Medical Imaging Process & Technology (2023) Volume 6 Issue 1
doi: 10.24294/mipt.v6i1.3138

Original Research Article

Measuring an efficiency aggregation of medical diagnostic laboratories: A window NDEA approach

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ABSTRACT

The efficiency evaluation of laboratories, as one of the most significant areas of healthcare, plays a key role in the quality of laboratory management. The classic data envelopment analysis (DEA) models have overlooked intermediate products, internal interactions and dealt with analyzing the network within the “Black Box” mode. This results in the loss of important information, and at times, a considerable modification occurs in efficiency results. This article evaluated the efficiency of some selected medical diagnostic laboratories in the city of Tehran according to the network data envelopment analysis (NDEA) approach. We considered a four-stage structure with additional inputs and undesirable outputs. We obtain the labs’ performance over a period of 6 months in 2022 by the NDEA window analysis process. To this aim, a four-stage structure model of three chief medical diagnostic laboratory processes as the pre-test, the test, and the post-test is designed. We considered sustainability criteria (economic, social, and environmental) to appraise the performance of laboratories, thus helping to improve the social, economic, and environmental problems of medical diagnostic laboratories. By using the Delphi viewpoint, the criteria for efficiency evaluation are achieved. The results showed that laboratory unit No. 22 maintained the highest average overall efficiency, since the high accuracy of this unit’s laboratory results had led to many physicians recommending this unit to their patients. We found that the only laboratory unit No. 20 had a decreasing trend, as it is located in an area that abounds with administrative and educational centers. At the beginning of the exam period, then the summer holidays, and finally the wave of end-of-summer trips, a decline occurs in efficiency over the period of six months.

Keywords: network data envelopment analysis; four stage process; sustainability criteria; medical diagnostic laboratories; window analysis

ARTICLE INFO

Received: 1 November 2023
Accepted: 13 November 2023
Available online: 6 December 2023

1. Introduction

Nowadays, medical diagnostic laboratories are one of the most vital elements of the health structure. The medical diagnostic laboratory plays a vital character in the arenas of healthcare, diagnosis, prevention of various diseases, control, and care. Therefore, 70% of diagnostic and follow-up cases are based on laboratory diagnosis. Due to the economic circumstances, social and environmental features of the medical diagnostic laboratories, there is an increasing demand for improved efficacy, decreased functional costs, and growing quality of such organizations. Nowadays, people are existing in an environment that is more and more moving on the road to a service-based economy. According to global standards, the share of laboratory services in the healthcare market is about 5.6%, which represents an important role. Efficacy, as the main pillar of development, is one of the most usually utilized mechanisms for evaluating and measuring the performance of a health care organization, including medical diagnostic laboratories.

So, it is of special importance to survey the performance of medical diagnostic laboratories by appraising productivity and efficiency. Recently, some approaches and methods have been offered for efficiency evaluation, according to two general parametric and non-parametric approaches. In this study, the DEA is utilized as a nonparametric viewpoint. This technique chooses the efficient DMUs and makes the efficiency frontier.

In this research, the efficiency of laboratories is investigated through a network data envelopment analysis method on three chief laboratory processes during a six-month (March to August) period in 2022. The proposed model also provides an overview of the process of changes in efficiency of laboratory units over time. In this case, the performance of a laboratory unit in a particular period is in contradiction to the performance of the said unit in other time periods, in addition to the performance of other laboratory units. The results can be used to understand whether or not laboratory units have been motivated to increase productivity.

Presently, performance evaluation is a very crucial subject for a better understanding of problems in a complex structure and designing for future development[1]. Data envelopment analysis is one of the most vital and suitable approaches for efficacy evaluation of decision-making units (DMUs)[2]. For the first time, Farrell[3] designed a model for efficacy measurement with an input and an output. The Farrell's model is extended for multiple inputs and outputs by Charnes, Cooper and Rhodes and called "CCR"[4]. Banker, Charnes and Cooper developed the data envelopment analysis models and called "BCC"[5,6]. In CCR and BCC models (classical DEA models), we evaluate the efficiencies of DMUs as a "Black Box" and do not study the intermediate measures of DMUs[7]. In other words, overlooking the intermediate measures leads to losing significant data[8]. Fare and Grosskopf[9] offered a network data envelopment analysis model (NDEA) to overcome this problem. The complex structure can be simulated by using the sub-DMUs in parallel or in series[10–14]. Some researchers have been performed research in relevance to network data envelopment analysis models. These include the Kao[15] and Yu and Lin[16] models, which can be indicated. The sub-DMUs have desirable or undesirable outputs in the network structure. Fare et al.[17] and Seiford and Zhu[18] developed the NDEA models and used the undesirable outputs initially. In recent years, Badiezadeh and Farzipoor Saen[19] and Jahanshahloo et al.[20] used the NDEA model to measure efficiency based on the role of undesired factors. Lu and Lo[21] categorized the approaches employed with undesirable outputs. One of the variations of DEA models is the window analysis model. The window analysis method was first introduced by Golany et al.[22]. This model provides an opportunity to observe the modification process of the enterprise's efficiency throughout a period of time. This feature can be used to understand whether or not firms have moved to increase productivity. The only study conducted in the field of health with a window analysis approach was accomplished by Flokou et al.[23]. They used a window analysis approach to measure the performance of National Health Services (NHS) hospitals in Greece from 2009 to 2013. The results indicated that a high level of technical efficiency was maintained throughout the 5-year period.

Producing a sustainable product as a practical method to minimize the environmental effects of a product is one of the most significant methods for reaching sustainability[24]. Though there is a main challenge in how to effectively produce undesirable outputs (to reduce environmental impacts) in the production process to accede eco-efficient product performance, environmental effects, such as undesirable outputs, can be in the shape of greenhouse gas emissions and solid waste. So as to measure eco-efficient performance, Chen, Zhu et al.[25] newly announced the concept of "sustainable performance". This concept describes how to reach the desired output. Sustainability assessment is not limited to environmental criteria. Therefore, three categories of sustainability factors (social, economic, and environmental) are offered in the literature. Determining sustainability goals requires some knowledge and comprehension of the current level of sustainability. This can be achieved through sustainability assessments that take into account all three factors of sustainability: "economic, social, and environmental"[26]. Since the evaluation of a system involves a wide range of economic, social, and environmental indicators, this leads to complex multi-criteria decision-making problems. A possible way to simplify the assessment is to define the concept of sustainability and determine the importance of economic, social, and environmental indicators[27]. Recently, researchers have utilized data envelopment analysis to estimate network efficiency while studying sustainability factors. Though several of these studies cover only the economic and environmental aspects, the social aspect has been ignored[28]. Typically, there are three ways to apply data envelopment analysis models in sustainability literature. The first way is traditional data envelopment analysis models with simple interpretations of data. The second way is traditional data envelopment analysis models, which treat undesirable results as inputs. The third way is data envelopment analysis models using the concept of poor technology[29]. Scholars have used data envelopment analysis models to address organizational, regional, and national sustainability matters[30]. In recent years, Khanjarpanah et al.[31] cited some articles in which performance evaluation had been conducted in the presence of sustained factors using the DEA technique. In that study, by taking advantage of sustainable and ecological indicators, evaluating the efficiency of candidate locations for switch grass cultivation was taken place. They used a data envelopment analysis approach to optimize candidate locations. The other articles are relevant to Tajbakhsh and Hassini[32], in which a two-stage data envelopment analysis network was presented. They measured the efficiency of power plants in terms of sustainability. From the standpoint of health services, Khan et al.[33] recognized in health care the dimensions of encouragement for social sustainability. A case study in the United Arab Emirates shows that among the service sectors, the health system has a good opportunity to influence sustainable performance. There are four reasons for this. 1) On average, the health system uses more energy than other services. 2) Hospitals produce an important amount of hospital waste. 3) The health system has a clinical social effect on its own society because the number of its staff is high in comparison to other organizations. 4) The chief target of this system is to provide service to patients and community health[34]. Therefore, the importance of sustainability in laboratories as an effective part in the field of health care is significant.

Data envelopment analysis has been suggested as a theoretical framework for efficiency measurement, but its application in the arena of health care has been very limited. Thereby, this study intends to present a four-stage structure model that involves three chief medical diagnostic laboratory processes (the pre-test, the test, the post-test) to evaluate the performance of this arena. Based on the above literature, the following lacks in the problems of the performance measurement of medical diagnostic laboratories can be defined: (1). A structure is planned to estimate the efficiency and ranking of medical diagnostic laboratory units by consideration of sustainability criteria (economic, social, and environmental). (2). The criteria for evaluation are obtained with the Delphi method. (3). The current paper studies the four-stage processes, with additional inputs, undesirable outputs, and intermediate measures. (4). In order to make results more realistic, a window NDEA viewpoint is used to measure efficiency. In continuation, the paper unfolds as follows: Part (2) describes the research methodology. Part (3) shows the modeling and solution. Part (4) describes the result of a case study. Part (5) shows conclusion.

2. Methodology

The methodology in this paper is considered in two steps: in the primary step, because variables are not recognized, the factors touching any dimension of the model by the interview, observation, analyzing organizational documents, and library studies will be founded. Then, for screening the findings of this phase, the Delphi technique is used to reach consensus about the influential factors. In the second step, a mathematical model (network data envelopment analysis window viewpoint) is presented to measure the performance of medical diagnostic laboratories.

Our case study is a medical diagnostic laboratory that consists of quantitative factors. One of the effective methods for identifying variables is the Delphi viewpoint. For this purpose, we use the Delphi method in this section to detect the effective indicators for evaluating the performance of laboratories. The process of implementing the steps in an overview is shown in **Figure 1**.

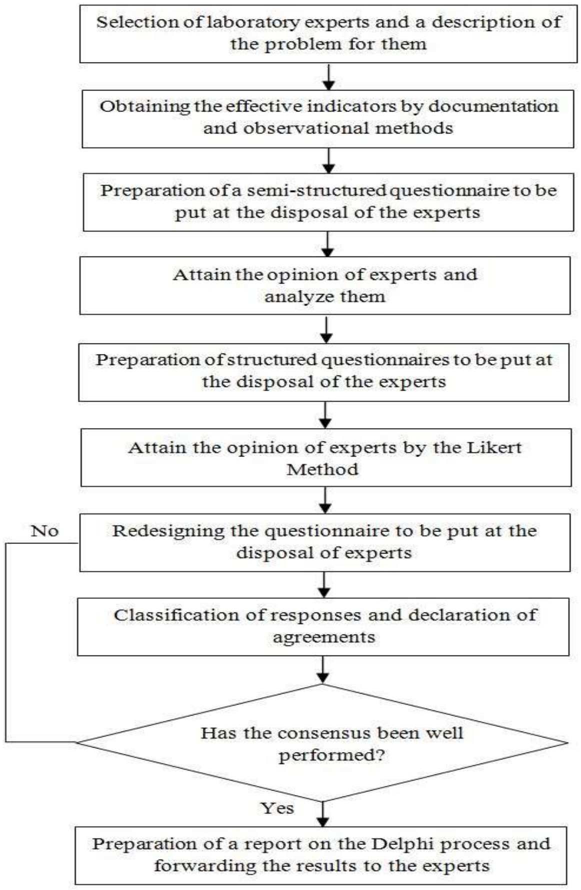

Figure 1. The execution of the Delphi method algorithm.

2.1. Delphi method

Step 1: The Delphi viewpoint is the most effective technique for classifying the indexes. This is a great way to reach a consensus among experts when reliable data is not available. To reach an appropriate team, experts that are knowledgeable in the laboratories were invited. So, we selected 11 experts in the arena. In **Table 1**, the Delphi team is exposed.

Table 1. Members of the Delphi team.

Row	Group		The amount of work experience	Names
1	Professors of University of Medical Sciences and Laboratory Sciences		20 years	Dr. Esmaeili Dr. Firoozabadi Dr. Rahimiyan Dr. Mohammadi Dr. Mola Dr. Bagher
2	Organizational and executive forces	Technical authorities	25 years	Ms. Shariati Ms. Hamidnejad Ms. Sohivand
3		Laboratory experts	15 years	Ms. Vaezzadeh Ms. Farahani

Step 2: Firstly, we utilized the two approaches of observation and documentation to find the most significant indicators in the medical diagnostic laboratory arena and to collect indicators. The indicators were in the form of reports and documents and were somewhat were gained by means of external and internal articles in the laboratory area. After going to laboratories, we received the total effective factors in medical diagnostic laboratory processes based on the observations of the organization. The applicable indicators are presented in **Table 2** following observations from the presence in medical diagnostic laboratories and a library study method.

Table 2. Effective indicators of medical diagnostic laboratories.

Row	Indicator	Documentation						Observation
		Checklist of quality assessment of labs	Leleu et al. (2014)	Asandului et al. (2014)	Hamid Abu Bakar et al. (2009)	Yousefi et al. (2017)	Patra and Ray (2018)	
1	Sum of the scores of the laboratory standards	√						
2	Garbage weight	√				√		
3	Average sample transfer time	√			√			
4	Number of patients' admitted		√	√			√	
5	Number of active experiments							√
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 first sequence of questionnaires was designed in a semi-structured manner, according to the data in **Table 2** and sent personally to all members of the group. After receiving the first round of answers, the information was collected, summarized, classified, and finally, a second questionnaire was designed.

Step 3: At this stage, the questionnaire was distributed structurally among the members of the Delphi team, and all the first phase responses were covered. Respondents were requested to specify the significance of the criteria by using the Likert scale (very low, low, medium, high, and very high). The goal of the second step, or any other subsequent step, is to reach consensus or stability among the members of the group.

Step 4: At this phase, the average of any criterion was taken using the ranking given by the experts from the second Delphi stage. At the third stage, questionnaires were distributed among the members, and they were requested to complete the questionnaire according to the mean of the previous step. At this step, respondents can approve or change their previous opinions. In addition, each expert has the opportunity to review his/her opinions and evaluate the opinions of other specialists, which is the same as moving toward consensus. Finally, after three repetitive periods, **Table 3** displays the last effective indicators in the arena of medical diagnostic laboratories by using the Delphi technique.

Table 3. Final effective indicators of medical diagnostic laboratories.

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

3. Model description

We considered a four-stage dynamic structure based on **Figure 2**. Thus, we determine any time period as a DMU and show it as $DMU_{\mathrm{j}}(\mathrm{j} = 1,2,\dots,\mathrm{n})$. The medical diagnostic laboratory involves three chief processes, such as pre-testing processes, testing processes, and post-testing processes. The first, second, third, and fourth phases are, respectively, the reception unit, the sampling unit, the test unit, and the test results unit. We signify the number of active experiments and the available space for service as desirable and undesirable inputs, which we denoted respectively as $x_{i_1 j}(i_1 = 1,2,\dots,I_1)$ and $x_{i_2 j}(i_2 = 1,2,\dots,I_2)$ in the reception unit. The income from admission and the average waiting time for sampling in the reception unit are considered as undesirable and desirable outputs of the first stage, signified respectively with $\mathrm{y}_{\mathrm{r}_1\mathrm{j}}(\mathrm{r}_1 = 1,2,\dots,\mathrm{R}_1)$ and $y_{r_2 j}(r_2 = 1,2,\dots,R_2)$. The number of patients' admissions is considered as intermediate measure between the reception unit and the sampling unit, which is introduced by $z_{d_1 j}(d_1 = 1,2,\dots,D_1)$. The additional inputs to the sampling unit, which include the cost of consumables and the safety cost of the sampling unit, are represented by $x_{i_3 j}(i_3 = 1,2,\dots,I_3)$. The undesirable output of the sampling unit is the average sample transfer time that is specified by $y_{r_3 j}(r_3 = 1,2,\dots,R_3)$. The number of samples is defined as intermediate measures of the sampling unit and the test unit represented by $z_{d_2 j}(d_2 = 1,2,\dots,D_2)$. The safety cost of test unit and the number of kits from the test unit as additional inputs are shown by $x_{i_4 j}(i_4 = 1,2,\dots,I_4)$. The undesirable outputs of the test unit include the number of false tests, test response time, and garbage weight, as presented by $\mathrm{y}_{r_4\mathrm{j}}(r_4 = 1,2,\dots,R_4)$. We define the correct number of tests as intermediate measures of the test unit, and the test results unit is represented by $z_{d_3 j}(d_3 = 1,2,\dots,D_3)$. In the test results unit, the staff wage is shown as an additional input represented by $x_{i_5 j}(i_5 = 1,2,\dots,I_5)$. Finally, we define the number of responses of the prepared tests, the sum of the scores of the laboratory standards, and lab profit as the outputs of the test results unit, which we introduce by $y_{r_5 j}(r_5 = 1,2,\dots,R_5)$. The reception, sampling, test, and test results units are interconnected in series.

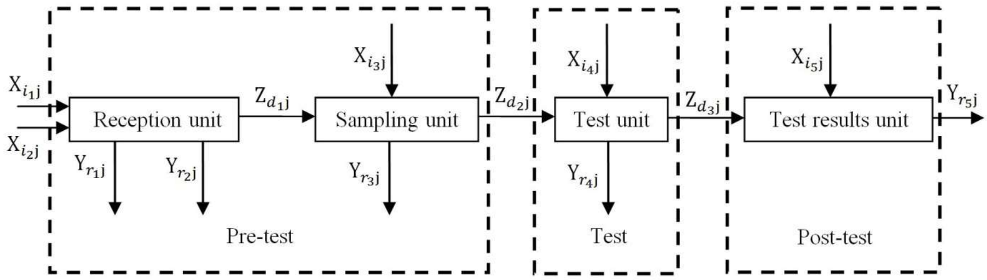

Figure 2. A four-stage network.

In this study, we use the input-axis model. This is a usual assumption in data envelopment analysis works. In accordance with Korhonen and Luptacik[35], we signify the undesirable outputs in the models with a negative mark. In the reception unit, we adopt v_{i_1} and v_{i_2} as the weights on the input variables $x_{i_1 j}(i_1 = 1,2,\dots,I_1)$ and $x_{i_2 j}(i_2 = 1,2,\dots,I_2)$, severally. We similarly define η_{d_1} as the weight associated with the intermediate measures of the reception unit to the sampling unit $z_{d_1 j}(d_1 = 1,2,\dots,D_1)$. Finally, let u_{r_1} and u_{r_2} denote the weights on the output variables $y_{r_1 j}(r_1 = 1,\dots,R_1)$ and $y_{r_2 j}(r_2 = 1,\dots,R_2)$, severally. $z_{d_1 j}(d_1 = 1,2,\dots,D_1)$ as intermediate measures have a dual role. Therefore, the reception unit η_{d_1} plays as the weight on the output. The efficiency of the reception unit is exposed with $\theta_0^{Reception\ unit}$. The efficiency of the reception unit in the first stage is defined in Equation (1) as follows:

$$\theta_0^{Reception\ unit} = max\frac{\sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 0}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0}}$$

$$s.t.\ \frac{\sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 j}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 j}} \leq 1, \qquad j = 1,\dots,n \tag{1}$$

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

In the sampling unit, where $v_{i_3}$is the weight on the input variable $x_{i_3 j}(i_3 = 1,\dots,I_3)$. We adopt η_{d_2} as the weight related with the intermediate measures of sample unit to the test unit $z_{d_2 j}(d_2 = 1,2,\dots,D_2)$. At the end, the weight u_{r_3} is allocated to the output variable $\mathrm{y}_{\mathrm{r}_3 \mathrm{j}}(r_3 = 1,\dots,\mathrm{R}_3)$. Given the dual role of intermediate measures $z_{d_2 j}(d_2 = 1,2,\dots,D_2)$ in the sampling unit, we define η_{d_2}as the weight of output. The weight of the intermediate measures η_{d_1} in the sampling unit has an input role. We display the efficiency of the sampling unit by $\theta_0^{Sampling\ unit}$. The efficiency of the sampling unit in the second stage is determinate in Equation (2), as below:

$$\theta_o^{Sampling\ unit} = \max\frac{\sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 o} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 o}}{\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 o}}$$

$$\mathrm{s.t.}\frac{\sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 j} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 j}}{\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 j} + \sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 j}} \leq 1\ ,\ j = 1,\dots,n \tag{2}$$

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

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 know that $z_{d_3 j}(d_3 = 1,\dots,D_3)$ as intermediate measure has a dual role. In the test unit, η_{d_3} is assumed as the weight of the output. The weight of the intermediate measures η_{d_2} in the test unit is the input weight additionally. We showed the efficiency of the test unit by $\theta_0^{Test\ unit}$. The test unit efficiency is expressed in Equation (3) as follows:

$$\theta_o^{Test\ unit} = \max \frac{\sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 o} - \sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 o}}{\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 o}}$$

$$\text{s.t.} \frac{\sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 j} - \sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 j}}{\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 j} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 j}} \leq 1 \ , \ j = 1,\dots,n \tag{3}$$

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

We consider v_{i_5} and η_{d_3} as the weights on the inputs to the test results unit $x_{i_5 j}(i_5 = 1,\dots,I_5)$ 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 allocated 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 calculated with solving the Equation (4) as follows:

$$\theta_0^{Test\ results\ unit} = \max \frac{\sum_{r_5=1}^{R_5} u_{r_5} y_{r_5 o}}{\sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 o}}$$

$$\text{s.t.} \frac{\sum_{r_5=1}^{R_5} u_{r_5} y_{r_5 o}}{\sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 j} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 j}} \leq 1 \ , \ j = 1,\dots,n \tag{4}$$

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

In this work, the intermediate measures regardless of the dual role (as inputs or as output of stages) are calculated and re-modeled. Thus, we utilized the similar weights for the intermediate measures. This is a usual assumption in data envelopment analysis works[13]. In the structure exposed in **Figure 2**, the reception, sampling, testing and test results units are linked in series with intermediate measures $z_{d_1 j}(d_1 = 1,2,\dots,D_1)$, $z_{d_2 j}(d_2 = 1,2,\dots,D_2)$ and $z_{d_3 j}(d_3 = 1,2,\dots,D_3)$. The total efficiency of the network can be considered with the means of Equation (5) based on the tandem system of Chen et al.[36]:

$$\theta_0^{overall} = w_1.\theta_0^{Reception\ unit} + w_2.\theta_0^{Sampling\ unit} + w_3.\theta_0^{Test\ unit} + w_4.\theta_0^{Test\ results\ unit} \tag{5}$$

where

$$w_1 = \frac{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0}}$$

$$w_2 = \frac{\sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0}} \tag{6}$$

$$w_3 = \frac{\sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0}}$$

$$w_4 = \frac{\sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_3=1}^{D_3} \eta_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0}}$$

Considering w_1, w_2, w_3 and w_4 as the user-specified weights to the reception, sampling, test and test results units, respectively, so that $w_1 + w_2 + w_3 + w_4 = 1$. The weights w_1, w_2, w_3 and w_4 are in proportions allotted to the total resources devoted to the reception, sampling, test and test results units. These multipliers can logically show the relative contribution of any stage to the total efficiency[37]. Therefore, the total efficiency of DMU_0 can be achieved with solving the fractional model as below:

$$\theta_o^{overall} = \max \frac{\sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 0} + \sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 o} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 o} + \sum_{d_3=1}^{D_3}\eta_{d_3} z_{d_3 o} - \sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 o} + \sum_{r_5=1}^{R_5} u_{r_5} y_{r_5 o}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_3=1}^{D_3}\eta_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 0}}$$

$$\text{s.t}\ \frac{\sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 j}}{\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 j}} \le 1, j = 1, \dots, n$$

$$\frac{\sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 j} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 j}}{\sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 j} + \sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 j}} \le 1, j = 1, \dots, n \tag{7}$$

$$\frac{\sum_{d_3=1}^{D_3}\eta_{d_3} z_{d_3 j} - \sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 j}}{\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 j} + \sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 j}} \le 1, j = 1, \dots, n$$

$$\frac{\sum_{r_5=1}^{R_5} u_{r_5} y_{r_5 j}}{\sum_{i_5=1}^{I_5} v_{i_5} x_{i_5 j} + \sum_{d_3=1}^{D_3}\eta_{d_3} z_{d_3 j}} \le 1, j = 1, \dots, n$$

$$\eta_{d_1}, \eta_{d_2}, \eta_{d_3}, u_{r_1}, u_{r_2}, u_{r_3}, u_{r_4}, u_{r_5}, v_{i_1}, v_{i_2}, v_{i_3}, v_{i_4}, v_{i_5} \ge \varepsilon, d_1 = 1,2, \dots, D_1;\ d_2 = 1,2, \dots, D_2;$$

$$d_3 = 1,2, \dots, D_3; r_1 = 1,2, \dots, R_1; r_2 = 1,2, \dots, R_2; r_3 = 1,2, \dots, R_3; r_4 = 1,2, \dots, R_4; r_5 = 1,2, \dots, R_5;$$

$$i_1 = 1,2, \dots, I_1; i_2 = 1,2, \dots, I_2; i_3 = 1,2, \dots, I_3;\ i_4 = 1,2, \dots, I_4; i_5 = 1,2, \dots, I_5.$$

Due to additional inputs and outputs, the Equation (7) cannot be changed to a linear program. In the next Section, we will offer a solution to this problem.

3.1. Model solution and efficiency analysis

By using the Charnes and Cooper[38] conversions, Equation (7) converts to a linear model. we use the following Charnes and Cooper[38] conversions and define the Equation (8) as follows:

$$\theta_o^{overall} = \max \sum_{d_1=1}^{D_1}\pi_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2}\omega_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1}\omega_{r_1} y_{r_1 0} + \sum_{d_2=1}^{D_2}\pi_{d_2} z_{d_2 o} - \sum_{r_3=1}^{R_3}\omega_{r_3} y_{r_3 0} + \sum_{d_3=1}^{D_3}\pi_{d_3} z_{d_3 0} - \sum_{r_4=1}^{R_4}\omega_{r_4} y_{r_4 0} + \sum_{r_5=1}^{R_5}\omega_{r_5} y_{r_5 0}$$

$$\text{s.t.} \sum_{i_1=1}^{I_1}\mu_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2}\mu_{i_2} x_{i_2 0} + \sum_{d_1=1}^{D_1}\pi_{d_1} z_{d_1 0} + \sum_{i_3=1}^{I_3}\mu_{i_3} x_{i_3 0} + \sum_{d_2=1}^{D_2}\pi_{d_2} z_{d_2 0} + \sum_{i_4=1}^{I_4}\mu_{i_4} x_{i_4 0} + \sum_{d_3=1}^{D_3}\pi_{d_3} z_{d_3 0} + \sum_{i_5=1}^{I_5}\mu_{i_5} x_{i_5 0} = 1$$

$$\sum_{d_1=1}^{D_1}\pi_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2}\omega_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1}\omega_{r_1} y_{r_1 j} - \left(\sum_{i_1=1}^{I_1}\mu_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2}\mu_{i_2} x_{i_2 j}\right) \le 0, j = 1, \dots, n$$

$$\sum_{d_2=1}^{D_2}\pi_{d_2} z_{d_2 j} - \sum_{r_3=1}^{R_3}\omega_{r_3} y_{r_3 j} - \left(\sum_{d_1=1}^{D_1}\pi_{d_1} z_{d_1 j} + \sum_{i_3=1}^{I_3}\mu_{i_3} x_{i_3 j}\right) \le 0, j = 1, \dots, n \tag{8}$$

$$\sum_{d_3=1}^{D_3}\pi_{d_3} z_{d_3 j} - \sum_{r_4=1}^{R_4}\omega_{r_4} y_{r_4 j} - \left(\sum_{i_4=1}^{I_4}\mu_{i_4} x_{i_4 j} + \sum_{d_2=1}^{D_2}\pi_{d_2} z_{d_2 j}\right) \le 0, j = 1, \dots, n$$

$$\sum_{r_5=1}^{R_5}\omega_{r_5} y_{r_5 j} - \left(\sum_{i_5=1}^{I_5}\mu_{i_5} x_{i_5 j} + \sum_{d_3=1}^{D_3}\pi_{d_3} z_{d_3 j}\right) \le 0, j = 1, \dots, n$$

$$\pi_{d_1}, \pi_{d_2}, \pi_{d_3}, \omega_{r_1}, \omega_{r_2}, \omega_{r_3}, \omega_{r_4}, \omega_{r_5}, \mu_{i_1}, \mu_{i_2}, \mu_{i_3}, \mu_{i_4}, \mu_{i_5} \ge 0, d_1 = 1,2, \dots, D_1; d_2 = 1,2, \dots, D_2; d_3 = 1,2, \dots, D_3; r_1 = 1,2, \dots, R_1; r_2 = 1,2, \dots, R_2; r_3 = 1,2, \dots, R_3; r_4 = 1,2, \dots, R_4; r_5 = 1,2, \dots, R_5;$$

$$i_1 = 1,2, \dots, I_1; i_2 = 1,2, \dots, I_2; i_3 = 1,2, \dots, I_3; i_4 = 1,2, \dots, I_4; i_5 = 1,2, \dots, I_5.$$

Given that the efficiency analysis in the network cannot be considered unique[13]. According to the priority of the stages, the efficiency of each stage in the optimum total efficiency and the optimal efficiency of the preceding phases is maximized. If the reception unit is given a preemptive priority, the linear model of the reception unit is calculated in Equation (9). The symbol (*) show the optimum efficiency.

$$\theta_0^{Reception\ unit} = \max \sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_1 0}$$

$$\text{s.t.} \sum_{i_1=1}^{I_1} \mu_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} \mu_{i_2} x_{i_2 0} = 1$$

$$\sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_1 j} - \left(\sum_{i_1=1}^{I_1} \mu_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} \mu_{i_2} x_{i_2 j} \right) \leq 0, \qquad j = 1, \dots, n$$

$$(1 - \theta_0^{verall*}) \left(\sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 0} + \sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2 0} + \sum_{d_3=1}^{D_3} \pi_{d_3} z_{d_3 0} \right) + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_1 0} - \sum_{r_3=1}^{R_3} \omega_{r_3} y_{r_3 o} \tag{9}$$

$$- \sum_{r_4=1}^{R_4} \omega_{r_4} y_{r_4 o} + \sum_{r_5=1}^{R_5} \omega_{r_5} y_{r_5 o} = \theta_0^{verall*} (\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{i_3=1}^{I_3} \mu_{i_3} x_{i_3 0} + \sum_{i_4=1}^{I_4} \mu_{i_4} x_{i_4 0} + \sum_{i_5=1}^{I_5} \mu_{i_5} x_{i_5 0})$$

$$\pi_{d_1}, \pi_{d_2}, \pi_{d_3}, \omega_{r_1}, \omega_{r_2}, \omega_{r_3}, \omega_{r_4}, \omega_{r_5}, \mu_{i_1}, \mu_{i_2}, \mu_{i_3}, \mu_{i_4}, \mu_{i_5} \geq \varepsilon, d_1 = 1,2, \dots, D_1 ; d_2 = 1,2, \dots, D_2;$$

$$d_3 = 1,2, \dots, D_3; r_1 = 1,2, \dots, R_1; \ r_2 = 1,2, \dots, R_2; r_3 = 1,2, \dots, R_3; \ r_4 = 1,2, \dots, R_4 ; \ r_5 = 1,2, \dots, R_5 ;$$

$$i_1 = 1,2, \dots, I_1 ; \ i_2 = 1,2, \dots, I_2; i_3 = 1,2, \dots, I_3; \ i_4 = 1,2, \dots, I_4 ; \ i_5 = 1,2, \dots, I_5.$$

When the sampling unit is given a precautionary priority, its efficiency is described by the use of Charnes and Cooper[38] and converted to Equation (10) as follows:

$$\theta_o^{Sampling\ unit} = \max \sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2 o} - \sum_{r_3=1}^{R_3} \omega_{r_3} y_{r_3 o}$$

$$\text{s.t.} \sum_{i_3=1}^{I_3} \mu_{i_3} x_{i_3 0} + \sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 0} = 1$$

$$\sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2 j} - \sum_{r_3=1}^{R_3} \omega_{r_3} y_{r_3 j} - \left(\sum_{i_3=1}^{I_3} \mu_{i_3} x_{i_3 j} + \sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 j} \right) \leq 0, \ \ j = 1, \dots, n$$

$$\left(1 - \theta_0^{verall*}\right) \left(\sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 0} + \sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2 0} + \sum_{d_3=1}^{D_3} \pi_{d_3} z_{d_3 0} \right) + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_1 0} - \sum_{r_3=1}^{R_3} \omega_{r_3} y_{r_3 o} \tag{10}$$

$$- \sum_{r_4=1}^{R_4} \omega_{r_4} y_{r_4 0} + \sum_{r_5=1}^{R_5} \omega_{r_5} y_{r_5 0} = \theta_0^{verall*} (\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} + \sum_{i_3=1}^{I_3} \mu_{i_3} x_{i_3 0} + \sum_{i_4=1}^{I_4} \mu_{i_4} x_{i_4 0} + \sum_{i_5=1}^{I_5} \mu_{i_5} x_{i_5 0})$$

$$\sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1 o} + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_2 o} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_1 o} = \theta_0^{Reception\ unit*} \left(\sum_{i_1=1}^{I_1} \mu_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} \mu_{i_2} x_{i_2 0} \right)$$

$$\pi_{d_1}, \pi_{d_2}, \pi_{d_3}, \omega_{r_1}, \omega_{r_2}, \omega_{r_3}, \omega_{r_4}, \omega_{r_5}, \mu_{i_1}, \mu_{i_2}, \mu_{i_3}, \mu_{i_4}, \mu_{i_5} \ \geq \ \varepsilon, d_1 = 1,2, \dots, D_1; \ d_2 = 1,2, \dots, D_2;$$

$$d_3 = 1,2, \dots, D_3; r_1 = 1,2, \dots, R_1; \ \ r_2 = 1,2, \dots, R_2; r_3 = 1,2, \dots, R_3; \ r_4 = 1,2, \dots, R_4 ; \ r_5 = 1,2, \dots, R_5;$$

$$i_1 = 1,2, \dots, I_1 ; i_2 = 1,2, \dots, I_2; i_3 = 1,2, \dots, I_3 ; i_4 = 1,2, \dots, I_4 ; \ i_5 = 1,2, \dots, I_5.$$

By giving preemptive priority to the test unit, its effectiveness to solve the linear programming Equation (11) is as below:

$$\theta_o^{Test\ unit} = \max \sum_{d_3=1}^{D_3} \pi_{d_3} z_{d_3 o} - \sum_{r_4=1}^{R_4} \omega_{r_4} y_{r_4 o}$$

$$\text{s.t.} \sum_{i_4=1}^{I_4} \mu_{i_4} x_{i_4 0} + \sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2 0} = 1 \tag{11}$$

$$\sum_{d_3=1}^{D_3} \pi_{d_3} z_{d_3j} - \sum_{r_4=1}^{R_4} \omega_{r_4} y_{r_4j} - \left(\sum_{i_4=1}^{I_4} \mu_{i_4} x_{i_4j} + \sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2j} \right) \le 0, \; j = 1, \dots, n$$

$$(1 - \theta_0^{overall*}) \left(\sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_10} + \sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_20} + \sum_{d_3=1}^{D_3} \pi_{d_3} z_{d_30} \right) + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_20} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_10} - \sum_{r_3=1}^{R_3} \omega_{r_3} y_{r_3o}$$

$$- \sum_{r_4=1}^{R_4} \omega_{r_4} y_{r_4o} + \sum_{r_5=1}^{R_5} \omega_{r_5} y_{r_5o} = \theta_0^{verall*} (\sum_{i_1=1}^{I_1} v_{i_1} x_{i_10} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_20} + \sum_{i_3=1}^{I_3} \mu_{i_3} x_{i_30} + \sum_{i_4=1}^{I_4} \mu_{i_4} x_{i_40} + \sum_{i_5=1}^{I_5} \mu_{i_5} x_{i_50})$$

$$\sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1o} + \sum_{r_2=1}^{R_2} \omega_{r_2} y_{r_2o} - \sum_{r_1=1}^{R_1} \omega_{r_1} y_{r_1o} = \theta_0^{Reception\ unit*} \left(\sum_{i_1=1}^{I_1} \mu_{i_1} x_{i_10} - \sum_{i_2=1}^{I_2} \mu_{i_2} x_{i_20} \right)$$

$$\sum_{d_2=1}^{D_2} \pi_{d_2} z_{d_2o} - \sum_{r_3=1}^{R_3} \omega_{r_3} y_{r_3o} = \theta_0^{Sampling\ unit*} \left(\sum_{i_3=1}^{I_3} \mu_{i_3} x_{i_30} + \sum_{d_1=1}^{D_1} \pi_{d_1} z_{d_1o} \right)$$

$$\pi_{d_1}, \pi_{d_2}, \pi_{d_3}, \omega_{r_1}, \omega_{r_2}, \omega_{r_3}, \omega_{r_4}, \omega_{r_5}, \mu_{i_1}, \mu_{i_2}, \mu_{i_3}, \mu_{i_4}, \mu_{i_5} \ge \varepsilon, d_1 = 1,2,\dots,D_1 ;\ d_2 = 1,2,\dots,D_2;$$

$$d_3 = 1,2,\dots,D_3; r_1 = 1,2,\dots,R_1;\ r_2 = 1,2,\dots,R_2; r_3 = 1,2,\dots,R_3;\ r_4 = 1,2,\dots,R_4 ; r_3 = 1,2,\dots,R_3;\ r_4 = 1,2,\dots,R_4 ;\ r_5 = 1,2,\dots,R_5 ;\ i_1 = 1,2,\dots,I_1 ; i_2 = 1,2,\dots,I_2; i_3 = 1,2,\dots,I_3; i_4 = 1,2,\dots,I_4$$

$$i_5 = 1,2,\dots,I_5.$$

Finally, the efficiency of the test results unit is calculated in Equation (12) as follows:

$$\theta_0^{Test\ results\ unit} = \frac{\theta_0^{overall*} - \left(w_1^*.\theta_0^{Reception\ unit*} + w_2^*.\theta_0^{Sampling\ unit*} + w_3^*.\theta_0^{Test\ unit*} \right)}{w_4^*} \tag{12}$$

Finally, if $\theta_0^{Reception\ unit} = \theta_0^{Reception\ unit*}$ or $\theta_0^{Sampling\ unit} = \theta_0^{Sampling\ unit*}$ or $\theta_0^{Test\ unit} = \theta_0^{Test\ unit*}$ or $\theta_0^{Test\ results\ unit} = \theta_0^{Test\ results\ unit*}$, we find that we have a unique efficiency decomposition.

3.2. DEA window analysis

One of the categories of the data envelopment analysis models is the window analysis, based on the modified average and is beneficial in finding the performance procedures of a unit during a time period. This feature can indicate whether the DMUs have functioned to improve efficiency. In authentic studies, most of the observations are relative to DMUs within a period of time and are in the mode of time-series data. It is of crucial importance that we survey the efficiency of the DMU throughout the time period and specify its modifications. Hence, in comparing the average weight, the behavior of the DMU can be studied through this time period in such a manner that its behavior is dissimilar to that of another phase or period. In this method, each unit is treated independently at varied phases. The advantages of this method lie in the fact that the efficiency of the DMU can be specified within a specific period, with its performance at another period of time, or with another DMU entirely. This condition leads to an increase in DMUs under survey in the analysis, and the matter is beneficial when studying samples with a smaller number of DMUs. The purpose of window analysis is to use DEA models in time-dependent conditions. Its initial name and concept revert to 1985. In window analysis, each DMU is considered as a different DMU at any period of time. Suppose n is the number of DMUs, p is the length of the window, k is the number of time periods and w is the number of windows. For the analysis of medical diagnostic laboratories in Tehran, the information available is from 25 medical diagnostic laboratories ($n = 25$) for a 6-month period ($k = 6$). We consider the length of the window ($p = 2$) with the opinion of the experts. Each DMU was treated as a diverse DMU for each month and for a period of 6 months. It is situated at the commencement of the window. The analysis was performed for 50 DMUs. Then, the window is shifted forward. Therefore, the analysis was carried out for the next period of (2 months) and for this, 50 other DMUs carried out the analysis. The process continues in the same manner, and the window is shifted a period forward each time. Finally, the fifth window and the last analysis were performed for 50 DMUs in another period of two months.

The number of windows= $w = k - p + 1 = 6 - 2 + 1 = 5$ (the number of times that the analysis has been performed).

The number of DMU per window= $n \times p= 25 \times 2= 50$.

The number of Different DMUs= $n \times p \times w = 25 \times 2 \times 5= 250$.

The specifications of these windows are shown in **Figure 3**.

Lab	Window1	
1	March	April
2	March	April
3	March	April
4	March	April
5	March	April
6	March	April
7	March	April
8	March	April
9	March	April
10	March	April
11	March	April
12	March	April
13	March	April
14	March	April
15	March	April
16	March	April
17	March	April
18	March	April
19	March	April
20	March	April
21	March	April
22	March	April
23	March	April
24	March	April
25	March	April

Lab	Window2	
1	April	May
2	April	May
3	April	May
4	April	May
5	April	May
6	April	May
7	April	May
8	April	May
9	April	May
10	April	May
11	April	May
12	April	May
13	April	May
14	April	May
15	April	May
16	April	May
17	April	May
18	April	May
19	April	May
20	April	May
21	April	May
22	April	May
23	April	May
24	April	May
25	April	May

. . .

Lab	Window	
1	July	August
2	July	August
3	July	August
4	July	August
5	July	August
6	July	August
7	July	August
8	July	August
9	July	August
10	July	August
11	July	August
12	July	August
13	July	August
14	July	August
15	July	August
16	July	August
17	July	August
18	July	August
19	July	August
20	July	August
21	July	August
22	July	August
23	July	August
24	July	August
25	July	August

Figure 3. The window analysis process.

DEA window analysis process is based on a dynamic viewpoint regarding similar decision making units in dissimilar periods of time as entirely dissimilar decision making units. Moving average technique is used to select a dissimilar reference set so as to determine the relative productivity of any decision making unit. That is to say, when the set window slides once. The primary period of any window will be removed, and a novel period will be added at the similar time. The advantage of this technique is to define the dynamic modification of the productivity of any decision making unit comprehensively, both vertically and horizontally. More highly, the number of decision making unit is increased in this technique; hence, it improves the discriminating power by increasing the amount of decision making units after a limited number of units are available[39–43]. The results of the described method (window analysis process) are shown in the case study section.

4. Case study

The variety of private medical diagnostic laboratories in Tehran has led to improved activity in this arena. Based on the statistics published in Iran, 5600 medical diagnostic laboratories are operating in the country. In Tehran, the volume of laboratory services is 16.6% of the overall share of the country. The percentage of medical diagnostic laboratories in the private and public parts is 43% and 57%, respectively. Unlike the number of laboratories in the country, which is mostly in the public sector, in Tehran, most laboratories are handled with the private sector. Therefore, in this study, we considered the private medical diagnostic labs in Tehran because of the importance of the private sector. In this study, we selected 25 private laboratories in different districts of Tehran by cluster sampling. In this section, we visualize the four-stage structure of a medical diagnostic test, as shown in **Figure 4**.

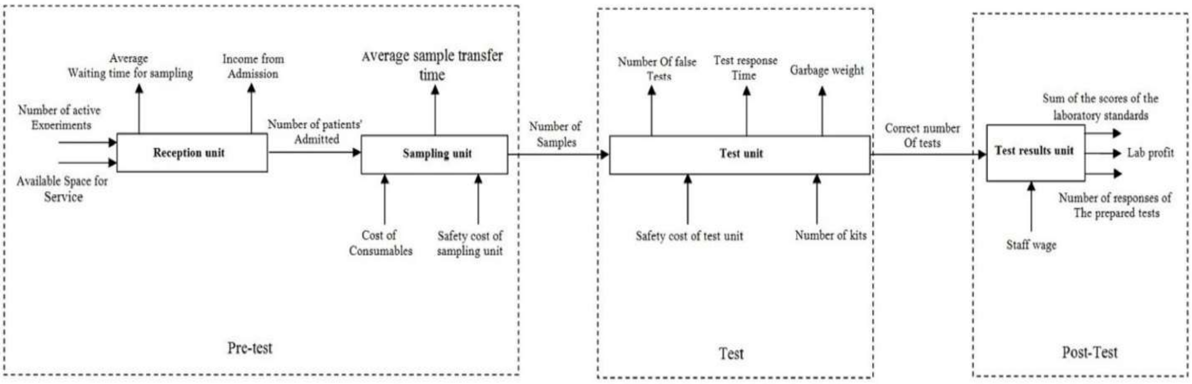

Figure 4. Four-stage structure of a private medical diagnostic laboratory.

The variables of the four-stage structure are introduced in the below **Table 4**:

Table 4. The notation of variables (input, intermediary, output).

Input variables		Intermediary variables		Output variables	
Number of active experiments	x_{1_1}	Number of patients' admitted	z_{1_1}	Average waiting time for sampling	y_{1_1}
Available pace for service	x_{1_2}	Number of samples	z_{1_2}	Income from admission (economic criterion)	y_{1_2}
Cost of consumables (economic criterion)	x_{1_3}	Correct number of tests	z_{1_3}	Average sample transfer time	y_{1_3}
Safety cost of sampling unit (social criterion)	x_{2_3}			Number of false tests	y_{1_4}
Safety cost of test unit (social criterion)	x_{1_4}			Test response time	y_{2_4}
Number of kits	x_{2_4}			Garbage weight (environmental criterion)	y_{3_4}
Staff wage (economic criterion)	x_{1_5}			Number of responses of the prepared tests	y_{1_5}
				Sum of the scores of the laboratory standards	y_{2_5}
				Lab profit (economic criterion)	y_{3_5}

After solving about 250 linear programming models, the results of the overall efficiency determination based on the window analysis method can be seen in **Table 5**. Note that in **Table 5**, the rows indicate the windows and the columns specify the months surveyed.

Table 5. Medical diagnostic laboratories efficiency of Tehran: A window NDEA approach.

DMU	Window	March	April	May	June	July	August	Average efficiency of each window
1	1	0.86904	0.88094					0.87499
	2		0.87198	0.93393				0.902955
	3			0.9288	0.88077			0.904785
	4				0.81631	0.85746		0.836885
	5					0.85974	0.85273	0.856235

Table 5. (*Continued*).

DMU	Window	March	April	May	June	July	August	Average efficiency of each window
	Average monthly efficiency	0.86904	0.87646	0.931365	0.84854	0.8586	0.85273	0.87517
2	1	0.86383	0.84386					0.853845
	2		0.85535	0.91233				0.88384
	3			0.91318	0.85197			0.882575
	4				0.78221	0.93802		0.860115
	5					0.9648	0.85966	0.91223
	Average monthly efficiency	0.86383	0.849605	0.912755	0.81709	0.95141	0.85966	0.878521
3	1	0.99830	0.93759					0.967945
	2		0.94081	0.96784				0.954325
	3			0.96668	0.92098			0.94383
	4				0.87583	0.97864		0.927235
	5					0.98616	0.94373	0.964945
	Average monthly efficiency	0.9983	0.9392	0.96726	0.898405	0.9824	0.94373	0.951656
4	1	0.89070	0.80582					0.84826
	2		0.78388	0.80885				0.796365
	3			0.80625	0.76553			0.78589
	4				0.72713	0.80392		0.765525
	5					0.82215	0.7495	0.785825
	Average monthly efficiency	0.8907	0.79485	0.80755	0.74633	0.813035	0.7495	0.796373
5	1	0.84249	0.84251					0.8425
	2		0.84557	0.85915				0.85236
	3			0.86665	0.88089			0.87377
	4				0.77653	0.84346		0.809995
	5					0.85941	0.83381	0.84661
	Average monthly efficiency	0.84249	0.84404	0.8629	0.82871	0.851435	0.83381	0.845047
6	1	0.88879	0.89746					0.893125
	2		0.89257	0.91022				0.901395
	3			0.91796	0.88033			0.899145
	4				0.79496	0.91454		0.85475
	5					0.91508	0.84293	0.879005
	Average monthly efficiency	0.88879	0.895015	0.91409	0.837645	0.91481	0.84293	0.885484
7	1	0.97129	0.91076					0.941025
	2		0.9081	0.92552				0.91681

Table 5. (*Continued*).

DMU	Window	March	April	May	June	July	August	Average efficiency of each window
	3			0.92999	0.8669			0.898445
	4				0.80582	0.96212		0.88397
	5					0.96678	0.85446	0.91062
	Average monthly efficiency	0.97129	0.90943	0.927755	0.83636	0.96445	0.85446	0.910174
8	1	0.89638	0.77962					0.838
	2		0.7729	0.76254				0.76772
	3			0.75954	0.79091			0.775225
	4				0.76809	0.89898		0.833535
	5					0.88349	0.76602	0.824755
	Average monthly efficiency	0.89638	0.77626	0.76104	0.7795	0.891235	0.76602	0.807847
9	1	0.85905	0.80369					0.83137
	2		0.79586	0.7441				0.76998
	3			0.75006	0.78981			0.769935
	4				0.72208	0.8358		0.77894
	5					0.83929	0.74354	0.791415
	Average monthly efficiency	0.85905	0.799775	0.74708	0.755945	0.837545	0.74354	0.788328
10	1	0.96966	0.96302					0.96634
	2		0.96334	0.96201				0.962675
	3			0.96226	0.96065			0.961455
	4				0.95181	0.97307		0.96244
	5					0.9732	0.95756	0.96538
	Average monthly efficiency	0.96966	0.96318	0.962135	0.95623	0.973135	0.95756	0.963658
11	1	0.96741	0.93847					0.95294
	2		0.9409	0.93329				0.937095
	3			0.92927	0.89529			0.91228
	4				0.82804	0.94896		0.8885
	5					0.95491	0.8756	0.915255
	Average monthly efficiency	0.96741	0.939685	0.93128	0.861665	0.951935	0.8756	0.921214
12	1	0.77014	0.72224					0.74619
	2		0.69135	0.78211				0.73673
	3			0.78243	0.69021			0.73632
	4				0.67364	0.72166		0.69765
	5					0.75083	0.68489	0.71786

Table 5. (*Continued*).

DMU	Window	March	April	May	June	July	August	Average efficiency of each window
	Average monthly efficiency	0.77014	0.706795	0.78227	0.681925	0.736245	0.68489	0.72695
13	1	0.97716	0.98471					0.980935
	2		0.98469	0.97988				0.982285
	3			0.98512	0.78809			0.886605
	4				0.76004	0.98401		0.872025
	5					0.98553	0.81497	0.90025
	Average monthly efficiency	0.97716	0.9847	0.9825	0.774065	0.98477	0.81497	0.92442
14	1	0.66952	0.78918					0.72935
	2		0.79308	0.76427				0.778675
	3			0.77687	0.68987			0.73337
	4				0.62815	0.73949		0.68382
	5					0.73741	0.67331	0.70536
	Average monthly efficiency	0.66952	0.79113	0.77057	0.65901	0.73845	0.67331	0.726115
15	1	0.76367	0.73199					0.74783
	2		0.72721	0.76882				0.748015
	3			0.79061	0.76571			0.77816
	4				0.72163	0.74129		0.73146
	5					0.7446	0.71705	0.730825
	Average monthly efficiency	0.76367	0.7296	0.779715	0.74367	0.742945	0.71705	0.747258
16	1	0.81478	0.95475					0.884765
	2		0.95487	0.94373				0.9493
	3			0.94423	0.70018			0.822205
	4				0.74266	0.87055		0.806605
	5					0.87102	0.71559	0.793305
	Average monthly efficiency	0.81478	0.95481	0.94398	0.72142	0.870785	0.71559	0.851236
17	1	0.74308	0.86903					0.806055
	2		0.86728	0.75353				0.810405
	3			0.80841	0.81155			0.80998
	4				0.78301	0.77381		0.77841
	5					0.75846	0.80886	0.78366
	Average monthly efficiency	0.74308	0.868155	0.78097	0.79728	0.766135	0.80886	0.797702
18	1	0.80584	0.79104					0.79844
	2		0.78758	0.82946				0.80852

Table 5. (*Continued*).

DMU	Window	March	April	May	June	July	August	Average efficiency of each window
	3			0.8365	0.82533			0.830915
	4				0.82573	0.79438		0.810055
	5					0.78505	0.85621	0.82063
	Average monthly efficiency	0.80584	0.78931	0.83298	0.82553	0.789715	0.85621	0.813712
19	1	0.74855	0.79710					0.772825
	2		0.79589	0.76100				0.778445
	3			0.79512	0.78651			0.790815
	4				0.73739	0.74668		0.742035
	5					0.74121	0.71812	0.729665
	Average monthly efficiency	0.74855	0.796495	0.77806	0.76195	0.743945	0.71812	0.762757
20	1	0.86347	0.84438					0.853925
	2		0.83081	0.80052				0.815665
	3			0.82809	0.79758			0.812835
	4				0.75447	0.82085		0.78766
	5					0.81675	0.75094	0.783845
	Average monthly efficiency	0.86347	0.837595	0.814305	0.776025	0.8188	0.75094	0.810786
21	1	0.96574	0.94562					0.95568
	2		0.95668	0.95909				0.957885
	3			0.95813	0.96658			0.962355
	4				0.95425	0.95367		0.95396
	5					0.95368	0.95973	0.956705
	Average monthly efficiency	0.96574	0.95115	0.95861	0.960415	0.953675	0.95973	0.957317
22	1	0.98535	1					0.992675
	2		1	0.97922				0.98961
	3			1	0.96315			0.981575
	4				0.94751	1		0.973755
	5					1	0.98232	0.99116
	Average monthly efficiency	0.98535	1	0.98961	0.95533	1	0.98232	0.985755
23	1	0.96385	0.69709					0.83047
	2		0.69384	0.68375				0.688795
	3			0.67947	0.68496			0.682215
	4				0.64545	0.67052		0.657985
	5					0.67523	0.70065	0.68794

Table 5. (*Continued*).

DMU	Window	March	April	May	June	July	August	Average efficiency of each window
	Average monthly efficiency	0.96385	0.695465	0.68161	0.665205	0.672875	0.70065	0.709481
24	1	0.78248	0.81968					0.80108
	2		0.82215	0.79300				0.807575
	3			0.82005	0.82502			0.822535
	4				0.7589	0.75815		0.758525
	5					0.75925	0.7588	0.759025
	Average monthly efficiency	0.78248	0.820915	0.806525	0.79196	0.7587	0.7588	0.789748
25	1	0.70448	0.71015					0.707315
	2		0.70687	0.6975				0.702185
	3			0.70423	0.73135			0.71779
	4				0.66523	0.70791		0.68657
	5					0.71169	0.65483	0.68326
	Average monthly efficiency	0.70448	0.70851	0.700865	0.69829	0.7098	0.65483	0.699424

Table 5 shows the results of the overall network performance shown in **Figure 3** with 5 windows for each DMU separately. For each DMU, we obtained the average monthly efficiency, the average efficiency of each window, and the average efficiency of the period. Similarly, we calculated the efficiency of the phases. The average overall efficiency and average efficiency of the phases for any DMU are exposed in below **Table 6**.

Table 6. Comparison of the results of the average total efficiency and the average efficiency of the stages by the window analysis.

DMU	Average overall efficiency	Average efficiency of the first stage	Average efficiency of the Second stage	Average efficiency of the third stage	Average efficiency of the fourth stage
1	0.87517	0.703797	0.984672	0.96336	0.775952
2	0.878521	0.706476	0.904741	1	0.790053
3	0.951656	0.732275	0.965319	0.924938	0.99429
4	0.796373	0.490047	0.906845	0.818074	0.779319
5	0.845047	0.800898	0.904505	0.973699	0.733225
6	0.885484	0.614388	0.919109	0.98722	0.861576
7	0.910174	0.890133	0.906974	0.936683	0.904575
8	0.807847	0.775983	0.984273	0.999452	0.466719
9	0.788328	0.691742	0.907228	0.891071	0.673377
10	0.963658	0.390797	0.912772	0.912424	1
11	0.921214	0.734135	0.908639	0.973412	0.888863
12	0.72695	0.34109	0.911884	0.801649	0.605752
13	0.92442	0.954452	0.38826	0.895992	0.984654
14	0.726115	0.424117	0.379925	0.957044	0.744934
15	0.747258	0.34244	0.269488	0.978584	0.94334

Table 6. (*Continued*).

DMU	Average overall efficiency	Average efficiency of the first stage	Average efficiency of the Second stage	Average efficiency of the third stage	Average efficiency of the fourth stage
16	0.851236	0.954862	0.28721	0.982326	0.77318
17	0.797702	0.62328	0.407235	0.973189	0.795132
18	0.813712	0.995087	0.884792	0.623641	0.978236
19	0.762757	0.956712	0.625016	0.807171	0.832897
20	0.810786	0.376501	0.879596	0.766801	0.937721
21	0.957317	0.043562	0.345721	0.876834	1
22	0.985755	0.972779	0.984073	0.988606	0.997684
23	0.709481	0.484785	0.967756	0.626366	0.629693
24	0.789748	0.468506	0.960967	0.904113	0.715062
25	0.699424	0.313704	0.708273	0.842938	0.680506

In above **Table 6**, the minimum and maximum mean efficiency is exposed in green and gray severally. The first column shows the overall efficiency of network over a six-month period. It can be seen that DMU_{22} with an average overall efficiency of 0.992675 and DMU_{25} with an average overall efficiency of 0.699424 have the highest and lowest efficiency among 25 DMUs, respectively. By comparing the average efficiency of each window in each DMU, we found that only DMU_{20} has a decreasing trend. But in other DMUs too, a systematic trend for the average efficiency of each window cannot be observed. In comparing the average monthly efficiency for each DMU, there is also no systematic tendency. Column 2 to 5 refers to the average efficiency of the phases in the 6-month period. The variations range of the average efficiency of the reception, sampling, test and test results units is [0.043562, 0.995087], [0.269488, 0.984672], [0.623641, 1], and [0.466719, 1], respectively. Based on the results of the second column of **Table 6**, the last ranking of laboratory units is as below.

$$\mathrm{DMU}_{22} > \mathrm{DMU}_{10} > \mathrm{DMU}_{21} > \mathrm{DMU}_{3} > \mathrm{DMU}_{13} > \mathrm{DMU}_{11} > \mathrm{DMU}_{7} > \mathrm{DMU}_{6} >$$
$$\mathrm{DMU}_{2} > \mathrm{DMU}_{1} > \mathrm{DMU}_{16} > \mathrm{DMU}_{5} > \mathrm{DMU}_{18} > \mathrm{DMU}_{20} > \mathrm{DMU}_{8} >$$
$$\mathrm{DMU}_{17} > \mathrm{DMU}_{4} > \mathrm{DMU}_{24} > \mathrm{DMU}_{9} > \mathrm{DMU}_{19} > \mathrm{DMU}_{15} > \mathrm{DMU}_{12} > \mathrm{DMU}_{14} > \mathrm{DMU}_{23} > \mathrm{DMU}_{25}$$

The activity of a business enterprise, such as the medical diagnostic laboratory, is the continuous activity over time and is not sectional. Therefore, the evaluation of monthly efficiency cannot offer a real response in relevance to the performance of medical diagnostic laboratories. The results of the performance of laboratories over the course of 6 months show that laboratory 22 is more efficient: 1) it has the highest number of admission of patients per month. Based on experts, medical diagnostic laboratories that have less than 42 patients per day are not economical. This is because fixed laboratory costs such as consumables costs, manpower costs, and safety costs are divided between the number of tests. Therefore, increasing the number of experiments will reduce the finished costs and increase the performance of the laboratory. 2) This is relative to one of the famous laboratories in Tehran. Part of its reputation is due to the long history and quality of service provided. A systematic management, as an important factor, has also been influential on the credibility of the laboratory. 3) It has the highest sum of the scores in view of laboratory standards. When customers return to the laboratory to attain services, they usually expect to regain the same level of quality, they experienced the first time. 4) by providing services to smaller laboratories, the geographic coverage of its services has increased. For growing the efficiency of other medical diagnostic laboratories, we suggest the next solutions: 1) Studies show that more than 60% of laboratories are in the form of traditional laboratories. Since the benefits of laboratories depend in securing a high volume assemblage of samples, thereby, it is advisable for managers to eliminate the traditional format and provide services to other small labs and labs of public hospitals to increase the admission capacity of patients. In incrementing the number of patients, the sample size elevates and with reducing the rate, higher efficiency will be obtained. 2) Advertising and marketing are one of the way to create distinct and successful brands. The ability to contact consumers through several channels of notification shall make this issue possible. 3) The standard of medical laboratories specifies quality requirements in laboratories. Commitment to standards and their implementation is one of the important competencies of a successful medical diagnostic laboratory. Extensive coverage of services using widespread sampling units and making use of data can lead to a rise in the productivity of medical diagnostic laboratories.

5. Conclusion

Efficiency measurement is important from both internal and external organizational aspects. The intra-organizational goal is to allocate resources more efficiently and minimize the total cost. The outsourcing goal is to make information available in relevance to the existing and potential investments of the organization to predict future growth as well as long-term planning. Identifying the weaknesses for each organization helps organization to improve its weaknesses. In fact, traditional accounting assessment models are not sufficient to determine the effectiveness of an organization and are not important in strategic affairs. But today, new techniques for performance evaluation are used, and these are according to parametric and non-parametric approaches. In this study, a nonparametric approach (a dynamic window analysis approach) is emphasized. A window analysis is a linear programming approach that estimates the efficiency of decision making units (companies under study) based on input and output indices that are compared to each other. Then, efficient and inefficient DMUs are determined. The results of this approach help each unit to identify the optimum use of inputs and the strengths and weaknesses of the DMUs, as well as to find ways to improve the efficiency of the DMUs. The services of laboratory centers are covered an important part of the activities of many health centers and research organizations. Since the performance of clinical and research laboratories plays a vital role in the quality and efficiency of health care and research activities, the need for solutions for evaluating and improving their performance has attracted the attention of the world's scientific and professional communities for many years. The performance measurement in laboratory centers is also important for managers and authorities in health centers and research organizations. By doing so, they can provide areas for improvement and increase productivity in the organization through identifying their strengths and weaknesses.

In this paper, we evaluated the efficiency of some selected medical diagnostic laboratories in the city of Tehran based on the NDEA method. Thus, the efficiency evaluation of 25 laboratories in Tehran was evaluated. To assess the efficacy of the private laboratory, there are some indicators that could be utilized for different methods. According to relevant literature, the evaluation indicators were classified in three categories: input, intermediary, and output. Then the appropriate indexes were identified based on the Delphi technique. The Delphi team was collected of eleven members, including experts in the field of medical diagnostic laboratories, professors, technical officials, and administrators. The final indicators included of seven, three, and nine respective inputs, intermediates, and output indicators. It is noteworthy that there were three criteria of sustainability (social, economic, and environmental) in some of the selected indicators. In this study, we considered a four-stage network of the pre-test, the test, and the post-test processes. In this relative, the process before the test includes the reception and sample units. The test process includes of a test unit. Lastly, the after test process includes the results unit. The findings showed that laboratory unit No. 22 maintained the highest average overall efficiency, since the high accuracy of this unit's laboratory results had led to many physicians recommending this unit to their patients. In addition, the reception unit had the highest amplitude in the variation of efficiency as compared with the sampling, test, and test results units, since the number of patients admitted does not have the same trend in the period from March to August. Based on the Persian solar calendar, the number of admitted patients increases in March due to the Nowruz holidays and decreases in August at the summer break of educational centers such as schools and universities. Also, by comparing the average efficiency of each window in each laboratory unit, we found that the only laboratory unit No. 20 had a decreasing trend, as it is located in an area that abounds with administrative and educational centers. At the beginning of the exam period, then the summer holidays, and finally the wave of end-of-summer trips, a decline occurs in efficiency over the period of six months.

Conflict of interest

The author declares no conflict of interest.

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