance joins a cluster of countries Australia, Ireland, Iceland, Japan, Finland, New Zealand and United Kingdom.

A. *Results of Multidimensional Comparison*

Table 3 contains the results of multidimensional comparative methods application.

For multidimensional comparative analyses we have used 8 variables, three stimulants $X10$, $X11$, $X12$ and five destimulants $X13$-$X17$. The variables of the third type, nominants (which have an "optimal" level and deviations either upwards or downwards are undesirable), like $X1$ – $X7$) are not suitable for this method.

The aggregate measure for each OECD country has been calculated as the average of the point b_{ij}, $i = 1, 2, ..., 34$ according to the formulas (2), (3). The higher the value of the average score, the higher the level of life expectancy and the lower is the level of the health risk factors. The rank assigned to the countries by ascending order from 1 to 34 we can see in Table 3.

We have used the Spearman rank correlations between average score S and each of the variables $X1$, $X2$, $X5$, $X6$, $X7$. These correlation coefficients range between -1 and +1 and measure the strength of the association between the variables. In contrast to the more common Pearson correlations, the Spearman coefficients are computed from the ranks of the data values rather than from the values themselves. Consequently, they are less sensitive to outliers than the Pearson coefficients.

The values of the coefficients are as follows: $r_{S,X1}$=-0,005, $r_{S,X2}$=0,0072, $r_{S,X5}$=0,119, $r_{S,X6}$=01825, $r_{S,X7}$=0,3034. From the values of these coefficients follows that rank of OECD countries by level of life expectancy and the health risk factors does not depend on health care expenditure and very little depends on the number of physicians, hospital beds and average length of stay in days.

Table 3: The results of multidimensional comparative analysis

Rank	Country	Score
1	Japan	67,387
2	Mexico	66,765
3	Iceland	66,576
4	Turkey	64,927
5	Israel	64,779
6	Korea	64,413
7	Sweden	63,481
8	Norway	62,450
9	Finland	61,692
10	Italy	61,396
11	Australia	59,295
12	Spain	58,874
13	Luxembourg	58,243
14	Portugal	57,021
15	Greece	56,856
16	Switzerland	56,306
17	Canada	56,108
18	Netherlands	55,393
19	United Kingdom	55,207
20	Denmark	55,108
21	New Zealand	55,024
22	France	54,456
23	Germany	54,449
24	Belgium	54,012
25	Austria	53,983
26	Slovenia	53,714
27	United States	53,139
28	Estonia	52,722
29	Ireland	52,562
30	Czech Republic	52,293
31	Chile	48,178
32	Slovak Republic	48,163
33	Poland	47,907
34	Hungary	44,486

IV. Conclusion

OECD health statistics is actually very detailed and extensive, tracks the amount of different indicators. The extensiveness and thus the opacity of data files is the reason that without at least a basic statistical analysis is the degree of provided information minimal.

Given the uniform method of reporting data for all OECD countries it is possible to use data for comparing different countries according to several selected indicators of the health care status and functioning of health systems.

The results of statistical analysis in this article confirm the appropriateness of the advanced multivariate methods and the suitability of the chosen indicators for comparison of health situation in OECD countries. The selected methods have enabled to extract four common factors instead of the original 14 variables. Possibility of graphical presentation of results has allowed obtaining transparent and visual information about the health situation in OECD countries. Cluster analysis and multidimensional comparative analysis have supplemented and deepened results of factor analysis.

The multidimensional comparative analysis provides some surprising results, such insignificant impact of health expenditure and health care activities on the health status in OECD countries. This suggests ineffective functioning of public health systems.

Acknowledgment

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