An evaluation of blood collection efficiency at the regional level: the case of Turkey

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Abstract

Purpose – The aim of this study is to analyze Turkey's blood collection efficiency at the regional level between 2018 and 2021 and discuss managerial implications.

Design/methodology/approach – The authors utilize data envelopment analysis (DEA) to evaluate the efficiency scores of the 18 regions for which the Turkish Red Crescent is responsible. The data set is obtained from the General Directorate of Blood Services in the Turkish Red Crescent.

Findings – The results reveal that the efficient regions over the years did not substantially change, and regions that were consistently efficient for a four-year period are identified. Another finding is that COVID-19 did not affect the blood collection efficiency of the regions. Moreover, the findings illustrate that concentrating on the operations would contribute more to the blood collection efficiency than changing the scale size. Furthermore, the authors observe that the service population is by far the most important variable in determining the efficiency of the regions.

Originality/value – In this study, the authors present a multi-dimensional perspective on the performance evaluation of blood collection operations. In addition, the authors present blood bank managers' feedback on the performance evaluation model, outlining managerial implications. Furthermore, the authors explore the effects of the pandemic on blood collection in Turkey and illustrate the changes in efficiency throughout a distinct period that incorporates the pandemic. The study would provide a guide for blood bank managers to improve the performance of their organizations.

Keywords Blood collection, Blood bank, Data envelopment analysis, DEA, Efficiency

Paper type Research paper

Introduction

Blood plays a key role in healthcare and is vital for saving many lives daily and globally (Williams *et al.*, 2020). More than one hundred million blood donations are collected worldwide (Drew *et al.*, 2017). In addition, blood is classified as a perishable product. However, the most important aspect of blood that distinguishes it from other perishable products is that its supply and demand are uncertain (Moslemi and Mirzazadeh, 2017). The uncertainty can cause product shortages and increase the mortality risk for patients who need blood. Furthermore, the costs of special equipment (blood storage and transport bags and boxes, etc.), personnel (doctor, phlebotomist, etc.) and technology investment (apheresis and mobile devices, etc.) to collect blood are also high. Therefore, this situation compels the blood center managers to provide effective and efficient blood service delivery.

The World Health Organization presents data and information on blood supply reported by various countries (WHO, 2022). According to 2020 figures, 106 million blood donations were

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collected from around 13,300 blood centers in 169 countries in the blood supply system. Among these, 79 countries collected more than 90% of the blood from voluntary, unpaid blood donors. 56 countries collected more than half of the blood as family/replacement or paid donors. In Turkey, the Turkish Red Crescent is responsible for the blood collection system within the scope of the "*National Safe Blood Supply Program*" in 2005 (Turkish Red Crescent, 2022a, b). Following this authorization, the Turkish Red Crescent began a rapid regional restructuring and established facilities with advanced technological infrastructure for safe blood supply (Turkish Red Crescent, 2022b). According to the Turkish Red Crescent Report (2021), there are 18 regional blood centers, 67 blood donation centers, 1,131 transfusion centers, four central laboratories and over 3,500 personnel in the Turkish blood system. The Turkish blood collection system is divided into 18 regions, and each region is coordinated by a single regional blood center. In addition, the Turkish Red Crescent collected approximately 2.5 million blood donations from about 2 million donors in 2020. The blood donation amount met 90% of the country's blood needs (Turkish Red Crescent, 2022a). The main goal of the Turkish Red Crescent is to meet all the blood needs of the country from voluntary and safe donors within a foreseeable time.

The objective of this research is to examine the regional blood collection efficiency in 18 regions of Turkey, using data envelopment analysis (DEA) for the years 2018–2021 and to discuss the managerial implications. The methodological approach to the problem has been selected as DEA since it is an effective method for measuring efficiency when the performance problem is multi-dimensional (Zhu, 2009) and blood collection fits into such a multi-dimensional structure since different types of resources (e.g. doctors, phlebotomists, mobile and permanent stations) are utilized. We aim to identify (1) which blood centers of Turkish Red Crescent operate technically efficient at regional level, (2) what are the improvement potentials, (3) which factors are affecting the efficiency at regional level and (4) if the Pandemic has an observable effect on the efficiency. DEA is capable of answering those questions by utilizing multiple input/output factors. Besides, such an analysis framework is important to provide insights for a more efficient use of resources for the Turkish Red Crescent, which currently evaluates its performance based on simple ratio analysis. A four-year time horizon is selected to especially observe the pre and post pandemic periods.

In the literature, there are few studies on the efficiency of blood banks or blood centers in terms of the collection and production phases. This gap in the literature is also emphasized in reviews and research (Beliën and Forcé, 2012; Moslemi and Mirzazadeh, 2017; Pereira, 2006). In addition, among these, the number of studies that use the DEA method to perform performance analysis is limited (Sommersguter-Reichmann and Rauner, 2015). Relying on that, the contributions of the research are threefold. First, we propose a multi-dimensional look at the performance of blood collection operations to replace simple ratio-based evaluations. Second, we discuss the findings and managerial implications with the decision-makers and present their point of view on the proposed methodology. Finally, we present the change in efficiency over a special period that involves the pandemic and discuss the effects of that unique period on blood collection in Turkey.

Materials and methods

Data envelopment analysis

DEA is a well-known method to investigate the relative efficiency of units producing multiple outputs from multiple inputs. Charnes *et al.* (1978) published the seminal work that introduced the method to the literature. Since their introduction, DEA models have been widely used in real-world healthcare organizations. For recent reviews of DEA in healthcare, the reader may refer to Kohl *et al.* (2019), Pelona *et al.* (2015) and Zakowska and Godycki-Cwirko (2020). Among different types of healthcare organizations, DEA is also utilized to measure the efficiency of blood banks or blood centers all over the world. Some of these studies evaluated the performance of the blood supply chain, while others only focused on organization-based performance evaluation. Studies focusing the efficiency of the blood supply chain provided insights into network performance (Moslemi and Mirzazadeh, 2017; Matin *et al.*, 2022) or informed performance-based network design (Haeri *et al.*, 2020; Hosseini-Motlagh *et al.*, 2020).

The studies in the organization-based evaluation domain focus on the performance measurement at the blood collection and production phase. Pitocco and Sexton (2005) investigated the efficiency of 70 blood centers in the USA using the DEA technique (both input-oriented and output-oriented). Their objective is to improve operational efficiency, increase the country's blood supply and propose strategies for these improvements. Pereira (2006) tested the effect of economies of scale on blood banking. An input-oriented DEA is implemented to calculate their scale efficiency and pure technical efficiency. His main result is that the size of the operation scale determined a decreasing effect beyond a certain size. Veihola *et al.* (2006, 2008a, b) compared European blood centers and blood banks using the DEA. Veihola *et al.* (2006) benchmarked their technical efficiency from the perspective of component preparation. In another study, Veihola *et al.* (2008a) also computed their relative efficiency concerning component preparation by including discarded components. Moreover, in Veihola *et al.* (2008b), the relative efficiency of the component production process of the blood banks was examined according to labor and cost. Laspa and Priporas (2008) evaluated the productive efficiency of blood banks in Greece. They use two benchmarking methods that are two-stage DEA and simple ratio analysis to measure the efficiency of 31 blood banks. These benchmarking approaches are compared, and it is determined that there is a high positive correlation between the results. Nielsen and Nielsen (2016) used DEA to investigate the productive efficiency of 65 community blood centers. They seek the answer to the question of how efficiency can be improved, what the financial implications are, and which operation scales are most efficient in terms of budget and personnel.

In DEA, a unit's efficiency is measured relative to all other units, with the basic axiom that all units must be on or below an efficient frontier. A linear programming model is solved for each unit in a data set to observe whether there is a way for that unit to improve its performance. Below, we provide the basic idea of modeling DEA. For further information, the reader is referred to Cooper *et al.* (2006).

Let us consider n units. We assume that each unit j for $j = 1, 2, \ldots, n$ uses m different inputs ($x_{ij}, i = 1, 2, \ldots, m$) and produces s different outputs ($y_{rj}; r = 1, 2, \ldots, s$). The original DEA model proposed by Charnes *et al.* (1978) is called the *Charnes Cooper Rhodes* (CCR) model. ϕ represents the efficiency score for unit o. Variables λ_j are introduced corresponding to each unit ($j = 1, 2, \ldots, n$). The units on the boundary (frontier) of the set are defined as efficient and attain the efficiency score of 100%, whereas the efficiency scores for others are measured relative to the frontier. The linear programming formulation to obtain the efficiency score of unit o is given below:

$$Max\, \phi \tag{1}$$

$$s.t.$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} i = 1, 2, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \phi y_{ro} r = 1, 2, \ldots, s$$

$$\lambda_j \geq 0 j = 1, 2, \ldots, n$$

The CCR model given above assumes that proportional increases or decreases in input and output values of the units are possible, and that the operating scale of a unit does not affect its efficiency. Therefore, it is labeled as Constant Returns-to-Scale (CRS) formulation. The CCR approach is modified by Banker *et al.* (1984) as BCC (*Banker Charnes Cooper*) model, which assumes variable returns-to-scale (VRS). The model can be modified into Variable Returns-to-Scale (VRS) form by omitting the proportionality assumption and simply adding the constraint in (2) to the model in (1).

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2}$$

In DEA modeling, the discussion of the returns-to-scale specifications is highly related to the size of the operations undertaken by the decision making units (DMUs). BCC models, assuming variable returns-to-scale, are developed to handle problems where proportionality is not applicable and to discriminate between technical and scale efficiencies. BCC models eliminate the impact of the operation's size on efficiency and provide a measure of pure technical efficiency. The outcomes of the BCC and CCR DEA models can be interpreted as different forms of efficiency. Technical efficiency is defined as "the degree to which a unit produces the maximum feasible output from a given bundle of inputs or uses the smallest feasible amount of inputs to produce a given level of output," according to Farrell (1957). Technical efficiency is further broken down into two parts: *Pure Technical Efficiency* and *Scale Efficiency*. Technical efficiency refers to the CCR score. The BCC score, on the other hand, is referred to as *Pure Technical Efficiency* because the scale effects are removed. A unit is said to be operating at the *Most Productive Scale Size* if it is 100% efficient in both the CCR and BCC models. If a unit has full BCC efficiency and a lower CCR score, then it is operating efficiently locally but not globally due to the scale size of the unit. The ratio of the two scores is characterized as the *Scale Efficiency* (Cooper *et al.*, 2006).

The objective function of the DEA models can be formulated in two ways: output-oriented (maximization) and input-oriented (minimization). In output orientation, a unit is not efficient in the given technology if it is possible to augment any output without increasing any input and without decreasing any other output. In the input orientation, a unit is not efficient if it is possible to decrease any input without augmenting any other input and without decreasing any output (Charnes *et al.*, 1981). The formulation in (1) presents the output orientation.

DEA is also be used to find benchmark units for inefficient units. Benchmark units are typically referred to as reference sets for inefficient DMUs because they can be identified by optimal λ values. The units on the frontier that are radially closest to the evaluated inefficient unit are the reference (or benchmark) units. The inefficient unit can improve its efficiency by adopting practices from the benchmark units.

Data

This research aims to assess the blood collection efficiency of the regions in Turkey between 2018 and 2021 using DEA. There are 18 regions managed by the Turkish Red Crescent (a.k.a. Kızılay), which is the leading blood institution in Turkey. The blood collection centers (one in each region) are responsible for pursuing the collection and distribution operations of blood throughout the country. The data set for each blood collection center has been acquired from the Turkish Red Crescent for the given years.

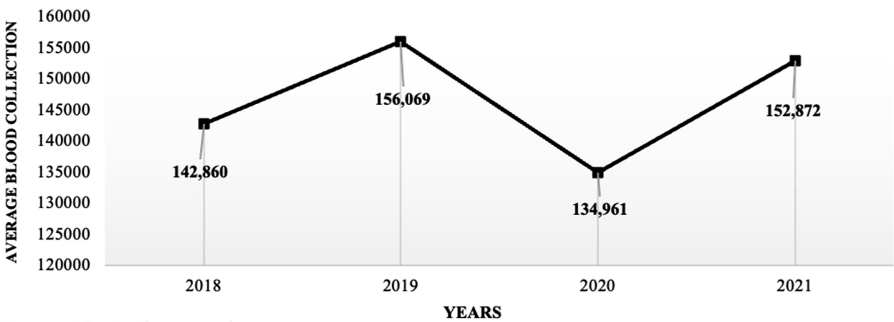
In the model design, to evaluate the efficiency of the regions operating all around Turkey, the input and output factors are identified in line with the related literature (Laspa and Priporas, 2008; Nielsen and Nielsen, 2016; Pereira, 2006; Pitocco and Sexton, 2005) and the opinions of decision-makers/managers from the Turkish Red Crescent. The descriptive statistics of the data are provided as a supplement to this study. The DEA model consists of a single output, which is the blood collection measured in blood units (1 unit = 500 mL of blood). The change in collected blood over time is given in Figure 1. The collection amount has an upward trend from 2018 to 2019. In 2020, we observe a severe decline, which can be tied to the pandemic. Following 2020 a rise in collected blood is observed.

For setting up our DEA model and assessing the efficiency of centers, we use five input variables in our DEA model. The variables of the model are listed in Table 1. The first two inputs are associated with personnel (doctors and phlebotomists) permanently employed in the regions. The third and fourth input variables are related to the number of stations where the blood is collected. There are two types of stations: mobile and permanent. The regions vary in the number of mobile and permanent stations. Mobile stations consist of buses, trucks and platforms that are operated in various locations in a given area. Permanent stations consist of blood collection buildings. The final input is the service population of the area within the region bounded. On the output side, the model consists of a single output that is the total blood collection (blood units) in the given year.

Utilizing 5 input variables and an output variable for 18 regions, DEA models have been developed in Microsoft Excel and solved using the Solver Add-in for each region. For coding the repetitive computations, the *Visual Basic Applications (VBA)* feature of Microsoft Excel is utilized. The Excel file for the analysis is included as a supplement to this study.

Results

The output-oriented CRS DEA (also known as CCR DEA) model is utilized to obtain the efficiency scores of 18 regions for each year between 2018 and 2021. The efficiency scores are presented in Table 2, in which the efficient units are highlighted in italic. We observed that the



Source(s): Authors work

Figure 1. Changes in average blood collection over time

Inputs	
1	Number of doctors
2	Number of phlebotomists
3	Total number of mobile stations
4	Total number of permanent stations
5	Service population
Output	
1	Total blood collection

Source(s): Authors work

Table 1. Input and output factors

	2018	2019	2020	2021
Region 1	0.766	0.774	0.767	0.878
Region 2	0.888	0.880	0.811	0.831
Region 3	0.896	0.888	0.866	0.899
Region 4	0.843	0.872	0.980	0.947
Region 5	0.853	0.786	0.820	0.862
Region 6	*1.000*	*1.000*	*1.000*	*1.000*
Region 7	*1.000*	*1.000*	*1.000*	0.975
Region 8	*1.000*	*1.000*	*1.000*	*1.000*
Region 9	*1.000*	*1.000*	*1.000*	*1.000*
Region 10	0.656	0.797	0.997	0.741
Region 11	0.970	0.855	0.705	0.844
Region 12	0.698	0.704	0.836	0.722
Region 13	0.766	0.754	0.732	0.758
Region 14	0.884	0.864	0.818	0.994
Region 15	0.799	0.838	0.766	0.795
Region 16	0.883	*1.000*	*1.000*	*1.000*
Region 17	*1.000*	*1.000*	*1.000*	*1.000*
Region 18	*1.000*	*1.000*	0.939	0.922

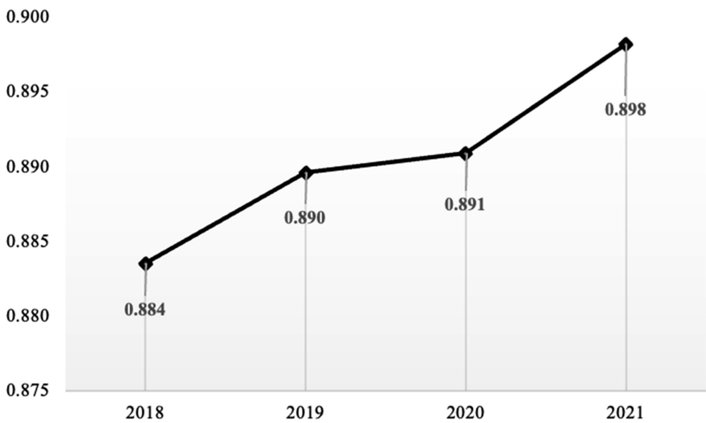
Source(s): Authors work

Table 2.
Technical efficiency scores of regions by years

efficient regions over the years did not substantially change. Regions 6, 8, 9 and 17 are consistently efficient over a four-year period.

When assigning the efficiency scores, the DEA model presented in (1) considers the distance to an efficient frontier and looks at the improvement potentials of the unit. If a unit is on the frontier, then there is no room for improvement (i.e. increasing the output) and thus, the efficiency score is 1. For inefficient units, in an output-oriented setting, the model gives us how much a unit is underperforming in terms of its outputs. An efficiency score of 0.766 means that the unit is relatively producing 76.6% of its relative potential in terms of output.

The average efficiencies are quite high over the years. In terms of average efficiency scores, an upward trend is observed, as given in Figure 2. When Figures 1 and 2 are evaluated



Source(s): Authors work

Figure 2.
Average efficiency over time

together, the results reveal that although the average blood collection decreases in 2020, the reflection of this decrease in average efficiency is trivial. The average efficiency scores in 2019 and 2020 have only a 0.001 difference.

As discussed in the previous section, the outcomes of the BCC and CCR DEA models can be interpreted as different forms of efficiency. The CCR scores presented in Table 2 refer to technical efficiency. There also exists BCC DEA modeling where the scale effects are removed. The *Scale Efficiency* of a unit is characterized by the ratio of the two scores and shows us how the efficiency of a unit is affected by its scale. To observe the scale efficiency scores, BCC DEA models are also utilized in our data set, and scale efficiency scores are obtained by dividing CCR scores and BCC scores. The scale efficiency scores are presented in Table 3. The high average scale efficiency scores (which are 0.954, 0.947, 0.949 and 0.945 for the years 2018–2021, respectively) indicate that the technical efficiency (CCR) and pure technical efficiency (BCC) scores are close to each other to a large extent, and the inefficiencies do not much rely on the operating scale of the units.

In addition, DEA can also provide the target values for the output that will make a unit relatively efficient in a given year. For this purpose, we analyze the model for 2021 (the most recent year) to observe the output targets for inefficient regions. Table 4 presents the target blood collection amounts measured by in blood units (1 unit = 500 mL of blood) for inefficient regions compared to the collected amount in 2021. With the help of DEA, the objectives of a region can be set effectively.

As mentioned, the model presented in (1) measures efficiency as relative distance to the efficient frontier. As for all linear programming models, DEA models also have dual formulations which focus on obtaining an optimal weight mix for inputs and outputs that will maximize the output/input ratio of a given unit. Known as multiplier models, these models produce the optimal weight structure of the units in identifying if they are efficient or not. In DEA applications, input (or output) weights obtained from multiplier models are also useful for determining the dominant factors underlying the efficiencies or inefficiencies. To obtain the input weights, we utilize the multiplier form of the CCR DEA model and obtain the weights for input factors. The average weights are presented in Table 5. According to the

	2018	2019	2020	2021
Region 1	0.894	0.880	0.844	0.937
Region 2	0.916	0.996	0.914	0.906
Region 3	0.989	0.993	0.978	0.998
Region 4	0.992	0.991	0.989	0.963
Region 5	0.999	0.950	0.991	0.946
Region 6	*1.000*	*1.000*	*1.000*	*1.000*
Region 7	*1.000*	*1.000*	*1.000*	0.975
Region 8	*1.000*	*1.000*	*1.000*	*1.000*
Region 9	*1.000*	*1.000*	*1.000*	*1.000*
Region 10	0.859	0.797	0.997	0.741
Region 11	0.970	0.855	0.705	0.844
Region 12	0.698	0.704	0.836	0.722
Region 13	0.987	0.961	0.957	*1.000*
Region 14	0.983	0.927	0.943	0.994
Region 15	0.998	0.995	0.950	0.996
Region 16	0.883	*1.000*	*1.000*	*1.000*
Region 17	*1.000*	*1.000*	*1.000*	*1.000*
Region 18	*1.000*	*1.000*	0.974	0.993
Average	0.954	0.947	0.949	0.945

Source(s): Authors work

Table 3. Scale efficiency scores of regions by years

	Collection (blood units)	Target (blood units)
Region 1	307,788	350,690
Region 2	76,487	92,087
Region 3	125,796	139,980
Region 4	190,681	201,275
Region 5	155,193	180,085
Region 7	126,456	129,715
Region 10	81,606	110,155
Region 11	62,828	74,423
Region 12	50,148	69,441
Region 13	139,322	183,813
Region 14	77,519	77,956
Region 15	103,966	130,715
Region 18	92,822	100,662

Source(s): Authors work

Table 4.
Efficient targets for inefficient units in 2021

Input factor	Average weight
Number of doctors	0.0256
Number of phlebotomists	0.1188
Total Number of mobile stations	0.0129
Total Number of permanent stations	0.0621
Service population	0.7806

Source(s): Authors work

Table 5.
Average weight values for input factors

table, the average weights are 0.0256 (number of doctors), 0.1188 (number of phlebotomists), 0.0129 (total number of mobile stations), 0.0621 (total number of permanent stations), and 0.7806 (service population). The results reveal that the most dominant factor in measuring the efficiencies of the regions is the service population by far.

Discussion

In this research, we investigate the blood collection efficiency of regions in Turkey between 2018 and 2021. We utilize the DEA methodology to obtain technical and scale efficiency scores as well as the optimal weights that explain efficiency. We present DEA as an effective tool for measuring blood collection efficiency with several implications.

First of all, we observe that the efficient regions do not fluctuate significantly over time, with four regions remaining consistently efficient over a four-year period. Secondly, even though the COVID-19 pandemic in 2020 had an impact on blood collection volumes, no considerable change in average efficiency scores from the prior year (2019) is observed. This might be related to the downsizing of the operations, such as reducing the number of mobile stations during the pandemic. In other words, fewer stations and personnel, i.e. resources, are utilized because of the shutdown. Therefore, even with lower output levels attained (collected blood), the output/input ratios of the centers are not significantly affected, resulting in a stable level of average efficiency score. Furthermore, by observing the scale efficiency scores obtained, we identify that the inefficiencies do not much rely on the operating scale of the units. Therefore, it can be said that to increase the blood collection efficiency, changes can be focused more on the operations rather than increasing or decreasing the scale size (i.e. changing the values of inputs). Another important implication obtained from the analysis is that the service population is by far the most important variable in determining the efficiency of the regions.

Our results reveal that the ratio of efficient regions (or centers) vary between 27% and 38% with a quite high average scores around 89% in the CCR model assuming CRS. Regarding the average performance, the numbers are higher as of Greek blood banks evaluated by Laspa and Priporas (2008), who report the average efficiency as 0.725 and 16% of the centers as efficient via CCR model. On the other hand, when compared to the study by Pitocco and Sexton (2005) in US blood banks, the number of efficient centers over the years is lower in Turkey since they have reported that nearly 50% of the centers in the US are efficient under CCR model. Naturally, the rates of efficient organizations would differ between the operations of countries since different socio-economic conditions, rules or regulations apply.

In dealing with real-world problems, it is important to report the implications to the decision-makers for policy-making purposes. Relying on that, the methodology and results of the study were discussed with two decision-makers/managers of the General Directorate of Blood Services in the Turkish Red Crescent. One of the managers has a background in accounting and financial management. The other is in charge of blood service inventory management. Besides, the discussions were completed in three rounds. Managerial reactions to the DEA implementation and results were classified under the six titles: (1) informing decision-makers on DEA, (2) validity of the DEA methodology, (3) determination of the inputs and outputs, (4) comparison of DEA and Turkish Red Crescent performance measurement systems results, (5) possible implementation of the DEA results, (6) the effects of the COVID-19 pandemic on DEA results. Below, we discuss these titles.

Regarding *decision-makers*, two managers have limited information on DEA. We informed them about the DEA methodology and results. They assured the researchers that DEA yielded useful information and objective results for the efficiency assessment of the regions.

When *DEA methodology* was explained, the managers expressed that the Turkish Red Crescent uses performance measurement systems based on simple ratio analyses. Besides, they emphasized that DEA could use as a supporting tool for efficiency assessment and accept the validity as a performance measurement tool. However, they specified that DEA cannot be treated as a substitute for the currently used performance measurement systems. Accordingly, it is sensible to utilize two systems together.

As far as the efficiency of blood centers is concerned, it is seen that different *inputs and outputs* are used in the related literature. Decision-makers' views were elicited through in-depth interviews and discussions on the inputs and outputs, and the interviews were completed in three rounds. As a result, they validated that the model has 5 inputs and 1 output, with population being the most important input.

The results of DEA have been *compared* to the current Turkish Red Crescent performance measurement system results. Currently, the institution utilizes performance measurement systems based on simple ratio analyses, such as the amount of collected blood per doctor and personnel, the amount of collected blood per population and the amount of collected blood by year. The managers were convicted of DEA results. They expressed that their DEA relative performance levels (excluding region 3) are compatible with their expectations and currently used systems. DEA results provided new insights on how to increase the amount of collected blood as an output in the DEA model.

Regarding the *implementation*, managers maintained that they were willing to implement DEA results and DEA results could have an influence on the decision-making process and allocation of resources/inputs. For example; when the efficiency scores are calculated for the relevant year, managers will not allocate in the following year excess resources for inputs such as personnel, or budget for inefficient units.

The effects of the COVID-19 pandemic were also discussed with the management. As also indicated by the data, the amount of collected blood decreased due to the COVID-19 pandemic shutdown in 2020. However, the average efficiency scores of the regions remained stable in 2020. Furthermore, with loosening of the pandemic shutdown implementations in 2021, both the amount of blood collected and the efficiency scores increased.

The research is not without its limitations. First of all, the original values of the budget variable could not be considered as an input variable since the provided values by the Turkish Red Crescent were censored with a 100% correlation with the collected blood. Another limitation is associated with the nature of the dataset. The dataset analyzed during the current research is not publicly available due to confidential institutional data. The officials of the Turkish Red Crescent provided the data set with the Region names coded with an ID. Therefore, it is not possible for us to list the actual names of the regions and accordingly it is not possible to associate efficiency by discussing the socio-economic conditions of the regions.

Conclusion

Providing patients with safe blood is a demanding task. Blood supply and demand are unpredictable, putting the patient's life at risk if the need is not satisfied. Only by properly regulating the blood supply system can this challenge be met. Considering the importance of blood collection, in this research, we evaluate the blood collection efficiency level of the regions operated by the Turkish Red Crescent (a.k.a. Kızılay) in Turkey between 2018 and 2021 using DEA. We observe that the efficient regions do not fluctuate significantly over time, with four regions remaining consistently efficient over a four-year period. Furthermore, the findings show that although the COVID-19 pandemic in 2020 affected the blood collection amounts, no major change in efficiency scores is observed in terms of average efficiency scores from the previous year (2019). The results are presented to the managers of the Turkish Red Crescent's General Directorate of Blood Services, and the findings are compatible with their expectations and currently used systems. In conclusion, the proposed DEA model has proven to be an effective tool to assess the efficiency of blood collection.

To expand upon these findings, future research could assess the performance of blood collection operations involving further processing of the blood, which separates it into transfusable components.

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Supplementary material

The supplementary material for this article can be found online.

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