

Comparable Study of Health Situations on the Basis of Health Care Attainment Panel Data

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Abstract:

Many policymakers have long been concerned with improving the performance of health systems. Reforms have targeted financing, provision, stewardship, and resource development etc. The impact of these reforms is increasingly being studied, but for the results to be useful, a consistent framework is needed for assessing performance and a measurable indicator.

There is ample evidence of widespread inefficiency in health care systems. Although the relative ability of a particular health system in transforming resources into outcomes differs across countries, the consensus is that overall there is considerable waste, which contributes to excessive expenditure. Responsiveness is an indicator used to measure how well a health system meets the legitimate expectations of the population for the non-health enhancing aspects. This study assessed whether seven dimensions proposed by the WHO to measure responsiveness (dignity, autonomy, confidentiality, prompt attention, social support, basic amenities, and choices of providers) are applicable in evaluating the health system of any country.

Keywords: Health Care System; Efficiency; Responsiveness; Expenditure

1. Introduction:

Assessing how well a health system does its job requires dealing with two large questions. The first is how to measure the outcomes of interest – that is, to determine what is achieved with respect to the three objectives of good health, responsiveness and fair financial contribution (attainment). The second is how to compare those attainments with what the system should be able to accomplish – that is, the best that could be achieved with the same resources (performance). Although progress is feasible against many of society's health problems, some of the causes lie completely outside even a broad notion of what health systems are. Health systems cannot be held responsible for influences such as the distribution of income and wealth, any more than for the impact of the climate. But avoidable deaths and illness from childbirth, measles, malaria or tobacco consumption can properly be laid at their door. A fair judgement of how much health damage it should be possible to avoid requires an estimate of the best that can be expected, and of the least that can be demanded, of a system. The same is true of progress towards the other two objectives, although much less is known about them.

According to David B Evans et al. (2001), Policymakers have long been concerned with improving the performance of health systems. Reforms have targeted financing (for example, social health insurance and user charges), provision (for example, managed care, autonomous hospitals), stewardship (for example, regulation of the private sector, health legislation), and resource development (for example, retraining of staff). The impact of these reforms is increasingly being studied, but for the results to be useful to policymakers across different settings, studies need a consistent framework for assessing performance and a measurable indicator.

The World Health Report (2000) defined three intrinsic goals of health systems improving health, increasing responsiveness to the legitimate demands of the population and ensuring that financial burdens are distributed fairly. For health and responsiveness, systems should improve levels and reduce inequalities. The report published first attempts to measure the attainment of these goals by 191 countries and considered how well countries were performing given their available resources. This project describes the methods used for measuring and monitoring performance of health systems. Since improving health is the defining goal of the health system, we report performance in terms of that goal.

According to report published in papers Ageing Report(2012), Maisonneuve and Martins, (2013), Medeiros and Schwierz, (2013), in almost all countries of the world, during most of the second half of the 20th century, health expenditure has been growing faster than national income. This strong growth can be attributed to demand and supply side factors, such as population ageing and medical innovation. The aim of this project is to compare health situations of different countries.

2. Literature Review:

This project describes the World Health Organisation (WHO) strategy for the measurement of responsiveness, one of the three intrinsic goals of health system performance measurement. Responsiveness is how well the health system meets the legitimate expectations of the population for the non-health enhancing aspects of the health system. It includes seven elements: dignity, confidentiality, autonomy, prompt attention, social support, basic amenities, and choice of provider. The study begins by putting responsiveness in the context of the other two intrinsic goals, health and fair financing. Since responsiveness is comparatively new, the paper elaborates on the rationale for responsiveness sharing the elevated status of an intrinsic goal.

2.1 Responsiveness within Context of Health System Goals:

2.1.1 Responsiveness as an Intrinsic Goal:

The WHO framework for health systems performance assessment begins by addressing the simple question: What are health systems for? **Murray CJL, Frenk J, (1999)**. The obvious answer to this question is that they are for improving and maintaining the health of the population. Thus, health is the defining goal of health systems. However, an equally compelling answer to the question is that health systems are for meeting the needs of the people they serve. Meeting these needs is the intrinsic health system performance goal that WHO calls responsiveness.

The three intrinsic goals are:

- Health – To improve and maintain the health of the population.
- Fair financing and financial risk protection – To assure that households do not become impoverished or pay an excessive share of their income in obtaining needed health care.
- Responsiveness – To enhance the responsiveness of the health system to the legitimate expectations of the population for non-health enhancing dimensions of their interactions with the health system.

When measuring health and responsiveness it is important to measure both the level of achievement (average over the whole population) as well as the distribution (equitable spread of this achievement to all segments of the population). Responsiveness as an intrinsic goal has the following values:

- It can be raised without affecting the other intrinsic goals. It is at least partially independent of the other intrinsic goals.
- There is merit in improving responsiveness even if the other intrinsic goals are not affected. Improvement of the well-being of the person is an important goal of the health system. It is desirable to raise it, in and of itself. Not to raise responsiveness is undesirable.

2.2. Understanding Responsiveness:

WHO is introducing the term responsiveness with the release of the World Health Report. However, it is grounded in an established body of research, from which common defining factors of responsiveness emerge.

In addition to making and keeping them healthy, consumers say that the health system should treat them with dignity, facilitate their role in decisions about their care, provide for clear communication with their health care providers and assure that their medical encounters are kept confidential, **De Silva A. (1999)**. These health system actions form the cluster within responsiveness known as respect for persons. Consumers have also called for the systems to provide prompt attention, access to social support, choice of provider and basic amenities of adequate quality. These form the cluster called client orientation **De Silva A. (1999)**.

Another way of looking at responsiveness as a measure of health system performance is to compare it to health measures. When assessing health one looks at health outcomes or reviews the clinical processes of care or health systems' disease prevention and health promotion programs. With the current state of the art in measuring responsiveness, one asks consumers within the health system to report on their experience with elements of care and other health system services that are as much measures of system performance, as are health measures. Responsiveness is based on consumers' reports on those factors (respect for persons and client orientation) that they care about and about which they are the best source of information.

There is evidence from developed countries, that satisfied patients are more likely to comply with medical treatment, provide relevant information to their health care provider and continue using medical services **Aharony L, Strasser S (1993), Ware JE, Snyder MK, Wright WR, Davies AR (1983)**. In developing countries it has been observed that patient satisfaction will influence utilisation of services and compliance with practitioners' recommendations **Wouters A (1991), McPake B (1993), Gilson L, Alilio M, Heggenhougen K (1994)**. But, we also know that responsiveness is important for its own sake, regardless of its impact on health. Within the WHO framework for assessing health system performance, the measurement of responsiveness is confined to those elements that relate to the individual's well-being and do not account for any health enhancing aspect. This is done so as to measure the achievement of the responsiveness goal apart from its impact on achieving the health goal. The argument that health is all that matters falters because there are ways to improve health that would do serious harm to people's well-being. For example, one could improve health by locking people up who have a communicable disease. That is not an acceptable solution. It may protect part of the population but at the cost of incarcerating the rest.

2.3. The Importance of Responsiveness:

Beyond its status as an intrinsic goal, responsiveness is important for a number of reasons.

- Addressing the legitimate expectations of people is at the heart of the stewardship function of health systems. For example, in its stewardship role, the health system has a major responsibility for maintaining a level playing field among the actors in a health system. Consumers are usually at a disadvantage in dealing with producers of health care and need the health system to help them level the playing field by providing them information and protection **De Silva A. (1999)**. Facilitating the effective flow of information between the health system and the population is a key element of responsiveness. This information is an excellent tool for the stewards of the system to use to address the imbalances that generally exist.
- Responsiveness is fundamental, because it relates to basic human rights. Health systems, education, economic, political and cultural systems share responsiveness as a goal. Each system to be successful must respond to the legitimate needs of its constituents. At the core of this shared responsiveness goal is protecting and enhancing the population's basic human rights. To not

address responsiveness within the health system would be denying this shared responsibility. As part of the research for developing the scoring system for the three intrinsic goals, WHO conducted a survey on its website. Respondents were persons who used the site and chose to answer the survey and included both WHO employees and others from outside WHO. The expectation was that respondents would give much the heaviest weight to health. There was remarkable consistency between the two groups of respondents in rating the importance of the three intrinsic goals. Respondents indicated that health should receive 50% of the weight, fair financing 25% and responsiveness 25%, **Gakidou EE, Frenk J, Murray CJL (2000)**. The importance placed on the responsiveness was borne out by these results.

- A health system can improve some of the elements of responsiveness without large investments. In particular, improving the respect shown for persons in the system may require significant changes in the attitude of health system personnel towards their constituents, but a minimal investment of funds. For example, training health care staff to be more responsive to the basic right of individuals to be treated with dignity requires a minimal expenditure of money. Making important improvements in responsiveness also does not necessarily entail a major investment in technology or staff that making improvements in health may. Improving responsiveness may not necessarily require new legislation to authorise it, as changes in fair financing may. However, not all changes in responsiveness are low in cost. Addressing the client orientation elements of responsiveness, such as choice of doctor or prompt attention, may require the application of additional resources to be fully realised. But, in general a health system can make measurable progress in responsiveness without major investment of funds.
- Improvements in responsiveness may come before changes in performance on either of the other two intrinsic goals. Because it does not require a major investment and because the results of interventions to improve it may show quick results, responsiveness can be improved much faster than health. For example, an improvement in whether staff in clinics treats persons with respect may be reflected quickly in persons' responses to a survey about responsiveness much faster than changes in behaviour lead to improvements in health.

There are two notes of caution: (1) quick fixes designed to "bump up" responsiveness scores without an effort to realise long term change, will not result in sustained improvement in responsiveness performance. Initial efforts must be followed by fundamental changes in the way the system responds; and (2) improvements in responsiveness will not necessarily lead to improvements in addressing the health and fair financing goals. While chances of attainment of these goals may be enhanced by improved responsiveness, the health system needs to address each intrinsic goal. One would expect a system that is responsive to the legitimate needs of its people for respect and client orientation to also seriously address improving health and fairness in financing. But, sustained change across all goals requires a multifaceted strategy designed to address all three goals continuously but not necessarily simultaneously.

In short, the intrinsic goal of responsiveness is important because it deals with basic human rights of individuals, reflects a positive orientation to those the system is designed to serve and holds

promise for meaningful improvement to be made in the well-being of the population. The objectives and components of the WHO strategy for achieving responsiveness in health systems are described in the sections that follow.

Data and Methodology:

3.1 Data Source:

<http://people.stern.nyu.edu/wgreene>.

3.2 Data Description:

These data have been used by many researchers to study the Health Care Survey assembled by WHO as part of the Year 2000 World Health Report. On the course bibliography, see, for example, Greene (2004a). Note, variables marked * were updated with more recent sources in Greene (2004a). Missing values for some of the variables in this data set are filled by using fitted values from a linear regression. To set the proper sample for panel data analysis, use observations for which $SMALL = 0$. To obtain the balanced panel, then use only observations with $GROUPTI = 5$.

140 countries have been taken for this project by making balanced panel data.

3.3 Indicator Details:

These indicators have been taken to analyse the performance of health of different countries. Name of the selected indicators are given below:

1. Composite measure of health care attainment
2. Disability adjusted life expectancy
3. Per capita health expenditure
4. Educational attainment
5. Gini coefficient for income inequality
6. Normalized per capita GDP
7. World bank measure of government effectiveness
8. Population density
9. Proportion of health expenditure paid by public authorities
10. World bank measure of democratization of the political process

3.4 Definition of selected Variables:

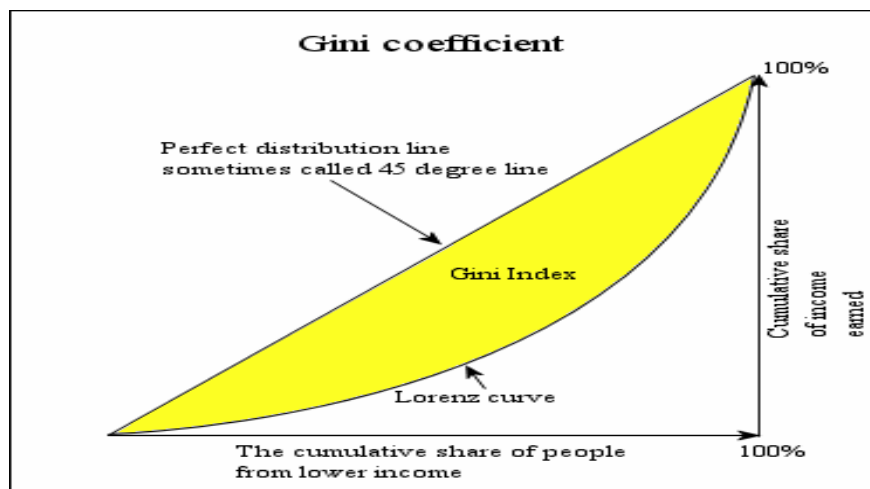
Disability-adjusted life expectancy:

Life expectancy is the number of years a person would be expected to live, starting from birth (for life expectancy at birth) or at age 65 (for life expectancy at age 65), on the basis of the mortality statistics for a given observation period. Disability-adjusted life expectancy (DALE) is a more comprehensive indicator than that of life expectancy because it introduces the concept of quality of life. DALE integrates data on mortality, long-term institutionalization and activity limitations in the population and represents a comprehensive index of population health status. Thus, the emphasis is not exclusively on the length of life, but also on the quality of life. To calculate DALE, a set of weights (relative values) is assigned to four states of health. These states are, in order from greatest to least weight: no activity limitations, activity limitations in leisure activities or transportation, activity limitations at work, home and/or school and institutionalization in a health care facility in order to establish units of equal value. These units are summed to yield a type of quality adjusted life expectancy.

Health expenditure per capita:

Total health expenditure is the sum of public and private health expenditure as ratio of total population. It covers the provision of the services (preventive and curative), family planning activities, nutrition activities, and emergency aid designated for health but does not include provision of water and sanitation

Gini Coefficient:



The Gini coefficient is a measure of inequality of a distribution. It is defined as a ratio with values between 0 and 1: the numerator is the area between the Lorenz curve of the distribution and the uniform distribution line; the denominator is the area under the uniform distribution line. The Gini index is the Gini coefficient expressed as a percentage, and is equal to the Gini coefficient multiplied by 100. (The Gini coefficient is equal to half of the relative mean difference.) The Gini coefficient is often used to measure income inequality. Here, 0 corresponds to perfect income equality (i.e. everyone has the same income) and 1 corresponds to perfect income inequality (i.e. one person has all the income, while everyone else has zero income). The Gini coefficient can also be used to measure wealth inequality. This use requires that no one has a negative net wealth. It is also commonly used for the measurement of discriminatory power of rating systems in the credit risk management.

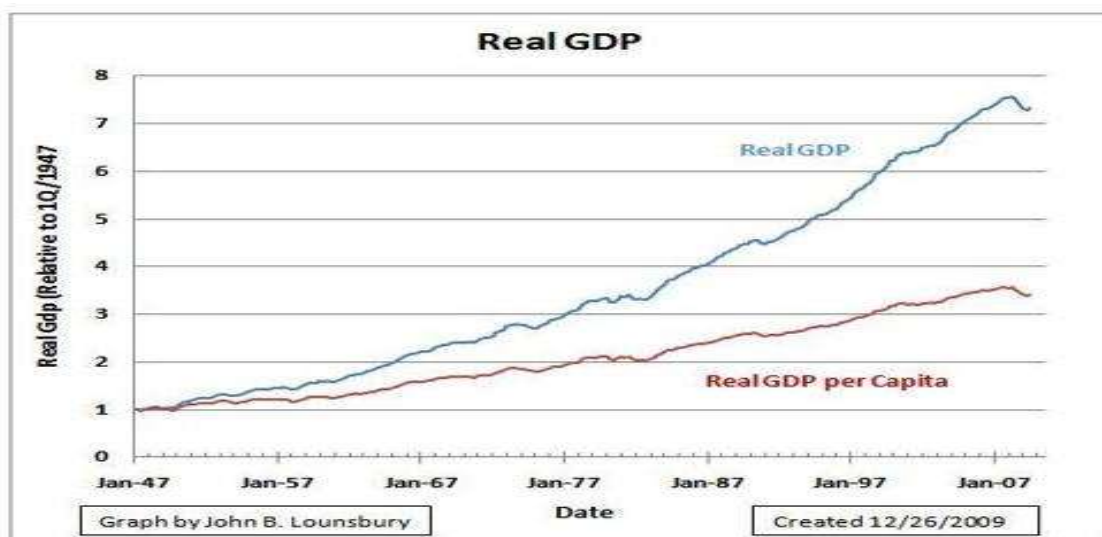
Normalized GDP:

This is real GDP per capita. The basis for normalizing real GDP to population is that a billion dollars of GDP for 150 million people has double the value to the national economy compared to the same amount for 300 million people.

There has been some discussion about whether or not GDP is the best measure of economic activity. We will not consider that question for now and use GDP as the measurement with which to examine the business cycle.

GDP per Capita:

The graph below compares Real GDP and Real GDP per capita. Both start at the same value on January 1, 1947.



Data: St. Louis Fed and U.S. Census Bureau

Normalized GDP (real GDP per capita) increased less than half as much as the real GDP not adjusted for population growth. Another way of stating this is that the per capita economic productivity (compared to real GDP) has lagged by more than half over the past 63 years.

Government effectiveness indicator:

This indicator measures the quality of public services, the quality of the civil service and its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to its stated policies.

3.5 Statistical tool used:

Principal component analysis (PCA):

PCA is a multivariate statistical technique used to reduce the number of variables in a data set into a smaller number of 'dimensions'. In mathematical terms, from an initial set of n correlated variables, PCA creates uncorrelated indices or components, where each component is a linear weighted combination of the initial variables. For example, from a set of variables X_1 through to X_n ,

$$PC1 = a_{11} X_1 + a_{12} X_2 + \dots + a_{1n} X_n$$

$$PC2 = a_{21} X_1 + a_{22} X_2 + \dots + a_{2n} X_n$$

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$$PCm = a_{m1} X_1 + a_{m2} X_2 + \dots + a_{mn} X_n$$

Where, a_{mn} represents the weight for the m^{th} principal component and the n^{th} variable. The weights for each principal component are given by the eigenvectors of the correlation matrix, or if the original data were standardized, the co-variance matrix. The variance (λ) for each principal component is given by the eigenvalue of the corresponding eigenvector. The components are ordered so that the first component (PC1) explains the largest possible amount of variation in the original data, subject to the constraint that the sum of the squared weights ($a_{11}^2 + a_{12}^2 + \dots + a_{1n}^2$) is equal to one. As the sum of the eigenvalues equals the number of variables in the initial data set, the proportion of the total variation in the original data set accounted by each principal component is given by λ_i/n . The second component (PC2) is completely uncorrelated with the first component, and explains additional but less variation than the first component, subject to the same constraint. Subsequent components are uncorrelated with previous components; therefore, each component captures an additional dimension in the data, while explaining smaller and smaller proportions of the variation of the original variables.

The higher the degree of correlation among the original variables in the data, the fewer components required to capture common information. Principal components are linear combinations of random or statistical variables which have special properties in terms of variances. For example, the first principal component is the normalized linear combination (the sum of squares of the coefficients being one) with maximum variance. In effect, transforming the original vector variable to the vector of principal components amounts to a rotation of coordinate axes to a new coordinate system that has inherent statistical properties. This choosing of a coordinate system is to be contrasted with the many problems treated previously where the coordinate system is irrelevant. The principal components turn out to be characteristic vectors of the covariance matrix. Thus the study of principal components can be considered as putting into statistical terms the usual developments of characteristic roots and vectors (for positive semi definite matrices).

Cluster Analysis:

Cluster analysis is an important element of exploratory data analysis. It is typically directed to study the internal structure of a complex data set, which cannot be described only through the classical second order statistics (the sample mean and covariance). Already in 1967, MacQueen [92] stated that clustering applications are considered more as an aid for investigators to obtain qualitative and quantitative understanding of a large amount of multivariate data than only a computational process that finds some unique and definitive grouping for the data. Later, due to its unsupervised, descriptive and summarizing nature, data clustering has also become a core method of data mining and knowledge discovery. Especially during the last decade, the increasing number of large multidimensional data collections has stepped up the development of new clustering algorithms.

Generally speaking, the classification of different things is a natural process for human beings. There exist numerous natural examples about different classifications for living things in the world. For example, various animal and plant species are the results of unsupervised categorization processes made by humans (more precisely, domain experts), who have divided objects into separate classes by using their observable characteristics. There were no labels for the species before someone generated them. A child classifies things in an unsupervised manner as well. By observing similarities and dissimilarities between different objects, a child groups those objects into the same or different group. At the time before the computers came available, clustering tasks had to be performed manually. Although it is easy to visually perceive groups from a two- or three-dimensional data set, such "human clustering" is not likely an inconsistent procedure, since different individuals see things in different ways. The measure of similarity, or the level and direction one is looking at the data, are not consistent between different individuals. By direction we mean the set of features (or combinations of features) that one exploits when classifying objects. For example, people can be classified into a number of groups according to the economical status or the annual alcohol consumption etc. These groupings will not necessarily capture the same individuals. The direction where the user is looking at the data set

depends, for example, on her/his background (position, education, profession, culture etc.). It is clear that such things vary a lot among different individuals. Numerous definitions for cluster analysis have been proposed in the literature. The definitions differ slightly from each other in the way to emphasize the different aspects of the methodology. In one of the earliest books on data clustering, Anderberg, defines cluster analysis as a task, which aims to finding of “natural groups” from a data set, when little or nothing is known about the category structure”. Bailey, who surveys the methodology from the sociological perspective, defines that “cluster analysis seeks to divide a set of objects into a small number of relatively homogeneous groups on the basis of their similarity over N variables.” N is the total number of variables in this case. Moreover, Bailey notes that “Conversely variables can be grouped according to their similarity across all objects”. Hence, the interest of cluster analysis may be in either grouping of objects or variables, or even both. On the other hand, it is not rare to reduce the number of variables before the actual object grouping, because the data can be easily compressed by substituting the correlating variables with one summarizing and representative variable. From the statistical pattern recognition perspective, Jain et al. define cluster analysis as “the organization of collection of patterns (usually represented as a vector of measurements, or a point in a multidimensional space) into clusters based on similarity”. Hastie et al. define the goal of cluster analysis from his statistical perspective as a task” to partition the observations into groups (“clusters”) such that the pairwise dissimilarities between those assigned to the same cluster tend to be smaller than those in different clusters”. Tan et al. states from data mining point of view that” Cluster analysis divides data into groups that are meaningful, useful, or both”. By meaningful they refer to clusters that capture the natural structure of a data set, whereas the useful clusters serve only as an initial setting for some other method, such as PCA (principal component analysis) or regression methods. For these methods, it may be useful to summarize the data sets before hand. The first definition emphasizes the unknown structure of the target data sets, which is one of the key assumptions in cluster analysis. This is the main difference between clustering (unsupervised classification) and classification (supervised classification).

In a classification task the category structure is known a priori, whereas the cluster analysis focuses on the object collections, whose class labels are unknown. Jain et al. suggest that the class labels and all other information about data sources, have an influence to the result interpretation, but not to the cluster formation process. On the other hand, the domain understanding is often of use during the configuration of initial parameters or correct number of clusters. The second and third definitions stress the multi-dimensionality of the data objects (observations, records etc.). This is an important notion, since the grouping of objects that possess more than three variables is no easy matter for a human being without automated methods. Naturally, most of the aforementioned definitions address the notion of similarity. Similarity is one of the key issues of cluster analysis, which means that one of the most influential elements of cluster analysis is the choice of an appropriate similarity measure. The similarity measure selection is a data-dependent problem. Anderberg does not use term “similarity”, but instead he talks about the degree of “natural association” among objects. Based

on the aforementioned definitions and notions, the cluster analysis is summarized as "analysis of the unknown structure of a multidimensional data set by determining a (small) number of meaningful groups of objects or variables according to a chosen (dis)similarity measure". In this definition, the term meaningful is understood identically with Tan et al. Even though the visual perception of data clusters is a suitable method up to three dimensions, in more than three dimensional spaces the visual perception turns to a complex task and computers become indispensable. As we know that a human classifier is an inconsistent classifier, also different algorithms produce different groupings even for the same data set. Hence, there exists not any universally best clustering algorithm. On this basis, Jain et al. advise one to try several clustering algorithms when trying to obtain the best possible understanding about data sets. Based on the authors' experience and theoretical considerations, Kaufman et al. propose six clustering algorithms (PAM, CLARA, FANNY, AGNES, DIANA and MONA) that they believe to cover a major part of the applications. PAM is a partitioning-based K-medoid method that divides the data into a given number of disjoint clusters. CLARA, which also partitions a data set with respect to medoid points, scales better to large data sets than PAM, since the computational cost is reduced by sub-sampling the data set. FANNY is a fuzzy clustering method, which gives a degree for memberships to the clusters for all objects. AGNES, an agglomerative hierarchical clustering method, produces a tree-like cluster hierarchy using successive fusions of clusters. The result provides a solution for different values of K. DIANA is also a hierarchical method, but it proceeds in an inverse order with respect to AGNES. At the beginning, DIANA puts all objects into one cluster and continues by splitting each cluster up to two smaller ones at each step. MONA is also a divisive algorithm, but the separation of objects into groups is carried out by using a single variable. The set of methods, which was just presented, should give a quite overall view to the internal structure of any data set. As mentioned earlier, the result interpretation step is a human process, in which one may utilize different visualization techniques (e.g., PCA and MDS (multidimensional scaling)). After the interpretation, a priori domain knowledge and any other problem-related information are integrated to the clusters.

The development of clustering methods is very interdisciplinary. Contributions have been made, for example, by psychologists, biologists, statisticians, social scientists, and engineers. Naturally, various names for cluster analysis have emerged, e.g., numerical taxonomy, automatic classification, bryology, and typological analysis. Also unsupervised classification, data segmentation, and data partition are used as synonyms for data clustering. Later, when data mining and knowledge discovery have grown further off the other original fields, and constituted its own separate scientific discipline, it has also contributed in a great amount to the development of clustering methods. This special focus has been on the computationally efficient algorithms for large data sets. Perhaps due to the interdisciplinary nature of the cluster analysis, the same methods are often invented with different names on different disciplines. There exist huge

amount of clustering applications from many different fields, such as, biological sciences, life sciences, medical sciences, behavioral and social sciences, earth sciences, engineering and information, policy and decision sciences to mention just a few. This emphasizes the importance of data clustering as a key technique of data mining and knowledge discovery, pattern recognition and statistics. The range of clustering applications is very wide. It may be analysis of software modules and procedures, grouping customers of similar behavior in marketing research, classification of unknown radar emitters from received radar pulse samples, optimal placement of radio ports in cellular networks, identification of subtypes of schizophrenia, archeological applications, peace science applications (identification of international conflicts), P2P-networks etc. The list above could be almost endless.

K-Means Clustering:

K-means clustering (MacQueen, 1967) is the most commonly used unsupervised machine learning algorithm for partitioning a given data set into a set of k groups (i.e. k clusters), where k represents the number of groups pre-specified by the analyst. It classifies objects in multiple groups (i.e., clusters), such that objects within the same cluster are as similar as possible (i.e., high intra-class similarity), whereas objects from different clusters are as dissimilar as possible (i.e., low inter-class similarity). In k -means clustering, each cluster is represented by its center (i.e., centroid) which corresponds to the mean of points assigned to the cluster.

K-means basic ideas:

The basic idea behind k -means clustering consists of defining clusters so that the total intra-cluster variation (known as total within-cluster variation) is minimized. There are several k -means algorithms available. The standard algorithm is the Hartigan-Wong algorithm (1979), which defines the total within-cluster variation as the sum of squared distances Euclidean distances between items and the corresponding centroid.

Hierarchical Clustering:

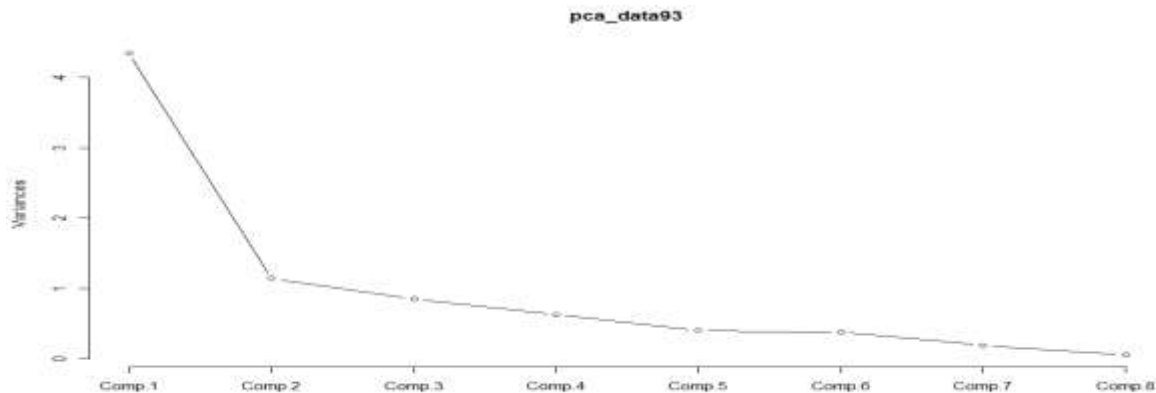
Hierarchical clustering [or hierarchical cluster analysis (HCA)] is an alternative approach to partitioning clustering (Part II) for grouping objects based on their similarity. In contrast to partitioning clustering, hierarchical clustering does not require to pre-specify the number of clusters to be produced. Hierarchical clustering can be subdivided into two types:

- Agglomerative clustering in which, each observation is initially considered as a cluster of its own (leaf). Then, the most similar clusters are successively merged until there is just one single big cluster (root).
- Divise clustering, an inverse of agglomerative clustering, begins with the root, in which all objects are included in one cluster. Then the most heterogeneous clusters are successively divided until all observation are in their own cluster. The result of hierarchical clustering is a

tree-based representation of the objects, which is also known as dendrogram. The dendrogram is a multilevel hierarchy where clusters at one level are joined together to form the clusters at the next levels. This makes it possible to decide the level at which to cut the tree for generating suitable groups of a data objects.

Results and Discussion:

Here we plot a scree plot for 1993 to see the variability of data so that we can select useful variables.



Scree plot for year 1993:

On the basis of scree plot we can see how many pc to retain and then we obtain the scores of selected pc in each year. Here we retained only one pc in each year because it explained 54.16% of the total variances.

Graph between countries and their Partition on the basis of their health condition for year 1993:

Partition of Countries on the basis of their health condition:

Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Burundi	United Arab Emir	Benin	Argentina	Australia
Burkina Faso	Armenia	Bangladesh	Bulgaria	Austria
Central African	Bahrain	Bolivia	Bahamas	Belgium
Cote d'Ivoire	Belarus	Brazil	Barbados	Canada
Cameroon	Colombia	Botswana	Chile	Switzerland
Congo	Ecuador	China (g)	Costa Rica	Germany
Ethiopia	Fiji	Comoros	Cyprus	Denmark
Gambia	Georgia	Cape Verde	Czech Republic	Spain
Guinea-Bissau	Guyana	Dominican Republ	Estonia	Finland
Equatorial Guine	Jamaica	Egypt	Greece	France
Haiti	Jordan	Ghana	Croatia	United Kingdom
Kenya	Kazakhstan	Guatemala	Hungary	Iceland
Lesotho	Lebanon	Honduras	Ireland	Israel
Mali	Sri Lanka	Indonesia	Republic of Kore	Italy
Myanmar	Latvia	India	Kuwait	Japan
Mozambique	Republic of Mold	Iran (Islamic Re	Lithuania	Luxembourg
Mauritania	Mexico	Iraq	Malta	Netherlands
Malawi	Mauritius	Morocco	Poland	Norway
Niger	Malaysia	Maldives	Portugal	New Zealand
Nigeria	Oman	Namibia	Qatar	Sweden
Nepal	Panama	Nicaragua	Singapore	United States of
Rwanda	Philippines	Pakistan	Slovakia	
Sudan	Romania	Peru	Slovenia	

Swaziland	Russian Federati	Paraguay	Trinidad and Tob	
Togo	Saudi Arabia	Senegal		
United Republic	Thailand	El Salvador		
Uganda	Tonga	Syrian Arab Repu		
Yemen	Tunisia	Tajikistan		
Zambia	Ukraine	Turkmenistan		
Zimbabwe	Uruguay	Turkey		
	Venezuela	Uzbekistan		
	Samoa	Viet Nam		
		South Africa		

Conclusion:

There are five clusters in which countries are divided on the basis of their health condition. Those countries which are included in cluster 1(like Burundi, Niger, Burkina Faso, Central African and all other) their health condition are very bad because their pc scores is very high compare to other clusters. That means their health expenditure per capita, educational attainment, life expectancy are very low. So cluster1 contains all those countries whose health care attainment is minimum. Niger is a country whose pc score is maximum 3.98386879 that means their health condition is very poor and Niger has attain lowest health care attainment.

Those countries which are included in cluster2 their health condition is bad. Those countries which are included in cluster3 their health condition are average. Those countries which are included in cluster4 their health condition is good but not so good. Those countries which are included in cluster5 their health condition is very good because their pc scores are very low as compare to other clusters. Therefore cluster5 contains all those countries who attain maximum health care attainment that means highest health expenditure, highest educational attainment, highest life expectancy etc. Switzerland is a country who attains maximum level of health care attainment because their pc score is very low -5.15536833 in compare to all other countries.

References:

1. **Aharony L, Strasser S (1993):** Patient satisfaction: what we know about and we still need to explore. *Medical Care Review* 50: 49-79.
2. **De Silva A (2000):** A Framework for Measuring Responsiveness. GPE Discussion Paper Series: No.32., Geneva: World Health Organization
3. **Evans David B, Tandon Ajay, Murray Christopher J L, Lauer Jeremy A (2001):** "Comparative efficiency of national health systems: cross national econometric analysis", pubmedcentralcanada.ca.
4. **Gakidou EE, Frenk J, Murray CJL (2000):** Measuring preferences on health system performance assessment. Geneva, World Health Organization, (Global Programme on Evidence for Health Policy Discussion paper No. 20).
5. **Gilson L, Alilio M, Heggenhougen K (1994):** Community satisfaction with primary health care services: an evaluation undertaken in the Morogoro region of Tanzania. *Social Science and Medicine* 39: 767-780.
6. **Maisonneuve C. and Martins J. (2013):** "A projection method of public health and long-term care expenditures", OECD Economic Department Working Papers No. 1048.
7. **McPake B (1993):** User charges for health services in developing countries: a review of the economic literature. *Social and Science and Medicine* 36: 1397-1405.
8. **Medeiros J. and Schwierz (2013):** "Estimating the drivers and projecting long-term public health expenditure in the European Union: Baumol's 'cost disease' revisited", *European Economy, Economic Papers* No. 507. OECD
9. **Murray CJL, Frenk J (1999):** A WHO Framework for Health System Performance Assessment. GPE Discussion Paper Series: No.6., Geneva: World Health Organization
10. **Ware JE, Snyder MK, Wright WR, Davies AR (1983):** Defining and measuring patient satisfaction with medical care. *Evaluation and Program Planning* 6: 247-263.
11. **WHO:** The World Health Report 2000., Geneva: World Health Organization.
12. **Wouters A (1991):** Essential national health research in developing countries: healthcare financing and the quality of care. *International Journal of Health Planning and Management* 6: 253-271.