Performance Assessment of Medical Diagnostic Laboratories: A Network DEA Approach

Short running title

Performance evaluation medical diagnostic laboratories

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Abstract

Rationale, aims and objectives

The main purpose of this paper is to measure the efficiency and ranking of medical diagnostic laboratories by applying a Network Data Envelopment Analysis.

Methods

In this study, each medical diagnostic laboratory is considered as a decision making unit (DMU) and a network data envelopment analysis (NDEA) model is utilized to calculate the efficiency of each medical diagnostic laboratory. Therefore, we design a series four-stage system composed of three main laboratory processes (the pre-test process, the test process and the post-test process). We also consider sustainability criteria in order to cover social, economic, and environmental problems of health care organizations.

Results

The results show that three of the 22 considered laboratories are efficient. Therefore, the network DEA approach can lead to performance scores and ultimately real ranking. Also, the average efficiency scores show that the decrease of the reception unit's efficiency results in a decrease of the efficiency of each laboratory. Therefore, the laboratories can increase the number of patients. Along with the intermediate values of the reception unit and the sampling unit, the efficiency of the reception unit increases, which results in an increase for the overall efficiency of each laboratory.

Conclusion

The proposed model can appropriately help the administrators and managers to identify inefficient units in their laboratory and ultimately improve the laboratory performance.

Keywords: Network Data Envelopment Analysis, Sustainability, Medical Diagnostic Laboratory, Performance assessment.

1. Introduction

Assessment of efficiency and profitability of laboratories plays a vital role in their selection as a member of the laboratories network. Theses efficiency results help managers make decision as to whether to keep or discard a member within the network. Obviously, we need appropriate tools for such an analysis of efficiency of medical prognosis labs [1]. Methods for measuring efficiency fall into two categories: parametric and non-parametric. Parametric methods are more difficult to use, due to the design of the production function and complicated mathematical formulas. At the level of non-parametric patterns, there are several methods for measuring efficiency. Data envelopment analysis (DEA) is a popular non-parametric linear programming approach which was first introduced by Charnes et al. [2].

The many advantages of DEA have led to the fact that DEA is often preferred to other methods of measuring efficiency. There are several advantages of DEA. First, DEA can be modified to accommodate the use of several inputs and outputs. Second, by determining the potential sources of inefficiency, rather than only the levels of inefficiency, DEA method is able to decompose economic inefficiency into technical and allocative components. Third, DEA not only pinpoints the problem, but is also capable of offering possible solutions. Having recognized the levels of inefficiency, the algorithm can be used to find similar organizations that suffer from the same kind of drawback and those that are efficient in comparison [3].

DEA approach has been developed by many researchers and it has been widely applied to identify sources of inefficiency, rank the DMUs, assess management and the effectiveness of program or policies, etc [4]. During the past decade, DEA has made significant advances both in the methodology and application, which has made it an important managerial tool for evaluating the performance of systems. The traditional DEA models disregard the internal operations or structure of the DMUs, typically referring each DMU as a "black box" with single-process converting the multiple inputs to the multiple final outputs. These approaches lead to incorrect performance scores or misleading results for system with complex internal structure [5]. The defects of traditional DEA models have led many former researchers to decompose the efficiency of DMUs into different ingredients. Network DEA considers the structure of DMUs as a system consisting of a network of sub-DMUs, which has intermediate measures.

During the past two decades, the healthcare sector has generally made significant progress in the area of health care operations. Improving health levels is not only a moral duty, but also a social and economic issue [6]. In recent years, health status has improved in most countries, taking into account sustainability criteria (economic, social, and environmental). Therefore, the need for services is based on the principles of sustainable development in order to achieve the appropriate service. The healthcare system as one of the largest fields in the public service sector has a suitable opportunity to influence sustainable performance. There are three reasons to consider sustainable performance by the health care systems: 1) In general, the healthcare system provides more services than other service sectors. 2) Health care services produce a significant amount of infectious waste. 3) The health system has a social effect on its own society [7]. In addition, the main goal of producing a sustainable service in health care sector is to minimize undesirable factors (such as reducing environmental impacts) in the service production process. Environmental effects, as undesirable factors in the health care systems, may be in the form of infectious waste. The DEA models, by considering undesirable factors, have managed to eliminate the problem of eliminating undesirable factors in the calculation of performance evaluation.

Here we briefly review the most prominent DEA studies in the literature. A review of related literature shows that a significant number of studies have attempted to evaluate performance in areas related to health care. For example, Audibert et al. [8] examined the performance of 24 urban hospitals in Weifang (Shandong) from 2000 to 2008 by using DEA approach. Leleu et al. [9] used the DEA method to measure inefficiency at 138 Florida hospitals in 2005. Popescu et al. [10] evaluated the efficiency of European health systems by applying DEA approach. Asandului et al.[11] studied the performance evaluation of public health systems in Europe based on a nonparametric DEA method and the statistical data applied was for the 30 European countries in 2010. Campos et al. [12] applied the input-oriented DEA approach to examine the efficiency of health systems in Spain (Autonomous Communities). Johannessen et al. [13] examined the effectiveness of full-time physicians (FTE) in 19 Norwegian hospitals from 2001 to 2013 hospitals using some Panel Analysis and DEA. Khushalani and Ozcan [14] calculated performance evaluation of United States hospital from 2009 to 2013 by using the Dynamic Network DEA method. Omrani et al. [15] used the combined DEA model and cooperative game approach to measure productivity and efficiency of 288 hospitals in 31 provinces of Iran. Şahin and İlgün [16] evaluated the oral and dental centers of located in 81 provinces of Turkey by using DEA method. Peykani et al.[17] proposed the Fuzzy DEA approach to examine a real data set to measure efficiency of 38 hospitals in United States. Further literature review of health care performance by using the DEA approach is provided in the Appendix A for readers.

Further review of the literature in the table A (in the appendix A) shows that measuring the performance of the healthcare facilities based on desirable and undesirable sustainability indicators has not been addressed in the studies. Also, the issue of uncertainty in the data of healthcare centers is not studied in the previous researches. In order to fill the gap of the literature, this paper proposes a network DEA (NDEA) model to measure the efficiency of the medical diagnostic laboratories. To this end, the required sustainability indicators, including economic, environmental, and social indicators, are defined for evaluating the efficiency of diagnostic laboratories. Also undesirable factors are considered in the developed NDEA model. The proposed NDEA model calculates the score of each lab and provides reliable information regarding quality of laboratories. The Additive method of Chen et al. [18] is applied to evaluate the performance of laboratories in a real case study in Iran.

The research continues as follows. Section 2, describes the research methodology including the Delphi method and the NDEA model. Section 3, introduces the case study, which considers 25 medical diagnostic laboratories of Tehran province in Iran. The results of the case study are presented and analyzed in Section 4. Finally, discussion is provided in Section 5.

2. Methodology

This research proposed a NDEA model in a four-stage network that consists of three main laboratory processes (pre-testing, testing and post-test), which is unprecedented in the field of health care thus far. Also due to the importance of undesirable inputs and outputs in healthcare sectors, in the proposed model undesirable data is considered. Then, a real case study of diagnostic laboratories in Iran is given to demonstrate the effectiveness of the model. The benefits of the proposed approach show that efficiency scores can help administrators manage their deficiencies and ultimately improve their business.

2.1 Fuzzy Delphi

Delphi technique is a strong process based on the group communication structure used for cases where incomplete and uncertain knowledge is available [19]. The main aim is to reach a consensus among experts [20]. In the classical Delphi method, experts' opinions are expressed in the structure of definite numbers, while those who are experts are using their mental competencies to express their opinion, which indicates the uncertainty that governs these conditions. Uncertainty is compatible with fuzzy sets. Therefore, it is better to obtain data in the structure of the verbal variables from the experts and analyze those using fuzzy sets.

2.2 NDEA Model description

Data Envelopment Analysis (DEA) is a non-parametric method for the relative assessment of a set of homogenous decision-making units. This method has wide applications in managerial assessment and recognizing inefficient units. Traditional DEA models cannot provide accurate information about the inefficiency of various units. This problem has been solved by network DEA models in real world. In this research, the internal structure of each lab consists of three stages (pre-test, test, and post-test). Assume that there are n DMUs (in this paper the DMUs are labs). Assume that each DMU_j(j=1,2,…,n) uses m inputs $x_{ij}(i = 1,2, … . , m)$ and produces s outputs $y_{rj}(j = 1,2, … , s)$. The inputs have unequal shares in producing the outputs. Technically, their impact coefficients are not the same. Charnes and Cooper [21] managed to solve the problem of coefficients. They improved the model of Farrell [22] and Fieldhouse and suggested a model that could measure efficiency with several inputs and outputs. This is known as the CCR model.

Consider an impact coefficient (weight) $v_i(i = 1,2, \ldots, m)$ for each input $x_{ij}(i = 1,2, \ldots, m)$ and an impact coefficient (weight) $w_i(i = 1,2, \ldots, m)$ for each output $y_{rj}(j = 1,2, \ldots, s)$. We can calculate the efficiency of each DMU using Model 1.

$$\text{Efficiency of } \boldsymbol{DMU_o} = \frac{\textit{sum weighted outputs of } DMU_o}{\textit{sum weighted inputs of } DMU_o} \quad (1)$$

$$\text{Subject to:} \quad \frac{\textit{sum weighted outputs of } DMU_j}{\textit{sum weighted inputs of } DMU_j} \leq \mathbf{1} \qquad \boldsymbol{j = 1, 2, \ldots, n}$$

$$\boldsymbol{v_i \geq 0} \quad , \quad \boldsymbol{u_r \geq 0} \qquad \boldsymbol{i = 1, 2, \ldots, m \; ; \; j = 1, 2, \ldots, s}$$

The proposed model for performance assessment of labs is an integral network data envelopment model, which was firstly suggested by Chen et al. [23]. This model is enunciated in the Appendix for interested readers.

3. Case study

The diversity and breadth of specialized laboratories in the province of Tehran has led to increased activity in this area. According to statistics released by the Iranian Health Institution, most of the labs in Tehran are managed by the private sector. Considering the importance of the private sector, the statistical population of this study consists of 25 private medical diagnostic laboratories in Tehran province.

First, in order to measure the performance of 25 laboratories, effective factors are obtained using the Fuzzy Delphi method.

In the present study, the following criteria have been considered for the selection of experts: (1) sufficient knowledge and experience in the field of study; (2) the willingness and time to cooperate in research; (3) effective communication skills. In order to reach a suitable team, experts with field-related records that are knowledgeable in the field were invited. Thus, 11 experienced experts in the field were selected. The members of the Delphi team are shown in Table 1.

Table1. Delphi Working Group

Row	Group		The amount of work experience
1	Professors of University of Medical Sciences and Laboratory Sciences		20 years
2	Organizational and executive forces	Technical authorities	25 years
3		Laboratory Experts	15 years

After selecting experts, a questionnaire was prepared relying on previous studies and available literature. In this way, we used two methods of documentation and observation to obtain the most important indicators in the laboratory area and to collect the indicators. Effective indexes after review by library studies and observation of the presence in laboratories are shown in Table 2.

Table2. Effective indicators in the evaluation of the performance of the diagnostic laboratories (extracted through documentation and observation)

Row	Indicator	Documentation						Observation
		Checklist of quality assessment of labs (Health Reference Lab)	Articles					
			Leleu et al. [9]	Asandului et al. [11]	Hamid Abu Bakar and Lukman Hakim [24]	Yousefi et al. [25]	Patra and Ray [26]	
1	Sum of the scores of the laboratory standards	✓						
2	Garbage weight	✓				✓		
3	Average sample transfer time	✓			✓			
4	Number of patients		✓	✓			✓	
5	Number of active tests							✓
6	Correct number of tests	✓						✓
7	Test response time							✓
8	Number of false tests	✓						✓
9	Available space for service	✓						
10	Average waiting time for sampling	✓						✓
11	Cost of consumables					✓		
12	Staff wage	✓						
13	Number of responses of the prepared tests	✓						
14	Safety cost of test unit	✓				✓		
15	Number of kits							✓
16	Safety cost of sampling unit	✓				✓		
17	Lab profit							✓
18	Income from admission	✓						
19	Cost of laboratory space and land value	✓						
20	Number of samples	✓						✓
21	Cost of staff welfare							✓

The research questionnaire was designed with the aim of consulting the experts about their agreement with the model criteria. Thus, experts have expressed their consent through verbal variables such as very low, low, moderate, high and very high. Since different characteristics of individuals affect their mental representations of qualitative variables, so by defining the range of qualitative variables, experts respond to the questions with the same mindset. These variables are defined in the form of triangular fuzzy numbers according to Table 3.

Table3. Triangular fuzzy numbers of Linguistic variables

Linguistic variables	Triangular fuzzy number
Very High	(0.75, 1, 1)
High	(0.5, 0.75, 1)
Medium	(0.25, 0.5, 0.75)
Low	(0, 0.25, 0.5)
Very Low	(0, 0, 0.25)

After three rounds of expert opinion polls, the following results were obtained. The total criteria for standardization of laboratories, the average time of sample transfer to different departments for testing, the weight of the waste, the number of laboratory tests, the number of false tests, the number of samples, the space available for service, the number of kits, the average time of waiting to take the sample, personnel wages, average test response time, income, cost of consumables, safety costs of testing unit, and safety costs of sampling unit all lie in the high to very high range.

Other criteria including the number of patients admitted, the number of correct tests, the number of replies to the prepared tests, and lab profits lie in the medium to high range.

By eliminating the two criteria "laboratory space and land value and personnel welfare costs", of the 21 effective criteria of diagnostic laboratories, in the three stages of the survey, 19 effective criteria were identified in the area of diagnostic laboratories. Table 4 illustrates the final effective criteria for evaluating the performance of the diagnostic laboratories by the Delphi method.

Table4. Effective indicators for assessing the performance of medical diagnostic laboratories

Row	Indicator
1	Sum of the scores of the laboratory standards
2	Garbage weight
3	Average sample transfer time
4	Number of patients
5	Number of active tests
6	Correct number of tests
7	Number of false tests
8	Available space for service
9	Staff wage
10	Number of kits
11	Income from admission
12	Cost of consumables
13	Safety cost of test unit
14	Safety cost of sampling unit
15	Average waiting time for sampling
16	Test response time
17	responses of the prepared tests
18	Lab profit
19	Number of samples

After identifying effective criteria in evaluating the performance of laboratory units, the performance evaluation of 25 units of laboratory will be possible using the network Data Envelopment Analysis model described in the research methodology section. An overview of the four-stage network structure of a medical diagnostic laboratory is given in Fig. 1.

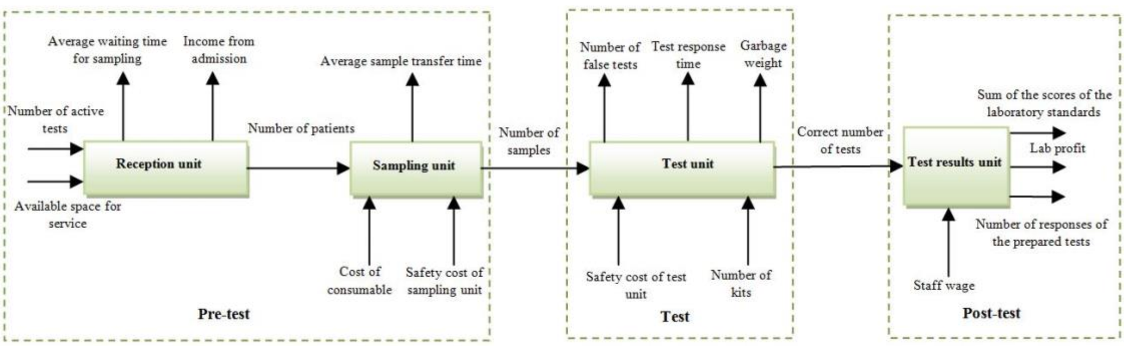

Figure 1 The four stage network of a medical diagnostic laboratory

Figure 1 shows that the pre-test process consists of two stages: the reception unit and the sampling unit. The pre-test includes inputs like the number of active tests and the cost of consumables and outputs like the average waiting time for sampling and the average sample transfer time. The testing process consists of a stage called the test unit. The testing includes inputs like the safety cost of test unit and outputs like the number of the number of false tests. The post-test process involves a stage defined the test results unit. The post-test includes inputs like the staff wage and outputs like the number of responses of the prepared tests.

The input, intermediary, and output variables are according to Table 5:

Table 5. The notation of input variables, Intermediary variables and output variables

Input variables	Intermediate variables	Output variables
Number of active tests	Number of patients	Average waiting time for sampling
Available pace for service	Number of samples	Income from admission (economic criterion)
Cost of consumables (economic criterion)	Correct number of tests	Average sample transfer time
Safety cost of sampling unit (social criterion)		Number of false tests
Safety cost of test unit (social criterion)		Test response time
Number of kits		Garbage weight (environmental criterion)
Staff wage (economic criterion)		Number of responses of the prepared tests
		Sum of the scores of the laboratory standards
		Lab profit (economic criterion)

The number of active tests shows how many test each lab can perform (it's just a number and therefore, dimensionless). The available pace for service shows the area of each lab (in units of square meters). The cost of consumables shows the cost of purchasing lab items such as gloves and syringes (in units of the Iranian currency, million Toomans). The safety cost of sampling unit shows the safety costs for lab staff such as vaccination against diseases like Hepatitis (in units of the Iranian currency, million Toomans). The safety cost of test unit shows safety costs of the test unit, such as acid-washing equipment, etc. (in units of the Iranian currency, million Toomans). The number of kits shows the number of used kits (dimensionless). The Staff wage shows costs for personnel salaries (in units of the Iranian currency, million Toomans). The number of patients shows the number of patients who visit a laboratory. The number of samples shows the number of samples taken and tested at each lab. The Correct number of tests shows the number of tests that were conducted and processed on good samples with acceptable results (dimensionless). The Average waiting time for sampling shows the average time that patients have to wait for sampling (in units of minutes). The Income from admission shows profit of the lab from receiving patients (in units of the Iranian currency, million Toomans). The average sample transfer time shows the average time to takes samples from the sampling to the test unit (in units of minutes). The number of false tests shows the number of invalid tests as a result of mistakes and errors which lead to incorrect results and should be repeated (dimensionless). The test response time shows the time taken for the test (in units of minutes). The garbage weight shows lab wastes (in units of kilograms). The number of responses of the prepared tests shows the time to prepare the results of the test (in units of minutes). The sum of the scores of the laboratory standards shows the sum of the marks that make up a standard mark for the lab which include physical standards (staff, equipment, and material standards), safety standards, standards regarding procedures (pre-test, test, and post-test). It should be noted that a maximum standard mark of 200 is achievable. The Lab profit variable shows the net profit of each laboratory (in units of Iranian currency, million Toomans).

Mean, standard deviation, minimum and maximum value of the selected inputs, intermediates and outputs used for the DEA analysis are shown in Table 6.

Table 6.The descriptive statistics of inputs, intermediates and outputs for medical diagnostic laboratories Tehran

Variable	Mean	Standard deviation	Min.	Max.
Inputs				
Number of active tests	337.917	146.220	140	600
Available pace for service	182.083	20.368	130	230
Cost of consumables	22452976.542	9777839.824	3025208	39873519
Safety cost of sampling unit	4646364.125	2041293.007	600315	7892857
Safety cost of test unit	11240072.792	5386998.900	1500788	19732143
Number of kits	208250	60213.569	100000	300000
Staff wage	65655000	45178699.194	2500000	145000000
Intermediates				
Number of patients	4232.833	2403.871	345	8973
Number of samples	8821.208	5296.096	524	18557
Correct number of tests	40293.500	17874.146	5201	69021
Output				
Average waiting time for sampling	15.083	3.999	7	26
Income from admission	461077970.542	201347110.365	60031530	786895417
Average sample transfer time	64.375	57.603	15	240
Number of false tests	47.125	51.829	7	214
Test response time	2032.500	2784.353	120.000	10080.000
Garbage weight	200.708	73.906	106	406
Number of responses of the prepared tests	4225.333	2413.707	345	8973
Sum of the scores of the laboratory standards	142.208	39.091	85	200
Lab profit	262491055.333	133483579.856	33905219	453500152

4. Results

Total efficiency, the efficiency of the acceptance unit, sampling unit and test unit & response unit are calculated using the proposed model by Chen et al. [15].

Table7. Comparison of total efficiency and efficiency of procedures for the 25 diagnostic laboratories in 2017

Labs	θ^{overall}	$\theta^{Reception\ unit}$	$\theta^{Sampling\ unit}$	$\theta^{Test\ unt}$	$\theta^{Test\ results\ unit}$
1	1	1	1	1	1
2	0.97234	1	0.9688	1	1
3	0.98893	0.92946	0.99897	1	1
4	0.89504	0.60327	0.99225	1	0.77828
5	0.97477	1	0.97262	1	1
6	0.96481	0.84208	0.983	1	1
7	0.97645	1	0.96708	1	0.88521
8	0.88254	0.82436	1	1	0.43085
9	0.84256	0.78999	0.97372	0.95972	0.67428
10	0.95112	0.47685	0.98857	1	1
11	0.98685	1	0.98556	1	1
12	0.87816	0.36721	1	1	0.61602
13	1	1	1	1	1
14	0.75497	0.69479	0.41786	1	0.80414
15	0.94776	0.71404	1	1	1
16	0.93421	1	0.59132	1	1
17	0.87509	0.70468	0.8758	1	0.96793
18	0.88459	1	1	0.83269	1
19	0.85575	1	0.75849	0.94397	0.89907
20	0.84001	0.39585	0.98465	0.95417	1
21	0.94142	0.30361	1	1	1
22	0.9948	1	1	1	1
23	0.8834	0.88076	1	0.68722	0.65757
24	1	1	1	1	1
25	0.96951	0.6088	1	1	1

The second column of the Table 7 shows the overall performance of the medical diagnostic laboratory units. We have identified efficient units in gray. The results show that three units are efficient and 22 units are inefficient. Also, the average efficiency of the reception unit, the sampling unit, the test unit and the results test unit are 0.80, 0.93, 0.97 and 0.90, respectively. The average efficiency scores show that the decrease of the reception unit's efficiency results in a decrease of the efficiency of each laboratory. Therefore, by decreasing the number of admitted patients as the intermediate values of the reception unit and the sampling unit, the efficiency of the reception unit decreases. In order to prevent the performance decrease of laboratories, laboratories should increase patients to the use of their laboratory services through appropriate management strategies. The performance ranking of 25 Labs is rated in Table 8 as follows:

Table8. Ranking results based NDEA model

Model	RANK
NDEA	$Lab_1 = Lab_{13} = Lab_{24} > Lab_{22} > Lab_3 > Lab_{11} > Lab_5 > Lab_7 > Lab_2 > Lab_{25} > Lab_6 > Lab_{10} > Lab_{15} > Lab_{21} > Lab_{16} > Lab_4 > Lab_{23} > Lab_{18} > Lab_8 > Lab_{12} > Lab_{17} > Lab_{19} > Lab_9 > Lab_{20} > Lab_{14}$

Where the ">" symbol means that the performance is better and the "=" symbol means that the function is the same.

5. Discussion

The performance evaluation of health care sector, including diagnostic services, is an important issue. In this paper, we proposed a NDEA approach to measure the efficiency of medical diagnostic laboratories. Here we presented a case study that used the NDEA model. Application of the model showed which laboratories were efficient and how they can be compared with inefficient laboratories so that managers can seek out strategies for improving their laboratories by understanding the causes of inefficiency.

The model results show that the inefficiencies of laboratories can be identified for the following reasons: (1) 71% of laboratories are private in Tehran. Thus, the type of competition and the monopoly amount in the private sector is very different from that of the public sector since a large number of small and medium laboratories are operating in the absence of large laboratories that form the industry. (2) The type of services offered by laboratories is almost the same. In fact, the additional services, service quality and service cost have caused distinction between competitors. According to experts, laboratories that have less than 42 patients per day are non-economic, while more than 60% of the existing laboratories accept less than 42 patients per day. (3) Factors such as currency fluctuations, price increases of kits, and the cost of implementing quality standards indicate the laboratories need to control and manage costs. On average, 45% of the total cost required is due to the consumables in each laboratory. Therefore, the management cost has a significant role in the enhancement of efficiency. (4) A broad geographic coverage of lab services is the distinction of a laboratory in service coverage. The large laboratories, due to the increase in amount and diversity and the capacity of the tests, expand their services by providing services to smaller laboratories. Considering the reasons mentioned for increasing the efficiency of laboratories, we propose the following solutions: (1) Reviewing all of medical diagnostic laboratory processes, including the pre-test process, the testing process, and the post-test process, will lead to reduced cost and increased quality. (2) The operation management approach by identifying and eliminating unnecessary factors leads to the reduction in the cost of additional of laboratory and increased productivity. (3) Better and more accurate monitoring and control on inputs will lead to savings in input resources. (4) Extensive coverage of services (geographic coverage) using extensive sampling units and utilizing the information and communication technology lead to an increase in the efficiency of the laboratories.

A limitation exists in this research. In this study, the number of samples (as an intermediate measure) is limited exclusively to patients are going to laboratories and we ignored the samples sent to the labs. Hence there is a potential limitation in this study. The revenues related to the samples sent to the labs are excluded from the analysis that can affect the actual profitability of the laboratory.

Therefore, this restriction affects the two outputs (Income from admission and Lab profit) that are in the first and third stages, respectively, which ultimately are affected the efficiency scores of the laboratories.

Authorship

Niloufar Ghafari Someh: Designing studying or analyzing and interpreting data

Mir Saman Pishvaee: Reviewing and modifying the article carefully and submit it.

Seyed Jafar Sadjadi: Editing the article

Roya Soltani: Editing the article

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Conflict of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Author statements

As data used in the study is open to everybody, both instutional permission and ethics committee approval are not necessary for this study.

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Appendix A

Table A: The Application of DEA in different healthcare sectors: A Literature Review

Year	Research	DEA	Network DEA	Undesirable data	Sustainability	Application			
						Diagnostic laboratory	Hospital	Health care system	Other health care centers
2013	Gok and Sezen[1]	•					•		
2013	Audibert et al.[2]	•					•		
2013	Huerta et al.[3]	•					•		
2014	Bilsel and Davutya[4]	•		•			•		
2014	Chowdhury et al.[5]	•					•		
2014	Leleu et al.[6]	•					•		
2014	Popescu et al.[7]	•						•	
2014	Asandului et al.[8]	•						•	
2014	Al-Refaie et al.[9]	•					•		
2015	Alonso et al.[10]	•					•		
2015	Cheng et al.[11]		•					•	
2015	Mitropoulos et al.[12]	•					•		
2015	Sommersguter-Reichmann and Stepan[13]	•					•		
2015	Matranga and Sapienza[14]	•		•			•		
2016	Azadeh et al.[15]	•						•	
2016	Campos et al.[16]	•						•	
2016	Misiunas et al.[17]	•						•	
2016	Lindlbauer et al.[18]	•					•		
2016	Fedotov and Iablonskii[19]	•		•			•		
2017	Johannessen et al.[20]	•					•		
2017	Khushalani and Ozcan[21]		•				•		
2017	Ihsan[22]	•					•		
2018	Şahin and İlgün[23]	•							•
2018	Omrani et al.[24]	•					•		
2018	Haghighi and Torabi[25]	•			•		•		
2019	Ilgun and Konca[26]	•					•		
2019	Abolghasem et al.[27]	•						•	
2019	Rajasulochana and Chen[28]	•							•
2019	Thorsen et al.[29]	•						•	
2019	Kohl et al.[30]	•					•		
2019	Yildirim et al.[31]	•					•		
2019	Peykani et al. [32]	•					•		
2019	**Our work**		•	•	•	•			

Appendix B

A four-stage series network, composed of three main laboratories processes (pre-testing, testing, and post-testing), is shown in Fig. 1. It actually simulates a medical diagnostic lab in the real world. The rectangles in the form of dashed line show three processes (pre-testing, testing and post-testing). In this section, we develop a four-stage network DEA model, shown in Fig.1. Suppose a set of n homogeneous DMUs denoted by DMU_j $(j = 1,2,...,n)$. The pre-test process consists of two steps called the reception unit and the sampling unit. In the process of testing, there is a stage called the test unit. Finally, in the post-test process, there is a stage called the results test unit.

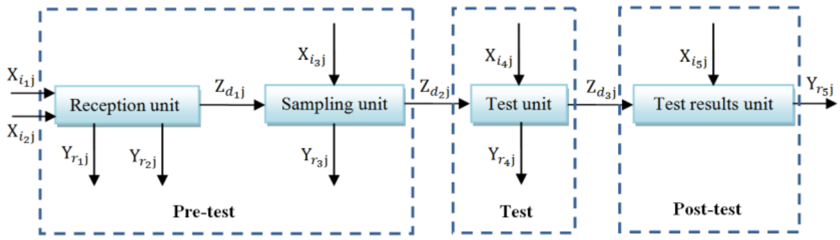

Figure 1 A Four-stage network series

In the reception unit, we adopt v_{i_1} and v_{i_2} as the weights on the input variables $x_{i_1 j}(i_1 = 1,2,...,I_1)$ and$x_{i_2 j}(i_2 = 1,2,...,I_2)$, respectively. We also denote η_{d_1} as the weight associated with the intermediate measures of the reception unit to the sampling unit$z_{d_1 j}(d_1 = 1,2,...,D_1)$. Finally, let u_{r_1} and u_{r_2} denote the weights on the output variables $y_{r_1 j}(r_1 = 1,...,R_1)$ and $y_{r_2 j}(r_2 = 1,...,R_2)$, respectively. The efficiency of the reception unit is shown by $\theta_0^{Reception\ unit}$. Typically, the efficiency of the reception unit is defined applying Model 1.

$$\theta_0^{Reception\ unit} = \max \frac{sum\ weighted\ outputs\ of\ Reception\ unit\ of\ lab_o}{sum\ weighted\ inputs\ of\ Reception\ unit\ of\ lab_o} = \max \frac{\sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 0}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0}} \quad (1)$$

$$\text{s.t.} \quad \frac{sum\ weighted\ outputs\ of\ Reception\ unit\ of\ all\ labs}{sum\ weighted\ inputs\ of\ Reception\ unit\ of\ all\ labs} = \frac{\sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 j}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 j}} \le 1 \quad , \quad j = 1,...,n$$

$$\eta_{d_1}, u_{r_1}, u_{r_2}, v_{i_1}, v_{i_2} \ge 0, d_1 = 1,2,...,D_1 ; r_1 = 1,2,....,R_1 ; r_2 = 1,2,...,R_2 ; i_1 = 1,2,..., I_1 ; i_2 = 1,2,...,I_2.$$

In the sampling unit, where $v_{i_3}$is the weight on the input variable $x_{i_3 j}(i_3 = 1,...,I_3)$. We adopt η_{d_2} as the weight associated with the intermediate measures of sample unit to the test unit $z_{d_2 j}(d_2 = 1,2,...,D_2)$. At the end, the weight u_{r_3} is assigned to the output variable $\text{y}_{\text{r}_3 \text{j}}(r_3 = 1,...,\text{R}_3)$. We show the efficiency of the sampling unit by $\theta_0^{Sampling\ unit}$. The efficiency of the sampling unit is calculated using Model 2.

$$\theta_o^{Sampling\ unit} = \max \frac{sum\ weighted\ outputs\ of\ Sampling\ unit\ of\ lab_o}{sum\ weighted\ inputs\ of\ Sampling\ unit\ of\ lab_o} = \max \frac{\sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 o} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 o}}{\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 o}} \qquad (2)$$

$$\text{s.t.} \quad \frac{sum\ weighted\ outputs\ of\ Sampling\ unit\ of\ all\ labs}{sum\ weighted\ inputs\ of\ Sampling\ unit\ of\ all\ labs} = \frac{\sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 j} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 j}}{\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 j} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 j}} \le 1\ ,\ \ j = 1, \dots, n$$

$$\eta_{d_1}, \eta_{d_2}, v_{i_3}, u_{r_3} \ \ge\ 0, d_1 = 1,2,\dots,D_1\ ;\ d_2 = 1,2,\dots,D_2\ ;\ i_3 = 1,2,\dots,I_3\ ;\ r_3 = 1,2,\dots,R_3.$$

Let v_{i_4} be denoted as the weights of the input variables $x_{r_4 j}(i_4 = 1, \dots, I_4)$ to the test unit. The weight η_{d_3} is assigned to the intermediate measures $z_{d_3 j}(d_3 = 1, \dots, D_3)$. Finally, we consider u_{r_4} as the weight of the output variable $y_{r_4 j}(r_4 = 1,2, \dots, R_4)$. We showed the efficiency of the test unit by $\theta_0^{Test\ unit}$. The test unit efficiency is expressed as the following Model 3.

$$\theta_o^{Test\ unit} = \max \frac{sum\ weighted\ outputs\ of\ Test\ unit\ of\ lab_o}{sum\ weighted\ inputs\ of\ Test\ unit\ of\ lab_o} = \max \frac{\sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 o} - \sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 o}}{\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 o}} \qquad (3)$$

$$\text{s.t.} \quad \frac{sum\ weighted\ outputs\ of\ Test\ unit\ of\ all\ labs}{sum\ weighted\ inputs\ of\ Test\ unit\ of\ all\ labs} = \frac{\sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 j} - \sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 j}}{\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 j} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 j}} \le 1\ ,\ \ j = 1, \dots, n$$

$$\eta_{d_2}, \eta_{d_3}, v_{i_4}, u_{r_4} \ \ge\ 0, d_2 = 1,2,\dots,D_2\ ;\ d_3 = 1,2,\dots,D_3\ ;\ i_4 = 1,2,\dots,I_4\ ;\ r_4 = 1,2,\dots,R_4.$$

We consider v_{i_5} and η_{d_3} as the weights on the inputs to the test results unit to $x_{i_5 j}(i_5 = 1, \dots, I_5)$ and $z_{d_3 j}(d_3 = 1, \dots, D_3)$, respectively. Finally, the weight $y_{r_5 j}(r_5 = 1, \dots, R_5)$ is assigned to the final output. We show the efficiency of the results test unit by $\theta_0^{Results\ test\ unit}$. The test results unit efficiency can be evaluated by solving the following Model 4.

$$\theta_0^{Test\ results\ unit} = \max \frac{sum\ weighted\ outputs\ of\ Test\ results\ unit\ of\ lab_o}{sum\ weighted\ inputs\ of\ Test\ results\ unit\ of\ lab_o} = max \frac{\sum_{r_5=1}^{R_5} u_{r_5} y_{r_5 o}}{\sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 o}} \qquad (4)$$

$$\text{s.t.} \quad \frac{sum\ weighted\ outputs\ of\ Test\ results\ unit\ of\ all\ labs}{sum\ weighted\ inputs\ of\ Test\ results\ unit\ of\ all\ labs} = \frac{\sum_{r_5=1}^{R_5} u_{r_5} y_{r_5 o}}{\sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 j} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 j}} \le 1\ ,\ \ j = 1, \dots, n$$

$$\eta_{d_3}, v_{i_5}, u_{r_5} \ \ge 0\ , d_3 = 1,2,\dots,D_3\ ;\ i_5 = 1,2,\dots,I_5\ ;\ r_5 = 1,2,\dots,R_5\ .$$

We show the overall efficiency of the four-stage process by $\theta_0^{\mathrm{overall}}$ that is calculated through Formula (5) conforming to the tandem system of Kao and Hwang[33]:

$$\theta_0^{overall} = w_1 . \theta_0^{Reception\ unit} + w_2 . \theta_0^{Sampling\ unit} + w_3 . \theta_0^{Test\ unit} + w_4 . \theta_0^{Test\ results\ unit} =$$

$$\frac{sum\ weighted\ inputs\ of\ Reception\ unit\ .\ \theta_0^{Reception\ unit} + sum\ weighted\ inputs\ of\ Sampling\ unit\ .\ \theta_0^{Sampling\ unit} +}{sum\ weighted\ inputs\ of\ (Reception\ unit + samplingt\ unit + Test\ unit + Test\ results\ unit)}$$

$$\frac{sum\ weighted\ inputs\ of\ Test\ unit.\ \theta_0^{Test\ unit} + sum\ weighted\ inputs\ of\ Test\ results\ unit.\ \theta_0^{Test\ results\ unit}}{sum\ weighted\ inputs\ of\ (Reception\ unit + samplingt\ unit + Test\ unit + Test\ results\ unit)}$$

Where w_1 ، w_2 ، w_3 and w_4 are the weights associated with the user-specified. So that, it is w1 + w2 + w3 + w4 = 1.

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