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RESEARCH PAPER

Evaluation of The OECD Countries' Healthcare System in Terms of Sustainable Development

Mehrdad Jalali Sepehr[1] , Abdorrahman Haeri[*2] & Rouzbeh Ghousi[3]

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ABSTRACT
In this paper, the healthcare conditions of 31 countries that are the members of the Organization for Economic and Co-operative Development (OECD) are measured by considering 14 indicators that are relevant to three main pillars of sustainable development.A hybrid Principle Component Analysis and Data Envelopment Analysis, PCA-DEA, is used to estimate health efficiency. For DEA, the additive model in both forms of envelopment and multiplier is used to determine efficiency scores and present benchmarks and improvement plans for inefficient countries. Then, Decision Tree Analysis is used to acquire a knowledge discovery process to determine influential situations affecting the efficiency status of a Decision-Making Unit (DMU). According to the PCA-DEA additive model, among 31 OECD countries, 16 countries have become inefficient such that the USA has experienced the lowest efficiency score. Among efficient countries, Iceland enjoys a suitable benchmark. Decision tree analysis also shows that exposure to PM2.5 is an influential factor in the health efficiency status of countries.This research gives an insight into the sustainable development and healthcare system and shows the impressive effect of environmental and social factors, such as exposure to PM2.5, water quality, insurance coverage, and AIDS, on the healthcare efficiency of OECD countries.

KEYWORDS: *PCA-DEA, Decision Tree, OECD Countries, Healthcare, Well-being, Exposure to PM2.5, water quality.*

1. Introduction

By following the sustainable development literature, this study has found that many studies consider sustainable development as a green paradigm associated with manufacturing or energy sectors; however, the most crucial objective of such measures is to provide a better lifestyle for humanity and future generations; therefore, the gap of social pillar of sustainability can be sensed dramatically. One of the most critical criteria used to see whether a country is developed or not is to look at its healthcare system, and a suitable health system can be considered as an influential factor in welfare state of a nation. The high efficiency of this sector can be considered to be one of the primary measures to evaluate the wellbeing and welfare state in a country. In this regard, public health has become a new issue for researches to investigate how to enhance these systems more effectively.

The present research uses DEA-PCA to measure the relative efficiency of 31 OECD countries as Decision-Making Units. In this regard, comprehensive features are selected according to previous researches and, then, their dimensionality is reduced by Principle Component Analysis technique. After data preprocessing, this study uses an additive variable return to scale model in both envelopment and multiplier forms to measure the relative efficiency of 31 OECD countries; then, for inefficient countries, the efficient countries are defined as the benchmarks based on which improvement plans for the inefficient countries can be determined. After performing the performance measurement analysis, Decision Tree Analysis is used to discover the knowledge behind the efficiency status of countries. To apply this technique, nations are labeled as efficient and inefficient ones to facilitate

* **Corresponding author:** ***Abdorrahman Haeri***
Ahaeri@iust.ac.ir

1. *Iran University of Science and Technology (IUST), School of Industrial Engineering Tehran, Iran.*
2. *Iran University of Science and Technology (IUST), School of Industrial Engineering, Tehran, Iran.*
3. *Iran University of Science and Technology (IUST), School of Industrial Engineering, Tehran, Iran.*

conducting a descriptive analysis. In the following, the previous studies in the area of health efficiency measurement with a focus on the international scope are reviewed.

J. Puig-Junoy [1] was a pioneer in the area of health efficiency and estimated the efficiency of 21 OECD countries by DEA and Tobit Regression analysis. In this study, variation of male and female life expectancy was taken as output, and six variables including the number of physicians, the number of non-physician personnel per 1000 inhabitants, the number of hospital beds per inhabitant, tobacco and alcohol consumption, and the number of residents under 65 years old were used as inputs. Y. Varabyova and J. Schreyögg [2] applied DEA and parametric stochastic frontier analysis (SFA) to calculate the efficiency scores of the hospital sector for OECD countries during 2009-2012. They used total hospital beds, total hospital employment, physicians, and nurses as inputs and, also, used discharge and mortality rates as two outputs. Moreover, their study consisted of nine environmental variables: health care expenditure, financing of health care, income inequality, market influence, education, length of stay, health status, population over 65 years old, and full-time employment. P. K. Samut and R. Cafri [3] assessed the health care of 29 OECD countries' hospital sectors through two-stage analysis. First, for each country, DEA was used to measure the efficiency of hospital sectors and, then, Panel Tobit Analysis was used to determine the impact of environmental factors on the efficiency scores. In their analysis [3], discharge rate and infant survival rate were used as outputs and five indicators related to health resources were selected as input variables. Beds, MRI, and Computerized Tomography scanners as material resources and the density of physicians and nurses per 1000 population as human resources were taken into consideration. To conduct the Panel Tobit Analysis, three environmental variables of GDP, health expenditure as a percentage of GDP in public and private hospitals, tertiary educational expenditure, the number of public hospitals, the number of private hospitals, and life expectancy were used. Adang and Borm [4] studied the association between satisfaction with health care system and economic performance and used output-oriented constant returns to scale DEA Malmquist model and Cohort analysis to examine this association for 15 OECD members. They used expenditure on health (percentage of GDP), the number of physicians per 1000 inhabitants, and tobacco consumption as inputs and life expectancy and infant mortality as outputs. A. Afonso and M. St.Aubyn [5] employed DEA and Free Disposable Hull (FDH) as two non-parametric approaches to measure the efficiency score of the health and educational system of countries. In terms of education, instruction time in public institutions, the number of teachers per student in secondary schools, and educational expenditure were defined as inputs, and the students' result in a particular test was chosen as an output. Moreover, to assess the health status of OECD countries, the number of doctors, nurses, and in-patient beds per 1000 inhabitants was considered as inputs, and infant survival rate and life expectancy were used as outputs in this analysis. In another study, A. Afonso and M. St. Aubyn [6] examined the efficiency of OECD countries' health systems by a two-stage DEA/Tobit and bootstrap procedure. According to the members of OECD, most of these countries are developed countries; however, C. A. Alexander, G. Busch and K. Stringer [7] presented a DEA model to measure the health sector efficiency of 51 developing countries during 2000 and 2003. In this regard, they considered life expectancy and infant mortality as outputs and the number of doctors, nurses, beds, and Magnetic Resonance Imagers (MRI) as inputs; in addition, PCA was used to reduce the dimensionality of the indicators. M. Campos, A. Fernandez-Montes, J. Gavilan, and F. Velasco [8] applied the DEA technique to measure the efficiency of the healthcare sector in 17 regions of Spain in 1999. As output indices, they defined disability-adjusted life expectancy for both men and women and used infant mortality rate, health expenditure, and GDP as inputs. P. De, A. Dhar and B. Bhattacharya [9] analyzed the efficiency of Spain's states. They used DEA/Tobit to choose the determinants in the efficiency scores. For those studies with an inter-country scope, one can make a reference to C. Suraratdecha and A. A. Okunade [10] who measured the efficiency of 10 major states of India. They considered women's life expectancy and under-five-year-old children's survival rates as outputs and, then, the number of doctors, nurses, hospitals, and hospital beds per 100000 populations as inputs. They also used the PCA technique for the variables to measure the efficiency of those ten states. M. Staat [11] used a DEA-bootstrapping method to calculate the efficiency of hospitals in Germany. To measure China's healthcare efficiency, S. Wu,

C. Wang, and G. Zhang [12] conducted research and used DEA, Tobit model, and Malmquist productivity index to examine the efficiency change since the significant reform of the healthcare system in china took effect. In this regard, a dataset that covers the years 2003 to 2011 for 31 provinces was used in their analysis; the number of health employees and beds per 1000 population was considered as inputs. For medical and public services, two different sets of outputs were used; the results showed that the reform could not make an improvement [12]. S. Hadad, Y. Hadad, and T. Simon-Tuval [13] implemented two DEA models to assess the healthcare efficiency of 31 OECD countries in 2010: the first DEA model included three discretionary inputs such as the number of physicians per 1000 population, hospital beds per 1000 population, health expenditure per capita; the second model included three non-discretionary inputs such as GDP per capita, vegetables and fruits usage per capita, and health expenditure per capita. Moreover, since outputs' life expectancy and infants' survival rate were considered, a regression model was used to illustrate the external determinant factors in health efficiencies including relevant indicators such as fat intake, vegetable usage, and socioeconomic and environmental factors. J. L. Navarro-Espigares and E. H. Torres [14] studied the association between efficiency and quality of hospitals in Spain between the years 1997 and 2004. In their research, the efficiencies of hospitals were estimated by DEA and Malmquist productivity index, and a weak association between quality and efficiency was concluded. K. Kounetas and F. Papathanassopoulos [15] used SFA and bootstrapped DEA to measure the efficiency of Greek hospitals and, then, regression analysis was applied to investigate the influence of environmental factors on the efficiencies. In the following, L. Steinmann, G. Dittrich, A. Karmann and P. Zweifel [16] applied DEA to assess the efficiency of German and Swiss hospitals separately, and then a comparative analysis between them was made. R. L. Murillo-Zamorano and C. Petraglia [17] evaluated the efficiency of 85 primary care centers (PCCs) by SFA and, in doing so, both quantitative and qualitative indicators were used. J. M. C. Ferrera et al. [18] estimated the efficiency of 89 PPCs by considering the qualitative and qualitative factors. In their analysis, a four-stage DEA model was used, and their developed model could use both qualitative and quantitative measures to estimate efficiency and, finally, by carrying out regression analysis, the influence of external factors on the efficiencies was determined. Y. A. Ozcan and J. Khushalani [19] used a new Dynamic Network DEA to evaluate changes of 34 OECD countries' efficiencies for the public health system and medical care system from 2000 to 2012. In this time period, the OECD countries made significant reforms in their health system. For the public health sector, inputs included Tobacco usage, alcohol consumption, obese population, and expenditure on public health; in addition, outputs were female and male life expectancy. The common variables for both public health and medical care are infants and maternal mortality and perceived health status. The links from the first stage (public health) to the second stage (medical care) are immunization, screening breast cancer, and cervical cancer. Meanwhile, inputs for medical care include the number of CT scanners, total employees in the health sector, and hospital bed; the outputs for this sector include the number of discharges per hospital and the number of visits per year; in addition to that, the number of new cancer cases is used as an undesirable variable for the next year. D. Retzlaff-Roberts et al. [20] used BCC input- and output-oriented DEA models to measure the efficiency of 27 OECD members. In their study, health inputs such as beds, Physicians (per 1000 population), MRI (unit per million population), and Health expenditure (percentage of GDP) and three social inputs including school expectancy, tobacco usage, and two outputs infant mortality and life expectancy were taken into consideration. J. Spinks and B. Hollingsworth [21] used both OECD and World Health Organization datasets during the years 1995-2000 and 1993-1997, respectively. They calculated technical efficiency change, technological change, and total factor productivity change during the given period for 28 OECD countries. Meanwhile, there are research papers in which best practices and planning systems are developed to help improve the efficiency of the public health by enhancing their infrastructure. In this regard, K. Roshan et al. [22] applied multi-objective simulated annealing (MOSA) to design a network of preventive healthcare facilities so as to minimize total travel and waiting time and decrease the establishment and staff cost. Y. Zare Mehrjerdi [23] introduced a system dynamics (SD) model to analyze the interconnections among human being weight, eating habits, exercise, body fat, take-in medication, drugs-uses, and health problems in general. The main contribution of his work is to show how a factor, such as weight, can affect heart attack, blood pressure, blood sugar, etc. and how all these are related to the overall expenses that an insurance company has to pay at last. Today, when the topic of infrastructures in health systems comes up, Information Systems (ISs) play a crucial role. In addition, Green Information Systems (GIS) that indicate a novice approach to the application of ISs are considered as necessary tools to realize the goals of environmental sustainability. H. Sayyadi Tooranloo and S. Rahimi [24] recognized these factors through the library method and review of the literature. Then, the relationships between these factors were analyzed and modeled using an interpretive structural approach. According to the results [24], the volume of social investment, research and development along with the senior management's insight, and commitment are the most important factors that affect Green ISs adoption in the health care centers. Such best practices and planning are very influential in empowering the public health managers to improve efficiency. The combination of DEA and DT has been defined as an expert system in some previous studies, showing the efficacy of this methodology for benchmarking and productivity improvement in different fields of studies such as process management [37], environmental technology management [38], and marketing [39]. For the public health, A. De Nicola et al. [40] estimated the efficiency of 390 Italian public hospitals in 2007. To do so, they used bootstrapped DEA. Then, they used classification and regression tree (CART) methodology based on the DEA results to investigate the relationships among health efficiency of the hospitals, physicians, nurses, beds, and discharges, while comprehensive cross-country results based on the combination of DEA results and DT have not been observed in the previous studies. Meanwhile, most of the studies have focused on the efficiency of health systems and have not used data mining techniques as a knowledge discovery approach to conceive the relations behind the public health data. Moreover, by employing decision tree analysis as a supervised approach, observations' classification is an important part of it; in this regard, the efficiency status of countries' public health has been taken into consideration. Such a hybrid methodology, which uses DEA results as the observations' classes in decision tree analysis, has not been observed in the previous studies. Another gap in this area is related to the features that are being analyzed, and indicators such as Cancer incidence, AIDS, population under insurance coverage, water quality, air pollution, social expenditure, and family's expenditure have not been detected in the recent papers. For instance, water quality is such a prominent factor that disregard for it will gravely affect people's health and, as is evident, these features encompass financial, social, and environmental aspects of the public health.

In the following, Section 2 presents an employed methodology in this research and includes definitions of indicators, the data preprocessing, PCA results, DEA model, and Decision Tree (DT) analysis. Then, the efficiency scores and benchmarks, improvement plan, and decision tree figures with their analysis are presented in Section 3 as the result of this study. Finally, discussion and conclusions are shown in Sections 4 and 5, respectively.

2. Methodology

The present research applies DEA-PCA to measure the relative efficiency of 31 OECD countries as Decision-Making Units. In this regard, comprehensive features are selected and, then, their dimensionality is reduced by the Principle Component Analysis technique. Decision Tree is used as a knowledge discovery behind the efficiency status of countries, and further explanations are presented in the following.

2-1 Dataset and data preprocessing

For the sake of the objective of this study, 14 indicators are chosen, seven of which are defined as inputs and seven others as outputs for a healthcare system. These indicators are published by OECD, which has categorized data into several fields as health, environment, social, etc., and our data are extracted based on this categorization and the mentioned gap in the previous studies in the literature view. Based on this assumption, the indicators must be suitable features in one of the sustainable development pillars (social, environmental, and economic). Moreover, for indicators in the environmental categories, based on previous studies, their relations with health are scrutinized; for example, in a study by E. Boldo et al. [26], a comprehensive analysis was carried out to illustrate the health-related effect of PM2.5 on 23 European countries' life expectancy and mortality; in addition to that, the effects of low water quality on health problems are proved in real-world cases such as water quality problems in Flint of Michigan [25]. There are also some missing values that are explained in the following. In the following, more information is given about the indicators, and Table 1 shows a statistical summary of the indicators.

***Input indicators*:**

The input variables include the total number of employees in the health sector, total expenditure on families, total social expenditure, total current expenditure on health, total hospital beds, water quality, and mean population exposure to PM 2.5 as an air pollution indicator.

a) ***Total health and social employment*** is defined as an input variable in this research [27]. This indicator represents the number of persons (head counts) working in healthcare and social fields.

b) ***Total public expenditure on families*** is chosen as an input factor in our model. This indicator is presented by OECD as the percentage of GDP for each country and, in the taxonomy of indicators, it pertains to the social protection and wellbeing [27].

c) ***Social expenditure (SOCX)*** is another variable in our study that is defined as an input factor. This indicator comprises all social programs that are related to the following: old age (Pension, early retirement pension, etc.), survivors (pension, other cash benefits and other benefits in kind), incapacity related (Disability pensions, occupational injury and diseases, paid sick leave, occupational injury and diseases and other sickness daily allowances, etc.), family (family allowances, maternal and paternal leave, early childhood education and care, etc.), active labor market programs, unemployment (unemployment compensation and early retirement for labor market seasons), housing (housing assistance and other benefits of the same kind), and other social policy areas (income maintenance, other cash benefits, social assistance, and other benefits of the same kind). This indicator also is measured in the percentage unit of GDP for each country [27].

d) ***Current expenditure on health*** is another input factor that has been used by some previous studies. This indicator shows all financing schemes of both government schemes and compulsory contributory healthcare financing schemes and, also, private expenditure. The unit of this measure is defined in percentage as a share of GDP for each country [27].

e) Concerning sustainability and the environmental pillar, ***mean population exposure to PM2.5*** is defined as an input variable in the present study. This indicator is revealed in terms of both environmental and better life indices. According to the World Health Organization (WHO), exposure to PM2.5 is more dangerous than other pollutants and, through inhaling these pollutants, some severe diseases, especially heart diseases, can be induced. The sensitive community of each society, e.g., children and elderly people, will be susceptible to harder effect of this kind of pollutants [27]. This indicator is measured in micrograms per cubic meter, and the value obtained in 2013 is used in this study for all DMUs. Authors [26] in another work attempted to verifiably show the health-related effect of PM2.5 on 23 European countries' life expectancy and mortality.

f) Another indicator pertaining to both environment and health is ***water quality***. This indicator is published among better life indices, and its unit of measurement is percentage, the value of which obtained in 2013 is used in this research [27]. It is notable that the low water quality will cause many health problems similar to the problems observed in Flint of Michigan [25].

g) ***Total hospital beds*** is another input variable in our study, which is in the category of healthcare resources. This indicator represents the number of hospital beds in each country [27].

***Output indicators*:**

The output variables that have been used in this research include the population covered by public or private insurance, infant mortality rate, maternal mortality, AIDS as a communicational disease, life expectancy for both men and women at birth, and cancer incidences. Except for cancer that belongs to the year 2012, all other indicators are chosen for the year 2013.

a) ***Total public and primary private health insurance*** represents the insurance coverage in each country. This indicator is available on the website of OECD in the category of *social protection* [27] and is presented in the total population percentage unit, which was last updated on October 7, 2016.

b) ***cancer*** is another output whose last update dates back to 2012. The measurement unit for this indicator is incidence per 100 000 populations and, in our research, malignant neoplasm (tumors) is taken into consideration [27].

C) There are two kinds of ***infant mortality***: no minimum threshold of gestation period or bright weight and a minimum threshold of 22 weeks or 500 Grams bright weight; however, in the proposed study, the first type is selected, and the measure for this factor is deaths per 1000 live births [27].

d) For ***maternal mortality*****,** the measure is deaths per 100 000 live births [27]. Note that, for the USA, the data for this indicator were just available from 1960 to 2007 and, accordingly, the mean of the indicator over the years 2000 to 2007 is used in our study.

e) For ***communicational diseases*** considered in our study, the incidence number of Acquired Immunodeficiency Syndrome (AIDS) in 2013 is defined [27].

F, g) ***life expectancy*** shows the average time in a year that each sex expects to live, and it is one of the fundamental indices to show how developed a country is. In this research, two such separate indicators as life expectancy for females and life expectancy for males at birth are determined [27]. Table 1 shows the data summary that includes all indicators, mean value, and maximum and minimum values.

By reviewing the above indicators, we could see that there are two kinds of indicators: desirable and undesirable indicators. According to the nature of DEA, especially the additive model, the DMU, which produces more outputs by consuming lower inputs, is the excellent one. Moreover, the model is not concerned with whether the indicator is a good (desirable) or a bad (undesirable) one. However, among the input variables, water quality is the variable that must be increased, and the letter I above the symbol of this variable in Equation (1) shows that it is an increasing input variable, whereas the other input variables should experience a reduction. For this purpose, Equation (1) is used to present the water quality indicator as an input that must increase. To do that, all values for water quality were multiplied by (-1) and added to Ki as the sum of the maximum value of water quality and 1. This study denotes DMUs by j=1,2...,n and inputs by i=1,2…,m; thus, Equation (1) is as follows [28],[29]:

$$X_{ij}^{-I} = -X_{ij}^{I} + K_i \geq 0 \text{Eq.} \qquad (1)$$

For output indicators, infant mortality, maternal mortality, AIDS, and cancer are undesirable outputs, and their values must vary such that the DMU with the highest value obtains the lowest amount. In this way, those DMUs with better health conditions get closest to the efficiency frontier. Equation (2) for outputs is shown in the following, tr is the sum of the maximum value for each field (undesirable indicator) and 1. Then, by adding the negative values $-Y_{rj}^{b}$, the new values will be achieved. Equation (2) is shown in the following, as j=1,2,…,n and r=1,2,…,s show the DMUs and outputs. In addition, the letter b above each Y emphasizes the undesirable output.

$$Y_{rj}^{-b} = -Y_{rj}^{b} + t_r \geq 0 \text{ Eq.} \qquad (2)$$

Table 1 Statistics concerning the input and output indicators used for PCA-DEA

Indicators	Mean value	Maximum		Minimum	
		Value	Country	Value	Country
Total employees in the health system (head counts)	1644656.77	19562000	USA	20600	Iceland
Total public expenditure on families(%GDP)	2.43	4	United Kingdom	0.4	Turkey
Total social expenditure (%GDP)	21.19	31.49	France	6.2	Mexico
Current expenditure on health(%GDP)	9.05	16.36	USA	5.0853	Turkey
Total hospital beds (number)	145553.04	914513	USA	1038	Iceland
Water quality(percent)	85.29	97	United Kingdom, Iceland	61	Turkey
Mean population exposure to PM2.5	13.31	28.79	Korea	6.0275002	Australia

Indicators	Mean value	Maximum		Minimum	
		Value	Country	Value	Country
(mg per m^3)					
Population covered by insurance (percent)	98.07	100	Australia, Canada, Czech Republic, Denmark, Finland, Iceland, Ireland, Italy, Korea, New Zealand, Norway, Portugal, Slovenia, Sweden, Switzerland, UK	85.5	USA
Infant mortality rate (per 1000 live births)	4.16	13	Mexico	1.8	Finland
Maternal mortality (per 100 000 live births)	7.38	38.2	Mexico	0.00	Iceland
AIDS (number of incidence)	1261.82	27135	USA	1	Iceland
Life expectancy for females (years)	82.92	86.1	Spain	77.4	Mexico
Life expectancy for male (years)	77.66	80.7	Switzerland	71.7	Mexico
Cancer incidence	275.26	338.1	Denmark	131.5	Mexico

Through the above equations, the undesirable outputs and increasing input are shifted and, for other outputs (desirables) and inputs (costs), their values are taken into consideration. Following the above process, the data are normalized by the Minimax method. The reason for this is that the nature of indicators and their values is different, and the indicators, such as financial ones, that are large in number and amount can become dominant in the weight allocation process including both Principle Component Analysis (PCA) and DEA techniques. By normalizing the indicators, their values range between 0 and 1 for the lowest and highest values, respectively. Normalization gives us a more appropriate condition to compare the indicators that are in different units. After the above process, Principle Component Analysis (PCA) is used to reduce the dimensionality of our dataset. Ueda and Y first introduced the PCA-DEA technique [30]. This technique provides us a new dataset that comprises new components as indicators. Each component is derived from the previous data that is a weighted combination of them. The main advantage of the hybrid PCA-DEA approach is to save the discriminatory power of the model in the presence of a few DMUs and many indicators. In such a situation, most DMUs become efficient, and it is impossible to conduct a proper analysis, although DEA is a non-parametric approach and there is not a deterministic proportion for the number of DMUs to their features. Therefore, it is common for DMUs to be three times the number of features. Moreover, in this analysis, there are 31 OECD countries and 14 indicators and, by using conventional DEA models, the results would be inexplicable. Figure 1 displays the methodology of this research as a diagram.

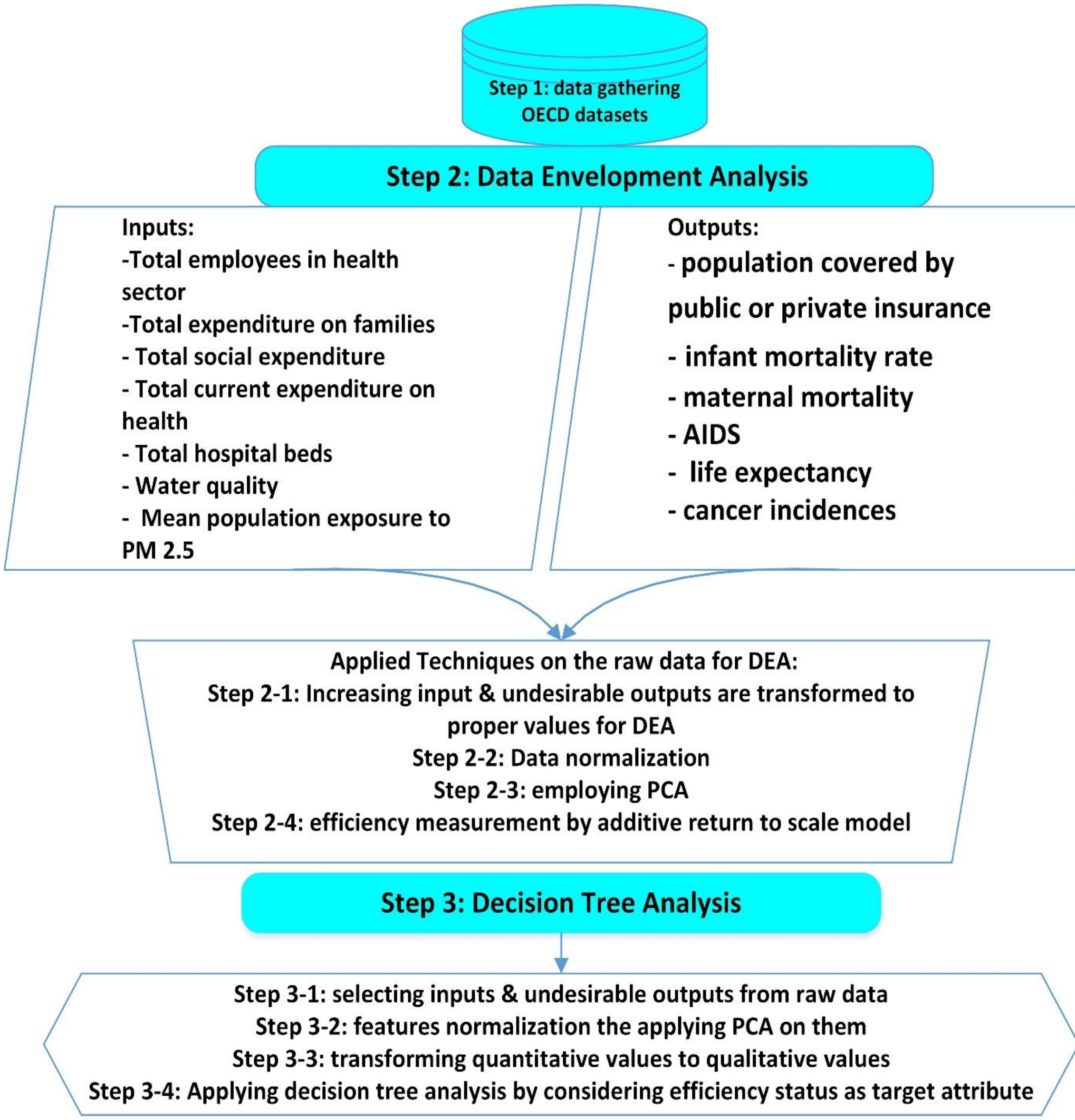

Fig. 1. Flow diagram of the research methodology

2-2 Principle component analysis:

Principal component analysis (PCA) is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. PCA is mathematically defined as an orthogonal linear transformation that transforms the data into a new coordinate system such that the greatest variance by some projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA can be done by eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after a normalization step of the initial data. The normalization of each attribute consists of mean centering – subtracting each data value from its variable's measured mean so that its empirical mean (average) is zero – and, possibly, normalizing each variable's variance to make it equal to 1. In the C1 to C5 columns in Tables 2 and 3, the scores of the Principle Components (PCs) for inputs and outputs are displayed. To interpret each component first, it must be noted that all features (seven dimensions of inputs or outputs) have been transformed into one PC for which the mid-point has a value of 0. The sign (positive or negative) tells the direction that a given indicator in that PC is going on a single dimension vector.

***Varimax Rotation*:**
Rotations represent a set of mathematical techniques to transform the loading matrix of principal component analysis into an interpretable concept. In this regard, the most common rotation technique is the Varimax Rotation. Varimax is so called because it maximizes the sum of the variances of the squared loadings (squared correlations between variables and factors). Preserving orthogonality requires a rotation that leaves the sub-space invariant. In this regard, two conditions should be taken into consideration. First, any given variable has high loadings on a single factor as opposed to the near-zero loadings on the remaining factors; second, any given factor is formed by only a few variables with very high loadings on this factor, while the remaining variables have near-zero loadings on this factor. If these conditions hold, the factor loading matrix is said to have a simple structure, and Varimax Rotation brings the loading matrix closer to such a simple structure [31].
For DEA, PCA is used twice, first for input indicators and then for output variables; for both of them, five components are found whose weights and cumulative variances are shown in the following Tables 2 and 4.

Tab. 2. PCA results for input indicators

Output indicators	Weights of indicators in each component				
	PC1	PC2	PC3	PC4	PC5
Total employees in the health system	0.295	0.914	-0.133	0.501	0.147
Expenditure on families	0.683	-0.433	0.288	-0.308	0.390
Total social expenditure	0.675	-0.168	0.578	0.402	-0.043
Current expenditure on health	0.770	0.529	0.006	0.089	-0.277
Total hospital beds	0.022	0.928	0.143	-0.143	0.214
Water quality	-0.817	0.152	0.218	0.407	0.263
Air pollution (PM2.5)	-0.592	0.273	0.638	-0.323	-0.241
%Proportion Variance	37.435	32.660	12.985	7.959	6.069
%Cumulative Variance	37.435	70.095	83.080	91.040	97.108

Tab. 3. PCA results by Varimax Rotation for Inputs

Output indicators	Weights of indicators in each component				
	I-RC1	I-RC2	I-RC3	I-RC4	I-RC5
Total employees in the health system	0.43	0.91	0.09	0.75	0.32
Expenditure on families	0.81	0.13	0.21	0.10	0.65
Total social expenditure	0.79	0.23	0.61	0.65	0.23
Current expenditure on health	0.87	0.64	0.12	0.32	0.11
Total hospital beds	0.17	0.94	0.15	0.15	0.48
Water quality	0.11	0.33	0.19	0.73	0.54
Air pollution (PM2.5)	0.14	0.41	0.84	0.12	0.09
Proportion Variance	0.29	0.41	0.13	0.08	0.06
Cumulative Variance	0.29	0.70	0.83	0.91	0.97

To conduct data analysis, the first three input components that form the cumulative variance of 0.83 are used in our evaluation. In other words, these three components consist of 83% input data.
According to Table 3, the first component I-RC1 is suitably representative of current expenditure on health, expenditure on families, and total social expenditure. Such an interpretation can be drawn from the value of features in each Rotated Component (RCs) in Table 3. As is evident, the RC values for the mentioned features are 0.87, 0.81, and 0.79, respectively. Meanwhile, I-RC2 is properly representative of total employees in the health system and total hospital beds. I-RC3 is a relevant feature for air pollution (exposure to PM2.5). Although water quality has a massive weight in I-RC4, the average share of this environmental feature among the first three RCs has just been taken into account to keep the

discriminatory power of the model. To interpret these components, it is evident that I-RC1 is mostly relevant to financial features, while I-RC2 is related to infrastructure and physical assets, and I-RC3 is related to environmental features. It should be noted that each RC is not crisp in nature, and it is also a minor combination of other indicators. This fact can become more tangible when considering the cumulative variance as the share of total data in each component.

For outputs, the proposed procedure is also the same. Table 5 shows the Varimax Rotation in PCA results; the first three components whose cumulative variance is 0.92 are selected as output indicators. It should be noted that Varimax Rotation makes the PCA results interpretable. According to Table 5, O-RC1 is suitably representative of life expectancy for females and males, infant mortality, the total population covered by insurance, and maternal mortality, while O-RC2 is mostly relevant to AIDS & cancer incidence. O-RC1 and O-RC2 encompass 77% of output indicators data. Although all output indicators are covered by just considering the two aforementioned components, it is common in PCA that the cumulative variance of components becomes more than 80 percent of the data; in this regard, O-RC3 is taken into account to increase the total share of data in the analysis.

Tab. 4. PCA results for output indicators

Output Indicators	Weight of indicators in each component (C)				
	PC1	PC2	PC3	PC4	PC5
Total population covered by insurance	0.802	0.503	0.114	-0.210	0.60
Infant mortality	0.852	-0.201	-0.323	0.177	-0.283
Maternal mortality	0.797	-0.196	-0.433	0.205	0.312
AIDS incidence	0.441	0.840	-0.260	-0.064	-0.050
Life expectancy for females	0.880	-0.049	0.333	0.250	-0.92
Life expectancy for males	0.811	-0.072	0.546	0.005	0.91
Cancer incidence	-0.690	0.501	0.135	0.496	0.037
% of Variance	58.690	18.508	11.430	6.140	2.884
%Cumulative Variance	58.690	77.198	92.628	94.768	97.652

Tab. 5. PCA results by Varimax Rotation for outputs

Output Indicators	Weight of indicators in each component (C)				
	O-RC1	O-RC2	O-RC3	O-RC4	O-RC5
Total population covered by insurance	0.87	0.64	0.22	0.13	0.52
Infant mortality	0.78	0.16	0.11	0.26	0.29
Maternal mortality	0.67	0.19	0.07	0.35	0.43
AIDS incidence	0.44	0.91	0.09	0.21	0.35
Life expectancy for females	0.96	0.24	0.56	0.48	0.01
Life expectancy for males	0.91	0.27	0.63	0.27	0.75
Cancer incidence	0.09	0.81	0.42	0.79	0.39
Proportion Variance	0.44	0.33	0.15	0.03	0.03
Cumulative Variance	0.44	0.77	0.93	0.95	0.98

2-3 Data envelopment analysis

Data envelopment analysis is a non-parametric approach to measuring the relative efficiency of a set of peers called decision-making units (DMUs). Each DMU consumes its inputs to produce the outputs. The first model of DEA is CCR, which is an abbreviation for Charnes, Cooper, and Rhodes, i.e., the names of its developers [32]. The CCR model measures the relative efficiency under the condition of Constant Return to scale (CRS), which assumes a linear relationship between inputs and outputs. To present another model that estimates the relative efficiency of DMUs under the condition of Variable Return to Scale (VRS), Banker, Charnes, and Cooper have developed the BCC model [33]. In 1998 [34], the additive model has been introduced; in both CCR and BBC models, one must distinguish between input- and output-oriented models; the level of outputs remains constant for input-oriented model and the number of inputs must be decreased to make a DMU an efficient one; for output-oriented models, the aforementioned condition is in reverse. However, for the additive model, both orientations are combined in such a way that the additive model considers the decreasing of inputs and increasing of outputs simultaneously. The Envelopment form and multiplier form of the additive model are displayed in the following models (3.a) and (3.b) such that j=1,2,3,…,n is the number of DMUS, i=1,2,3,…,m is denoted as input variables, and r =1,2.3,…,s is denoted as the number of output variables. Model 3.a is the envelopment form of the additive model:

$$Min\ Z = \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

s.t:

$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0},$ i=1,2,3,…,m

$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0},$ r=1,2,3,…,s

$\sum_{j=1}^{n} \lambda_j = 1$Eq.(3.a)

$s_i^- \geq 0,$ i=1,2,3,…,m

$s_r^+ \geq 0,$ r=1,2,3,…,s

$\lambda_j \geq 0$ j=1,2,3,…,n

Model 3.b is the multiplier form of the additive model:

$$Max\ Y_0 = \sum_{r=1}^{s} y_{r0}\, u_r - \sum_{i=1}^{m} x_{i0}\, v_i + w$$

S.t:

$\sum_{r=1}^{s} y_{rj} u_r - \sum_{i=1}^{m} x_{ij}\, v_i + w \leq 0,$ j=1,2,3,…,n

Eq. (3.b)

$\sum_{r=1}^{s} u_r \geq 1,$ r=1,2,3,…,s

$\sum_{i=1}^{n} v_i \geq 1,$ i=1,2,3,...,m

$u_r, v_i \geq 0$

W free.

2-4 Decision tree

In the literature of data mining, decision tree analysis is one of the most famous methods to build a classifier learning model [35] [36]. By this method, the acquired knowledge will be introduced in the form of a tree containing different features of the indicators' conditions shown on each branch. This illustration facilitates interpreting the discovered knowledge more easily. To implement this approach, we have first estimated the efficiency of the DMUs and, then, defined their efficiency status as the label for each DMU, ***efficient or inefficient***. Then, all data normalized by the minimax method were grouped into five categories. It must be noted that, for decision tree analysis, only fourteen indicators of the same data are shown without considering undesirable outputs or increasing input. The fourteen indicators are just normalized and, then, are transformed into ordinal data based on the ranges presented in Table 6. Therefore, by using this ordinal data, the decision tree will become more tractable for interpretation.

Tab. 6. limitations used for converting quantitative values into qualitative ones for decision tree analysis

Class names	Lower Limit -Upper limit
Very Low	0.00-0.20
Low	0.21-0.40
Average	0.41-0.60
High	0.61-0.80
Very High	0.81-1.00

Further, PCA is applied to perform decision tree analysis; however, varimax rotation is not presented, because the focus is not on the whole indicators and their interpretation. The massive weights of environmental indicators for inputs and undesirable indicators as outputs direct us to the needed component. In addition, after component selection, their values for DMUs are normalized.

For decision tree analysis, all input indicators are transformed into 5 components by PCA. As shown in Table 7, the weights of indicators in each input component are presented. In this analysis, the input component (1), which mostly represents health expenditures, and the input component (3), which represents exposure to PM 2.5, are specified for Decision Tree. For outputs, indicators are divided into two desirable and undesirable groups. Table 8 displays the undesirable outputs that are more critical and are used for the decision tree. There are four undesirable output components: the first component is selected as representative of infant and maternal mortality and the second undesirable output component as an agent for AIDS and cancer incidence.

Tab. 7. Weights of input indicators in each component extracted by PCA for DT

Input indicators	Weights of indicators in each component				
	C1	C2	C3	C4	C5
Total employees in health	0.295	0.914	-0.133	-0.051	-0.147
Expenditure on families	0.683	-0.433	0.288	0.308	-0.390
Social expenditure	0.675	-0.168	0.578	-0.402	0.043
Total expenditure on health	0.770	0.526	0.006	-0.089	0.277
Total hospital beds	0.022	0.928	0.143	0.143	-0.214
Water quality	0.817	-0.152	-0.218	0.407	0.263
Exposure to PM2.5	-0.592	0.273	0.638	0.323	0.241

Tab. 8. Weights of undesirable output indicators in each component extracted by PCA for DT

Undesirable output indicators	weights of indicators in each component			
	C1	C2	C3	C4
Infant mortality rate	0.932	0.011	0.148	0.332
Maternal mortality rate	0.913	0.024	0.303	-0.273
AIDS incidence	0.337	0.916	-0.215	-0.027
Cancer incidence	-0.787	0.432	0.435	0.064

Results

In this section, the results of the DEA and Decision Tree are presented. First, according to the PCA-DEA additive model, efficiency scores of the OECD countries are estimated. Then, by measuring the projection points, an improvement plan for inefficient countries is presented, which contains benchmarks and relevant changes in their value to become an efficient DMU. Table 9 shows the efficiency scores of DMUs, and the closest efficient countries to the inefficient countries' positions on the efficiency frontier are defined as the benchmarks for them. Table 9 shows the efficiency scores of DMUs. Moreover, the closest efficient countries to the inefficient countries' positions on the efficiency frontier are determined as the benchmarks for them. The measured scores by the additive model are not in the range of 0 to 1, whereas this model gives us the deviation from the efficient frontier, and the countries that are zero or close to it are efficient ones. However, to handle this issue for presentation, all the efficiency scores are considered as undesirable indicators and, then, are normalized.

Tab. 9. Efficiency score of DMUs and benchmarks

Country	Efficiency score by the additive model	Normalized efficiency score by the additive model	Countries as benchmarks for inefficient DMUs
Australia	0	1	
Austria	1.95	0.8477	Finland, Iceland, Portugal, Spain
Belgium	4.64	0.6377	Iceland, Turkey
Canada	0	1	
Chile	0.11	0.9914	Estonia, Iceland, Luxembourg, Mexico, Turkey
Czech	3.95	0.6916	Iceland, New Zealand, Turkey

Country	Efficiency score by the additive model	Normalized efficiency score by the additive model	Countries as benchmarks for inefficient DMUs
Republic			
Denmark	3.68	0.7127	Iceland, New Zealand
Estonia	0	1	
Finland	0	1	
France	4.25	0.6682	Australia, New Zealand, Spain
Germany	5.22	0.5925	Iceland, Turkey
Hungary	4.91	0.6167	Iceland, Luxembourg, Turkey
Iceland	0	1	
Ireland	1.06	0.9172	Iceland, Turkey
Italy	0	1	
Korea	0	1	
Luxembourg	0	1	
Mexico	0	1	
Netherlands	2.52	0.8032	Iceland, Spain, Turkey
New Zealand	0	1	
Norway	0.8	0.9375	Iceland, New Zealand, Turkey
Poland	5.49	0.5714	Iceland, Turkey
Portugal	0	1	
Slovak Republic	4.59	0.6416	Iceland, Luxembourg, Turkey
Slovenia	1.92	0.8501	Iceland, Spain, Turkey
Spain	0	1	
Sweden	0	1	
Switzerland	0	1	
Turkey	0	1	
United Kingdom	2.57	0.7993	Iceland, New Zealand, Turkey
United States	12.81	0.00	Iceland, Luxembourg, New Zealand, Turkey

By solving the multiplier form of the additive model (3.b), the projection points have been estimated. The projection points offer us how much of an increase or a decrease in the inputs and outputs of the inefficient country can make an inefficient country efficient. Although the projection points are original values, for more conception, the amount of an increase and a decrease in the indicators is presented in percentage. Table 10 shows a decrease or an increase in each component is required to become an efficient DMU.

Tab. 10. improvement plan for inefficient DMUs (values are in not in measured percentage)

Countries	Input 1	Input 2	Input 3	Output 1	Output 2	Output 3
Austria	-0.8069	-0.0087	-1.7302	-0.0101	0.0153	-2.3904
Belgium	-0.7729	1.7583	-1.5687	-0.0042	-1.8829	-1.2678
Chile	0.0014	0.0815	0.0039	-0.0572	0.0404	-0.0024
Czech Republic	0.0019	0.0048	-2.5067	-0.0109	4.1061	-1.1678
Denmark	-0.5996	-0.0067	-2.6031	0.1188	-1.6808	-2.5358
France	-0.7777	-1.4134	-1.4293	-0.0016	-0.8385	0.0033
Germany	-0.9428	-1.4518	-2.2231	0.0077	1.6961	-1.8335
Hungary	-0.0108	0.0074	-1.2223	-0.9561	0.4918	-1.3743
Ireland	-0.3408	0.8357	0.3824	-0.0016	-4.4898	-1.6084

Countries	Input 1	Input 2	Input 3	Output 1	Output 2	Output 3
Netherlands	-0.0137	-4.0746	-4.2606	-0.0009	-2.6080	-9.5345
Norway	-0.2876	0.0538	0.2767	-0.0002	-0.8058	-0.0951
Poland	0.7376	-0.3086	-1.9999	0.0044	-9.7194	-1.3084
Slovak Republic	-0.0052	0.0103	-28.6055	-0.7344	-6.3922	-1.1973
Slovenia	0.0183	0.2132	-6.3852	-0.0069	1.8110	-1.7226
United Kingdom	-1.0000	13.7988	5.1438	0.0124	0.0456	-0.0100
United States	-1.8295	-1.0135	-0.0023	-0.0021	-1.1956	-0.0017

According to Table 10, among the inefficient DMUs, the USA spent excessive expenditure on healthcare, while it could not get the best outcomes. Based on the first input component (I-RC1), which is representative of spending in public health, the USA needs the highest cost reduction (-182.95%). However, it cannot be a decent solution; from another viewpoint, such countries should attain higher efficiency by planning better strategies, which could utilize the expenditures most suitably. For instance, Slovak republic, Hungry, and the Netherlands are inefficient DMUs, however; it seems that they could allocate financial resources suitably. In this regard, these three countries need the lowest amount of reduction in their expenditures (I-RC1). Meanwhile, Poland, Slovenia, Czech Republic, and Chile are the countries whose lack of spending is one of the reasons that makes them inefficient, especially Poland that required a 73.76 % increase in its expenses.

The second input component (I-RC2) represents the total hospital beds and total employees (physical and human resources) in the public health, and it appears that the Netherlands needs the highest reduction in the two aforementioned factors in its health sector. The UK is also a DMU that has experienced a lack of enough employees and beds in its health system and required the highest increase for them; meanwhile, Denmark and Australia are the countries that needed just a bit of reduction in their employees and beds in their health sector, respectively.

The third input component (I-RC3) mostly represents the exposure to PM2.5 (air pollution), and the Slovak republic needed the highest amount of reduction in this component to become efficient. However, the UK, Norway, Ireland, and Chile seem to be very clean countries in comparison to their peers and do not need any reduction in the third component.

Concerning the outputs, the first output component (O-RC1) is suitably representative of life expectancy for females and males, infant mortality, the total population covered by insurance, and maternal mortality. This component is somehow representative of well-being. Regarding these factors, among OECD, Hungary and the Slovak Republic are the countries that require the steepest decline.

The second output component (O-RC2) is mostly relevant to AIDS & cancer incidence. O-RC1 and O-RC2 encompass 77% of output indicators data, although all output indicators are covered by just considering these two components, it is common in PCA that the cumulative variance of components becomes more than 80 percent of the data. In this regard, RC3 is also taken into account to increase the total share of data in the analysis. Since Denmark has had the highest cancer rate, O-RC2 also indicates that this country must decrease the number of cancer occurrences more seriously than others.

Fig.2 illustrates the decision tree that is drawn by the mentioned components in the previous section in Tables 7 and 8. In this decision tree, 15 branches are specified.

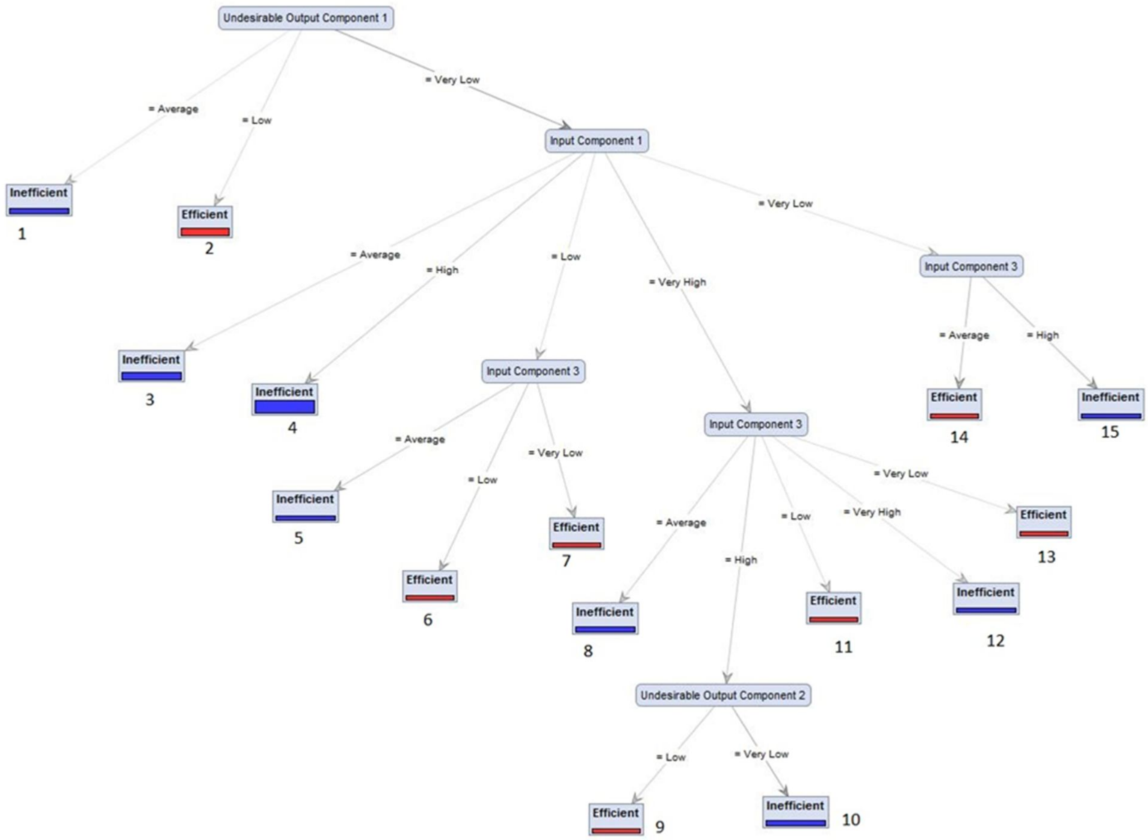

Fig. 2. Decision tree by considering 4 components: inputs and undesirable outputs and efficiency status as the target

For more explanation and better resolution, Fig.1 is divided into three subfigures, as presented in Figs. 2, 3, and 4. As shown in Fig. 1, the undesirable output component (1), which represents the infant and maternal mortality, has been chosen as the decision node (root) in the decision tree. This component shows the significance of these two factors to determine an efficient DMU such that the DMUs, even with an average value, are defined as inefficient DMUs based on those factors (Branch 1) and only those with the low value could become efficient (branch 2). Branches 3 and 4 show that there are some DMUs that their infant and the maternal mortality rate is very low; however, their high and average values in the input component (1) (I-PC1) that is a composition of health expenditures have made these countries inefficient. This indicates the relative importance of input to output in a system considered by the DEA model. Moreover, the reason why countries with low-level undesirable output components are recognized as efficient while their peers with the lowest level are defined as inefficient results from the nature of their input and output ratios and conditions.

Branch 5 emphasizes the critical point of air pollution. It displays countries with delightful conditions that are characterized by very low undesirable outputs and low inputs (expenditures) merely because of their average value in the input component (3), which represents air pollution that makes countries inefficient; further to that, only the countries with low and very low levels of air pollution in this component have become efficient (Branches 6 and 7). To sum up, among OECD countries, the countries with lower air pollution (input component 3), low expenditures (input component 1), and a very low rate of infant and maternal mortality can become efficient.

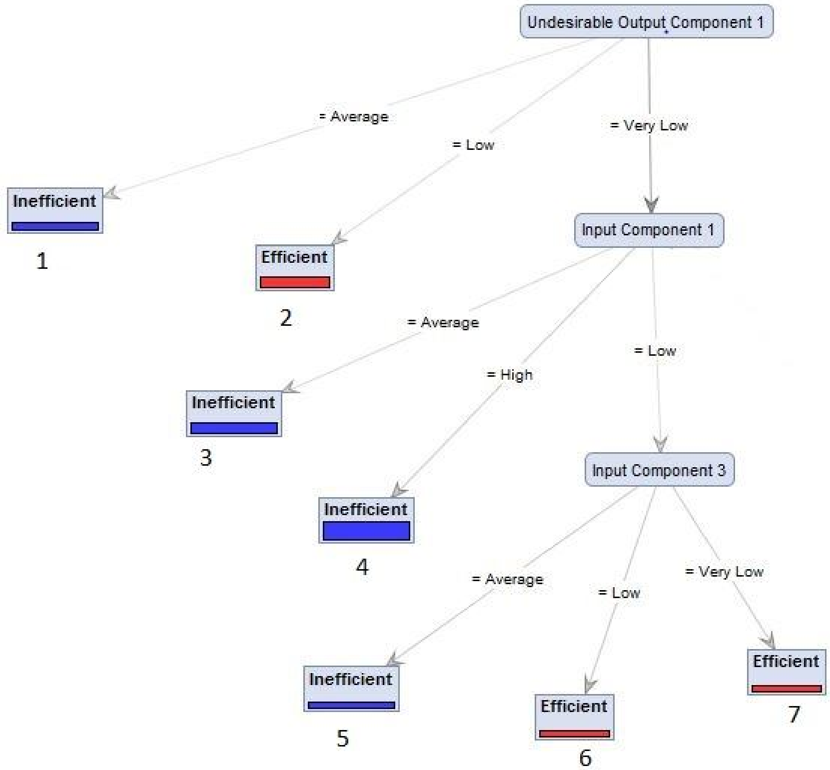

Fig. 3. Branches 1 to 7 from decision tree in fig. 2

Branches 11 and 13 in Fig. 4 illustrate that despite very high health expenditures (input component 1), countries with low and very low levels of exposure to PM 2.5 (input component 3) and very low-level infant and maternal mortality (undesirable output component 1) have become efficient. This fact shows that among OECD countries that are mostly developed countries, low infant and maternal mortality and exposure to PM 2.5 can be regarded as competitive advantages. Here, it has become clear that PM 2.5 has a powerful effect on public health and, also, health expenditure has a direct relationship with the health of infants and mothers. By this assumption, the hospitals are provided with a higher hygiene level and better equipment; therefore, all in all, efficient health systems do not seem to be out of reach.

Branches 8 and 12 in Fig. 4 indicate that some countries have become inefficient due to their very high health expenditures and the very high and average level of exposure to PM 2.5. However, as mentioned earlier, in the conditions of the input and output, for the countries with a high level of PM 2.5, the level of AIDS and the number of cancer incidences (undesirable output component (2)) will determine their efficiency status. It was shown that countries with low rates of AIDS and cancer could become efficient.

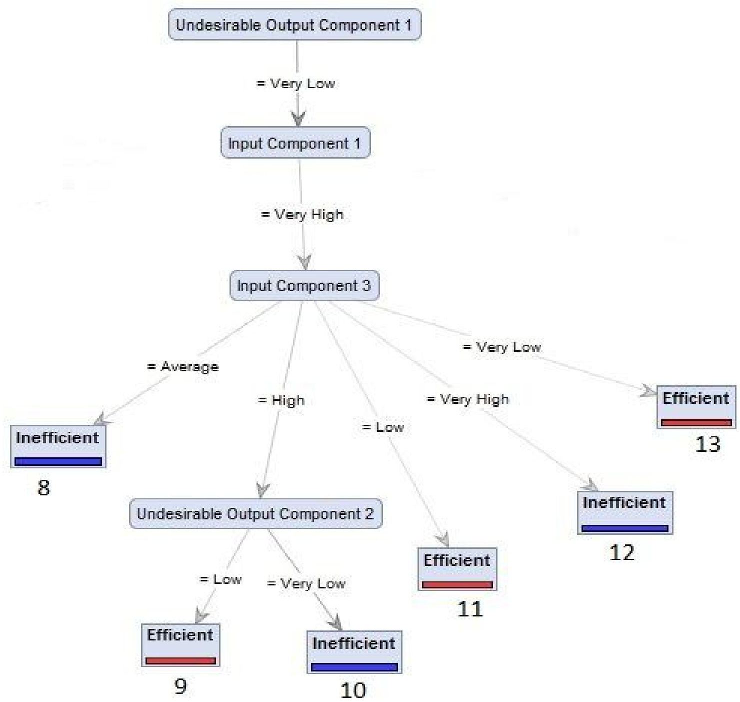

Fig. 4. Branches 8 to 13 from decision tree in fig. 2

Branches 14 and 15 in Fig.5 advocate the influence of air pollution on health efficiency. In this way, the countries with a very low level of infant and maternal mortality rate and expenditures on healthcare have become inefficient only because of their high exposure to PM2.5, while other countries with the same conditions concerning expenditures and mortality rate by an average exposure to PM 2.5 have become efficient.

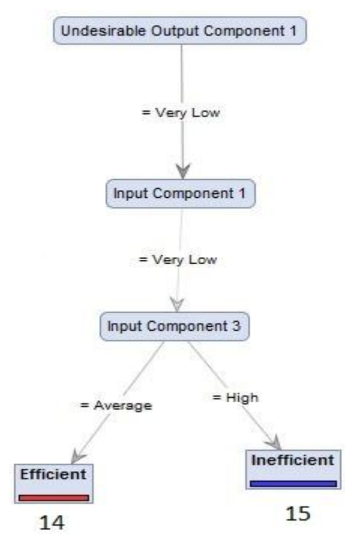

Fig. 5. Branches 14 and 15 from decision tree in Fig. 2

Discussion

With regard to sustainable development, to make policies to ensure better lives for the present generation and the next, countries must concentrate on economic, social, and environmental pillars. According to what this study has found, one can conclude that an efficient sustainable health system is the one that marks (a) financial factors such as social expenditure, expenditure on families, total health expenditure, hospital beds, and employees in the health system and (b) factors such as insurance coverage, cancer incidence, infant mortality, maternal mortality, AIDS and life expectancy, and wellbeing that are classified as social factors. Moreover, exposure to PM2.5 (air pollution) as an environmental factor shows a critical role in the countries' health efficiency status. Given the development level of the OECD members that are mostly developed countries and based on the health efficiencies obtained from the DEA model and the decision tree analysis, it can be argued that health conditions for countries will vary depending on the amount of output per input. However, the significant point that can be extracted from the data is the relationship between the four components that represent maternal and infant mortality, health expenditures, air pollution, and AIDS and cancer incidence. Low infant and maternal mortality rates have been identified as a significant contributor to health efficiency; therefore, even countries with a moderate value in this index have been inefficient. After this case, the low level of health expenditure is the factor that affects efficiency. Given that the two classes of inefficient and inefficient countries are first extracted from the DEA method and, then, used in the decision tree, it can be seen that some countries with higher health expenditures have not been able to exploit the best output in comparison with their peers. After satisfying these two conditions, the next major indicator is air pollution, which determines the country's health efficiency. Branches 5, 12, and 15 in Fig. 2 show that despite the similar rates of infant and maternal mortality, countries with average and high levels of exposure to PM 2.5, even with varying health conditions, are inefficient. In Branch 14, because of the nature of the ratio of output to input in the DEA and the very low level of health expenditures, some countries have become efficient in spite of the average level of exposure to PM 2.5. The case of countries with very high health expenditures and low emission rates is also shown in Figures 11 and 13.

Conclusion

Using the PCA-DEA approach based on the additive variable return to scale model, this study evaluated the efficiency of health system in 31 OECD countries by considering a wide range of indicators, some of which such as infant mortality, employees in health, health expenditure, etc. have been seen in the previous studies and some others like exposure to PM2.5 as representative of air pollution, water quality, total population covered by insurance, AIDS, cancer incidence, and even social and family expenditure have not been seen in the last studies. Some of these indicators can also be regarded in the field of wellbeing. In such a view, this study attempted to make a comprehensive assessment in terms of sustainability. To this end, this study covered indicators that were relevant to healthcare and wellbeing and were related to one of the economic, social, and environmental areas. Through the performance measurement analysis, it was found that, for the peers of the OECD countries, Iceland showed a perfect performance in the health system. Thereby, it has been chosen as a benchmark for most of the inefficient countries. Moreover, according to the methodology of this study, the USA has been regarded as a DMU that requires more reformation and improvement in its health system. Before conducting the analysis, the data investigation makes it clear that the USA had not only the maximum level in three of the resources (inputs), but also the highest and lowest levels for two outputs of AIDS and population covered by insurance, respectively. From the decision tree analysis, it can be concluded that those countries characterized by a suitable resource allocation, especially financial ones, and the lower undesirable outcomes such as infant and maternal mortality, AIDS, and cancer incidence could become efficient; meanwhile, exposure to PM2.5 that indicates the level of air pollution in each country plays an important and critical role, which has received further analysis in the sections associated with the results of the decision tree and discussion.

One of the most important issues in macro health planning is the use of optimal and comprehensive methods to improve health status. As extracted from the results of this study, determining indicators that affect the health system of a community is very complex, and the more comprehensive the model and indicators are, the more accurate the results will be. In the case of methods, such as the DEA, that can measure the output-to-input ratio, such models focus on the logic of decreasing inputs and maximizing desirable outputs.

This study has shown direct and indirect implications. One way to select the best practices is to identify the influencing factors, which we have attempted to identify in this study. The study identified the strengths and weaknesses of the country's public health; the results presented in this study can be considered as a direct implication. With regard to the efficiency scores, improvement plans, recognized benchmark countries, and ultimately decision tree analysis, policymakers can identify key indicators of their respective country's health performance to improve their conditions.

As for indirect implications, health expenditure is a significant factor in health efficiency, and decision-makers can consider the results of this research as one of their references for resource allocation decisions. The high health efficiency score can be regarded as an assurance that those countries can utilize the allocated budget more efficiently; thus, policymakers can even allocate more budgets for their development. In other words, countries that have become inefficient can identify the best practices to pursue in this area. For example, countries that are weak on environmental issues, such as high exposure to PM 2.5, can invest in ways to reduce this problem, or countries that could not provide adequate insurance coverage for their society can enhance their performance by changing their health economic system.

For future studies, it is recommended that researchers measure the healthcare systems' quality and wellbeing with more qualitative indicators and their relevant methods. Employing some factors such as the extent to which patients feel comfortable in hospitals, the behavior of health personnel, their satisfaction from the hospital's internal architecture and its atmosphere, and the happiness indicators that can pertain to the health systems can bring about significant contributions to this area.

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Availability of Data and Materials

The dataset that is used in this research is available online on the OECD website [27].

Competing Interests

The authors declare that they have no competing interests.

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