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Statistical Analysis of Hospitalized Morbidity Indicators based on DRG in Romanian Public Hospitals

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Abstract

Starting from the idea that in the public hospitals in Romania, in time, was formed an ever-increasing gap in terms of funding, we performed an analysis to identify whether the level of funding for similar hospital services depends on the costs incurred by treatment with the same type of patient. Analysis of the correlation between the complexity of diagnoses treated and quantitative indicators of a hospital allowed us to identify how these parameters affect finally efficiency and performance of the hospital. Our approach used advanced statistical analysis to study four hospitalized morbidity indicators based on diagnostic groups (number of patients discharged, average length of stay, number of days of hospitalization and case-mix index) and an indicator of organizational structure of the hospital (number of beds) for the 61 municipal hospitals in Romania in 2013.

Keywords: public administration, public hospitals, health funding, performance indicators, diagnosis-related groups.

Introduction

Public hospitals in Romania are funded by the state based on the classification system in Diagnosis-Related Groups (DRG). This system is a scheme of classifying patients according to diagnosis (Reinhold *et al.*, 2009; Tan *et al.*, 2014; Bertali & Grembi, 2017; Di Giacomo *et al.*, 2017). This system is similar to International Classification of Diseases System, in which diagnoses are classified into classes and subclasses. Contrast to this, the DRG system using an additional criterion for classification, namely the cost of resources used for patient care. In this way,

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through DRG system, patients can be classified simultaneously as both after pathology (Tlacuilo-Parra *et al.*, 2014; Yoo, Chung, & Kim, 2014; Bystrov *et al.*, 2015; Kim *et al.*, 2016, Nunley *et al.*, 2017) and after the cost of care (Lee *et al.*, 2011; Street *et al.*, 2012; Gaertner *et al.*, 2015; Guerra *et al.*, 2015, Joannidis *et al.*, 2018), which provides facility to associate types of patients with hospital costs incurred. For patients classified in the same group of diagnoses, the diagnoses, the procedures performed and the costs are similar. This aspect of Diagnosis-Related Groups (DRG) is considered important and actual from both aspects medical and economic as performances (Wenke *et al.*, 2009; Bermueller and Schulz, 2011; Thalheimer, 2011; Hamada, Sekimoto, & Imanaka, 2012; Chok *et al.* 2018; Riessen *et al.*, 2018; Zafirah *et al.*, 2018).

Diagnosis-Related Groups are of two types - medical and surgical, depending on the presence or absence of surgery and are designed to cover the pathology associated acute patients that requires hospitalization. In order to classify each patient discharged in a diagnostic group (a DRG) is required the following steps: (1) Availability of clinical data about patients discharged. DRG classification requires mandatory seven variables for each patient: age, gender, duration of hospitalization, primary and secondary diagnoses, surgery or other procedures performed, discharge status and birth weight (for newborns); (2) Encoding of data required for diagnostics and procedures for the use of a standardized language for these variables and for easily usage; (3) Collecting in electronic form of these clinical data from patient clinical record; (4) The classification of each patient discharged in a group of diagnoses using a DRG classification system. This process is done by automatically sending of each patient in a group of diagnoses using software called *grouper*[6].

To use the DRG system to finance hospitals, once patients assigned in DRG, it requires completion of two stages: (1) Setting costs for each diagnostic group (or relative values of costs); they are based on costs adjacent to the patients in each DRG, and can be imported together with DRG system or can be developed by each country; Once calculated these costs, they are converted into tariffs and used for all hospitals participating in the financing scheme; (2) Budget allocation for hospital care to hospitals, starting from the number and type of discharged patients (case-mix index of each hospital) and list of costs (or relative values) for each DRG.

Therefore, DRG system allocate similar patients in diagnostic groups homogeneous in terms of clinical disease and the resources used in the treatment and to the hospital is paid a cost per weighted case (CWC)[7].

[6] Grouper - software that enables to automatically assign of a patient in a certain DRG based on data that characterize each case discharged, available at http://www.drg.ro/index.php?p=drg&s=glosar (accessed on June 25, 2014)

[7] The cost per weighted case (CWC) is an average cost, pre-calculated and weighted for each DRG; CWC is the reimbursement value of a weighted case at hospital level, CWC value is fixed for each hospital separately, and is established by the framework contract.

As long as the DRG system is used effectively, with data actually made by hospitals, it is really a management tool to estimate and control the costs of hospital services. In the practice of health sector in Romania, DRG system is used only as a method of funding hospitals, because it uses standard data required by legislation, obviously for reasons related to Romanian imperative - saving all extremely limited resources, with serious consequences for the Romanian health system widely publicized and well known.

DRG based financing system is one of a kind "money follows the patient", i.e. hospitals that have many patients with complex pathology will receive more resources, and those with fewer patients will have less resources. In this way the allocation of financial resources to hospitals is based on hospital outcomes and less the structure. From the reverse of this principle, it follows in practice a number of inconsistencies caused by the current DRG system that blocked out objective resource allocation to hospitals, such false reports or modified - experience shows that when known exactly, the types of patients who benefit from better funding, hospitals will seek to *adjust* the data reported to benefit *more* patients (false reporting) or *complicated* patients (modified reports). This phenomenon is frequent and is known as DRG *creep* and can generate even fraud by reporting data for nonexistent patients, through re-hospitalization of some patients and *complication* of patient.

By appeal to the peculiarities of the health system in Romania, we try through this analysis to identify how justified are maneuvers a hospital management when to increase financing, are used false reporting (DRG creep), fictive admissions, compromising the quality by admitting more patients regardless whether it is necessary or not, or selecting patients (with more complex pathology or less duration of hospitalization). To identify exactly what is "optimal" in terms of the performance of a public hospital (municipal, in our case) and to capture exactly what influences the efficiency of hospital services, we proceeded to an analysis of the performance indicators of all public municipal hospitals from Romania in 2013. This paper is equal contribution of all authors.

Methods

In our paper we started from the following *working hypotheses*: (1) Level of funding of similar hospital services depends on the costs incurred by treating the same type of patient: (2) There is a strong and direct correlation between the complexity of diagnoses treated and quantitative indicators of a hospital (number of patients, length of stay and number of beds) which influences hospital efficiency and performance.

In order to obtain a more precise classification of municipal hospitals in Romania in terms of efficiency in our approach we used the following methodology of work. We used advanced statistical analysis to study on-line official data provided by the

Center for Research and Evaluation of Health Services. In this regard, the variables selected in our analysis are the four indicators of hospitalized morbidity[8] according to diagnostic related groups (DRG) and an indicator of organizational structure of the hospital (number of beds) for the 61 municipal hospitals in Romania in 2013, respectively: number of patients discharged; average length of stay on an episode of hospitalization (ALOS); number of hospitalization days (hospitalization days per person in a year); case-mix index of complexity of cases treated (CMI); number of beds approved into organizational structure of the hospital.

The complexity of cases concern types of patients treated in a hospital, according to diagnosis and severity. Case-Mix Index (CMI) is the index of the complexity of the cases, respectively a relative value assigned to a DRG expressing the resources of the hospital according to treated patients. CMI is directly influenced by the severity of the case reflected through correct encoding of main diagnosis, secondary diagnoses (comorbidities and complications), procedures and major paraclinical investigations, and the proportion of severe cases the whole number of treated cases. In practice there are two categories of CMI: CMI contracted with Health Insurance House (HIH) - determined annually for each hospital in part by the framework contract, and CMI realized by hospital - actually achieved for patients treated and discharged from hospital, validated by NSPHMPD[9] and sent to HIH for settlement to the hospitals.

For comparison relevance were selected only municipal hospitals, with similar structure, number of beds, workload and complexity. Thus, for the processing and presentation of data in tabular form it was proceeded to collect the four indicators on the website http://www.drg.ro, for the 61 municipal hospitals, listed in *Table 1*, columns 1-5. Approved number of beds per hospital (column 6 of *Table 1*) was extracted from the organizational structure approved by the Ministry of Health of each municipal hospital in part, available on the websites of hospitals.

Data selection methodology has provided a large volume of information, which requires statistical processing and systematization in order to identify the most relevant indicators. Thus, in analyzing the data matrix presented in *Table 1*, to obtain quality statistical information, we used the SPSS Statistics application.

Factor analysis

Factor analysis is a statistical method of correlation performed using several techniques: principal component method, varimax criterion and rotation axes. The aim was to research the links of interdependence of the five variables. In

[8] Morbidity is a mass phenomenon of illnesses that arise or evolve in a defined population in a specified period of time (one year). It is an important indicator of the health of the population, expressing the number of diseases. Hospitalized morbidity is an indicator for measuring the disease in a population and refers to hospitalized persons.

[9] National School of Public Health, Management and Professional Development (NSPHMPD) is the body that verifies, validates and quantifies into DRG system all cases discharged in public hospitals in Romania (http://www.snspms.ro/en)

the analysis we have proposed defining of factors to condense most of the initial information (original variables). Through principal component analysis are built new variables, as linear combinations of the original variables (the four primary indicators selected), uncorrelated with each other and by maximum variance. In principal component analysis we try to explain the whole variance of the variables, assuming that there is a link between the original variables, a correlation, they following to be grouped by principal components exactly based on these correlations.

In the first stage, we will identify new variables to express synthetically the old variables, so that the total amount of information is not be lost otherwise than in a controlled manner. Thus, after elaboration of data matrix we proceeded to analyze them by using the SPSS, noting that all the features pursued, namely morbidity indicators, are continuous variables, their scale of measurement being easily identifiable.

The higher complexity of a phenomenon is, the larger influential factors, and hence the greater variability of terms from a series of distribution. Central tendency indicators do not give any explanation of scattering, i.e. how the series terms deviate between them or from the mean. Therefore, for the individual variables we calculated in *Table 1*, both centering and variation indicators (scattering), such as: mean, minimum value, maximum value and standard deviation.

In *Table 1* we performed descriptive statistical analysis, obtaining information on each variable independently. It reveals major differences: for variable *Number of hospitalization days* maximum value is 101,541 days and a mean of 35,143.87 days, standard deviation being very high (18,003.391). The explanation is that a part of hospitals have discharged besides acute patients, patients with chronic diseases (9%) having an average length of stay greater (27.52 days compared to a mean of 6.0569 days).

Table 1: Descriptive Statistics

Variable	N[a]	Minimum	Maximum	Mean	Std. Deviation
Number of patients discharged	61	2,152	14,708	5,119.92	2,105.178
Average length of stay	61	4.16	8.49	6.0569	.81606
Number of hospitalization days	61	13,364	101,541	35,143.87	18,003.391
Case-mix index	61	.5914	1.3076	.810887	.1317577
Number of beds	61	48	323	138.97	64.645
Valid N (listwise)[b]	61				

[a] *The number of cases for which respective variable has a different value for missing values, in this case, all 61 hospitals*

[b] *The number of valid cases, which have different values for missing values for all variables in the table, in this case all 61 hospitals*

After initial data standardization, when we detached of measurement scale of the variables, the correlation matrix will be equivalent to the covariance matrix, and thus we perform principal component analysis using standardized data matrix (*Z score*). Through SPSS analysis we obtained information on the mean and the standard deviation of each standardized indicator. Thus, given that mean is 0 and dispersion is 1, *Table 2* confirms that the data are standardized.

Table 2: Factor Analysis - Descriptive Statistics

Variable	Mean	Std. Deviation	Analysis N
Z score: Number of patients discharged	.0000000	1.00000000	61
Z score: Average length of stay	.0000000	1.00000000	61
Z score: Number of hospitalization days	.0000000	1.00000000	61
Z score: Case-mix index	.0000000	1.00000000	61
Z score: Number of beds	.0000000	1.00000000	61

For the application of factor analysis there must be correlations between variables large enough to make sense reducing the size. Therefore, we performed a correlations analysis to identify the variables that are not correlated with each other and which may be excluded eventually from the analysis. Therefore we requested in SPSS correlation matrix calculation to see if all variables calculated are independent or not and to realize how many principal components are needed in the analysis. It is noted in *Table 3* that the correlation matrix (which contains standardized variables) are only positive correlations, negative ones missing. Existence of many strong correlations between variables analyzed diminishes individual significance of the latter, on the one hand, and would reveal the redundancy of information on the other (namely there is a significant amount of information dissipated in links between variables) (Armeanu *et al.*, 2012).

Table 3: Correlation Matrix

	Variable	Z score: Number of patients discharged	Z score: Number of patients discharged	Z score: Number of patients discharged	Z score: Number of patients discharged	Z score: Number of patients discharged
Correlation	Z score: Number of patients discharged	1.000	.215	.853	.354	.746
	Z score: Average length of stay	.215	1.000	.434	.251	.418
	Z score: Number of hospitalization days	**.853**	.434	1.000	.338	**.837**
	Z score: Case-mix index	.354	.251	.338	1.000	.343
	Z score: Number of beds	.746	.418	.837	.343	1.000

In our analysis we identify that there are two relatively strong correlations, close to the value 1 between indicators *Number of patients discharged* and *Number of hospitalization days* (0.853) and between indicators *Number of hospitalization days* and *Number of beds* (0.837), which indicates the possibility of eliminating two indicators of analysis without knowing exactly which one. Consequently, for eliminate subjectivity in decision making we use principal components analysis in SPSS in order to identify two synthetic indicators which help us in achieving purpose of the analysis. Therefore, we want a reduced data structure and explanation of covariance between variables through a minimum number of common factors. Thus, we studied further the aspect “point cloud” (in this case, the hospitals) to analyze the relationship between these two variables, following the information provided by SPSS:

Common variance calculation (Communalities) - the total variance of variables due to common factors. Communalities or common character of a variable is the part of the variance of the variable that is common with variance of other variables. The minimum values of the common character for certain variables indicate that the variables are not well represented by factorial model applied (Carbuneanu, 2010). In our case, most variables are well represented by factorial model used, as shown in *Table 4*. The variance of the standardized variable *"Number of patients discharged"* is due 100% to correlations in the data set (initial communality of this variable is 1.000). Following extraction factors, a percentage of 91.6% of the variance of the variable *"Number hospitalization days"* is explained by model factors, extracted communality being 0.916 (*Table 4*).

Table 4: Communalities

Variable	Initial	Extraction
Z score: Number of patients discharged	1.000	.894
Z score: Average length of stay	1.000	.752
Z score: Number of hospitalization days	1.000	**.916**
Z score: Case-mix index	1.000	.493
Z score: Number of beds	1.000	.839
Extraction Method: Principal Component Analysis		

Identification of variance explained by each component, initial and after rotation of factors. The first factor extracted will correspond to the largest Eigenvalue, i.e. first extracted factor is one that explains most of the variance of observed variables. The following factor extracted will explain as much of the rest of variance remained unexplained. An own variant greater than 1 for a component indicates that the component has a greater contribution than an initial variable, so it is recommended to be extracted.

Table 5 shows that, initially, to recover largest as possible quantity of information from the original data, we need one main component, one with a value over 1 (selection criteria: Eigenvalue > 1). So first extracted factor explains the variance corresponding to 3.038 variables, and all other factors explain less than the variance of a variable (<1). Columns *"Extraction Sums of Squared loadings"* provides Eigenvalues *(Total)*, the variance explained *(% of Variance)* and cumulative variance *(Cumulative %)*, in the context of the original solution *(Initial Eigenvalues)*, the one before rotation.

Table 5: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.038	60.760	60.760	3.038	60.760	60.760	2.521	50.414	50.414
2	.856	17.120	77.880	.856	17.120	77.880	1.373	27.466	77.880
3	.775	15.500	93.379						
4	.226	4.529	97.908						
5	.105	2.092	100.000						
Extraction Method: Principal Component Analysis.									

The variance explained by each factor is distributed as follows: the first factor explains 60.760% of the total common variance of the variables, and the second 17.120%. Together, the first two factors extracted explain 77.880% of the common variance of the variables.

Columns *"Rotation Sums of Squared Loadings"* shows the values for both factors after rotation procedure. The data in *Table 5* shows us that after rotation of factors is obtained a better "vision": in context of the same total variance (77.880%) is noticed a redistribution of variance explained by each factor, as follows: first factor 50.414% and second factor 27.466%. As can be seen, by the method of rotation the first factor is losing from saturation level in favor of the second factor. Thus, the saturations value of each factor is changing, but does not change the sum of squares of these saturations *(Table 5)*.

Whereas we asked in SPSS the explanation of *point cloud* by two axes (two factors), and the rank of correlation matrix is 5, in *Table 5* we find that by adjusting the *point cloud* by two factorial axes (namely by accepting two synthetic indicators), we recover a total of 77.880% of the variance, which is a good result for our analysis (if we have requested three factors, then we have explained 93.379% of total variance).

In order to determine the number of components (factors) which must be extracted, we called into SPSS application for displaying the diagram of Eigenvalue – *Screen Plot*

Once it has been determined the number of principal components retained in the analysis (in our case were extracted two components), further we proceeded to interpretation of principal components obtained, by determining the correlation coefficient between the original variables and principal components *(Table 6)*.

Table 6: Component Matrix[a]

Variable	Component	
	1	2
Z score: Number of patients discharged	.873	-.363
Z score: Average length of stay	.543	.676
Z score: Number of hospitalization days	.940	-.181
Z score: Case-mix index	.527	.464
Z score: Number of beds	.905	-.138

Extraction Method: Principal Component Analysis

[a] *2 components extracted*

Following the request of the correlation matrix of principal components, the SPSS output has generated values of Factor Score.

Both original data and the component 1 ranked Targu Carbunesti Hospital on the first place (Number of hospitalization $days_{max}$ = 101,541 and $FACT1\_1_{max}$ = 4.1327). Instead, when we consider the component 2, the situation changes significantly, Targu Carbunesti Hospital being ranked 30 (1st place being Pucioasa Hospital with $FACT2\_1_{max}$ = 2.0946).

Checking into initial matrix the data of Pucioasa Hospital, we see that, indeed, this hospital has the highest economic efficiency: in the context of similar structures with Targu Carbunesti Hospital (300 beds), it has discharged 8,707 patients (with 41% less than Targu Carbunesti Hospital), who had been hospitalized for 78,368 days (with 23% less than Carbunesti Hospital), and for which the hospital has received with 48% less from HIH. Thus CWC in 2013 was 1,433 lei[10], and we have: (1) Pucioasa Hospital – 8,707 cases x 0.8676 x 1,433 lei = 10,825,159 lei; (2) Targu Carbunesti Hospital – 14,708 cases x 1.0028 x 1,433 lei = 21,135,578 lei.

Knowing the financing of the two hospitals in 2013, we can estimate which is the economic efficiency by calculating the average cost per patient discharged and average cost per a day of hospitalization in *Table 7*.

10 LEU/LEI Romanian Currency; the average exchange rate for Romanian currency in the analyzed period: 1 leu = 4.25 EUR; 1 leu = 3.14 USD

Table7: Indicators on the financing and costs

Name city hospital	Number of patients	Number of hospitalization days	CMI realized by hospital	CWC (lei)	Financing (lei)	Average cost per patient discharged (lei)	Average cost per a day of hospitalization (lei)
0	1	2	3	4	5=1x3x4	6=5÷1	7=5÷3
Pucioasa Hospital	8,707	78,368	0.8676	1,433	10,825,159	1,243	138
Targu Carbunesti Hospital	14,708	101,541	1.0028	1,433	21,135,578	1,437	208

Pucioasa Hospital has an average cost per patient lower with 13.5% and a cost per day of hospitalization with 33.6% lower than Targu Carbunesti Hospital, although it has a higher average length of stay (8.49 days to 6.51 days).

Next, the principal component analysis was performed with orthogonal rotation "varimax" of the factors. This data reduction technique minimizes the number of variables with high factorial saturations for each factor, thus simplifying the interpretation of factors. Thus, the two columns of *Table 8* contain principal components or new synthetic indicators calculated. Rotated Component Matrix is used to obtain a clear and accurate interpretation so as to achieve higher correlations with one of the components, and lower correlations with the other components remaining.

Table 8: Rotated Component Matrix[a]

Variable	Component	
	1	2
Z score: Number of patients discharged	**.939**	.108
Z score: Average length of stay	.145	.855
Z score: Number of hospitalization days	**.909**	.300
Z score: Case-mix index	.234	.662
Z score: Number of beds	**.858**	.320
Extraction Method: Principal Component Analysis		

Rotation Method: Varimax with Kaiser Normalization
[a] Rotation converged in 3 iterations

Notice in *Table 8* by varimax rotation technique the data have not changed significantly in terms of component 1: indicators *Number of patients discharged*, *Number of hospitalization days* and *Number of beds* are equally strongly correlated (positively) with principal component 1 (correlation coefficients are 0.939, 0.909 and 0.858). Meanwhile, the three indicators are very weak correlated with the principal component 2 (correlation coefficients are 0.108, 0.300 and 0.320), but this time in a positive way to the matrix before rotation (Table 6).

Therefore, we can say that the indicator *Number of patients discharged* may be considered a synthetic indicator for our analysis. Despite this, the principal component 2 is difficult to interpret, with a high correlation coefficient (positive) with the indicator *Average length of stay*, which records at the same time a very low correlation with the principal component 1 (only 0.145). Data from *Table 8* allow us to conclude on the structure of factors for the variables analyzed: (1) Factor 1 explains 50.414% of the total variance of the variables (Eigenvalue 3.038) and consists of variables *Number of patients discharged* (correlation 0.939), *Number of hospitalization days* (correlation 0.909) and *Number of beds* (correlation 0.858), the reason that we named this factor *Hospitalized morbidity index*, because describes the addressability of patients and length of stay, both reported to hospital capacity; (2) The second factor consists mainly of variable *Average length of stay* (0.855), which is why we keep the same name.

The principal components are nothing but linear combinations of the initial variables (originals) with the new reduced-space versors. These versors are given by the Eigenvectors corresponding to Eigenvalues greater than 1. *Table 9* represents the versors matrix containing the Eigenvectors corresponding to Eigenvalues retained.

Table 9 : Component Score Coefficient Matrix

	Component	
	1	2
Z score: Number of patients discharged	.457	-.230
Z score: Average length of stay	-.229	.777
Z score: Number of hospitalization days	.373	-.034
Z score: Case-mix index	-.113	.558
Z score: Number of beds	.339	.004
Extraction Method: Principal Component Analysis		

Rotation Method: Varimax with Kaiser Normalization
Component ScoreS

Cluster analysis

Cluster analysis is a classification method that aims to group the objects (cases or variables, in our case hospitals) characterized by different variables in a limited number of homogeneous classes (clusters). In our approach we have chosen *Hierarchical Cluster Analysis* technique[11], which is a hierarchical grouping technique, where each class is contained entirely in another class (once two objects are joined in a cluster, they remain together until the last stage).

The hierarchy starts by finding the closest pair of objects (in our case, hospitals) which combine them to form a *cluster*. The algorithm continues step by step, joining pairs of objects, pairs of clusters, or an object with a cluster until all data are grouped in a cluster. Classes grouping together the objects most similar to each other by values of variables, while the classes created are most different. A cluster formed in an earlier stage of the analysis contains clusters from a previous stage, which in turn contain clusters of another previous stage.

Since the objective of cluster analysis is grouping similar objects together, some units of measurement are required observing the differences and similarities between objects. We chose to use "dissimilarity" as unit for measuring, based on the distance between pairs of objects or *Euclidean Distance*, most commonly used in practice. Clustering is characterized by the development of a hierarchy of tree type and hierarchical methods can be agglomeration or dispersion. We will use a method of grouping by agglomeration, aggregation of data being accomplished by *Single Linkage* or "nearest neighbors". Single linkage method is based on the minimum distance rule to the nearest neighbor.

In *Table 10* are explained systematically all stages of clustering of cases according to distances from dissimilarity matrix (*Coefficients*). Each row in the

[11] We mention that SPSS provides a second technique: K-Means Cluster Analysis (iterative partitioning analysis).

table represents a step in the process of grouping the variants, numbered from 1 to 60. The last stage (step 60 in our case) consists of all variants in a single cluster. In the column *Cluster Combined* are shown grouped cases, alongside the coefficients of distances between grouped elements. The column *Stage Cluster First Appears* indicates the stage that has been encountered an already formed cluster (each of the two elements), and the column *Next Stage* indicates the next step to which will be seen the first combination of clusters formed, and in which phase it will change.

Table 10: Single Linkage - Agglomeration Schedule

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	20	54	.245	0	0	43
2	30	57	.255	0	0	6
3	12	37	.282	0	0	13
4	14	18	.320	0	0	30
5	27	51	.341	0	0	24
6	30	42	.393	2	0	42
7	36	47	.486	0	0	46
8	21	58	.496	0	0	22
9	22	38	.496	0	0	14
10	2	23	.505	0	0	16
11	5	15	.537	0	0	13
12	8	41	.587	0	0	16
13	5	12	.625	11	3	26
14	22	59	.626	9	0	39
15	48	60	.638	0	0	35
16	2	8	.647	10	12	21
17	1	3	.648	0	0	26
18	7	39	.661	0	0	34
19	19	26	.664	0	0	21
20	53	55	.677	0	0	27
21	2	19	.679	16	19	23
22	21	61	.682	8	0	28
23	2	34	.706	21	0	38
24	27	46	.714	5	0	27
25	44	49	.718	0	0	32
26	1	5	.724	17	13	28
27	27	53	.734	24	20	30
28	1	21	.736	26	22	29
29	1	13	.754	28	0	32
30	14	27	.765	4	27	31
31	14	35	.780	30	0	33
32	1	44	.802	29	25	37
33	14	29	.848	31	0	36
34	7	25	.861	18	0	44
35	9	48	.865	0	15	44
36	14	43	.869	33	0	38
37	1	45	.876	32	0	39
38	2	14	.880	23	36	40
39	1	22	.892	37	14	40
40	1	2	.893	39	38	41
41	1	52	.907	40	0	42
42	1	30	.913	41	6	43
43	1	20	.929	42	1	45
44	7	9	.931	34	35	47
45	1	4	.943	43	0	48
46	36	40	.961	7	0	47
47	7	36	1.008	44	46	48
48	1	7	1.055	45	47	49
49	1	50	1.097	48	0	50

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
50	1	11	1.145	49	0	51
51	1	17	1.157	50	0	52
52	1	56	1.190	51	0	53
53	1	28	1.253	52	0	55
54	10	31	1.354	0	0	55
55	1	10	1.487	53	54	56
56	1	24	1.955	55	0	57
57	1	16	2.037	56	0	58
58	1	33	2.147	57	0	59
59	1	6	2.526	58	0	60
60	1	32	3.533	59	0	0

As shown in *Table 10*, in the first stage are grouped the case 20 to the case 54, the distance between them being the smallest (0.245).

Conclusions cluster analysis can be found in *Table 11*, where are presented composition and description of the 3 classes from dendrogram.

Table 11: Composition and description of classes from dendrogram

Class	Composition (Hospitals)	Description (Indicators)
Clasa 1	Abrud, Agnita, Alesd, Baia de Arama, Baicoi, Bals, Baraolt, Beclean, Bolintin Vale, Brezoi, Buhusi, Campeni, Cernavoda, Corabia, Cugir, Deta, Faget, Faurei, Filiasi, Gaesti, Gura Humorului, Harlau, Harsova, Hateg, Horezu, Huedin, Ineu, Jibou, Jimbolia, Lehliu Gara, Ludus, Macin, Mioveni, Mizil, Moldova Noua, Moreni, Nasaud, Negresti Oas, Nehoiu, Novaci, Otelu Rosu, Panciu, Rovinari, Rupea, Sannicolau Mare, Segarcea, Simleu Silvaniei, Sinaia, Siret, Targu Bujor, Targu Lapus, Targu Neamt, Valenii de Munte, Viseu de Sus, Zarnesti, Zimnicea	Number of patients discharged: 4,864 Average length of stay: 6.03 days Number of hospitalization days: 31,972 Case-mix index: 0.8004 Number of beds: 129
Class 2	Costesti, Pucioasa, Oravita, Turceni	Number of patients discharged: 6,306 Average length of stay: 6.35 days Number of hospitalization days: 62,948 Case-mix index: 0.9096 Number of beds: 228

Class 3	Targu Carbunesti	Number of patients discharged: 14,708 Average length of stay: 6.51 days Number of hospitalization days: 101,541 Case-mix index: 1.0028 Number of beds: 323

We see in *Table 11* that the majority of hospitals in Romania (56 hospitals) are grouped in *class 1*. These are general hospitals that treat acute patients and have an average of 5 + 1 medical specialties (general surgery, internal medicine, obstetrics and gynecology, neonatology, pediatric + anesthesia and intensive therapy). This hospital has obtained an average funding of 5.58 million lei in 2013 (cases discharged x CMI x CWC_{2013} = 4,864 x 0.8004 x 1,433 lei = 5,578,985 lei). The population served by these hospitals is about 60,000 inhabitants, having a geographical range of addressability of 40-60 km.

In *class 2*, SPSS has grouped four hospitals, appreciating major dissimilarity compared to class 1. These hospitals are characterized by a double number of hospitalization days (62,948 days, compared with 31,972 days of class 1) in relation to a number of beds as high (228 beds compared to 129 beds of class 1). The explanation resides in the fact that three of these hospitals (Pucioasa, Oravita and Turceni) have into structure in addition to the 5 general acute care wards, and one or two additional chronic care wards (psychiatric, medical rehabilitation, physical medicine & balneology or pneumophtisiology). Cases of chronic patients into the 3 hospitals have a share of 14% of all patients discharged, and require a much larger hospitalization (49 days). For this reason, a class 2 hospital has obtained into 2013 an average funding of 8.22 million lei (cases discharged x CMI x CWC_{2013} = 6,306 x 0.9096 x 1,433 = 8,218,495 lei). The remaining indicators regarding the complexity of cases or addressability of patients are similar to class 1.

We specify that into *class 2* it is noted especially Costesti Hospital with a particular economic efficiency, the more that this hospital belongs to class 1 as organizational structure and addressability. Although Costesti Hospital has no chronic care wards (is a general acute care hospital) and has the same geographical range like first class hospitals[12], obtained indicators seem "too" perfect, almost unreal; this hospital discharged a total of 5,082 patients in 2013, hospitalized for

[12] *According to the website Costesti Hospital from Arges county, population served is 67,408 inhabitants out of a total of 17 villages located on an area of 1,225 km², at a*

5.31 days / episode of hospitalization, and the diagnoses treated have the greatest complexity of all hospitals analyzed (CMI = 1.3076).

In *class 3* was selected just Targu Carbunesti Hospital which, moreover, does not fit into homogeneous majority of municipal hospitals: in addition to acute care wards, includes a section for chronic diseases and two health centers, as external wards merged. This explains the atypical indicators performed: 14,703 patients in 101,541 hospitalization days per 323 beds. Also, Targu Carbunesti Hospital obtained the highest funding of 21.13 million lei (Cases discharged x CMI x CWC_{2013} = 14,703 x 1.0028 x 1,433 = 21,135,578 lei).

Finally, since in class 3 was selected one hospital with atypical values of the indicators analyzed, we can appreciate that the most economically efficient hospital is Costesti Hospital.

Based on the classification derived from statistical analysis, respectively classification of hospitals after grouping in dendrogram in *Table 12* we used the indicators needed to calculate funding received from HIH: number of patients discharged, case-mix index and cost per weighted case. CMI realized by each hospital were collected, as noted above, from database online of Center for Research and Evaluation of Health Services, CMI contracted with HIH and CWC were collected from the Methodological Norms for enforcement the Framework Contract concerning the conditions of providing medical assistance within HIH (Romanian Government, 2008).

Table 12: The ranking of municipal hospitals in 2013 according to SPSS dendrogram[a]

Order of grouping in dendrogram	Municipal Hospital	CMI contracted with HIH	CMI realized by hospital	CWC (lei)	Discharged patients	Value contracted with HIH (lei)	Value realized by hospital (lei)	Differences
A	B	1	2	3	4	5=1x3x4	6=2x3x4	7=5-6
1	Cernavoda	0.6011	0.5914	1,433	4,088	3,521,306	3,464,483	56,824
2	Deta	0.5826	0.5939	1,433	3,972	3,316,087	3,380,405	-64,318
3	Novaci	0.8884	0.8889	1,433	5,435	6,919,175	6,923,069	-3,894
4	Jimbolia	0.9140	0.8986	1,433	5,288	6,926,021	6,809,325	116,697
5	Corabia	0.8773	0.8805	1,433	6,096	7,663,714	7,691,668	-27,954
6	Campeni	0.9742	0.9523	1,433	5,954	8,311,954	8,125,102	186,853
7	Gaesti	0.9606	0.9695	1,433	5,913	8,139,480	8,214,892	-75,413
8	Alesd	1.0067	1.0157	1,433	3,956	5,706,930	5,757,950	-51,021
9	Bals	1.0143	1.0055	1,433	4,982	7,241,297	7,178,472	62,825
10	Huedin	1.0315	1.0497	1,433	7,222	10,675,123	10,863,478	-188,354
11	Filiasi	1.0568	1.0476	1,433	6,330	9,586,117	9,502,664	83,452

distance of 27.5 km from the nearest hospital; available at http://www.spitalregelecarol.ro/despre-noi.html (accessed on August 20, 2014)

Order of grouping in dendrogram	Municipal Hospital	CMI contracted with HIH	CMI realized by hospital	CWC (lei)	Discharged patients	Value contracted with HIH (lei)	Value realized by hospital (lei)	Differences
A	*B*	*1*	*2*	*3*	*4*	*5=1x3x4*	*6=2x3x4*	*7=5-6*
12	Hateg	0.9026	0.8707	1,433	5,789	7,487,642	7,223,011	264,631
13	Nehoiu	0.7639	0.7426	1,433	5,527	6,050,234	5,881,534	168,700
14	Lehliu Gara	0.7759	0.7714	1,433	5,428	6,035,202	6,000,199	35,002
15	Zimnicea	0.5966	0.5947	1,433	5,783	4,944,047	4,928,302	15,745
16	Faget	0.6399	0.6543	1,433	5,475	5,020,447	5,133,425	-112,978
17	Segarcea	0.7496	0.7596	1,433	5,546	5,957,385	6,036,859	-79,474
18	Gura Humorului	0.7090	0.7181	1,433	5,305	5,389,864	5,459,043	-69,179
19	Sinaia	0.6846	0.6853	1,433	5,432	5,328,965	5,334,414	-5,449
20	Harlau	0.6392	0.6405	1,433	4,335	3,970,746	3,978,821	-8,076
21	Bolintin Vale	0.7575	0.7811	1,433	6,020	6,534,695	6,738,284	-203,589
22	Valenii de Munte	0.6629	0.7182	1,433	6,942	6,594,454	7,144,572	-550,118
23	Baraolt	0.6911	0.6461	1,433	3,103	3,073,045	2,872,948	200,097
24	Baia de Arama	0.6891	0.6562	1,433	2,824	2,788,644	2,655,505	133,139
25	Brezoi	0.7367	0.7206	1,433	3,493	3,687,529	3,606,941	80,588
26	Baicoi	0.7191	0.7637	1,433	3,218	3,316,053	3,521,722	-205,668
27	Jibou	0.8061	0.7360	1,433	2,642	3,051,883	2,786,486	265,398
28	Harsova	0.8365	0.8413	1,433	2,831	3,393,532	3,413,005	-19,473
29	Macin	0.7890	0.8464	1,433	3,126	3,534,371	3,791,498	-257,127
30	Panciu	0.8686	0.8878	1,433	3,834	4,772,194	4,877,682	-105,487
31	Rupea	0.7765	0.7525	1,433	2,685	2,987,665	2,895,323	92,343
32	Targu Lapus	0.8424	0.7572	1,433	3,161	3,815,830	3,429,899	385,932
33	Mioveni	0.8417	0.8024	1,433	3,593	4,333,719	4,131,372	202,347
34	Otelu Rosu	0.7493	0.7504	1,433	3,982	4,275,660	4,281,937	-6,277
35	Abrud	0.8313	0.8438	1,433	4,310	5,134,300	5,211,503	-77,203
36	Cugir	0.8254	0.8130	1,433	4,375	5,174,742	5,097,002	77,740
37	Faurei	0.7348	0.7884	1,433	2,152	2,265,988	2,431,281	-165,293
38	Mizil	0.6746	0.6702	1,433	4,068	3,932,543	3,906,893	25,650
39	Siret	0.6667	0.6934	1,433	2,340	2,235,592	2,325,123	-89,531
40	Ineu	0.8735	0.8657	1,433	3,132	3,920,404	3,885,397	35,008
41	Buhusi	0.9657	0.9770	1,433	6,354	8,792,971	8,895,861	-102,890
42	Ludus	0.9471	0.9254	1,433	6,236	8,463,464	8,269,548	193,915
43	Moreni	0.8635	0.8619	1,433	7,269	8,994,628	8,977,962	16,666
44	Simleu Silvaniei	0.7473	0.7823	1,433	6,537	7,000,348	7,328,212	-327,863
45	Horezu	0.7234	0.7474	1,433	7,029	7,286,488	7,528,229	-241,741
46	Nasaud	0.7417	0.7167	1,433	5,942	6,315,491	6,102,619	212,872
47	Viseu de Sus	0.8816	0.8801	1,433	7,395	9,342,346	9,326,451	15,896
48	Negresti Oas	0.8159	0.8540	1,433	8,103	9,473,904	9,916,306	-442,402
49	Targu Neamt	0.8650	0.9448	1,433	9,219	11,427,365	12,481,589	-1,054,224
50	Agnita	0.7706	0.8242	1,433	2,187	2,415,038	2,583,019	-167,981
51	Zarnesti	0.6927	0.7240	1,433	3,544	3,517,913	3,676,872	-158,959

Order of grouping in dendrogram	Municipal Hospital	CMI contracted with HIH	CMI realized by hospital	CWC (lei)	Discharged patients	Value contracted with HIH (lei)	Value realized by hospital (lei)	Differences
A	*B*	*1*	*2*	*3*	*4*	*5=1x3x4*	*6=2x3x4*	*7=5-6*
52	Moldova Noua	0.7073	0.6754	1,433	5,518	5,592,829	5,340,586	252,243
53	Sannicolau-Mare	0.8400	0.8671	1,433	6,293	7,575,010	7,819,394	-244,384
54	Targu Bujor	0.7636	0.7393	1,433	3,437	3,760,899	3,641,216	119,683
55	Beclean	0.7580	0.7732	1,433	2,855	3,101,141	3,163,327	-62,186
56	Rovinari	0.8812	0.8651	1,433	4,780	6,035,991	5,925,710	110,281
57	Pucioasa	0.9116	0.8676	1,433	8,707	11,374,153	10,825,159	548,994
58	Oravita	0.7187	0.7324	1,433	7,706	7,936,387	8,087,672	-151,285
59	Turceni	0.7026	0.7306	1,433	3,727	3,752,440	3,901,982	-149,542
60	Costesti	1.2063	1.3076	1,433	5,082	8,784,887	9,522,605	-737,718
61	Targu Carbunesti	1.0132	1.0028	1,433	14,708	21,354,775	21,135,578	219,196
	Total	**x**	**x**	**x**	**312,315**	**369,313,046**	**371,341,381**	**-2,028,335**

[a] *Table 12 was conducted by the authors based on the centralization of information consulted through online database of the Center for Research and Evaluation of Health Services and Framework Contracts*

Extrapolating the calculation approach from previous subchapter, from hospital level to national level, we see once again a huge funding gap. Therefore, municipal hospitals have treated in 2013 a total of 312,315 patients for whom ought to collect from HIH an amount of 371,341,381 lei; taking into account the real complexity of the cases treated, hospitals have received, at least theoretically, with 2,028,335 lei less, i.e. 369,313,046 lei (*Table 12*). We say “at least theoretically” because in 2013, HIH bought only 67% of discharged cases, and therefore the amount received by hospital was significantly lower.

Results

From our observation, the five individual variables analyzed are characterized by high levels of volatility, but are strongly correlated each other (such as the indicators *Number of patients discharged* and *Number of hospitalization days*), which means that, besides intrinsic informational content of each variable, there is a significant amount of information dissipated in the unobserved links directly between variables. In this context, the principal component analysis proved to be a useful tool of study, because managed synthesizing the information, but also removing the information redundancy.

Applying the principal components method in our data set, we obtained two components summarizing approximately 77.880% of the information contained in the original data. The halving of variables was performed in the conditions of minimum information loss by 22.12%. Therefore, we conclude that the indicator *Number of patients discharged* is not really necessary to analyze the efficiency of a municipal hospital, as long as the indicator *Number of hospitalization days* provides more relevant information. Depending on the complexity and pathology of disease, an episode of hospitalization may take 2-3 up to 10-15 days for acute care patients or even up to 40-50 days (or more) for patients with chronic disease. Thus, there may be 10 patients who accumulate 20 days of hospitalization or only one patient hospitalized for 20 days, but costs, at least those for accommodation (food, utilities, linens, personal hygiene products and cleaning materials) are the same for one patient or 10 patients with the same cumulative hospitalization of 20 days.

Regarding the performance of hospitals, it is very difficult to assess which hospital is more economically efficient: a hospital with more patients (higher value of indicator *Number of patients discharged*) or a hospital with patients "more complicated" due to medical care or complexity of diagnosis (higher value of indicator *Case-mix index*), a hospital with patients "complicated" due to prolonged hospitalization (higher value of indicator *Average length of stay*) and more. Our statistical analysis has achieved its intended purpose and managed to clarify these issues: redundancy of information was eliminated (Targu Carbunesti Hospital is atypical for our analysis), we obtained a homogeneous mass of the majority of municipal hospitals (class 2) and we have identified a benchmark of economic efficiency (Costesti Hospital). The best provider of healthcare has recorded the best values of the indicators of efficiency. Although, the case-mix index of the hospital increased compared to other providers, it has managed to achieve appropriate values, leading to the first place ranking. In other words, the optimum of efficiency is owned, obviously, by the hospital that manages to rapidly treat a number of patients appropriate to hospital capacity, but at the same time with highly complex diagnoses. Correspondingly, such a hospital will get from HIH sufficient funding to cover the costs of hospital services performed and will be able to use resources attracted in an economically manner.

At the other extreme there are the hospitals which forces the length of hospitalization, artificially - to get more funding, or wrongly - because there are doctors who admitted patients that do not are suitable for continuous hospitalization (many hospitals treating patients in continuous hospitalization, even though the diseases in question can be treated in daily hospitalization). These ways of increasing the length of stay determined implicitly an increase equally artificial of the complexity of cases treated and much lower than the costs involved, a fact reflected into insufficient funding to cover large expenses, not always justified.

All these inequalities in funding is due, as we have shown, to differences in the complexity of diagnoses treated and causing serious financial failures to hospitals. In addition to initial underfunding, the costs are much higher: complex medical casuistry (CMI realized by hospital > CMI contracted with HIH) inherently involves high costs (more drugs and medical supplies, prolonged hospitalization and many surgeries and laboratory investigations).

Conclusion

Our study *infirm* the initial hypothesis that t*he level of funding of similar hospital services depends on the costs incurred by treating the same type of patient*. Thus, our statistical analysis of five variables for 61 municipal hospitals in Romania has demonstrated that there are hospitals by similar category and structure, treating the same type of patient (same diagnosis), receiving the same HIH financing (by paying an identical cost per weighted case), but which provides medical services very different both qualitatively and quantitatively, and therefore sustains different costs.

Regarding the last working hypothesis, *that there is a strong and direct correlation between the complexity of diagnoses treated and quantitative indicators of a hospital (number of patients, length of stay and number of beds) which influences hospital efficiency and performance*, the conclusions of the analysis revealed the following:

– Factor analysis performed by principal components method identified a first component, which can be analyzed in terms of *hospitalized morbidity, corresponding to capacity of hospitalization*, because we noticed that there is a very strong correlation between the total number of patients discharged in a year, the number of days hospitalization per person in a year and the number of hospital beds.

– The second component can be analyzed in terms of the complexity of cases treated or hospitalization period, the statistical analysis capturing exactly the close correlation between the two indicators. *The analysis confirms the hypothesis only partially***,** demonstrating that there is no connection between the complexity of the disease and greater or smaller number of patients discharged, **but**, obviously, the hospital beds are crowded (high number of days of hospitalization) due to a high bed turnover rate (high number of patients discharged). Statistical analysis identified some correlation between performance indicators of hospitals. So about the correlation between the number of patients discharged and case-mix index, we noticed that the increased number of patients implicitly determines an increase of costs and, in this regard, we believe that increasing the complexity index (DRG complexity) must to ensure an optimum level of resources required to hospital in accordance with patients treated.

– Concerning the value of reimbursement of the cost per weighted case, it must not be set at a relatively low level, because it results in underfunding of medical services and increasing hospital debts. Given that complexity index requires a certain level of performance, we believe that for some hospitals, relatively high values of CMI does not justify the current degree of obsolescence and wear and tear of medical devices or lack of staff.
– Referring to determine influence of the indicators analyzed on the settlement value of a DRG, the case-mix index and the cost per weighted case should be the "key issues" when contracting hospital services with HIH, since these indicators should have more influence on DRG value (case discharged and settled). Since the CMI is big part of hospital costs and CWC is a "source" for financing these costs, we believe it is useful as influence of these indicators on DRG value should have another proportion.

Our statistical analysis performed reinforces the idea that, over time in the Romanian public hospitals has been created an ever increasing gap in terms of funding. Thus, given that theoretically, the cost of a weighted case is the same, it is our opinion that in terms of necessary resources should not be recorded major differences between hospital care providers.

We appreciate that our paper was marked by some *limits of research* determined both by objective factors and subjective factors, limits that need to be overcome and transformed into openings for further research. Thus the main factor that has limited our approach of empirical research was the difficulty of collecting activity indicators, structure and performance of 61 municipal hospitals, which resulted in a very large volume of data processed in a long time.

In our analysis we identified differences between the values of certain indicators reported by various hospitals (*Number of patients discharged or Number of hospitalization days)*, issue that has questioned somehow the veracity of some data reported by hospitals. Study of practical experience has allowed us to attribute explanations for these atypical values: either hospitals are "forced" to fit into the contracted value of HIH, or they resort to "modified" or false data to obtain better financing.

Consequently, analysis of hospitalized morbidity indicators based on diagnosis-related groups help the management team to know better the hospital, with its weaknesses and strengths, and to act accordingly, based on accurate and relevant information, in increasing the quality and efficiency of medical services provided.

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