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Authors: Selin Ceren TURAN, Mehmet Ali CENGİZ

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Determining the Factors that Influence the Effectiveness of the Health Sector in the OECD Countries

Selin Ceren TURAN^{*1}, Mehmet Ali CENGİZ²

Abstract

The purpose of this study is to determine the factors that influence the effectiveness of the health sector by combining Stochastic Frontier Analysis (SFA), Generalized Linear Models (GLM) and Heuristic Algorithms methods. In accordance with this purpose, firstly, the health system efficiencies of 29 OECD countries are estimated by the SFA method. Within the scope of this study, it is also aimed to select the factors influencing the efficiency of the health systems in OECD countries by employing Heuristic Algorithm methods such as Artificial Bee Colony Algorithm, Genetic Algorithm, and Differential Evolution Algorithm. Furthermore, GLM's such as Truncated, Normal, Gamma and Tweedie distributions are employed for comparisons.

Keywords: Efficiency, Generalized linear models, Heuristic algorithms, SFA

1. INTRODUCTION

The budget that countries earmark for health expenditures is an important factor for the improvement of quality in healthcare. These expenditures have recently accelerated in order to improve the health systems of the countries. Health policymakers have initiated reforms to provide information for the countries so as to enhance the quality and performance of their health systems.

Nonparametric methods, such as Data Envelopment Analysis (DEA), and parametric

methods, such as Stochastic Frontier Analysis (SFA), can be used to compare the efficiencies of performances of health systems. DEA methods have been widely employed in measuring the efficiency of health systems of the countries in the Organization for Economic Co-operation and Development (OECD). Afonso and Aubyn [1] investigated the efficiency of the health system by using DEA. They used the life expectancy at birth, infant survival rate, and maternal mortality as output variables; while the number of hospital beds per thousand, and physician and nurse numbers were used as input variables. Spinks and Hollingsworth [2] conducted some analyses after

*Corresponding Author: scturan1@gmail.com

¹Ondokuz Mayıs University, ORCID: <https://orcid.org/0000-0002-0290-5298>

²Ondokuz Mayıs University, E-Mail: macengiz@omu.edu.tr
ORCID: <https://orcid.org/0000-0002-1271-2588>

determining education, income, per capita health expenditure as input variables, and life expectancy at birth as an output variable. Afonso and Aubyn [3] conducted another study using by DEA approach with non-discretionary inputs. Kujawska [4] applied DEA with additive and super efficiency models to estimate the efficiency of the health sector of OECD countries. Çetin and Bahçe [5] estimated the efficiency of the health systems of OECD countries by using input-oriented DEA. Özcan and Khushalani [6] calculated the health system efficiency of OECD countries by using Dynamic Data Envelopment Analysis.

SFA, which is a parametric method, has been used only a few times in the literature to compare health system efficiency in OECD countries since the World Health Organization (WHO) reports in 2000. Wranik [7] evaluated the policy-based characteristics of a healthcare system in terms of their contribution to the efficiency of health systems measured through the SFA method. The study of De Cos and Moral-Benito [8] focuses on the significant factors influencing the effectiveness of the health systems in OECD countries. They firstly examined and classified the health system efficiencies in OECD countries by benefiting from parametric and nonparametric methods. They also listed the efficiency values and determined the effective countries in accordance with the scores obtained via their estimations. Then, they regressed the efficiency scores on 20 different indicators obtained from the survey conducted in 2010 on the health sector determinants of OECD countries.

Şenel and Cengiz [9] use a similar dataset as in De Cos and Moral-Benito [8]. Firstly, they investigated the efficiency of health care system in 29 OECD countries using Bayesian Stochastic Frontier Analysis (BSFA). For this step, the variables used are obtained from the OECD Health Database for the time period between 1997 and 2009. Furthermore, the variables on the characteristics of the health system are chosen from the study carried out by Paris et al. [10] and cover the year 2009. Later, Bayesian beta regression has been performed to bring out the

relationship between the health system efficiency and the features of healthcare models in the relevant countries. In their study, they suffered overfitting problems. In regression analysis, overfitting a model is a real problem. An overfit model can cause the regression coefficients, p-values, and R-squared to be misleading. A modelling error which occurs when a function is too closely fit a limited set of data points. Overfitting the model generally takes the form of making an overly complex model to explain idiosyncrasies in the data under study. In reality, the data being studied often has some degree of error or random noise within it. Thus, making the model conform too closely to slightly inaccurate data can infect the model with substantial errors and reduce its predictive power. We suggest heuristics algorithm methods to avoid this problem.

At the first step of this study, the health system efficiency of OECD countries are estimated by Stochastics Frontier Analysis and then the factors affecting the health system efficiency across OECD countries are selected using truncated, normal, gamma and tweedie distributions in the context of Generalized Linear Models (GLM) and Heuristic algorithm methods such as Artificial Bee Colony Algorithm, Genetic Algorithm and Differential Evolution Algorithm.

2. MATERIAL AND METHODS

2.1. Stochastic Frontier Analysis

Stochastic Frontier Analysis assumes that a parametric function exists between production inputs and outputs. SFA is a parametric method that uses econometric methods. SFA establishes a functional relationship between the explained variables like cost, profit and production, and the explanatory variables like input, output, and other possible factors. In order to establish this relationship, the SFA model includes an error term. It is assumed that the error term in the model consists of two components. One of these components is the technical efficiency which is defined as achieving maximum output with the

existing inputs. The other component is the allocative efficiency which indicates the ability of these inputs to be used at the optimal rate when optimum prices for the inputs are available.

SFA approach proposed by Aigner et al. [11] can be specified as follows:

$$y_i = x_i \beta_i + \varepsilon_i$$

$$\varepsilon_i = v_i - u_i, i = 1, 2, \dots, N \quad (1)$$

where y_i is the log output, x_i is a vector of input measures, β_i is an unknown parameter vector, ε_i is the combined error term, v_i is the independent and identically distributed error term, and u_i is technically ineffective (non-negative random variable). Error term $\varepsilon_i = v_i - u_i$ has asymmetric distribution.

2.2. Generalized Linear Models

In simple linear regression models, the dependent variable and errors are assumed to have a normal distribution. Normality assumption may not be provided in cases where the dependent variables are discrete variables or binary. In such cases, classical linear models cannot be used. In addition, there may be situations where the dependent variable is continuous and does not show normal distribution. Generalized Linear Models (GLMs) are used in the analysis of data consisting of such variables.

GLMs, which are the generalized version of classical linear models, are tasked with modelling the transformed average as a linear function of explanatory variables. GLMs allow to fit regression models, if the dependent variable is from the exponential distribution family. If the probability density function of the dependent variable belongs to the exponential distribution family, the probability density function is as follows:

$$f(y) = \exp \left\{ \frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi) \right\} \quad (2)$$

Here, θ is the natural parameter and depends on the observations y_1, y_2, \dots, y_n . ϕ is the scale parameter related to the variance of the dependent variable (y) and is constant for each observation. $c(y, \phi)$ is a function of observations and dispersion parameter [12].

2.3. Heuristic Optimization Methods

Problems that arise in many areas can be modelled as linear or nonlinear optimization problems. When we look at the structure of the problems, we notice that most of the problems have nonlinear structures. Many methods have been developed for solving non-linear problems. Apart from that, it can be difficult to solve problems according to types of data and variable numbers. Therefore, sometimes the results cannot be reached or can be reached within the unacceptable time frame. To eliminate these problems, heuristic optimization methods have been developed.

Nowadays, there are many optimization algorithm methods available to solve optimization problems that use mathematical and heuristic methods. Classical algorithms are usually designed for a problem or trying to solve the problem by scanning the entire solution space of the problem. Usage of these algorithms is very costly and time-consuming in large problems. However, the heuristic algorithms are algorithms that can reach the closest solution in a very short period of time without scanning the whole solution space.

Artificial Bee Colony Algorithm (ABC), developed by Karaboğa [13], is an algorithm based on swarm intelligence which is the result of examining the nutritional search processes of honey bees. In the process, the nutritional search behaviours of the bees are modelled. The model consists of 3 components. These components are employed bees, unemployed bees, and food sources. A bee waiting on the dance area for making the decision to choose a food source is called onlooker and a bee going to the food source visited previously by itself is named employed bee. A bee carrying out a random search is called scout.

Like all living things, bees also need food to sustain themselves and survive. That is why they have to look for food. Therefore, these processes are carried out by organizing themselves and making a division of labour among them. There is a responsible bee for each food source. The number of bees in the algorithm equals the number of total food sources. In the ABC algorithm, the first half of the colony consists of employed artificial bees and the second half constitutes the onlookers. Employed bees are researching randomly while conducting a nutritional search in nature. The locations of the nutrient sources of the bee colonies correspond to the possible solutions to the present problem. In addition, the quantity of nutrients indicates the quality of the solution. Therefore, the artificial bee colony algorithm aims to determine the location of the source where the most nutrients are found and try to find the solution that gives the minimum or maximum of the problem from the search space solutions [14].

Genetic Algorithm (GA), developed by Holland [15], provides modelling of natural selection and genetic populations by taking the process of living creatures in nature as an example. It is a kind of heuristic algorithm that can be used in problems where mathematical modelling cannot be done and the final solution cannot be achieved. This algorithm is based on sustaining their lives if new individuals from the previous generation meet the necessary criteria. It is based on the principle that the good generations protect their own lives while the bad generations disappear. GA is different from other heuristic algorithm methods. The reason of this difference is the method of searching solution space. While GA seeks for the the solution in the population of points, other heuristic algorithms looks from point to point. [16].

In the solution of a problem with the GA method, the variables representing the chromosomes are firstly coded into arrays. In this coding process, (0, 1) binary system is widely used. The initial population is formed by the chromosomes which are obtained after coding. At this stage, chromosomes are subject to an evaluation

criterion in order to decide which chromosome will participate in the population. Fitness values are calculated to determine the success rates of chromosomes. In the selection phase, chromosomes with high fitness values are added to the population. Then, it is aimed to obtain new chromosomes with crossed and mutated chromosomes. Thus, the newly produced chromosomes participate in the new population. In this population where new chromosomes exist, the optimal solution is sought for the problem. These operations continue until a specified stop criterion is met. When the specified criterion is met, the algorithm stops.

The Differential Evolution Algorithm (DE) was developed by Storn and Price [17]. DE, which is a population-based and development-based heuristic algorithm method, has been developed for the minimization of functions with real-valued parameters. The DE and GA methods are similar algorithms. However, the most important distinction of the DE and GA is that the DE contains real-valued parameters. Unlike the GA method, each operator is subjected to the entire population in turn. With the DE method, it is possible to optimize a wide range of problems that are encountered in science, engineering and business environments.

DE is also based on mutation, crossover and selection operators. However, none of the previously defined probability-based mutations is used as in GA. Unlike the GA method, each operator is sequentially subjected to the entire population. Chromosomes are handled one by one and then it is aimed to obtain a new individual by using chromosomes along with other randomly chosen chromosomes. In this process, mutation and crossover operators are used. The fitness values of the new chromosomes obtained with the existing chromosomes are compared and checked again to determine the quality of the resulting solutions. The chromosome with a better fitness value is sent to the next population as a new individual. Thus, the algorithm is completed using the selection operator [18].

The simple mutation operation used in the DE increases the performance of the algorithm. Thus, it allows for the creation of new research areas, which makes it a more stable algorithm. This algorithm is structurally simple and fast. It is also very effective in solving complex problems. DE has advantages over other algorithms. They are easy to code, have effective global optimization capability, do not need a derivation of the objective function or constraint functions, and low cost of calculation since they do not have matrix multiplication and sorting operations.

2.4. Model Selection Criteria

Criteria are important in choosing a model or deciding which model is better. Information criteria can be used to interpret the results of the obtained models and reach the best estimation model. The Akaike Information Criterion (AIC) proposed by Akaike [19] was designed to be an approximately unbiased estimator of the Kullback-Leibler index of the fitted model relative to the true model. With this suggestion, which has led to improvements in statistical modelling and evaluation of models, AIC has become an asymptotic criterion frequently used in model selection. Hurvich and Tsai [20] presented a corrected version of AIC, denoted Modified Akaike Information Criterion (AICC), which is less biased in the finite sample case. The criterion proposed by Schwartz [21] and called the Bayesian Information Criteria (BIC) is a similarly consistent criterion based on Bayesian reasoning. Another important and widely used criterion is the Consistent Akaike Information Criterion (CAIC) proposed by Bozdogan [22].

Table 1
Information criteria

Criteria	Formula
AIC	$-2L + 2p$
BIC	$-2L + p \log(n)$
AICC	$-2L + 2p^n / (n - p - 1) - 2L$
CAIC	$-2L + p(\log n + 1)$

Table 1 contains the formulas for commonly used information criteria in the model selection stage

³ <https://data.oecd.org/health.htm>

of GLM and Heuristic Algorithms. Here, L denotes the maximum value of log likelihood, log pseudo-likelihood or log semi-likelihood. p indicates the size of the model. n indicates the size of the data. These measures are model dependent sizes. In model selection, the model with the minimum value of these criteria is preferred.

3. RESULTS and DISCUSSION

In this section, first, we measured the health system efficiencies of 29 OECD countries by SFA using the data from the OECD Health Database³. Determining the decision-making units (DMUs) is a crucial step of SFA. In this stage of the investigation it was primarily required to address the countries included in the OECD countries health sector determinants survey conducted by Paris et al. [10]. This dataset presents the information provided by 29 of OECD countries in 2009. The dataset was created according to this condition. Although they fulfilled this requirement and could be applied at this stage, the data of variables belonging to some countries to be used in the second stage could not be reached. This led us to exclude some countries from the study. In addition, countries with values that would disrupt the homogeneity of DMUs on the basis of variables were determined and were not included in the analysis.

The input and output variables used in the study were selected from the variables used in the health system efficacy analysis in the literature. Total health expenditure, public expenditure on health, practicing nurses, hospital beds, tobacco consumption, alcohol consumption, GDP per capita, education are used as input variables, while life expectancy at birth is used as an output variable for the SFA approach in the study. Statistical analyses in this study were carried out using MaxDEA, RStudio and IBM SPSS 20 programs.

The results of the SFA method, which is the first step of our study, are summarized in Table 2 by taking the averages of the technical efficiency

values obtained and the efficiency scores of all countries as well as their ranking according to their efficiency status.

Table 2
Efficiency scores derived from SFA

No	Countries (DMU)	Efficiency Scores	Ranks
1	Australia	0.844	19
2	Austria	0.914	7
3	Belgium	0.878	14
4	Canada	0.849	18
5	Czech Republic	0.765	25
6	Denmark	0.785	23
7	Finland	0.829	21
8	France	0.974	2
9	Germany	0.836	20
10	Greece	0.936	5
11	Hungary	0.698	28
12	Iceland	0.879	12-13
13	Ireland	0.859	16
14	Italy	0.976	1
15	Japan	0.945	4
16	Korea	0.694	29
17	Luxembourg	0.864	15
18	Mexico	0.789	22
19	Netherlands	0.893	9
20	New Zealand	0.766	24
21	Norway	0.897	8
22	Poland	0.742	26-27
23	Portugal	0.929	6
24	Slovakia	0.742	26-27
25	Spain	0.968	3
26	Sweden	0.890	10
27	Switzerland	0.879	12-13
28	Turkey	0.858	17
29	United Kingdom	0.883	11

In the second stage, the efficiency values obtained at the first stage are taken as a dependent variable, and other potential variables affecting this efficiency are considered as explanatory variables and different regression models such as are truncated, normal, gamma, gamma-power(2), tweedie and tweedie-power(2) were examined. These regression models also identify which factors may affect countries' health system efficiencies and which factors should be given priority to raising countries' health system effectiveness. For these models, 20 different variables from OECD countries' health sector determinants survey conducted in 2010 were used as explanatory variables in analyses. Those variables choice of insurer (x_1), insurer level for

competition (x_2), over the basic coverage (x_3), degree of private provision (x_4), volume incentives (x_5), regulation of prices billed by providers (x_6), user information on quality and prices (x_7), regulation of the workforce and equipment (x_8), the patient choice among providers (x_9), gatekeeping (x_{10}), price signals on users (x_{11}), priority setting (x_{12}), the stringency of the budget constraint (x_{13}), regulation of prices paid by third-party payers (x_{14}), degree of decentralization (x_{15}), degree of delegation to insurers (x_{16}), consistency in responsibility (x_{17}), breadth (x_{18}), the scope of basic coverage (x_{19}), and depth of coverage (x_{20}).

As seen in Table 3, estimated models with various distributions are calculated. Here, the model distributions and link functions are expressed. As a result of the analysis, it was concluded that gamma - power (2) and tweedie - power (2) models are the models with the most explanatory variables affecting the efficiency scores of countries ($p < 0.05$).

Table 3
Comparison of models

Distribution Link Function	Truncated		Normal identity		Gamma identity		Gamma power (2)		Tweedie identity		Tweedie power (2)	
	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P
Intercept	-0.33	0.47	-0.26	0.53	-0.18	0.66	-0.91	0.18	-0.20	0.63	-0.95	0.17
x ₁	0.02	0.23	0.02	0.21	0.02	0.18	0.03	0.14	0.02	0.19	0.03	0.15
x ₂	-0.03	0.10	-0.03	0.08	-0.03	0.07	-0.05	0.05	-0.03	0.07	-0.05	0.06
x ₃	0.01	0.18	0.01	0.21	0.01	0.19	0.02	0.15	0.01	0.20	0.02	0.16
x ₄	0.00	0.89	0.00	0.87	0.00	0.86	0.00	0.86	0.00	0.87	0.00	0.87
x ₅	0.00	0.77	0.00	0.79	0.00	0.87	0.00	0.87	0.00	0.85	0.00	0.85
x ₆	-0.02	0.33	-0.01	0.34	-0.01	0.33	-0.03	0.29	-0.01	0.33	-0.03	0.30
x ₇	-0.03	0.12	-0.03	0.15	-0.03	0.15	-0.04	0.12	-0.03	0.15	-0.04	0.13
x ₈	-0.03	0.03	-0.02	0.04	-0.03	0.02	-0.05	0.01	-0.03	0.02	-0.05	0.01
x ₉	0.02	0.01	0.02	0.01	0.02	0.00	0.03	0.00	0.02	0.00	0.03	0.00
x ₁₀	0.02	0.01	0.02	0.02	0.02	0.01	0.04	0.01	0.02	0.01	0.04	0.01
x ₁₁	0.06	0.12	0.05	0.13	0.06	0.10	0.10	0.08	0.06	0.11	0.10	0.09
x ₁₂	0.02	0.20	0.02	0.21	0.02	0.29	0.02	0.34	0.02	0.27	0.02	0.32
x ₁₃	-0.02	0.02	-0.02	0.01	-0.02	0.01	-0.03	0.01	-0.02	0.01	-0.03	0.01
x ₁₄	0.03	0.17	0.02	0.22	0.02	0.25	0.04	0.20	0.02	0.25	0.04	0.20
x ₁₅	0.02	0.09	0.02	0.11	0.02	0.07	0.03	0.04	0.02	0.08	0.03	0.04
x ₁₆	0.03	0.11	0.02	0.16	0.03	0.13	0.05	0.09	0.03	0.13	0.05	0.10
x ₁₇	0.01	0.52	0.01	0.51	0.00	0.64	0.00	0.72	0.00	0.61	0.01	0.68
x ₁₈	-0.05	0.16	-0.04	0.24	-0.05	0.13	-0.09	0.06	-0.04	0.16	-0.09	0.07
x ₁₉	0.06	0.09	0.05	0.09	0.05	0.11	0.07	0.12	0.05	0.10	0.07	0.11
x ₂₀	0.17	0.01	0.16	0.01	0.16	0.01	0.28	0.00	0.16	0.01	0.27	0.00

The information criteria specified in Table 4 were used to determine the model quality for each distribution and to select the correct model. Table 4 shows the calculated test results to determine the quality of the models and to select the models.

Table 4
Information criteria of distributions

Criteria	Normal	Gamma	Gamma Power (2)	Tweedie	Tweedie Power (2)
AIC	-61.86	-61.94	-63.84	-61.86	-63.56
AICC	106.81	106.73	104.83	106.81	105.11
BIC	-31.78	-31.87	-33.76	-31.78	-33.47
CAIC	-9.78	-9.86	-11.76	-9.78	-11.47

When we compare the information criteria given in Table 4, the information criterion with the smallest value should be selected. When we consider each information criterion in Table 4, it can be said that the gamma - power (2) distribution is the most suitable distribution for modelling because it has the smallest value.

In this study, the heuristic optimization methods such as BC, DE and GA used to identify which factors may affect countries' health system

efficiencies. For this purpose, the parameters and values of these algorithms used are given in Table 5.

Table 5
Parameters used in heuristic algorithms

Parameters	Value
ABC algorithm:	
Number of individuals in the population	50
Number of elements in the row	40
Cross rate	0.8
Mutation rate	0.1
Number of iterations	1000
GA Algorithm:	
Number of individuals in the population	100
Cross rate	0.7
Scale parameter	1.2
Lower limit value	0
Upper limit value	1
Number of iterations	1000
DE algorithm:	
Quantity of food	20
Number of worker bees	20
Onlooker bee	20
Limit	100
Lower limit value	0
Upper limit value	1
Number of iterations	1000

Crossing rate, mutation rate and population size, which are control parameters, were determined as a result of preliminary tests. The combinations given in Table 5 converged to the better solution faster than the other tested combinations for the used parameter values. Thus, it has been seen that these decided combinations have optimal search capabilities in the solution spaces of the each algorithms. For the fixed number of iterations, as the population sizes increase, the solution time of the algorithms will increase, so the population sizes were taken as 50 for the ABC algorithm, 100 for the GA and 20 for the DE algorithm. Tests for 1000 iterations were carried out on the dataset. In addition, binary system was used in the coding process.

We had found that the model with the most explanatory variables affecting the efficiency scores of OECD countries is the gamma - power (2) model after applying SFA. Here, our main is to consider ABC, DE, and GA algorithms for gamma regression in variable selection process. These algorithms were used to achieve the selection task by minimizing a fitness function. The objective function value of the problem is computed as the fitness function value [17]. We selected AIC, AICC, BIC, and CAIC as the fitness function to compare the performance of the competitive models. All applications were made with packages in RStudio.

Table 6
Results of the information criteria of heuristic algorithms

Criteria	ABC	DE	GA
AIC	-75.27359	-75.27359	-75.27359
AICC	-88.48888	-88.48888	-88.48888
BIC	-61.36138	-61.36138	-61.36138
CAIC	-67.82476	-67.82476	-67.82476

Table 6 shows the results of the information criteria for the ABC, DE, and GA algorithms. In order to compare the models obtained by using ABC, DE and GA algorithms, which are part of the second stage of our study, AIC, AICC, BIC and CAIC information criteria were taken into consideration. When Table 6 is observed, we can conclude that the information criteria results of these three algorithms are converged to each

other. According to the criteria results, it can be said that it is appropriate to use these three algorithms in parameter selection. Also, it is seen that the AICC criterion has the lowest value for each heuristic algorithm and we stated that the AICC model, with which four of the four criteria agreed, would be chosen as the best model. Thus, in line with the data used in this study, the AICC model is can be said to be the best in identifying other indicators that affect the efficiencies of 29 OECD countries for which health system efficiency is calculated.

Table 7
AICC model of heuristic algorithms

AICC model	Coefficients	p value
constant	-1.09748	0.04587*
x_1	0.05102	0.06656
x_2	-0.08747	0.00794*
x_8	-0.03801	0.01554*
x_9	0.02650	0.02293*
x_{10}	0.01946	0.09319

*p<0.05

In Table 7, the variable coefficients and significance values of the model obtained according to AICC criteria for ABC, DE and GA are given. Considering Table 7, it can be said that the x_2 , x_8 and x_9 variables are important in determining the indicators affecting the health sector efficiencies of 29 OECD countries according to the AICC model, while the other variables are not.

All models obtained within the scope of this study are given in Table 8.

Table 8
Determination of significant variables

Models	Significant variables
Generalized Linear Models	
Truncated	$x_8, x_9, x_{10}, x_{13}, x_{20}$
Normal	$x_8, x_9, x_{10}, x_{13}, x_{20}$
Gamma	$x_8, x_9, x_{10}, x_{13}, x_{20}$
Gamma – Power (2)	$x_8, x_9, x_{10}, x_{13}, x_{15}, x_{20}$
Tweedie	$x_8, x_9, x_{10}, x_{13}, x_{20}$
Tweedie – Power (2)	$x_8, x_9, x_{10}, x_{13}, x_{15}, x_{20}$
Heuristic Algorithms (ABC, DE, GA)	
AIC	$x_2, x_9, x_{10}, x_{11}, x_{13}, x_{15}, x_{20}$
AICC	x_2, x_8, x_9
BIC	$x_2, x_8, x_9, x_{11}, x_{13}, x_{20}$
CAIC	$x_2, x_8, x_9, x_{11}, x_{13}, x_{20}$

The significant variables in the models with various distributions in the context of GLM are given in table 8, taking into account Table 3. Then, the significant variables included in the models obtained as a result of the applications performed using heuristic algorithms were summarized according to the information criteria. When the established GLMs with truncated, normal, gamma and tweedie distribution are examined, it is seen that x_8 , x_9 and x_{10} variables are common variables in each model. Similarly, when the models established as a result of the heuristic algorithms were compared, it is seen that the x_2 and x_9 variables are included in the model according to four information criteria. The point to note in Table 8 is that the models obtained by using each heuristic algorithm show similarity. That is, when the models obtained with ABC, DE and GA algorithms are compared, it is seen that the optimal solutions are the same.

4. CONCLUSION

In the first stage of this study, an efficiency analysis was carried out by the SFA approach to examine the health system efficiency status of OECD countries. The input variables used in this stage are total health expenditures per capita, public expenditures, number of nurses, number of beds, tobacco consumption, alcohol consumption, GDP per capita, and educational status. Life expectancy at birth is used as an output variable. The analysis was performed in software program R. Using the results obtained from the SFA approach, the efficiency scores of the countries are ranked and the most effective and least effective countries are determined. Among the 29 selected OECD countries, Italy was found to be the most effective country in terms of health system efficiency. This finding reveals that Italy is the country that completes the output transformation process of selected input variables for the study in the most efficient way. Additionally, according to the results of the SFA approach, it can be said that the country with the lowest health system efficiency is Korea.

In the second stage of this study, we aimed to identify the other indicators that could affect the health system efficiencies of 29 OECD countries and determine the factors that should be given priority for countries to increase their efficiencies in this sector. For this purpose, the effect of the 20 different indicators obtained from the 2010 health sector determinants surveys on OECD countries on the efficiency scores estimated by the SFA approach was analysed using different regression methods and heuristic algorithm methods in the context of generalized linear models. Parameter estimations made for GLM are based on IBM SPSS 20 package program. As a result of using heuristic algorithm methods, we decided that it is appropriate to use the three algorithms discussed in this study. Applications of the algorithms have been benefited from the R software program again.

While the insurer level for competition (x_2), the patient choice among providers (x_9) were related according to the heuristic algorithms, the regulation of the workforce and equipment (x_8), the patient choice among providers (x_9), gatekeeping (x_{10}) were related factors with the health system efficiency factors according to GLM.

In particular, the lowest effective countries should reconsider the health system policy and take precautions to improve the health system efficiency paying attention to important factors mentioned and highlighted above.

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The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

Authors' Contribution

MAC contributed to designing the study and providing data for the study. SCT conducted all statistical analyses and wrote the manuscript. All authors discussed the results and contributed to the final manuscript.

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The authors declare that this document does not require an ethics committee approval or any special permission.

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