Determinants of Health Inequalities in European Countries

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Abstract: - The object of this article is to assess the health status of the population of selected European countries and to identify and quantify the determinants causing health inequalities in monitored countries. Health status and its supposed determinants are multidimensional categories, specified by a number of selected indicators from the *OECD Health Statistics 2018* database, therefore the monitored countries are those countries of Europe that are also OECD member countries. To reach the objective of the article have been used multivariate statistical methods, namely correlation, factor analysis, cluster analysis and linear ordering of countries using synthetic variable. The results of the analysis are presented in the form of tables and graphical outputs from the SAS and Statgraphics statistical packages and using the Excel spreadsheet.

Key-Words: - Health status, health determinants, health inequalities, factor analysis, cluster analysis, synthetic variable.

1 Introduction

Quality health care system is a priority for citizens of each country and a precondition for economic prosperity. Significant differences in health status exist between European countries and regions. Health inequalities exist along many demographic or social dimensions, including sex, age, geographic area and socio-economic status.

The Europe 2020 strategy, which aims to deliver smart, sustainable and inclusive growth with high levels of employment, productivity and social cohesion, is the main vehicle for achieving this. Europe 2020 sets targets against which the process will be measured and emphasises that a major effort is needed to reduce health inequalities to ensure that everybody can benefit from economic growth. [1]

Actions to improve health are an important part of two of the seven flagship initiatives that contribute to implementing Europe 2020. Achieving the Europe 2020 targets, particularly the target of reducing by 20 million the number of people in or at risk of poverty and social exclusion, will contribute substantially to creating a more equitable distribution of health. [2]

2 Problem formulation

Over the last century, average health status improved in Europe. However, these gains are not evenly distributed across countries or across social groups within the same country. Health inequities can be observed in higher and lower income countries across the European Region. Despite improvements of health status in European countries, important questions about how successful countries are in achieving the Europe 2020 targets [2] 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 advanced multidimensional statistical method [3], [4] on a selected set of indicators of health and health system functioning in selected European countries could summarize some of the relative strengths and weaknesses and can be useful to identify possible priority areas for actions.

According to the above mentioned we have used correlation, factor and cluster analysis [3], [4] on a selected set of health and social indicators from the OECD Health Statistics [5], [6] and OECD Social Statistics databases [7], so selected countries are the European countries that are the members of

OECD. For analysis were used the most recent data available.

2.1 Selected indicators

In accordance with the objectives of analysis and by publications [7] - [12] we have selected 19 indicators. Indicators (variables) H1 to H7 together characterize the state of health, E1 to E3 the state of healthcare expenditure, C1 to C5 healthcare resources and indicators S1 to S4 the social determinant of health of the inhabitants in the selected European countries.

Table 1. Indicators (2016 or latest available year)

Health status	
H1	Life expectancy at birth
H2	Healthy life expectancy
H3	Healthy life years at age 65
H4	Mortality Circulatory syastem (standardized death rates per 100 000 inhabitants)
H5	Mortality Cancer (standardized death rates per 100 000 inhabitants)
H6	Amenable deaths of residents (standardized death rates per 100 000 inhabitants)
H7	Perceived health status good/very good health status, total 15+ (% of population)
Health expenditures	
E1	Health expenditure as a share of GDP
E2	Health expenditure per capita (US PPP)
E3	Expenditures Long-term care (% of total expenditure on health care)
Health care	
C1	Employment in health and social work as a share of total employment
C2	Doctors (total) per 1000 inhabitants
C3	Nurses (total) per 1000 inhabitants
C4	MRI units (per million population)
C5	Computed tomography scanners (per 1 000 000 population)
Social determinants	
S1	Poverty rate (relative threshold)
S2	Living in working households
S3	Disposable income (US dolar at PPP rates)
S4	Unemployment rate (% of labour force aged 15+)

Source: OECD Health Statistics 2018

2.2 Selected multidimensional methods

2.2.1 Factor analysis

Factor analysis [3] [4] is a statistical approach that can be used to analyse interrelationships among a large number of variables and to explain these variables in terms of their common underlying factors. The general purpose of factor analytic techniques is to find a way of condensing (summarizing) the information contained in a number of original variables into a smaller set of new composite factors with a minimum loss of information. Numerous variations of the general factor model are available. The two most frequently employed approaches are principal component analysis and common factor analysis. The component model is used when the objective is to summarize most of the original information (variance) in a minimum number of factors. The Scree Plot 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 factors. [13] - [16]

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, there tend to be some high loadings (i.e., close to -1 or +1) and some loadings near 0 in each column of the matrix. The *Factor Loadings* show the correlation between the original variables and the factors and they are the key to understanding the nature of a particular factor. The *Factor Scores* in output of Factor analysis procedure display the values of the rotated factor scores for each of *n* cases, in our analysis for each of 25 European countries. Factor score show where each country falls with respect to the extracted factors. [13] - [16]

2.2.2 Cluster Analysis

Cluster Analysis procedure is designed to group observations (countries) into clusters based upon similarities between them. A number of different algorithms is provided for generating clusters and are described in detail in many statistical publications, for example in [3], [4]. We have used the agglomerative algorithm, beginning with separate clusters for each observation or variable 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. The results of the analysis are displayed in a *dendrogram*.

The distance between two observations we calculate by Euclidean distance, defined as

$$d_E(x_i, x_j) = \sqrt{\sum_{k=1}^{m} (x_{ik} - x_{jk})^2} \quad (1)$$

and distance between two clusters by Ward's method. Ward's method 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. [17]

2.2.3 Linear ordering of multidimensional objects

Linear ordering of multidimensional objects [20], or multidimensional comparative analysis deals with the methods and techniques of comparing multi feature objects, in our case selected European countries. One of the particular problems here is that of establishing a linear hierarchy (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 health care, health status, etc.). We can also consider them as methods of linear ordering of multidimensional objects using a synthetic variable created from the original variables. Number of applications of these methods can be found in the publications of Polish statistics and econometrics, for example [21], [22]. Examples of their use in publications of Czech authors are [13] - [16].

At the beginning of the analysis, the type of each variable must be defined. It is necessary to identify whether the high values of a variable positively influence the analyzed processes (such variables are called stimulants) or whether their low values are favorable (these are called destimulants). The original variables are usually expressed in different units of measurement and must be standardized to create a synthetic (aggregate) variable. A number of formulas are used for standardization.

$$u_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \quad (2)$$

$$u_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \quad (3)$$

We have used formula (2) for stimulants and formula (3) for destimulants.

The synthetic variable allows to replace the whole set of origin standardized variables into one aggregated variable. There is variety of methods for creating a synthetic variable. In this paper the synthetic variable for i-th country, $i = 1, 2, \dots, n$, has been calculated as the sum of the values $u_{\mathrm{i,j}}$, $j = 1, 2, \dots, m$, where the subscript i stands for the country number, and the subscript j stands for the variable number.

2.2.4 Spearman rank correlation

The matching in the order of the countries by each pair of synthetic variables can be quantify using Spearman's rank correlation coefficient, which for any two variables *X*, *Y* can be calculated according to the formula

$$r_S = 1 - \frac{6 \cdot \sum_{i=1}^{n} (i_x - i_y)^2}{n \cdot (n^2 - 1)} \quad (4)$$

where i_x, i_y are the ranks of the values of the variables X, Y. These correlation coefficients range between -1 and +1 and inform about degree of compliance of the ranks.

3 Problem solution

3.1 Results of correlation analysis

The results of the correlation analysis in graphic form show the correlation coefficients between each pair of indicators and their clusters. The results indicate a strong positive dependence of health indicators on E1-E3 healthcare expenditure, employment in health and social work (C1), as well as the number of nurses per 1000 inhabitants (C3 indicator), moderate dependence on the number of physicians and technical C4 and C5 sources and strong negative dependence on social determinants S1-S4.

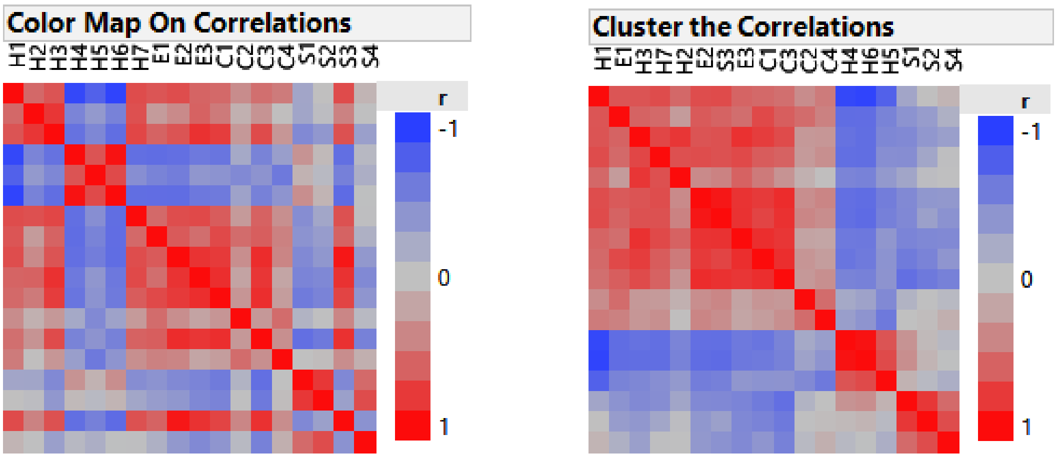

Fig. 1 Correlation maps of selected health indicators

Source: OECD Health Statistics 2017, self-processed in SAS JMP

3.2 Results of factor analysis

By application of factor analysis we try to obtain a small number of common factors which account for most of the variability in the original variables. To assess the suitability of indicators for the factor analysis, we applied the Kaiser-Meyer-Olkin measure. The KMO = 0.7544399 show suitability of the source variables for factor analysis.

Number	Eigenvalue	Percent	Cum Percent
1	9.7698	54.277	54.277
2	2.9625	16.459	70.735
3	**1.5489**	8.605	**79.340**
4	0.8082	4.490	83.830
5	0.7163	3.979	87.810
6	0.5457	3.032	90.841
7	0.4304	2.391	93.232
8	0.4042	2.245	95.478
9	0.2751	1.529	97.006
10	0.1786	0.992	97.998
11	0.1245	0.692	98.690
12	0.0739	0.411	99.101
13	0.0542	0.301	99.402
14	0.0355	0.197	99.599
15	0.0324	0.180	99.779
16	0.0163	0.091	99.870
17	0.0133	0.074	99.944
18	0.0101	0.056	100.000

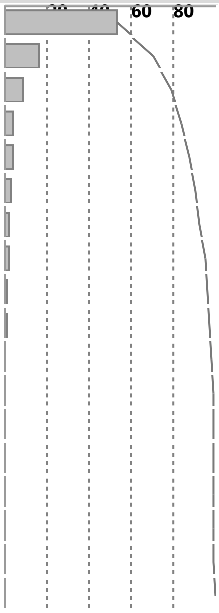

Fig. 2 Eigenvalues and percent of explained variability

Source: OECD Health Statistics 2017, self-processed in SAS JMP

Factor loadings which present the correlation between the original variables and the factors and they are the key to understanding the nature of a particular factor. After varimax rotation we obtained factor loadings shown in Table 2. Rotation is performed in order to simplify the explanation and naming of the factors. Based on those factor loadings, we found out that the 1st factor has strong positive correlation with the indicators of health status and health expenditures, the 2nd factor demonstrated rather moderate positive correlation with the indicators of Employment in health and social work and Disposable income and strong negative correlation with other social indicators, the 3rd factor showed strong positive correlation with the indicators of personal and technical resources. The high values of each factor mean a high level of the observed reality.

Table 2. Factor loadings Matrix After Varimax Rotation

Indicator	Factor 1	Factor 2	Factor 3
H1	0.9065	-0.0093	0.3180
H2	0.7889	0.0524	-0.2008
H3	0.7684	0.4269	0.1247
H4	-0.9113	-0.0519	-0.1991
H5	-0.6334	0.0930	-0.2964
H6	-0.9005	-0.0784	-0.2532
H7	0.8074	0.2508	0.1064
E1	0.6609	0.3428	0.4638
E2	0.6590	0.5295	0.3305
E3	0.6772	0.5204	0.0721
C1	0.5144	0.6341	0.1922
C2	0.1521	0.1163	0.7518
C3	0.4812	0.3068	0.7522
C4	0.2197	-0.0342	0.8489
C5	-0.0227	-0.0249	0.8418
S1	-0.2725	-0.7907	0.0451
S2	0.0026	-0.9027	0.0647
S3	0.6658	0.5115	0.3179
S4	0.1169	-0.8778	0.0657

Source: self-processed in Statistica 12

Based of above mensioned we have named three common factor as:

- ***F1*** *– Factor of health status and health expenditures*
- ***F2*** *– Factor of social determinants of health*
- ***F3*** *– Factor of personal and technical resources of healthcare*

Table 3. Table of Factor Scores

Country	Code	F1	F2	F3
Austria	AT	2.004	1.743	4.466
Belgium	BE	5.083	3.293	0.571
Czech Republic	CZ	-5.453	0.115	-3.718
Denmark	DK	5.731	6.992	3.072
Estonia	EE	-12.255	-6.22	-4.459
Finland	FI	4.555	4.453	3.078
France	FR	4.558	1.434	0.596
Germany	DE	3.033	3.954	5.771
Greece	GR	-2.626	-10.1	1.149
Hungary	HU	-13.41	-3.78	-8.10
Iceland	IS	7.468	4.947	3.917
Ireland	IE	4.168	3.130	-1.21
Italy	IT	-0.058	-4.87	2.993
Latvia	LV	-17.993	-8.90	-4.540
Luxembourg	LU	5.159	1.838	-0.01
Netherlands	NL	5.143	4.324	0.072
Norway	NO	12.210	8.345	4.505
Poland	PL	-9.244	-4.73	-6.377
Portugal	PT	-5.062	-5.59	-0.953
Slovakia	SK	-12.125	-4.27	-5.299
Slovenia	SI	-3.720	-1.35	-3.782
Spain	ES	1.855	-7.69	0.832
Sweden	SE	10.245	5.531	3.112
Switzerland	SW	9.444	6.362	7.318
United Kingdom	UK	1.290	1.118	-3.00

Source: Self-processed in Statistica 12

Table 3 shows the factor scores for each monitored country. The Factor Scores displays the values of the rotated factor for each country. Graphical display of countries in a two-dimensional coordinate system with the axes of the selected factors allows us to quickly assess the observed situation in each country and also compare the situation in different countries.

In the coordinate system of the factors F1 and F2 three groups of countries were created, one with high values of both factors, including all the old EU countries, the second with low values of both factors, including the new EU countries and the third with the middle level of the first and the low to medium level of the second factor.

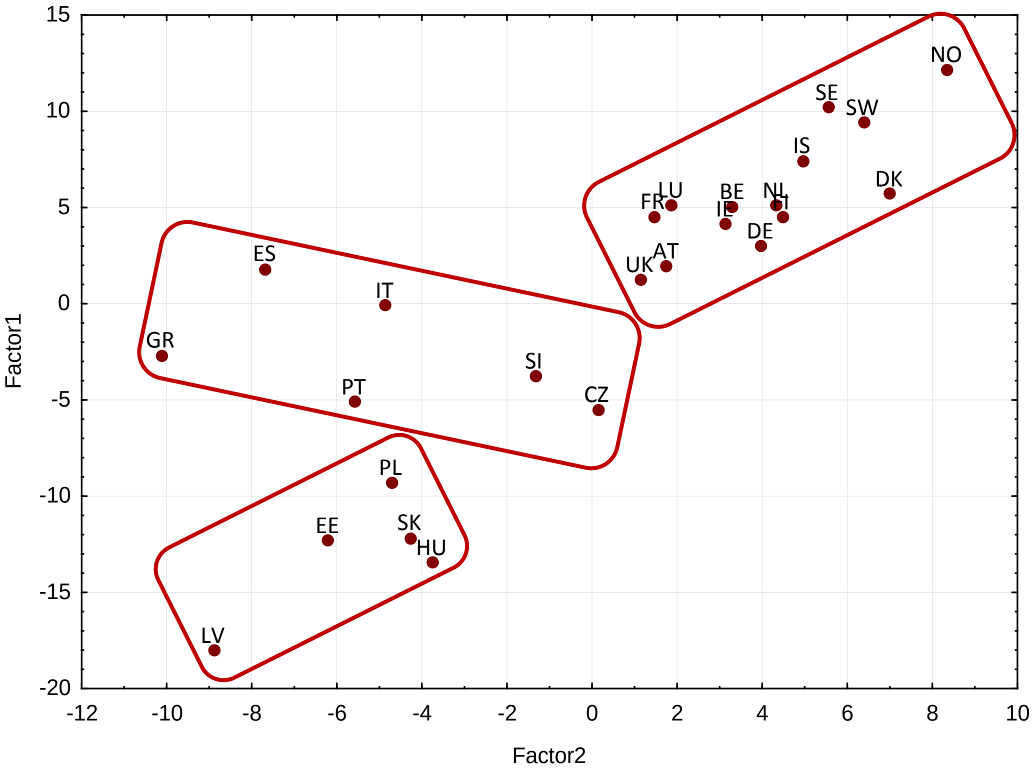

Fig. 3. Location of countries in the coordinate system of the factors F1, F2
Source: self-processed in Excel

Figure 4, showing the location of Europe's monitored countries in the coordinate systems of factors F1 and F3, indicates that F3 - Factor of personnel and technical resources of health care has a positive effect on F1 - Health and healthcare expenditure. Three clusters of monitored countries were created. One group consists of states of Northern and Western Europe with high values of both factors, the group with the lowest level of both factors again forming the same five countries as in Figure 2 and third, the most numerous group of countries with medium level of both factors, again belonging the Czech Republic.

Figure 5 shows the dependence of Factor F3 - Factor of Personal and Technical Resources of Health Care and Factor F2 - Factor of Social Determinants of Health. Again, there is a direct dependence of these two factors and, similarly to Fig. 3. We can observe the specific situation of the groups of countries of Greece, Spain, Italy and Portugal where, even at a low level of social determinants of health, the medium to high level of personnel and technical resources of health care. Unfortunately, the group of five new EU Member States with the lowest level of both factors is the same as in Fig. 3 and Fig. 4.

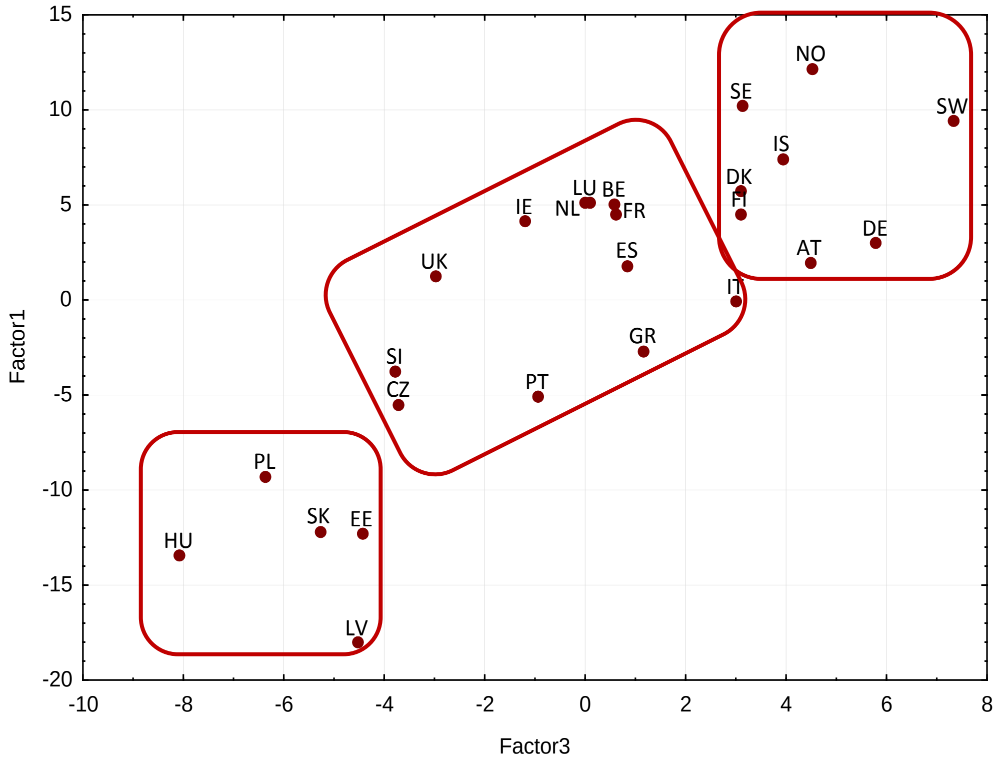

Fig. 4. Location of European countries in the coordinate system of the factors F3, F1

Source: self-processed in Excel

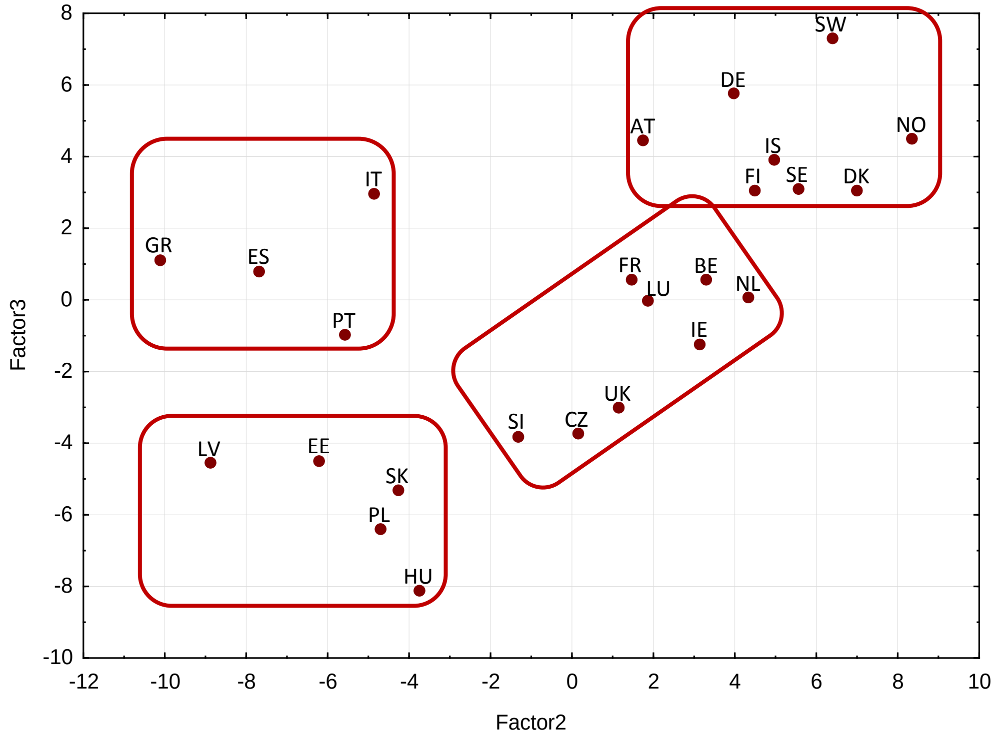

Fig. 5. Location of European countries in the coordinate system of the factors F2, F3

Source: self-processed in Excel

3.3 Results of cluster analysis

The factor analysis based on principal component method resulted in 3 mutually independent factors, each representing one dimension of health situation. These factors are appropriate for the cluster analysis. Dendrogram and parallel plots represent the results in the visual form.

According to the legend, the red colour presents the high, so desired value of each factor, and the size of the values is indicated by the intensity of the colour. Low factor values are analogously shown in blue.

The colour map in the 1st column refers to the 1st factor of the health status and health expenditures, the 2nd column of colour map represents the social determinants of health and the 3rd column represents the 3rd factor of personal and technical resources of healthcare.

According to the dendrogram of Ward's method we have considered 5 different clusters. The first red cluster includes 8 countries with high values of all three factors. In the five countries of the green cluster there are the slightly lower values of the first two factors and the significantly lower value of the third factor. In the blue cluster of 3 countries there are again degraded values of all three factors compared with the previous two clusters. The brown cluster of four countries is characterized by poor social determinant of health. To the last cluster belong the countries with the lowest level according to all three factors.

Analogous interpretation of five clusters from the dendrogram in Fig. 6 also provide parallel graphs in Fig. 7.

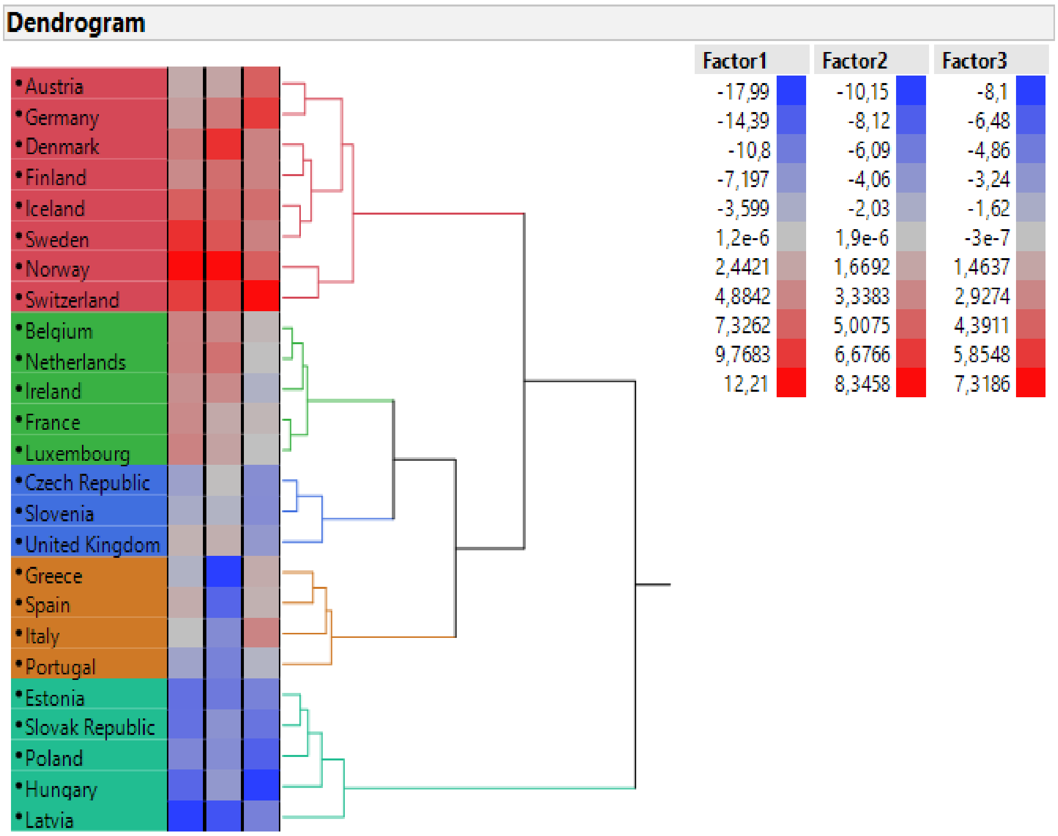

Fig. 6 Dendrogram of the European countries clusters according to extracted factors

Source: self-processed in SAS JMP

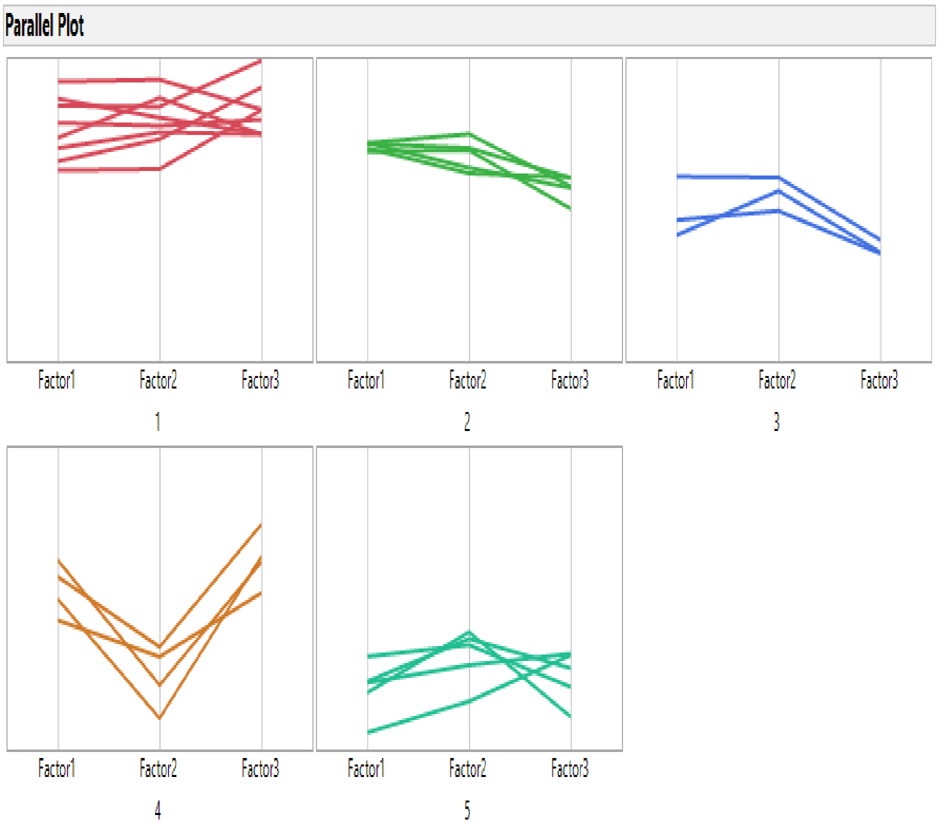

Fig. 7. Parallel plots of the European countries clusters according to extracted factors
Source: self-processed in SAS JMP

3.4 Results of linear ordering

The synthetic variables defined in sub-subsection 2.2.3 by equations (2), (3) allow to replace the whole set of variables into one aggregated variable and to transform multidimensional space in one-dimensional. Created synthetic indicators in this article allow to quantify the interrelation of indicators of health status, health expenditures, health care and social determinants of health status in monitored European countries.

Among the original variables (Table 1) the variables H1, H2, H3, E1, E2, E3,C1, C2, C3, C4, C5 and S3 have been identified as stimulants, while the variables H4, H5, H6, S1, S2 and S4 as destimulants by sub-subchapter 2.2.3. Have been created a few synthetic variables: synthetic variable total ST of the all 19 indicators in Table1, synthetic variable of health status SHS of the indicators H1 to H7, synthetic variable of the health determinants SHD of the indicators E1 to E3, C1 to C5 and S1 to S4, synthetic variable of health expenditures SHE of the indicators E1, E2, E3, synthetic variable of health care SHC of the variables C1 to C5 and synthetic variable of social determinants SSD of the indicators S1 to S4 as the averages of the standardized indicators by the formulas (3), (4). The lower the value of each synthetic variable, the higher the level of the monitored health dimension.

The values of all created synthetic variables contains Table 4.

Table 4. Table of values of the synthetic variables

Country	Code	ST	SHS	SHD	SHE	SHC	SSD
Austria	AT	**0.3684**	0.3832	0.3598	0.3963	0.4189	0.2585
Belgium	BE	**0.3579**	0.2566	0.4170	0.3020	0.5873	0.2903
Czech Rep.	CZ	**0.5542**	0.5227	0.5725	0.7141	0.7444	0.2515
Denmark	DK	**0.2701**	0.3258	0.2376	0.2814	0.2846	0.1461
Estonia	EE	**0.7385**	0.7419	0.7365	0.8590	0.7608	0.6142
Finland	FI	**0.3275**	0.3198	0.3320	0.3830	0.4121	0.1936
France	FR	**0.3941**	0.2500	0.4782	0.4492	0.6005	0.3471
Germany	DE	**0.3134**	0.3825	0.2731	0.3175	0.2619	0.2537
Greece	GR	**0.5996**	0.3269	0.7586	0.8109	0.6038	0.9129
Hungary	HU	**0.7604**	0.8149	0.7285	0.8292	0.8803	0.4633
Iceland	IS	**0.2509**	0.1330	0.3197	0.4621	0.3476	0.1780
Ireland	IE	**0.3878**	0.2528	0.4665	0.4150	0.6157	0.3187
Italy	IT	**0.4843**	0.3384	0.5695	0.6234	0.4829	0.6373
Latvia	LV	**0.8268**	0.9451	0.7578	0.9414	0.6741	0.7247
Luxembourg	LU	**0.3936**	0.2613	0.4708	0.3804	0.6573	0.3054
Netherlands	NL	**0.3619**	0.3014	0.3972	0.2633	0.5764	0.2737
Norway	NO	**0.1734**	0.1085	0.2112	0.1602	0.2791	0.1645
Poland	PL	**0.6959**	0.5961	0.7541	0.8815	0.8806	0.5004
Portugal	PT	**0.6038**	0.4810	0.6755	0.7484	0.6898	0.6029
Slovak Rep.	SK	**0.7143**	0.7508	0.6931	0.9050	0.7826	0.4221
Slovenia	SI	**0.5694**	0.4718	0.6264	0.6691	0.8105	0.3643
Spain	ES	**0.5410**	0.2153	0.7310	0.6367	0.6967	0.8446
Sweden	SE	**0.2354**	0.0802	0.3259	0.2144	0.4354	0.2725
Switzerland	SW	**0.2004**	0.2093	0.1951	0.1093	0.2580	0.1809
United King.	UK	**0.4751**	0.3331	0.5580	0.4438	0.7769	0.3699

Source: authors' calculations

The linear ordering of monitored European countries by synthetic variable ST, which has been created from all indicators in Table 1, in graphical form represents Fig. 8.

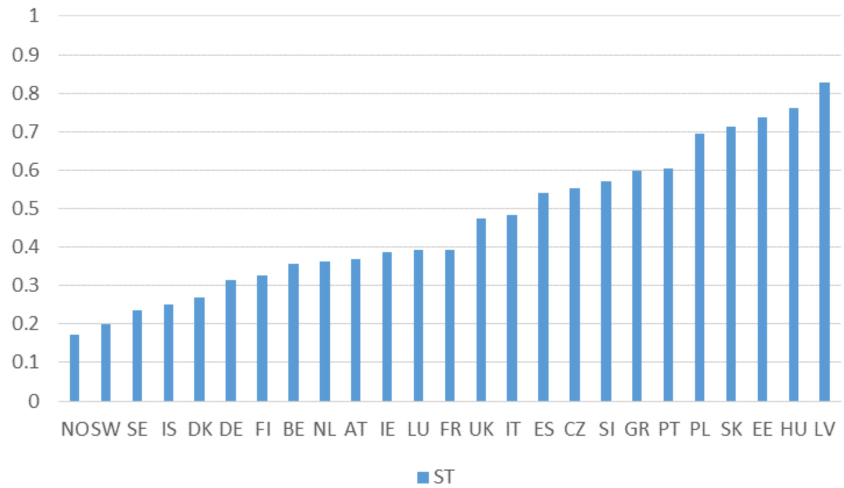

Fig. 8. Linear ordering of the European countries by synthetic variable ST
Source: self-processed in Excel

The graphic view of values of the synthetic variable ST in Figure 8 makes it easy to assess the differences in situation monitored with help of 19 indicators from Table 1 in European countries. The best situation is in countries Norway, Switzerland, Sweden, Iceland and Denmark, where the values of the synthetic variable ST is less than 0.3. A slightly worse but very similar situation is in countries Germany, Finland, Belgium, Netherlands, Austria, Ireland, Luxembourg and France, where the values of the synthetic variable ST are from 0.3 to 0.4. Values of synthetic variable ST from 0.4 to 0.5 we can observe in United Kingdom and in Italy and from 0.5 to 0.6 in countries Spain, Czech Republic, Slovenia, Greece and Portugal. A significant jump in the values of the variable ST has been observed in former socialist countries Poland, Slovak Republic, Estonia, Hungary and Latvia, in which the monitored health situation and health determinants were the worst.

T**able 5.** Spearman Rank Correlations

	ST	**SHS**	**SHD**	**SHE**	**SHC**	**SSD**
ST		0.82	0.95	0.93	0.86	0.83
SHS	0.82		0.66	0.76	0.63	0.48
SHD	0.95	0.66		0.90	0.84	0.91
SHE	0.93	0.76	0.90		0.78	0.74
SHC	0.86	0.63	0.84	0.78		0.68
SSD	0.83	0.48	0.91	0.74	0.68	

Source: authors‘calculations

Table 5 shows Spearman rank correlations between each pair of synthetic variables. These correlation coefficients range between -1 and +1 and measure the strength of the association between the variables. We can observe a strong positive correlation of the synthetic variable ST with all other synthetic variables, especially with the synthetic variable of health determinants SHD and synthetic variable of health expenditures SHE. The synthetic variable of health status SHS depends on the synthetic variable SHD, made from all selected indicators of health expenditures, health care and social determinants to 65.62%. Synthetic variable of the health determinants SHD correlates the most strongly with synthetic variables SHE and SSD, surprisingly, at least correlates with synthetic variables of health care SHC.

4 Conclusion

The results of the selected multidimensional methods have confirmed the usefulness of their use to reduce the dimension of large-scale data sets of health indicators in Europe, assessing health inequalities and identifying some of its determinants.

The correlation analysis provided quantification of causal relationships of health indicators, health care expenditures, personnel and technical resources, and social determinants of health care. The application of factor analysis allowed to replace the 19 original indices with three common factors explaining almost 80% of variables of the original variables. Identifying these factors using factor loadings has made it possible to assess the impact of social determinants and personnel and technical resources on health status as well as health inequalities in monitored countries caused by these factors. Charts 1 to 3 confirm that despite the efforts and actions of the European Commission, these inequalities are significant. This fact also confirms the results of cluster analysis that are consistent with the results of factor analysis.

The use of appropriate statistical software packages and Excel spreadsheet allows the publication of the results of advanced statistical methods in clear visual form, understandable also to people without thorough knowledge of these methods.

Synthetic variables are a useful tool for linear ordering and comparison of multidimensional objects. We have used them for a comprehensive assessment of the state of health and its determinants in selected European countries and the quantification of their dependence.

The results of article confirm, that advanced statistical methods aimed at reducing the dimension and quantification of causal relationships can provide significant information added value.

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