# A DATA ENVELOPMENT ANALYSIS OF THE RESPONSE OF HEALTHCARE FACILITIES TO CORONAVIRUS PANDEMIC: EVIDENCE FROM ROMANIA

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## Abstract

*The coronavirus pandemic overwhelmed hospitals all over the world. Our paper aims to analyze the response of the Romanian hospitals to this health crisis. The objectives are to estimate the technical efficiency of 18 hospitals designated as support-units for COVID-19 treatment and to identify the optimal allocation of hospital resources for the inefficient units. Data Envelopment Analysis was used to estimate technical efficiency scores of the hospitals, under the assumption of variable returns to scale, using 3 different models. The results show that the average technical efficiency increases from one model to another, as new inputs are added. The resources allocation analysis demonstrates that a slight reduction in resources would have been possible keeping steady the outputs vector. This study is the first one regarding the impact of COVID-19 on Romanian hospitals and offers a basis for future research. Our analysis could support implementation of emergency measures in hospitals management.*

*Keywords:* coronavirus pandemic, support-hospitals, technical efficiency, Data Envelopment Analysis

## Introduction

Health systems around the world have been highly challenged by the COVID-19 pandemic. The disease caused by the severe acute respiratory syndrome SARS-CoV-2 spread rapidly worldwide and most governments-imposed lockdown. The hospitals, that have the expertise to respond to this kind of public health crisis, were overwhelmed. The pandemic has uncovered important shortage of resources:

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critical-care nurses, personal protective equipment, ventilators, and other vital supplies. As a coping and restrictive measure, at the same time, all non-emergent medical services provided by hospitals were cancelled in all countries. In this way, the hospital resources were free up for the COVID patients, but the total number of in-patients and surgical procedures has significantly dropped, compared to the pre-pandemic year 2019 (Deloitte, 2020). Trauma services were maintained but the efficiency of trauma operating theatres has been seriously affected by the pandemic. Also, chronic patients had no access to specialized medical services during lockdowns, except for the telehealth that was used in the developed countries (Kaye *et al*., 2020). Important changes have occurred in utilisation of healthcare services during the COVID-19 crisis, firstly due to the lockdown politics and secondly due to fear of becoming infected while visiting a healthcare facility or by the avoidance of unnecessary care. Various countries have reported substantial decreases of over 80% in the number of healthcare visits, the number of admissions and in the use of diagnostic and imaging procedures in the first months since the coronavirus outbreak. U.S studies have reported large reductions even in the number of visits to Emergency Departments up to 42% (Moynihan *et al*., 2021).

Romania entered the pandemic with two major vulnerabilities of the health system: underfunding and a significant shortage of medical staff, due to the mass exodus of these professionals after European Union (EU) accession in 2007. The most recent statistics show that the physicians and nurses in 2017 were 2.8 doctors per 1000 inhabitants, and 6.4 nurses per 1000 inhabitants, respectively. These figures are relatively low compared to the EU averages of 3.5 doctors and 8.4 nurses per 1000 population (OECD/European Observatory on Health Systems and Policies, 2019). Public hospitals with 131.709 beds[1] are the main healthcare providers for a population of 19.12 million people; this means an average of 6.88 beds per 1000 inhabitants. Since the beginning of the pandemic, Romania has registered a COVID death rate of 2.7%. Compared to other Eastern European countries, the number of deaths per 100 000 population is lower, Romania being on the 7$^{th}$ position, with 150 COVID-19 deaths per 100 000 population[2]. In March 2020, by Order 533 of the Ministry of Health, two hospital lines were designated to fight against the coronavirus pandemic: in the first line were designated the specialized hospitals in infectious and respiratory diseases and for the second-line, other 64 healthcare facilities were nominalized to support the first-line hospitals if overloaded, while providing care for non-COVID emergency cases. The Ministerial Order has also established the reduction by up to 80% of the scheduled hospitalizations for chronic patients and of the elective surgeries in the hospitals from the university centres. In the first phase, it was recommended that the support

[1]According to National Institute of Statistics (2020), (retrieved from https://insse.ro/cms/ro/tags/activitatea-unit%C4%83%C5%A3ilor-sanitare).

[2]According to data from the website: https://coronavirus.jhu.edu/data/mortality (accessed:12/05/2021).

facilities not to be represented by major emergency hospitals in the area, which provide complex services for medical and surgical emergencies. Thus, in the network of support units were included municipal hospitals, hospitals with specialized wards on infectious diseases and hospitals in networks other than Ministry of Health, such as Ministry of National Defense or Ministry of Transport.

Given the pre-pandemic chronic vulnerabilities of the Romanian health system, the aim of this paper is to investigate the response of the healthcare facilities to the coronavirus pandemic by estimating the technical efficiency of the COVID' support-hospitals. Data Envelopment Analysis (DEA) was applied on data from 18 municipal hospitals that were in the second line treatment facilities in the fight against coronavirus in 2020. The employed analysis was oriented toward inputs and sought not only to estimate the efficiency scores for the hospitals in the sample but also to determine the optimal allocation of resources for the inefficient units.

The paper is organized as follows. Section 2 presents a review of previous research on the response of the health sector to COVID-19 pandemic, using DEA. Section 3 describes data, the method used and the selection of the variables. Section 4 provides the results of the empirical study and discussions. Section 5 concludes.

## 1. Previous research with DEA during the health crisis

Data Envelopment Analysis is a widely used nonparametric method to evaluate the productive efficiency of healthcare providers. There are two main features of DEA that made it appeal for scholars: it can handle multiple inputs and multiple outputs at the same time and does not require an a priori specification of the functional form relating inputs to outputs (Bowlin, 1998). It is also an effective benchmarking tool, comparing similar organizations, called Decision Making Units (DMUs). The applications of DEA usually seek to identify the sources and the amounts of relative inefficiency in each compared unit. In the hospital setting, such analysis can provide a quantitative basis for the hospital management and resource reallocation among the investigated units (Golany and Roll, 1989). Also, ranking hospitals based on their efficiency scores allows to the inefficient ones to learn from their efficient peers and to improve efficiency through best practices. In the medical field, DEA was first applied by Sherman (1984), who assessed the efficiency of Medical Surgical area for a sample of U.S. teaching hospitals, using 3 inputs and 4 outputs to characterize their activities. Since then, the method has known a large applicability in the healthcare sector, both at macro- and micro-level, especially after the promotion by WHO of the mechanisms for monitoring the efficiency of the health sector for a better use of resources (Kohl *et al*., 2018).

The way healthcare facilities all over the world have handled the current health crisis has been in the public eye. Since the hospital resources are limited, this has led in a short time to hospitals overloading and exhaustion of the medical workers. The coronavirus pandemic has taken a "physical and an emotional toll", at the same time (Gold and Evans, 2020)[3]. Therefore, there is a growing interest of researchers to investigate hospitals efficiency during crisis, using the advantages of DEA, to estimate operational efficiency and production capacity of medical units. Such investigations could potentially support policymakers to put in place measures to increase the response capacity to a health crisis and to prevent health systems collapse. Although most of the studies conducted in the pandemic period have targeted the efficiency of the health sector at a macro-level, all of them included hospital resources as main inputs.

Aiming to provide an optimal number of beds that could be reallocated for potential COVID-19 cases, Nepomuceno *et al*. (2020) applied DEA on the most important Brazilian hospitals. 3772 beds were identified as feasible to be evacuated from the inefficient units and to be reallocated in one year for new COVID-19 cases. The authors argue that reallocation of beds is possible if new services and protocols are formalized in the inefficient units and by decreasing the length of stay through best practices and postponing non-emergent surgeries. Ferraz *et al*. (2021) extended the DEA-analysis on the Brazilian health sector response to the coronavirus pandemic, creating a COVID-index. They aimed to analyze hospital structure (healthcare equipment and human capital) in relation to the pandemic and its results: infected people and number of deaths. The Brazilian micro-regions were considered as DMUs and a high heterogeneity of hospital structures between micro-regions was revealed. The relocations of resources and patients between each state's regions were possible during the health crisis only between wealthier regions since poor regions were found with lack of hospital infrastructure.

The response of healthcare systems to the coronavirus pandemic was investigated by various studies. Ordu *et al*. (2021) used DEA to investigate the preparedness of health sector from 16 countries and found that most countries have lost their ability to cope with COVID-19 over time and only five countries could maintain their efficiency during the analyzed period (among them, China, France and Sweden). Weekly efficiency scores were computed for 5 weeks after the occurrence of the 100$^{th}$ case for each investigated country. These results follow to those obtained by Breitenbach *et al*. (2021) which have investigated with DEA the efficiency of 31 countries in containing the spread of the virus during the first 100 days since the outbreak of the COVID-19. The authors have selected the countries with the highest rate of infection to establish how efficient these countries were in using their resources to get the flattening of the infections curve. They found that the states harder hit by the virus, such as Italy, France or Belgium were more efficient in containing the spread of the virus during the first 100 days since the outbreak than some of the richest countries, such as U.S.A., Germany or Canada.

[3] Gold, R. and Evans, M. (2020), Why did Covid overwhelm hospitals? A years long drive for efficiency, *Wall Street Journal,* 17 September (retrieved from https://www.wsj.com/articles/hospitals-for-years-banked-on-lean-staffing-the-pandemic-overwhelmed-them-11600351907).

Almost half of the U.S. states were efficient in the fight against coronavirus as it was found by Xu *et al*. (2021). In addition to hospital resources (medical workers and number of beds), the authors also considered as inputs the number of tested and the public funding for the design of the DEA-model. In a second stage of the analysis, the most important factors in determining the efficient response of the U.S. states to the pandemic were identified as being the social distancing, the hospital beds, population in urban areas and the number of tested.

Another health system that proved to have a strong preparedness for the pandemic and an effective allocation of resources was the Malaysian system. Hamzah *et al*. (2021) used network DEA for an in-depth examination of the processes involved in the management of the health crisis in Malaysia, also considering population density. The analysis consisted in measuring the efficiency of community surveillance (quarantine of individuals presume to have been exposed to COVID-19), the efficiency of hybrid hospitals, which have admitted both, COVID cases and non-COVID emergency cases, and the efficiency of the hospitals that have provided care exclusively for critical COVID-19 cases. Community surveillance and hospitals for critical cases were highly efficient in areas with high density population, while hybrid hospitals proved their efficiency in areas with low-density population. The Malaysian results are consistent with those obtained in Brazil, demonstrating that the performance of the response to a health crisis depends essentially on the allocation of resources and this allocation must be made according to local infrastructure, population density and socioeconomic levels.

The Romanian health system was previously analyzed with DEA by Asandului *et al*. (2015), comparing it to the health systems from other EU countries. The efficiency of the Romanian health system proved to be quite low (44%), in agreement with the Euro Health Consumer Index ranking, in which Romania has the 34$^{th}$ place among the 35 analyzed countries (Health Consumer Powerhouse, 2019). Despite consistent analysis that sustain the inefficiency of the Romanian health sector, recent results obtained with DEA reveal a good management of the public hospitals (Nistor *et al*., 2017).

## 2. Data and methods

In the current study, the Romanian healthcare facilities response to the coronavirus pandemic was quantified firstly by running a descriptive analysis on the main inputs and outputs of the support-hospitals included in the sample. Secondly, the efficiency scores of these facilities were computed using the non-parametric method Data Envelopment Analysis. Hollingsworth (2008) argued that the evaluated hospitals should be of the same type and should provide the same services, since DEA is sensitive to outliers. The inclusion of divergent units would confound the results which are often „conditional upon basic differences in sample or study design, rather than real variation of efficiency" (Hollingsworth, 2008, p. 1113). Thus, in order to have a homogeneous study sample, 18 municipal hospitals, that were support-hospitals for COVID cases in 2020 and are similarly in terms of capacity, resources and level of competence, were considered as statistical analysis units.

The main outputs of the hospitals included in the descriptive analysis, in the first stage, were *total number of discharges*, *the number of surgical procedures* and *the number of in-hospital deaths*, comparing data from the pre-pandemic year 2019 with data from the pandemic year 2020. These data were collected from the website of the Romanian Health Services Research and Evaluation Centre[4], where the reports of public and private healthcare facilities are centralized. The resources of the hospitals included in the descriptive analysis were *number of beds*, *number of doctors* and *number of nurses*. These data were collected from the Ministry of Health reporting platform for public hospitals[5].

For the computation of the efficiency score in the second stage, the data included in the analysis accounts for the whole year 2020. No distinction was made between the quarters of the year as the pandemic began in the first quarter of 2020. Three DEA models were constructed, following the guidelines of Ozcan (2008) for a robust DEA model and DEA literature in the selection of input / output variables. Thus, the variables used as inputs were (1) *the number of beds*, which are considered a proxy for hospital capital (Ozcan, 2008), (2) *the number of doctors* and (3) the *number of nurses*. All together are discretionary resources, which have proven to be insufficient in all countries during the current health crisis. The output variables taken into consideration were (1) *the total number of discharges in 2020, adjusted with the case-mix*[6] and (2) *the number of patients discharged with a respiratory condition as main diagnosis, accounting for COVID patients* also case-mix adjusted (see table 1). The data accounting for the main diagnosis at discharge were also collected from the website of the Romanian Health Services Research and Evaluation Centre where the major diagnosis categories for the reported discharges of the hospitals are also centralized. In 2020, the first diagnosis category for the support-hospitals was that corresponding to diseases and disorders of the respiratory system, indicating that these hospitals have admitted and treated in 2020 mainly COVID patients. The presence of the slacks demonstrates overused inputs or underproduced outputs or both.

[4] www.drg.ro , Indicators section
[5] monitorizarecheltuieli.ms.ro
[6] The case-mix index reflects the diversity, the severity and the complexity of the cases treated by each hospital from the point of view of the necessary resources (retrieved from https://www.definitivehc.com/resources/glossary/case-mix-index, accessed on 20/06/2021).

**Table 1. Input and output variables used in DEA analysis**

| Input / Output | Variables | Definition |
|---|---|---|
| **Discretionary inputs** | Number of beds | Number of beds approved through the National Plan of Hospital Beds and contracted by each hospital with the Insurance House |
| | Number of doctors | Full-time equivalent and part time at year end |
| | Number of nurses | Full-time equivalent and part time at year end |
| **Outputs** | Total number of discharges (case-mix adjusted) | Total number of patients discharged in 2020 |
| | Number of COVID patients discharged (case-mix adjusted) | Total number of patients discharged in 2020 with a respiratory condition as main diagnosis |

*Source:* authors'design

Data Envelopment Analysis was used for the computation of the efficiency scores, running 3 different models under the assumption of variable returns to scale (VRS), input oriented. DEA is a nonparametric method for the estimation of the efficient production frontier, method that was introduced by Charnes *et al*. (1978). It is a linear programming method that examines the relationship between the inputs and the outputs of a production process and allows the evaluation of the technical efficiency (TE) of non-for-profit entities, named decision making units (DMUs). The DMUs are similar entities that produce the same type of outputs using a set of similar inputs. Charnes *et al*. (1978) and later Banker *et al*. (1984) have generalized the engineering-science definition of efficiency, understood as single-output to single-input ratio of the production process, to the multiple outputs/inputs' configuration, by applying a mathematical linear dual formulation. Thus, DEA identifies the best practice frontier which is formed by the optimal input/output combinations and determines the relative inefficiency level of each unit, as deviance from the frontier, by comparing it either to a single reference unit from the frontier or a convex combination of reference units (Ersoy *et al*., 1997; Sánchez, 2009). The efficient DMUs are envisaged as role models for the inefficient ones, which are expected to learn and to improve their efficiency. Technical efficiency can range from 0 (0%) to 1 (100%). The DMUs with a score of 1 are considered technically efficient, whereas a score of less than 1 indicates inefficiency, meaning that other units in the sample could produce the vector of outputs with a smaller vector of inputs.

The advantages of DEA are not only the possibility to handle multiple inputs/outputs configurations, but also the fact that DEA does not require an assumption regarding a functional form between inputs and outputs, neither apriori choice of weights (Charnes and Cooper, 1984). The dual envelopment of the observed production possibilities allows the estimation of the efficiency score from an input-oriented or an output-oriented perspective, getting a measure of efficiency like a Pareto optimum (Cooper *et al*., 2006). In the input-orientation (inputs are under the control of the DMUs), DEA results indicate the degree up to which the inputs can decrease by better unit operations and not due to inputs decrease, keeping steady the output vector. In the output-orientation (outputs are under the control of the DMUs), DEA results indicate the degree up to which the outputs can increase by better unit operations and not due to input increase (Farantos, 2015). DEA can be carried out under the constant or variable returns to scale assumption (CRS or VRS), minimizing inputs given the amount of outputs or maximizing outputs, given the mix of inputs, according to chosen orientation.

The efficiency measure proposed by Charnes, Cooper and Rhodes (CCR model), employed under the CRS assumption, is obtained as „the maximum of a ratio of weighted outputs to weighted inputs, subject to the condition that similar ratios for every DMU be less than or equal to unity" (Charnes *et al.*, 1978, p. 430). Under the CRS assumption, a proportionate increase in all inputs yields an increase in outputs in the same proportion. The efficiency measure that is computed represents the overall technical efficiency, also including scale efficiency (the size of operations).

The model proposed by Banker, Charnes and Cooper (the BCC model) uses the VRS assumption, adding a convexity constrain (the weights should equal to 1). Thus, the reference point on the production function for each compared unit will be „a convex combination of the observed efficient DMUs" (Golany and Roll, 1989, p. 249). The BCC model brings the distinction between scale efficiency (the size of operations) and pure (managerial) technical efficiency, the latter being the score computed in DEA-BCC models. Along with the CRS assumption, the VRS assumption provides the possibility to detect if the productivity is affected either by the scale of operations or by the DMU's practices (Alatawi *et al.*, 2020).

For the current study, the managerial perspective was considered and the basic BCC model input-oriented was performed under the VRS assumption, described in Table 2. The efficiency is given by the ratio of the weighted sum of outputs to the weighted sum of inputs, and the relative efficiency score is obtained based on the following relation (Golany and Roll, 1989, p. 243):

$$\theta_0 = \sum_r u_r y_{r0} / \sum_i v_i x_{i0}, \qquad (1)$$

where $\theta_0$ is the relative efficiency of $DMU_0$, $y_{r0}$ and $x_{i0}$ are the values of the $r$ th output and $i$ th input of $DMU_0$ and $u_r$, $v_i$ are virtual multipliers (weights) for output $r$ and input $i \geq \varepsilon$, which is a small positive number.

**Table 2. Mathematical details of the input-oriented BCC model**

| |
|---|
| *Minimize* $\boldsymbol{\theta - \varepsilon\,(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)}$ |
| $\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad i = 1,\ldots..m$<br>$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1,\ldots..s$<br>$\sum_{j=1}^{n} \lambda_j = 1 \qquad j = 1,\ldots\ldots.n$<br>$\lambda_j \geq 0, \qquad j = 1,\ldots\ldots..n$ |
| **where**<br>$\theta$ = the efficiency score for the DMU under evaluation;<br>$\varepsilon$ = non-archimedean constant which is smaller than any positive valued real number; its presence allows a minimization over the efficiency score to pre-empt the optimization of slacks, $s_i^-$ and $s_r^+$;<br>$s_i^-$ = slacks corresponding to input *i* (the superscripted minus sign indicates possible inputs reduction)<br>$s_r^+$= slacks corresponding to ouput *r* (the superscripted positive sign on output slacks requires augmentation)<br>$\lambda_j$ = the vector of weights for $DMU_j$<br>$y_{rj}$= the amount of output *r* produced by $DMU_j$<br>$x_{ij}$ = the amount of input *i* produced by $DMU_j$<br>*r* = 1,.....,*s* and *s* represents the number of outputs<br>*i* = 1,.....,*m* and *m* represents the number of inputs<br>*n* = number of DMUs |

*Source:* Ozcan, 2008

The weights are obtained in favour of each DMU by the optimisation process. Therefore, depending on the scale of operations and keeping everything else constant, the lower the usage of resources involved in the production plan, the higher the operational efficiency of each hospital (Nepomuceno *et al.*, 2020). The presence of inefficiencies indicates that a DMU has excess inputs or insufficient outputs (slacks) compared to the reference ones from the efficiency frontier.

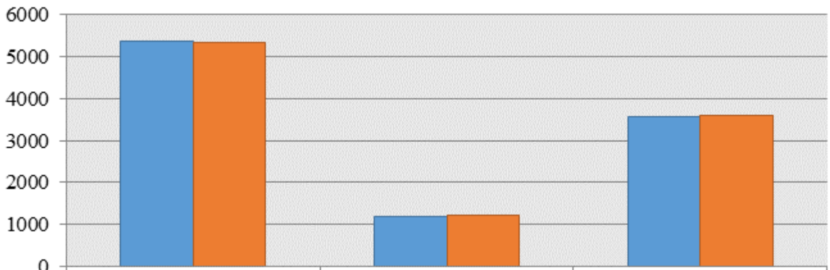
All variables used in the analysis were normalized before running the models, to deal with different units and scales. The output variables (total number of discharges and the number of discharges for COVID cases) were adjusted with the case-mix index[7] accomplished by each hospital in 2020, as it is recommended in the literature (O'Neill *et al.*, 2008). All computations were conducted in RStudio, using deaR package.

[7] The case-mix index reflects the diversity, the severity and the complexity of the cases treated by each hospital from the point of view of the necessary resources (https://www.definitivehc.com/resources/glossary/case-mix-index, accessed: 20/06/2021).

## 3. Results and discussion

Figures 1 and 2 illustrate the results of the descriptive analysis for the main inputs and outputs of the investigated hospitals, accounting for 2019 and 2020. Compared to the pre-pandemic year 2019, in 2020 the total number of physicians (both attendings and residents) increased with 3.45% and the number of nurses increased with 1.20%, while the number of hospital beds registered a very slight decrease with 0.20% (see Figure 1).

**Figure 1. Comparative indicators 2019/2020 for the main inputs of the hospitals**

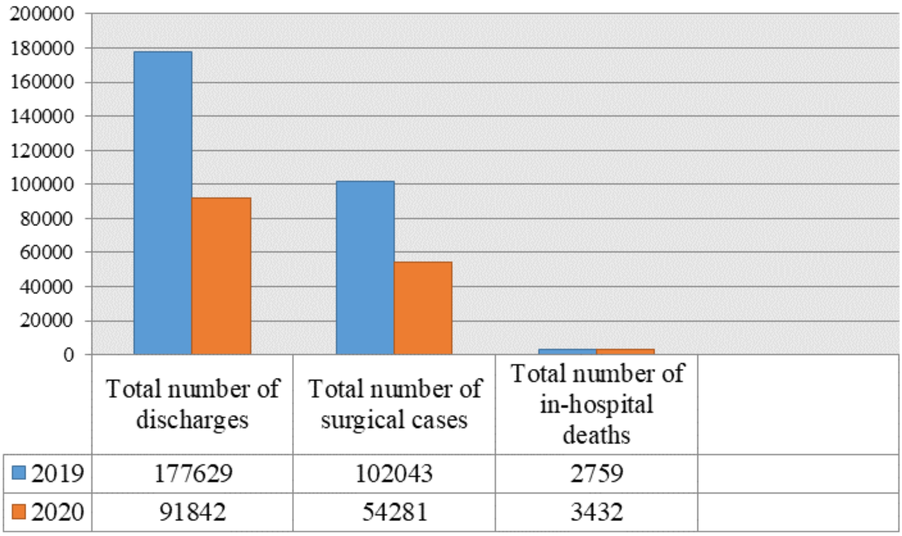



| | Number of hospital beds | Number of physicians | Number of nurses |
|---|---|---|---|
| 2019 | 5361 | 1184 | 3559 |
| 2020 | 5350 | 1226 | 3603 |

*Source:* authors' processing

In terms of outputs, the results show a significant decrease in the number of discharges with 48.30% and with 46.81% in the number of surgical cases. These results are due to the ministerial decisions to reduce the scheduled hospitalizations for chronic patients, but they are also due to the safety and coping measures that were put in place to free up hospitals resources for COVID patients. As for the hospital mortality, an increase in the number of in-hospital deaths with 19.60% was registered as an effect of the pandemic, since most of the admitted cases in the evaluated hospitals were COVID patients (Figure 2).

**Figure 2. Comparative Analysis 2019/2020 for the main outputs of the hospitals**




*Source:* authors'processing

**Table 3. Descriptive statistics of the inputs and outputs of the 18 hospitals**

| Variables | Min | Max | Mean | Std. Dev | Coefficient of variation |
|---|---|---|---|---|---|
| ***Inputs*** | | | | | |
| *Hospital beds* | 172 | 495 | 297.22 | 91.82 | 30.89 |
| *Physicians* | 22 | 132 | 50 | 27.49 | 55.11 |
| *Nurses* | 108 | 343 | 200 | 67.35 | 33.65 |
| ***Outputs*** | | | | | |
| *Total number of discharges, adjusted with the case-mix* | 2279 | 10161 | 5102.33 | 2034.08 | 39.87 |
| *The number of COVID patiens, adjusted with case-mix (patients discharged with respiratory disorder as the main diagnosis)* | 582 | 2810 | 1315.17 | 607.33 | 46.18 |

*Source:* authors' processing

Table 3 presents the descriptive statistics of the variables used for the DEA models. In order to have a homogenous sample study and to comply with the conditions for the application of DEA[8], only municipal hospitals were included in the study. These units are similar in terms of capacity and human resources. Still,

[8] no. of DMUs must be 2 x (no. of inputs + no. of outputs) (Golany and Roll, 1989, p. 239)

the heterogeneity of the sample on *physicians* variable was high ( > 50%) because initially residents psysicians were also accounted and their number varies significantly from one facility to another, as their employment is temporary, and they are not included in the list of positions. Consequently, to reduce the heterogeneity of the sample on this variable, for the DEA models only the attending physicians were finally considered.

Thus, the number of attending physicians in the sample study ranges from 22 to 132, with a mean of 50 doctors. The average number of nurses is 200, ranging from 108 to 343. The average hospital capacity is 297.22 beds, with a range of 172-495 beds. As for the outputs, the average discharged patients which have received in-patient care in 2020 are, 5102. From these, 1317 cases were, on average, COVID patients, having as main diagnosis at discharge a respiratory disorder. The number of patients with respiratory disorders ranges from 582 to 2810.

Table 4 presents the results for the DEA models and the average technical efficiency score computed under the VRS assumption. The technical efficiency of the hospitals increases from one DEA model to another, a s new input variables are added. The average efficiency scores range from 0.88 in model 1, using one input, to 0.92 in model 3, using 3 inputs. In the model 1, that uses only hospital beds as an input, 72% of the hospital in the sample study are inefficient and the average efficiency score indicates that these units would, on average, need to improve their efficiency by 12%. By adding the variable on human capital in the third model, 50% of the support-hospitals prove to be technically efficient. The remaining inefficient ones would, on average, need to improve their efficiency by 8%.

**Table 4. Pure technical efficiency scores for support-hospitals in 2020**

| DMUs | DEA-BCC model 1 | DEA-BCC model 2 | DEA-BCC model 3 |
|---|---|---|---|
| Adjud Municipal Hospital | 0.98 | 0.98 | 0.98 |
| Blaj Municipal Hospital | 0.80 | 0.80 | 0.85 |
| Câmpina Municipal Hospital | 0.67 | 0.67 | 0.67 |
| Caracal Municipal Hospital | 0.68 | 0.68 | 0.68 |
| Caransebeș Municipal Emergency Hospital | 1 | 1 | 1 |
| Carei Municipal Hospital | 0.90 | 0.92 | 0.96 |
| Craiova Municipal Clinica Hospital „Philanthrophy” | 1 | 1 | 1 |
| Fagaras Municipal Hospital | 1 | 1 | 1 |
| Fetești Municipal Hospital | 1 | 1 | 1 |
| Lugoj Municipal Hospital | 0.68 | 0.72 | 0.89 |
| Lupeni Municipal Hospital | 0.88 | 0.88 | 1 |
| Medgidia Municipal Hospital | 0.92 | 1 | 1 |
| Oltenița Municipal Hospital | 0.82 | 0.82 | 0.89 |
| Râmnicu Sărat Municipal Hospital | 1 | 1 | 1 |

| | | | |
|---|---|---|---|
| Roșiorii de Vede „Caritas” Municipal Hospital | 0.79 | 0.79 | 0.84 |
| Sighişoara Municipal Hospital | 0.84 | 0.84 | 0.84 |
| Târgu Secuiesc Municipal Hospital | 0.90 | 0.90 | 1 |
| Tecuci Municipal Hospital | 0.89 | 1 | 1 |
| Average efficiency | 0.88 | 0.89 | 0.92 |
| Efficiency units | 5 | 7 | 9 |
| Inefficiency units | 13 | 11 | 9 |

*Source:* authors’ processing

The units that form the efficiency frontier in model 3, which includes all main resources of the hospitals are reported in Table 5, together with their inefficient peers for whom they are benchmarks. The inefficient units can become efficient either by reducing inputs keeping the same level of hospitalizations, either by admitting and treating more patients using the same level of resources or by a combination of both.

**Table 5. The efficient hospitals in the sample and their inefficient peers**

| DMUs | Beds | Physicians | Nurses | Inefficient peers |
|---|---|---|---|---|
| „Philanthropy” Municipal Hospital of Craiova | 495 | 132 | 343 | No inefficient peer |
| Municipal Hospital of Făgăraș | 305 | 57 | 235 | 6 units: Municipal Hospitals of Sighişoara, Blaj, Caracal Câmpina, Carei and Adjud |
| Municipal Hospital of Râmnicu Sărat | 419 | 43 | 251 | 1 unit: “Caritas” Municipal Hospital of Roșiorii de Vede |
| Municipal Hospital of Fetești | 172 | 22 | 123 | 9 units: Municipal Hospitals of Sighişoara, Blaj, Oltenița, Caracal, Câmpina, Carei Roșiorii de Vede, Lugoj and Adjud |
| Municipal Emergency Hospital of Caransebeș | 388 | 59 | 226 | 3 units: Municipal Hospitals of Caracal, Roșiorii de Vede and Lugoj |
| Municipal Hospital of Medgidia | 310 | 42 | 193 | No inefficient peer |
| Municipal Hospital of Târgu Secuiesc | 250 | 58 | 137 | 3 units: Municipal Hospitals of Blaj, Carei and Lugoj |
| Municipal Hospital of Tecuci | 265 | 44 | 194 | 2 units: Municipal Hospitals of Blaj and Carei |
| Municipal Hospital of Lupeni | 195 | 31 | 108 | 1 unit: Municipal Hospital of Oltenița |

*Source:* authors’ summary

The slacks analysis for the models 2 and 3 revealed that "Philanthropy" Municipal Clinical Hospital of Craiova is weakly efficient, having slacks greater than zero. For the inefficient units, inputs slacks analysis indicated only slight reductions in resources usage to reach efficiency, which are summarized in Table 6.

**Table 6. Potential average input reductions in model 3**

| Inputs | Percentage variation (slacks) |
|---|---|
| **Beds** | -0.003% |
| **Physicians** | -0.12% |
| **Nurses** | -0.01% |
| **Average inputs'slacks** | -0.05% |

*Source:* authors' processing

These results indicate that, in 2020, the investigated hospitals could have treated the same number of patients with less doctors and nurses: the number of doctors could have been reduced by 0.12% and the number of nurses could have been reduced by 0.01%. A very slight reduction in the number of beds is also suggested. As for the output's possible increases, the identified slacks were for the COVID patient's variable, indicating that the hospitals in the sample could have treated with 0.01% more COVID patients, given the resources.

These results must be related to the complex pandemic context. If the figures are interpreted without considering the contagious nature of COVID-19 disease, the increase in number of the medical staff in 2020 compared to 2019 is not justified. But, if the need to ensure additional shifts for medical workers with COVID-19 is considered, then the indicated slight reductions in relation with the possibility to hospitalize only with 0.01% more COVID patients, proves that the human capital has been used to the fullest.

## Conclusions

The efficiency of the health systems and of the healthcare facilities has become a major preoccupation for policymakers and health economists ever since World Health Organization published the first major report on this topic in 2000, proposing a performance assessment framework. All governments were interested to put in place evaluation methods to monitor the performance of healthcare industry and resource usage for the sustainability of the medical sector and a universal coverage of medical service. DEA has proved to be a powerful tool for efficiency assessment and has reached an impressive number of applications in healthcare.

In Romania, after the EU accession in 2007, the healthcare sector has known some significant changes, such as decentralization of hospitals, evaluation of the performance of hospitals' management and hospitals' accreditation by the National

Authority for Quality Management in Healthcare. Despite the increased autonomy and the implemented evaluation systems, the Romanian healthcare sector maintains a low performance mainly due to chronic underfunding. Therefore, it was not prepared for a health crisis of such a large scale as COVID-19 pandemic. In fact, as recent conducted studies have proven, no country was prepared for this crisis, not even the richest ones, needing to adjust in real-time and to fix on the spot management errors made in the previous years. In the near term, the main issues raised by COVID-19 are the burnout of the medical workers and the worn-out of the hospital's infrastructure. On the long term, the backlog of healthcare procedures is likely to emerge into a disruption of chronic diseases management.

This study is the first one done towards the evaluation of the Romanian healthcare facilities efficiency during the health crisis, aiming to highlight the impact of the pandemic. The hospitals under evaluation were hybrid hospitals, which have provided support in the treatment of patients tested positive for COVID-19 and have insured, at the same time, emergency treatment for non-COVID patients. The DEA-BCC model, under the assumption of VRS and input-oriented was used to estimate the technical efficiency scores for the investigated hospitals from a managerial perspective, as this model runs the comparisons considering the size of the operations. Three different models were constructed and employed, adding a new input variable each time, and keeping steady the output vector. The results have proven that the efficiency scores increase from one model to another, as new inputs are added. At the third model, the average efficiency of the investigated hospital reached 0.92, half of the hospitals placing on the efficiency frontier. No hospital had an efficiency score lower than 0.60. Also, the slacks analysis has proven that the possible inputs reduction is very small, implying a good management of the hospital beds and human capital during the COVID-19 pandemic.

These good results are encouraging and they reveal good management. The management of activities and services offered to patients was carefully monitored and oriented towards the application of strict rules both for medical staff and for patients, but the learning had many facets. This could be the next step in research, to consider external factors such as population density, socio-economic status, number of tested and funding to identify the determinants of Romanian hospital efficiency during the health crisis.

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