Intensive Care Unit Services Preparedness for the Pandemic: An Efficiency Analysis

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Songul Cinaroglu

Department of Health Care Management, Faculty of Economics and Administrative Sciences (FEAS), Hacettepe University, Beytepe Ankara, Turkey.

ABSTRACT: Intensive care unit (ICU) services efficiency and the shortage of critical care professionals has been a challenge during pandemic. Thus, preparing ICUs is a prominent part of any pandemic response. The objective of this study is to examine the efficiencies of ICU services in Turkey right before the pandemic. Data were gathered from the Public Hospital Statistical Year Book for the year 2017. Analysis are presented at hospital level by comparing teaching and non-teaching hospitals. Bootstrapped data envelopment analysis procedure was used to gather more precise efficiency scores. Three analysis levels are incorporated into the study such as, all public hospitals (N = 100), teaching (N = 53), non-teaching hospitals (N = 47), and provinces that are providing high density of ICU services through the country (N = 54). Study results reveal that average efficiency scores of ICU services obtained from teaching hospitals (eff = 0.65) is higher than non-teaching (eff = 0.54) hospitals. After applying the bootstrapping techniques, efficiency scores are significantly improved and the difference between before and after bootstrapping results are statistically significant ($P < .05$). Province based analysis indicates that, ICU services efficiencies are high for provinces located in southeast part of the country and highly populated places, such as İstanbul. Evidence-based operational design that considers the spatial distribution of health resources and effective planning of critical care professionals are critical for efficient management of intensive care. Study results will be helpful for health policy makers to deeply understand dynamics of critical care.

KEYWORDS: Intensive care units, teaching hospital, efficiency, Turkey

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CORRESPONDING AUTHOR: Songul Cinaroglu, Department of Health Care Management, Faculty of Economics and Administrative Sciences (FEAS), Hacettepe University, Beytepe Ankara 06800 Turkey. Emails: songulcinaroglu@gmail.com; cinaroglus@hacettepe.edu.tr

Introduction

Intensive care units (ICUs) were organized under the assumption that critically-ill patients require constant attention and often quick response action, depend on high technology life support systems and skilled personnel.[1] In this regard, critically ill patients and ICUs have become the focus of public health economics, which attribute a large proportion of the increase in health expenditure, operations, and maintenance.[2] Resource allocation in public health sector and in particular through the increase of the ICU's system capacity are essential strategies for better management of public health resources.[1] Effective planning of critical care services becomes a great concern for global health managers in the age of Coronavirus disease (Covid-19) pandemic.[3] Thus, there will be an immense strain on overstretched resources, particularly in the intensive care setting.[4]

Covid-19 is a serious health concern which alerts all healthcare professionals worldwide.[5] This is a tremendously challenging health problem which has aroused the concern for more effective planning of critical care units by the health professionals.[6] A common lore in level of development and Covid-19 pandemic states that, deaths and costs associated with a pandemic may be greater in developing countries than developed ones.[7] In this regard, there would have a significant bearing on the efficient planning of ICU services. However, there exists little empirical evidence about preparedness of ICUs in developing countries into this pandemic. Turkey is one of the developing countries and have some advantages to fight against Covid-19 pandemic such as, high number of skilled beds and low percentage of people in the 65 years of age and older among total population.[8] In order to verify that, in Turkey, total percentage of the population over 65 years of age and older is 8.8% for Turkey and OECD average is 17.1%.[9]

In Turkey, a number of hospitals and capacity of ICU services are significantly improved under reorganization plans with health transformation program (HTP) since 2003.[8,9] Under HTP total number of ICU beds by years are increased from 2214 in 2002 to 38 098 in 2018. Number and distribution (%) of ICU unit beds by types and sectors show that the total number of beds in ICUs is high for MoH hospitals with 16 086, university hospitals with 6039 and private hospitals with 15 973, for the year 2018, respectively. Additionally, distribution of number of ICU beds per 10 000 population by NUTS-1 is 5.6 for Mediterranean, 5.1 for Southeastern Anatolia, and 4.8 for Istanbul, respectively.[9-12] Turkey faced with the lack number of health professionals in critical care. To verify this, MoH statistical year book state that, Turkey came in last in OECD ranking of physicians per capita with 187 physicians per 100 000 people. The nurse and midwife per capita in Turkey is 301 professionals per 100 000 people.[9] Moreover, the average number of curative (acute) care beds per 1000 population is 3.59. Turkey has low number of acute care beds per 1000 population with 2.58 for the year 2017.[13] On the other hand, despite critical care nurses have significant responsibilities in ensuring patient safety and preventing errors, in Turkey low number of critical care nurses is an existing problem and it is particularly salient within the field of critical care nursing.[11]

Pandemic environment creates an enthusiasm for effective planning and deep understanding of ICU services efficiency. In Turkey, despite previous knowledge provided evidence that efficiency of health services differs according to rural and urban settlement in Turkey[14,15] there is a lack knowledge about efficiency of ICU services by considering regional differences. It is highly believed that, this study will provide many lights to fill this gap and will go one step further by exploring whether efficiencies of ICU services differs according to their teaching status and rural-urban location. This study was designed to explore ICU services preparedness for pandemic in Turkey, particularly by focusing on efficiency of intensive care services and highlighting spatial heterogeneity of intensive care services efficiency around the country. Moreover, capacity improvement efforts to enhance ICUs capacity and bed planning will help health policy makers to foster better critical care and to fight against pandemic. However, there is a lack knowledge about the efficiency analysis of ICUs and regional planning of these services. This study aims to fill this void by analyzing the efficiency of ICUs with DEA approach by incorporating bootstrapping procedure. This study contributes to the existing body of knowledge in 2 ways. First, our study results provide a deep understanding of ICU services efficiency in the age of pandemic. Secondly, study findings provides many lights for deep understanding of regional differences in ICU services efficiencies.

Methods

The objective of this study is to explore the efficiency of intensive care unit services in Turkey just before the pandemic and to make recommendations for effective management of intensive care resources. In this study, a DEA bootstrapping procedure was used to analyze efficiency of intensive care services in Turkey and to make suggestions. DEA is a nonparametric method that uses the linear programming method to explore an efficiency frontier of highest performing units by using input and output variables.[16] In this study input oriented variable returns to scale (VRS) was applied.[17] The calculation of DEA efficiency scores are explained using mathematical notations. The efficiency scores (θ_o) for a group of peer DMUs ($j = 1 \ldots n$) are computed for the selected outputs ($y_{rj} = 1, \ldots, m$) by using the following formula:[16]

$$Maximize\, \theta_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \quad (1)$$

$$subject\ to\ \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad (2)$$

$$u_r, v_i \ge 0\ for\ all\ r\ and\ i.$$

In these equations, the weights for the outputs and inputs, respectively, are u_r and v_i and "o" denotes a focal DMU (ie, each hospital, in turn, becomes a focal one when its efficiency score is being computed relative to others). The input and output values, as well as weights are assumed by the formulation to be greater than zero. The weights u_r and v_i for each DMU are determined entirely from the output and input data of all DMUs in the peer group of data.[16]

In our case, bootstrap techniques are incorporated into the DEA procedure to gather bias-corrected efficiency scores. DEA models integrated with the bootstrap procedure allow more precise calculations of efficiency scores, which can better reflect the performance of health centers.[18,19] To build a bootstrap sample of the original DEA scores, the following steps are implemented:[20]

To apply the homogenous bootstrap algorithm for a set of bootstrap estimates, $\left\{ \hat{\lambda}_b^*(x, y) \middle| b = 1, \ldots, B \right\}$, for a given fixed point (x, y), the following steps must be considered:

(1) From the original data set, compute to $\hat{\lambda}_{VRS}$.
(2) Apply the "*rule of thump*" to determine the bandwidth parameter, h.
(3) Generate $\beta_1^*, \ldots, \beta_n^*$ by drawing with replacement from the set, $\left\{ \hat{\lambda}_1, \ldots, \hat{\lambda}_n, \left(2 - \hat{\lambda}_1\right), \ldots, \left(2 - \hat{\lambda}_n\right) \right\}$.
(4) Then, draw ε_i^*, $i = 1, \ldots, n$ independently from the kernel function, $K(.)$, and compute $\beta_i^{**} = \beta_i^* + h\varepsilon_i^*$ for each $i = 1, \ldots, n$.
(5) For each $i = 1, \ldots, n$, compute β_i^{***} as: $\beta_i^{***} = \bar{\beta}^* + \frac{\beta_i^{**} - \bar{\beta}}{(1 + h^2 \sigma_k^2 \sigma_\beta^2)^{1/2}}$, where $\bar{\beta}^* = \sum_{i=1}^{n} \beta_i^* / n, \sigma_\beta^2 = = \sum_{i=1}^{n} (\beta_i^* - \bar{\beta}^*) / n$, and σ_k^2 is the variance of the probability density function used for the kernel function. Additionally, λ_i^* can be computed as $\lambda_i^* = \begin{Bmatrix} 2 - \beta_i^{***} \forall \beta_i^{***} < 1 \\ \beta_i^{***} \quad otherwise \end{Bmatrix}$.
(6) The bootstrap sample is created as $X_n^* = \left\{ (x_i^*, y_i) \middle| i = 1, \ldots, n \right\}$, where $x_i^* = \lambda_i^* \hat{x}^{\partial}(y_i) = \hat{\lambda}_i^* \hat{\lambda}_i^{-1} x_i$.
(7) We calculate the DEA efficiency scores, $\hat{\lambda}_i^*(x_i, y_i)$, for each original sample observations using the reference set, X_n^*, in order to obtain a set of bootstrap calculations.
(8) Finally, we repeat steps 3 to 7 B times to get a set of bootstrap estimates: $\left\{ \hat{\lambda}_b^*(x, y) \middle| b = 1, \ldots, B \right\}$

The bootstrap bias estimate for the original DEA estimator, $\hat{\lambda}_{DEA}(x, y)$, is calculated as follows:

$$B\hat{I}AS_B\left(\hat{\lambda}_{DEA}(x,y)\right) = B^{-1}\sum_{b=1}^{B}\hat{\lambda}^{*}_{DEA,b}(x,y) - \hat{\lambda}_{DEA}(x,y). \quad (3)$$

Moreover, $\hat{\lambda}^{*}_{DEA}(x,y)$ are the bootstrap values, and B is the number of bootstrap replications (200 replications in our case). Then, a bias corrected estimator of $\lambda(x,y)$ can be calculated as:

$$\hat{\hat{\lambda}}_{DEA}(x,y) = \hat{\lambda}_{DEA}(x,y) - B\hat{I}AS_B\left(\hat{\lambda}_{DEA}(x,y)\right) = 2\hat{\lambda}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\lambda}^{*}_{DEA,b}(x,y). \quad (4)$$

Bias correction can create additional noise. In this regard, the sample of variance of the bootstrap values $\hat{\lambda}^{*}_{DEA}(x,y)$, have to be calculated. The calculation of the variance of the bootstrap values is highlighted as follows:

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}[\hat{\lambda}^{*}_{DEA,b}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\lambda}^{*}_{DEA,b}(x,y)]^2. \quad (5)$$

Moreover, it is necessary to prevent the bias correction highlighted in equation (5), unless

$$\frac{\left|B\hat{I}AS_B\left(\hat{\lambda}_{DEA}(x,y)\right)\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}}. \quad (6)$$

Finally, when the bias is higher than the standard deviation (σ), the bias-corrected estimates are chosen to the original values.[20]

Datasets and input/output variables used for empirical analysis

In this study, intensive care services bootstrapping efficiencies are examined for all public hospitals, teaching, and non-teaching hospitals, respectively. The final analysis level is province based to present the spatial distribution of ICU services efficiency scores. These 4 levels of analysis provide comprehensive assessment of the efficiency of public ICU services. Data were gathered from the Public Hospital Statistical Year Book for the year 2017.[21] In this study, totally 100 hospitals are included into the analysis which are representing the hospitals that have high number of inpatients in the ICUs. Thus, the inclusion criteria of hospitals: the top 100 hospitals with the highest number of ICU services hospitalizations for the year 2017. A set of input and output variables were defined by using literature about intensive care services efficiency.[2,22-24] Input variables were operationalized as follows: (i) number of beds in ICUs; (ii) the total number of physicians who are full time employees in the hospitals, including specialists and general practitioners; (iii) total number of nurses who are full time employees in the hospital, including midwives. Output variable of this study is total number of inpatients in the ICU services (unadjusted).

Results

Descriptive statistics of this study is presented in Table 1. There are 100 hospitals having high number of inpatients in intensive care services, for the year 2017. Among these hospitals, 53 of them have teaching status and 47 of them don't have teaching status. All of these hospitals are equipped with advance health personnel and technological equipments, such as a ventilator for high quality of intensive care. These hospitals are located in 54 provinces throughout the country. In Turkey, teaching hospitals are tertiary hospitals that provide specialty training and undertake research. Teaching hospitals affiliated with either university and MoH and they are responsible for giving specialized education for physicians. Roles of top 100 hospitals having high number of inpatients in intensive care services are classified by MoH as A1, A1-branch, A2, and A2-branch. Among these hospitals, A1 and A1-branch hospitals have teaching status and A1-branch hospitals are serving in special branches. A1 hospitals are general and inpatient treatment hospitals and they are providing teaching in at least 5 branches and their training staff has been completed (eg, Istanbul MoH Dr. Said Konuk Teaching Hospital). A1-branch hospitals have teaching status but their training staff has not been completed yet. These hospitals are serving in special branches (eg, Ankara MoH Dr. Abdurrahman Yurtaslan Oncology Teaching Hospital). A2 and A2-branch hospitals don't have teaching status and A2-branch hospitals are serving in special branches. A2 hospitals are general hospitals and don't have teaching status and they are providing secondary care (eg, Bursa Cekirge Public Hospital). A2-branch hospitals don't have teaching status and they are serving in special branches (eg, Diyarbakir Children's Hospital).[25] Output variable of this study is number of inpatients in ICUs. This indicates the total number of ICU admissions. Descriptive statistics shows that, average scores obtained from teaching hospitals with regard to all study variables are relatively high compared with all public hospitals and non-teaching ones. In other words, teaching hospitals have faced with high density of input and ouput indicators compared with other hospitals.

In this study, before DEA analysis process, Spearman rank correlation coefficient was used to detect the presence of multicollinearity among input and output indicators. It is seen that, all correlations are under <0.70, thus there is no fear for multicollinearity problem. One of the limitations of DEA is that it is sensitive to the number of DMUs. The error of the production frontier estimation is increases with a decreasing number of DMUs.[26] Moreover, efficiency scores depend on the number of DMUs and piecewise frontier, making the estimation of efficiency scores sensitive to data sampling errors.[28] To overcome these limitations, bootstrapping provides many insights, because it ensures statistical inference into the degree of efficiency.[27]

Table 1. Descriptive statistics.

ANALYSIS LEVELS	LEVELS		MINIMUM	MAXIMUM	MEAN	STANDARD DEVIATION
1	Top 100 public hospitals in terms of high density of inpatient services in ICUs (N = 100)					
		Number of ICU beds	3	169	59.33	29.579
		Number of physicians	20	553	246.59	125.841
		Number of nurses	22	1284	566.21	242.011
		Number of inpatients in ICUs	3157	15 174	5891.81	2587.205
2	Teaching hospitals (A1-A1 branch) (N = 53)					
		Number of ICU beds	3	169	68.26	30.327
		Number of physicians	20	545	294.06	133.753
		Number of nurses	206	1284	627.23	236.149
		Number of inpatients in ICUs	3294	14 784	6441.62	2869.961
3	Non-teaching hospitals (A2-A2 branch) (N = 47)					
		Number of ICU beds	3	106	49.26	25.448
		Number of physicians	62	553	193.06	91.298
		Number of nurses	22	1131	497.40	232.131
		Number of inpatients in ICUs	3157	15 174	5271.81	2086.570
4	Provinces (N = 54)					
		Number of ICU beds	19	678	109.87	120.504
		Number of physicians	96	3697	446.24	643.155
		Number of nurses	301	6625	1048.54	1101.460
		Number of inpatients in ICUs	3243	70 354	10 910.76	11 920.766

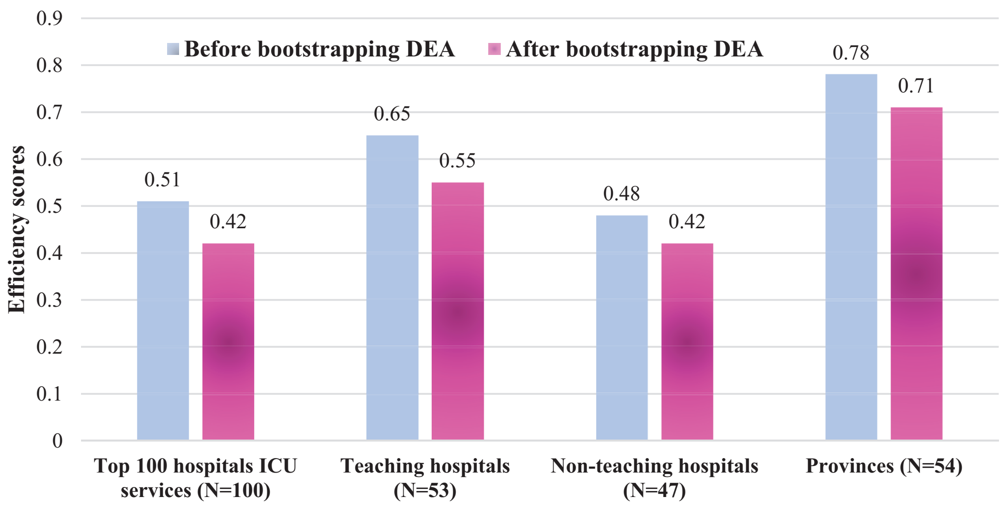

Figure 1. Visual presentation of average efficiency scores before and after bootstrapping.

Figure 1 highlights average efficiency scores obtained from datasets top 100 hospitals in ICU services density, teaching, non-teaching and province levels before and after bootstrapping. It is seen that, lower average efficiency scores were obtained from all 3 datasets after bias was corrected with bootstrapping. It is seen that, the bootstrapped DEA approach is improved the accuracy of the estimated efficiency scores and bias-corrected scores were more precise than traditional DEA models.

Table 2 presents distribution and sensitivity analyses of the efficiency scores by using 4 different data sets in terms of

Table 2. Distribution and sensitivity analysis of the efficiency scores using before and after bootstrapping results.

ANALYSIS LEVELS	BOOT STRAPPING	N	MIN.	MAX.	MEAN	STD. DEV.	MEAN RANK	*U*	*P*
Top 100 hospitals in terms of ICU services density (N = 100)	Before	100	0.13	1	0.51	0.25	109.70	4080	.025*
	After#	100	0.11	0.86	0.42	0.18	91.30		
Teaching hospitals (N = 53)	Before	53	0.29	1	0.65	0.21	60.62	1027	.017*
	After#	53	0.27	0.87	0.55	0.16	46.38		
Non-teaching hospitals (N = 47)	Before	47	0.21	1	0.54	0.22	54.16	791.50	.018*
	After#	47	0.16	0.78	0.44	0.15	40.84		
Province level (N = 54)	Before	54	0.45	1	0.78	0.17	61.40	1085	.022*
	After#	54	0.41	0.93	0.71	0.14	47.60		

Abbreviation: *U*, Mann–Whitney *U*-test.
#For the bootstrapping process, the data set is non-parametrically resampled $B = 200$ times.
*$P < .05$.

Table 3. Distribution of the bias.

Analysis levels	Top 100 hospitals ICU services (N = 100)	Min.	Max.	Mean	Std. dev.
		0.02	0.34	0.08	0.08
	Teaching hospitals (N = 53)	Min.	Max.	Mean	Std. dev.
		0.02	0.28	0.09	0.06
	Non-teaching hospitals (N = 47)	Min.	Max.	Mean	Std. dev.
		0.04	0.32	0.10	0.07
	Province level (N = 54)	Min.	Max.	Mean	Std. dev.
		0.03	0.20	0.07	0.04

ICU services efficiency. By considering the maximum values of efficiency scores, we can conclude that conventional (traditional) DEA scores tend to overestimate efficiency. The average efficiency scores of ICUs gathered from the province level analysis, which includes 54 DMUs through the country is higher than other analysis levels (eff > 0.70). Average efficiency scores obtained from 53 teaching hospitals are high, secondly (eff ⩾ 0.55). It is critical to advise that, according to the empirical results obtained from bias-corrected scores, hospitals should reduce their inputs to improve their ICU services efficiency. In our case, the incorporation of bootstrapping procedure enable to produce more precise efficiency scores. It is seen that, the mean rank differences between efficiency scores obtained from before and after bias correction were statistically significant for all datasets ($P < .05$).

Table 3 presents the distribution of bias. Average bias is positive for all study models for the 4 different analysis levels. Mean bias obtained from general non-teaching hospitals dataset (Mean = 0.10; SD: 0.07) is high with comparison to other datasets.

Table 4 shows selected examples of bias-corrected efficiency scores' lower and upper bound confidence intervals obtained from 4 data sets. Note that, all bias-corrected efficiency scores were in the middle points of the lower and upper confidence levels. The standard DEA tended to overestimate the actual efficiency scores. Moreover, study findings show statistically significant mean-rank differences before and after bias-corrected scores. To verify that, the mean values obtained from standard DEA were higher than the upper confidence levels of the bootstrapped scores gathered from specific examples of the 4 different analysis levels.

Spatial distribution of efficiency scores of provinces in terms of ICU services are presented in Figure 2. Efficient provinces, according to the DEA scores are presented with the red colors and they are labeled with bias-corrected (eff.bc) efficiency scores. According to the conventional model results, there exists totally 11 efficient provinces throughout the country. After bias correction of efficiency scores, recalculated efficiency scores for efficient provinces shows that, minimum and maximum efficiency scores obtained from provinces ranges between the values of 0.80 and 0.93. It is seen that,

Table 4. Specific examples of confidence intervals for 4 datasets.

ANALYSIS LEVELS	LEVELS	ORIGINAL SCORE	CORRECTED SCORE	95% CONFIDENCE INTERVAL	
				LOWER BOUND	UPPER BOUND
1	Top 100 hospitals in ICU services (N = 100)				
	İstanbul MoH Dr. Siyami Ersek Thoracic and Cardiovascular Surgery Training and Research Hospital	1	0.81	0.70	0.93
	İzmir Dr. Behçet Uz Children's Education and Research Hospital	1	0.66	0.54	0.95
2	Teaching hospitals (N = 53)				
	Diyarbakir Gazi Yaşargil Education Research Hospital	1	0.84	0.73	0.97
	Nigde Ömer Halisdemir University Training and Research Hospital	1	0.79	0.71	0.89
3	Non-teaching hospitals (N = 47)				
	Kahramanmaraş Necip Fazıl City Hospital	1	0.68	0.56	0.97
	Adana Maternity and Child Diseases Hospital	1	0.78	0.67	0.94
4	Province level (N = 54)				
	Diyarbakır	1	0.90	0.83	0.99
	İstanbul	1	0.82	0.66	0.98

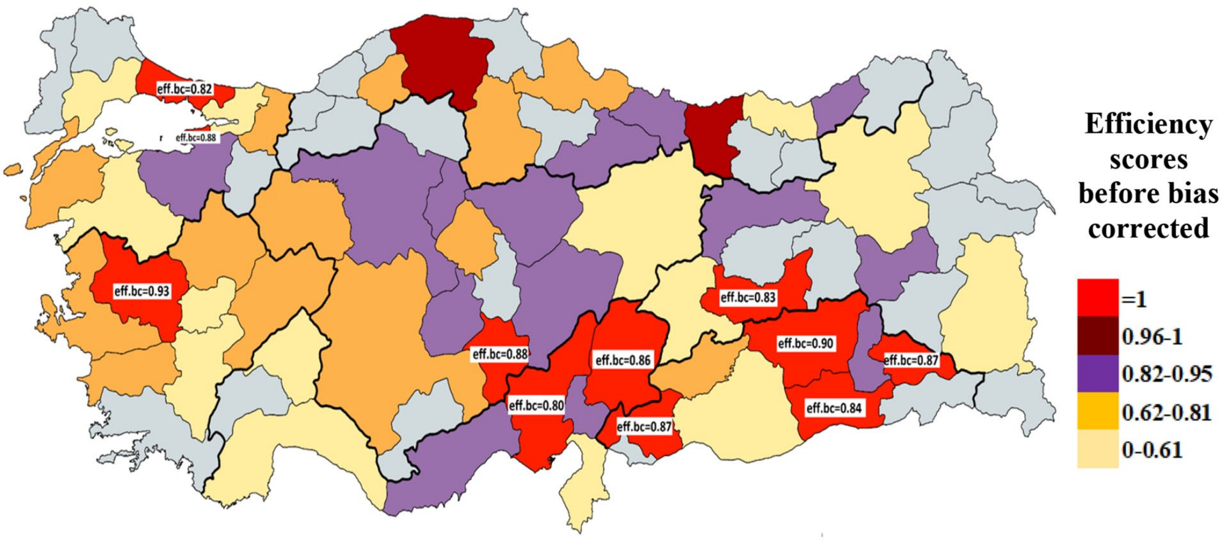

Figure 2. Spatial distribution of efficiency scores of ICU services in Turkey.

conventional model magnifies the efficiency scores of provincial ICU services. Red colors presents efficient provinces (eff = 1); dark brown color presents second (0.96 ≤ eff < 1); purple color shows third (0.82 ≤ eff ≤ 0.95); orange color shows fourth (0.62 ≤ eff ≤ 0.81) and light yellow color indicate less efficient (0 ≤ eff ≤ 0.61) provinces. In this map, provinces represented with gray colors are not among the top 100 hospitals by means of ICU services density. According to the traditional DEA scores, 11 efficient provinces in terms of ICU services are located in the southeastern part of the country. One of the efficient provinces is İstanbul, which is highly populated and metropolitan city of the country. It is critical to note that, provinces located in the east part of the country not faced with high density of ICU services and they have low level of efficiency scores.

Discussion

Key findings

The findings of this study provides an up-to-date account of knowledge about the efficiencies of public ICU services by emphasizing the differentiating role of teaching status and geographic location of ICU operations in Turkey. Pandemics are unique challenges for ICU services preparedness. The results of this study highlights the preparedness of ICU services in Turkey, in terms of efficiency, just before the pandemic times. Study findings uncover the following key facts: (a) Preliminary findings of the study emphasize high density of ICU study variables in teaching hospitals. (b) Average efficiency scores obtained from teaching hospital ICU services are higher than non-teaching and all public hospitals. (c) Spatial distribution of efficiency scores highlights that, efficient provinces in terms of ICU services are mostly clustered in the southeastern part of the country. (d) ICU services efficiency is high for Istanbul which is highly populated city in the country and faced with high service density. (e) There is no province in eastern part of the country that have faced with high density of ICU services, specifically these provinces are not include any of the top 100 public hospitals, that have high number of inpatients in ICU services.

Assessment of critical care performance is a significant challenge of health care systems, especially for emerging countries, that have faced with scarcity of resources.[29] Despite mortality is a well-known performance indicator of ICUs, comprehensive efficiency evaluation of critical care services by considering specific input and output indicators is to be needed due to the critical status of ICUs.[23,30] In line with this, preparedness of critical care services during global health crisis, such as Covid-19 pandemic mitigates the success of the health system to fight against this pandemic.[7] In this regard, efficiency analysis of ICUs will inevitably have a global effect on better management of scarce health resources and improve efforts toward resource allocation to deal with a high density of demand in developing countries.[24] Turkey has been experiencing a reform process in health care with HTP since 2003 and high investments are on the road with city hospitals.[9] Despite enormous capacity improvement efforts, there is a scarcity of knowledge about efficiency of public ICU services and preparedness of ICU services efficiency for turbulent pandemic times in Turkey.

The results of this study are in line with empirical findings and state that efficiency scores obtained from provinces faced with a high demand for ICU services is high, such as İstanbul. The operation of hospitals is currently determined by continuous investments in new technology and by an increased demand for high quality of ICU services. Thus, during pandemic times an excessive demand for ICU services has become noticeable in general health systems.[2] In this regard, ICU planning is comprised a significant part of any effective regional operationalization of care. Key findings of this research help to disentangle some of the main efficiency drivers in the analysis of ICU services. The results of this study emphasize that teaching status contributes positively into the ICU services efficiency. Bear in the mind that, average scores obtained from study variables are also posed that teaching hospitals are faced with high density of ICU services. Teaching hospitals are not only providing direct patient care, but also they are used training source for residents.[31] These additional responsibilities increase total costs of care in teaching hospitals compared with their non-teaching counterparts. Thus, the comparison of efficiencies of teaching and non-teaching hospitals takes a great interest of health operations researchers.[31-33] Despite the existing literature provides some lights to compare teaching and non-teaching hospital performances, there is a lack knowledge with regard to specific care areas such as, ICU services. It has been stated that, increased competition leads to higher efficiency without compromising teaching role.[31]

On the other hand, the results constitute an important finding about the unequal geographic distribution of ICU services efficiency in Turkey. It is seen that, spatial distribution of ICU services efficiency scores of provinces shows that efficient provinces are mostly clustered in southeastern part of the country. Interestingly, provinces in southeastern part of the country are less developed ones, they are not highly populated and represents rural parts of the country. The literature states that, rural hospitals have fewer resources to provide a range of definitive care services. In this regard, lower mortality rates in ICU services is obvious for these hospitals.[34] Therefore, examination of the ICU services utilization and interhospital transfers will provide many useful insights into rural hospital efficiency analysis and comparisons.[34] There exist some specific attributes of ICU services in the provinces located in the southeast part of the country such as, Şanlıurfa. Previous study results about intensive care services efficiency states that, careful monitoring, appropriate management and early recognition of complications are noticeable in ICU services in Şanlıurfa.[35] Note that, high ICU patient transfers from rural parts of the country in the urban areas is obvious for ICU services located in eastern part of the country.[36] Moreover, it is essential to improve usage of remote health technologies in ICU services to cope with regional imbalances. These systems enable health professionals to continuously monitor critically ill patients and rapidly communicate with the bedside team if necessary.[37] Study results call attention to the need for improving usage of high technologies in ICU to better operationalize and to provide equal ICU services for vulnerable groups, living in rural parts of the country.

Limitations of the study

Despite the interesting findings and the practical implications for effective management of ICU services, this study is not without limitations. Limitations of data availability and low number of ICU professionals in Turkey is one of the obstacles of this study. Despite most systems require a certain number of medical and nursing staff employed in ICU (per critical care bed), in Turkey the adequacy of ICU professionals and efficiency of staff allocation is one of the limitations of Turkish ICU services. Thus, in this study total number of physicians and nurses employed in the hospitals were used as input indicators. It is highly advisable for future studies, to incorporate number of medical and nursing staff employed in ICU per critical care beds, rather than in the hospital itself. On the other hand, in this study no adjustment for severity (acuity/complexity for the actual cases) is applied. It is highly advisable for future studies to incorporate and discuss the severity of illness case-mix groups to better understand patient-centric way of beneficial patient and intensive care.

Recommendations for better management of critical care services

Other side of the coin, the results of this study offer some remarks about balanced distribution of not only better usage of critical care resources, but also health professionals and better regional planning of ICU services. Turkey is on the lag of developed OECD countries in terms of total number of physicians and nurses.[9] As has been indicated in the MoH Strategic Plan 2019 to 2030, the health workforce does not have enough staff to address the demand for health care. Moreover, shortage of critical care nurses is obvious in Turkey, who are essential during health crisis such as pandemic treatment.[38] Therefore, managing the capacity building, better operationalization of human and health technology resources is an essential part of critical care planning and to ensure quality and equity of care.[39]

Conclusions

The findings of this research emphasize that there exists an unequal spatial distribution of efficiency scores obtained from ICU services in Turkey. Efficient provinces in terms of critical care services are grouped in rural parts of Turkey. There is an urgent need for effective planning of intensive care professionals for better preparedness of health crisis. It is hoped that the results of this study will inspire health policy makers about equal distribution of scarce critical care resources by considering high density, teaching status and the need for critical care professionals. In the light of the results of this study, further research is necessary for crisper understanding of associated socio-demographic factors with ICU demand, the level of quality and outcomes of ICU services in rural and urban parts of the country.

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Songul Cinaroglu is also affiliated with Hamburg Center for Health Economics, Esplanade 36, 20354, Hamburg, Germany.

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Author Contributions

Songul Cinaroglu is design the study, prepared the dataset, analyzed wrote and edited the manuscript.

ORCID iD

Songul Cinaroglu https://orcid.org/0000-0001-5699-8402

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