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Forecasting sustainability of healthcare supply chains using deep learning and network data envelopment analysis

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ABSTRACT

The main objective of this study is to propose a network data envelopment analysis (NDEA) model and a deep learning approach for forecasting the sustainability of healthcare supply chains (HSCs). Technological advances manifested in approaches such as deep learning, artificial intelligence (AI), and Blockchain are of substantial importance throughout HSCs and are understood as competitive advantages. Furthermore, applying advanced performance evaluation techniques, including DEA in HSCs for enhancing performance has attracted momentous attention over the last two decades. To make use of these approaches, a network DEA (NDEA) model and a deep learning approach are developed to predict the sustainability of HSCs. The developed model in this paper can determine the optimal value of bounded connections. Using the DEA capabilities, the threshold of each of these bounded connections is obtained to maximize the efficiency of decision making units (DMUs). It also identifies the role of the dual-role connections for each DMU. The results show that HSCs that use the least facilities and have the most desirable output, as well as the least undesirable output, are in the top ranks.

1. Introduction

Healthcare as one of the most important service sectors has significantly changed because of increased awareness and digital technologies (Kraus, Schiavone, Pluzhnikova, & Invernizzi, 2021). In healthcare systems, factors such as over-crowdedness, unavailability, and inaccessibility have resulted in serious disruptions in providing services to customers. The disruptions are increased by unexpected disasters, including earthquakes, floods, fire, and pandemic outbreaks resulting in irreparable damages in terms of economic, environmental, and social not only in the healthcare sector but also in many other vital sectors (Kristoffersen, Mikalef, Blomsma, & Li, 2021). These unexpected events make the healthcare systems inefficient and off-balance and push them into bottlenecks (Leone, Schiavone, Appio, & Chiao, 2021). To tackle these challenges, particularly in crises, different parts of healthcare supply chains (HSCs) should play their key roles effectively (Sharma & Sehrawat, 2020). The recent pandemic Covid-19 has shown that different components of HSCs are unable to play their roles in face of crises and are ineffective owing to the lack of applying advanced digital technologies (El Baz & Ruel, 2021). Therefore, developing operative HSCs using advanced digital technologies is unavoidable (Tortorella et al., 2021).

HSCs consist of different components such as vendors, manufacturers, hospitals, blood centers, and pharmacies in a network structure aimed at supplying required demands and providing high-quality service to patients (Beaulieu & Bentahar, 2021). The first echelon of HSCs usually is suppliers supplying medical equipment and devices and the last echelon are patients. Each echelon in HSCs plays a key role as any mistake or disruption can threaten human lives as well as result in irretrievable outcomes. HSCs are distinguished from other supply chains (SCs) in terms of intricacy, variety, type of services, uncertainty, and targets (Imran, Kang, & Ramzan, 2018). Digital technologies such as big data analytics, artificial intelligence, Blockchain, and cloud computing have improved HSCs significantly over the last decade (Kokshagina, 2021). Applying and developing these technologies in healthcare systems provide many novel business opportunities as well as creating

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novel business models for improving performance and creating expected values (Kraus et al., 2021). As such, investigating potential opportunities for advanced digital technologies to manage omnichannel HSCs effectively has been a hot topic for scholars and healthcare managers. A case in point is applying and developing these technologies with a combination of methods such as statistics and mathematics to produce the Covid-19 vaccine.

In recent years, deep learning has demonstrated significant improvements in many manufacturing and service systems for different purposes such as resource allocation, scheduling, production planning, and control (Shrestha, Krishna, & Von Krogh, 2021). Deep learning is a novel research direction in the machine learning approach based on artificial neural networks and non-linear sequence learning (Pustokhin et al., 2021). A key feature of deep learning is to retain the information across time steps for time-series forecasting. In addition, deep learning techniques can observe, analyze, learn, and make decisions regarding complicated situations using abstraction in a hierarchical method (Shrestha et al., 2021). In SCs, the rise of interactions and impact of unexpected occurrences such as earthquakes and pandemic outbreaks have forced organizations to seriously assess and forecast their capabilities for facing unusual disruptions using data-driven methods (Punia, Singh, & Madaan, 2020). Applying data-driven approaches, including deep learning and big data analytics can improve SC capability in organizations for mitigating impacts of unforeseen disruptions (Cadden, Dennehy, Mantymaki, & Treacy, 2021).

Performance evaluation of sustainable SCs has received substantial attention over the last decade (Liu, Eckert, Yannou-Le Bris, & Petit, 2019; Mariadoss, Chi, Tansuhaj, & Pomirleanu, 2016). Despite the considerable significance of performance assessment in many key areas, it has not been addressed sufficiently in healthcare. Network data envelopment analysis (NDEA) is a rigorous nonparametric approach and is used in many key areas, including healthcare for performance evaluation objectives (See, Hamzah, & Yu, 2021). Conventional NDEA models are unable to forecast the performance of decision-making units (DMUs) (Yousefi, Shabanpour, & Farzipoor Saen, 2021). This can be seen particularly in natural and man-made disasters such as the Covid-19 pandemic outbreak and fire. However, advanced digital technologies such as deep learning and text learning can be applied successfully to forecast and analyze results and tackle such situations (Sharma, Adhikary, & Borah, 2020; Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021; Zhu, Chang, Ku, Li, & Chen, 2021). Therefore, developing and applying powerful performance evaluation models and advanced digital technologies, including deep learning and text learning need to be paid substantial attention.

In the current study, research questions are as follows: 1) how can we develop an NDEA model for assessing sustainable HSCs, 2) how patients can be clustered using a deep learning approach, 3) how the optimal threshold of each variable and the nature of dual-role connections can be modeled in assessing the sustainability of HSCs, and 4) how deep learning approach can be developed to forecast the need of each stage for receiving equipment and medications considering influential factors. To answer these research questions, the main objective of this paper is to forecast the sustainability of healthcare SCs using NDEA and deep learning. The model is designed to evaluate a variety of topologies considering the connections among stages in HSCs. In defining the connections among stages, various connectivity features have been used that can be applied in different types of networks. One of the contributions of this study is to determine the optimal values of bounded connections. Using the data envelopment analysis (DEA), the threshold of each of these bounded connections is obtained to maximize the efficiency of the decision making units (DMUs). It also identifies the nature of the dual-role connections for each DMU. Furthermore, a deep learning approach is developed to forecast the need of each stage to receive equipment and medications. The applicability of the presented approach is demonstrated using a case study by evaluating the efficiency of drug SCs, equipment, laboratories, and hospitals. In the case study, relying on the medical laboratory responses and using deep learning, patients are clustered based on micro-factors, results, and symptoms, and patients are classified into three clusters. Furthermore, using deep learning, the number of visits to each of the hospitals and laboratory units is forecasted. Therefore, we can forecast and allocate the equipment and medicine to each of them.

Since the introduction of the DEA model in 1978, widespread criticisms have been raised regarding the classical DEA (Charnes, Cooper, & Rhodes, 1978). Meanwhile, a wide range of approaches has been proposed to address the drawbacks of the initial DEA models. In this section, some of these criticisms are mentioned, and this study attempts to respond to the following criticisms: Classical DEA evaluates DMUs solely based on final inputs and outputs. The classical approach does not allow the analyst to identify the strengths and weaknesses of each SC. However, in the NDEA approach, the steps (that make up each DMU) are analyzed in detail. Therefore, the stages in which the SC has inefficiency/drawbacks can be identified in advance (Shabanpour et al., 2021).

Another critique of classical models is the purely positive (incremental) view of outputs, while some outputs may be seen as negative and undesirable factors. For example, the number of patients who died in a hospital or the volume of pollutants emitted from a power plant (Yousefi, Soltani, Bonyadi Naeini, & Farzipoor Saen, 2019). Although several previous research works have addressed these critiques, DEA models (from classical models to the present approaches) still have the nature of 'the action after the occurrence'. Meaning that DEA evaluation (in many previous studies from 1978 to the present) is based on the past performance of DMUs. Nevertheless, in a sustainable evaluation, for example, in the HSC, it is necessary to forecast future efficiency (control before the occurrence of inefficiency). That is why we apply a preventive approach using NDEA and deep learning with desirable and undesirable outputs to forecast the needs of different stages of the HSCs.

From the theoretical point of view, this paper is a transition approach from backward-looking evaluation models toward a preventive approach for evaluating the sustainability of HSCs. For this purpose, we apply the deep learning technique. To do this, first, the needs of the stages of the HSC are forecasted, and accordingly, the clustering of patients is done to provide medical services according to the severity of the disease. Finally, the efficiency and rank of each SC are determined by the NDEA model. The main contributions of our proposed approach are as follows:

- For the first time, deep learning is used with NDEA to optimize the sustainability of HSCs.
- Patients are clustered in three main clusters using deep learning.
- The optimal threshold of each variable and the nature of dual-role connections such as R&D costs are determined.
- A deep learning approach is developed to forecast the need of each stage to receive equipment and medications considering influential factors.
- A real case study is provided in the healthcare sector.

In the next section, the literature review is presented. Section 3 discusses the proposed method. In Sections 4 and 5 case study and conclusions are given, respectively.

2. Literature review

2.1. Assessing healthcare SCs

Chen, Preston, and Xia (2013) developed a model by combining variables that affect the performance of healthcare SCs. Bhattacharjee and Ray (2014) developed a system for modeling patients' flow and efficiency analysis of healthcare SCs. Nyaga, Young, and Zepeda (2015) addressed the effect of intra-and inter-organizational arrangements on the performance of healthcare. They applied motivation schemes and

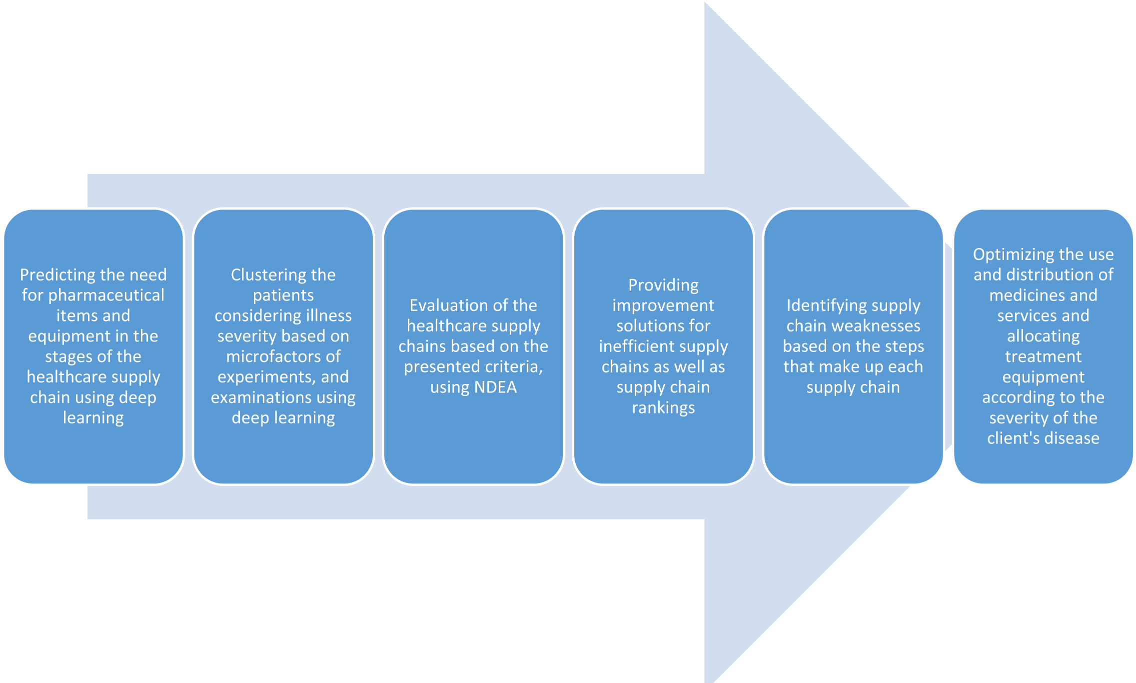

Fig. 1. The study steps.

the collaboration of healthcare personnel who play a leading role in regulating the acquisition of supply provisions as intra-arrangements. To evaluate the performance of healthcare SCs, Supeekit, Somboonwiwat, and Kritchanchai (2016) developed a multi-criteria decision-making approach by integrating techniques of the decision-making trial and evaluation laboratory (DEMATEL) and enhanced analytic network process (ANP). Misiunas, Oztekin, Chen, and Chandra (2016) incorporated DEA and ANN as a healthcare analytic approach to forecasting organ recipient functional status. Khushalani and Ozcan (2017) investigated the performance of quality in healthcare centers and their subunits in different periods using dynamic NDEA. They used multinomial logistic regression for determining healthcare centers and market features that contribute to improving quality outputs. To assess Turkish healthcare SCs, Göleç and Karadeniz (2020) proposed a fuzzy model based on competency operations. They used a fuzzy heuristic algorithm and a fuzzy rule-based system for evaluating different levels of healthcare SCs. Chorfi, Berrado, and Benabbou (2019) proposed a hypercube sampling method for distinguishing crisp data from interval data. Then, they applied DEA for evaluating the performance of healthcare SCs. De Oliveira Gobbo, Mariano, and Gobbo (2021) defined various stages for integrating DEA and social networks aimed at creating the selection employment contracts effectiveness index. They applied the proposed index in the healthcare sector. De Oliveira Gobbo et al. (2021) also used some conventional DEA models such as Charnes, Cooper, and Rhodes (CCR) (1978) and Banker, Charnes, and Cooper (BCC) (1984) and a normalization criterion for breaking down the index based on the quality and quantity of selected employment contracts. Pereira, Ferreira, Figueira, and Marques (2021) presented an NDEA model for assessing the performance of healthcare providers. They also applied Monte Carlo simulation for addressing the lack of connections between medical services.

2.2. Network data envelopment analysis (NDEA)

The DEA models fail to assess the performance of DMUs in complex systems such as SCs (Yadolladi & Matin, 2021). Initially, Färe and Grosskopf (1996) looked at such systems and presented an NDEA model. Kao and Hwang (2008) decomposed the efficiency of DMUs in network structures by addressing the series relationship. They showed that the overall efficiency of network structures is the product of divisions' efficiencies. Tone and Tsutsui (2009) proposed a network slacks-based measure (SBM) model with a specific weight for each division. Tone and Tsutsui (2009) presented a dynamic network SBM model. They addressed good and bad carry-overs in network structures in free and fixed forms and applied their developed model for the performance evaluation of electric power companies. Faramarzi, Khodakarami, Shabani, Farzipoor Saen, and Azad (2015) developed an NDEA model for evaluating the sustainability of combined cycle power plants. To assess the sustainability of SCs, Kalantary and Farzipoor Saen (2019) developed an inverse network SBM model. Fathi and Farzipoor Saen (2018) proposed a bidirectional NDEA model to assess sustainable SCs in the transport sector. In their proposed NDEA model they addressed bounded connections. Zhou et al. (2019) presented a dynamic NDEA model to assess the sustainability of SCs. To address uncertainty in evaluating the sustainability of SCs they used type-2 fuzzy data. Izadikhah, Azadi, Toloo, and Hussain (2021) proposed a fuzzy chance-constrained two-stage DEA model for measuring the sustainability and resilience of SCs. They applied their model to the food industry.

2.3. Deep learning

Deep learning is considered an artificial intelligence and machine learning tool that deals with a considerable amount of layer functions. Layers embedded in deep learning assist in learning and transforming the input data (Punia, Nikolopoulos, Singh, Madaan, & Litsiou, 2020; Luo & Choi, 2021). Deep learning is used for different purposes such as forecasting, risk management, and decision support (Kraus & Feuerriegel, 2019). Fischer and Krauss (2018) forecasted the financial time series by applying long short-term memory (LSTM) networks. Shabanpour et al. (2021) proposed a dynamic NDEA and deep neural technique for forecasting the performance of sustainable SCs. To forecast the demand in the retail industry, Punia et al. (2020) integrated random forest and LSTM networks. The approach can model complicated temporal and regression relations for providing high accuracy outputs. Punia et al. (2020) presented a cross-temporal forecasting framework for forecasting each layer of retail SCs. They applied deep learning as a fundamental

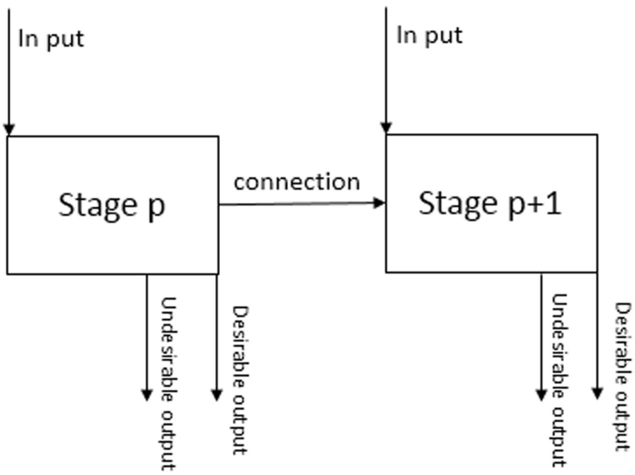

Fig. 2. Network topology.

forecasting approach in the cross-temporal forecasting framework. Mai, Tian, Lee, and Ma (2019) examined the use of textual disclosures to recognize business failure related to deep learning techniques. They applied deep learning techniques for extracting variables from the text and built a dataset for illustrating the veracity enhancement through text data. Chaudhuri, Gupta, Vamsi, and Bose (2021) applied deep learning to explore customers' behavior using a big dataset. They showed that deep learning provides more advantages than other machine learning techniques such as random forest (RF), neural network (NN), and decision tree (DT).

2.4. Knowledge gap

Although the assessment of sustainable HSCs is important, very few studies have addressed it in the literature. The majority of the existing studies are unable to assess the sustainability of HSCs using advanced models and frameworks. While deep learning and NDEA as advanced approaches have been developed and applied in some sectors, there is no research on using deep learning in NDEA to assess sustainable HSCs. The literature also shows that the optimal threshold of each variable and the nature of dual-role connections in sustainable HSCs have not been modeled to date. Moreover, the existing studies show that the used approaches are unable to predict the need of each stage for receiving equipment and medications considering influential factors. For the first time, in this paper, we address these research gaps using NDEA and deep learning to assess and forecast the sustainability of HSCs.

Theoretically, this paper is a step-by-step attempt to propose a proactive model for evaluating the sustainability of HSCs. Meaning that there was a need for a transition from the previous backward-looking and retrospective evaluations of HSCs to preventive and forward-looking approaches. For this purpose, we applied the deep learning technique in this evaluation. To do this, first, the needs of the stages of the HSC were predicted, and accordingly, the clustering of patients was specified to provide medical services according to the severity of the disease.

2.5. The study steps

Considering the theoretical background and knowledge gap, the steps of this study are displayed in Fig. 1.

As is shown in Fig. 1, in the first stage, suppliers allocate equipment and medicine to the medical centers according to the needs of hospitals and laboratories. Using this approach, we prevent unnecessary medicine depots in the SC. Therefore, pharmaceutical equipment and items are provided to SCs per real needs. In the next step, in the laboratories, we apply deep learning to assign each patient to different clusters based on the results extracted from micro factor tests and medical examinations. In this way, we provide appropriate services for the patients according to the severity of their disease. This leads to an optimized allocation of treatment resources to the patients such as treatment space and specialists, etc. Finally, we evaluate various HSCs to identify the top SCs and also provide improvement solutions for other inefficient HSCs. With the model presented in this article, we only evaluate and manage the undesirable outputs, but also identify the weaknesses of each SC and provide an improvement solution for the inefficient HSC.

Table 1
The notations.

Notations	Descriptions
j	jth network, $j = 1,\ldots, J$
P	Number of stages in each network $(p = 1,\ldots, P)$
o	Network under evaluation
x_{ijp}	ith input $(i = 1,\ldots, I)$ of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$
y^{+}_{rjp}	rth desirable output $(r = 1,\ldots, R)$ of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$
y^{-}_{rjp}	rth undesirable output $(r = 1,\ldots, R)$ of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$
d_{qjp}	qth bounded connection $(q = 1,\ldots, Q)$ of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$
c_{wjp}	uth dual-role connection $(w = 1,\ldots, W)$ of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$
g_{tjp}	tth desirable connection $(t = 1,\ldots, T)$ in the forward flow of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$
b_{ujp}	sth undesirable connection $(u = 1,\ldots, U)$ in the forward flow of the jth network $(j = 1,\ldots, J)$ in the pth stage $(p = 1,\ldots, P)$

3. Proposed method

3.1. Network structure of SCS and definition of variables

In this research, each network is made up of nodes and carry-overs (connections). The nodes can consist of stages of an SC such as warehouses, branches, agencies, or even workstations. Since the model presented can evaluate various network types, in the modeling section, we use the word "stage" to introduce "each node". Fig. 2 delineates the network topology and variables, as well as the connections among stages.

As is seen in Fig. 2, we have three types of connections:

Inputs: The inputs include transfers that enter the stages from outside of the network. These inputs can include branch costs, warehousing costs, the safety of warehouse workers, etc. In general, these factors are negative per se and decision-makers seek to reduce them.

Connections: Connections are the links that connect stages. These connections have different roles.

Outputs: The outputs can be desirable or undesirable. Decision-makers normally try to increase the desirable outputs and reduce the undesirable ones.

In this paper, each stage has four types of connections:

Connections among bounded stages: Some connections lead to reduced network performance if their value decreases or increases. These types of connections are between ranges of values. Managerially, some connections' values should be kept within a certain range to assure continuity of the efficacy of DMU.

Dual-role connections: The dual-role connections are factors that the role of some connections between the stages cannot be determined easily. For instance, R&D funds are undesirable as they are cost per se. On the other hand, they are desirable as they are a proxy for innovations.

Desirable connections: Some connections among stages normally increase the efficiency of the network. The proposed model tries to maximize these sorts of criteria.

Undesirable connections: They are connections between the stages, and their increase leads to a decrease in the efficiency of DMU. In

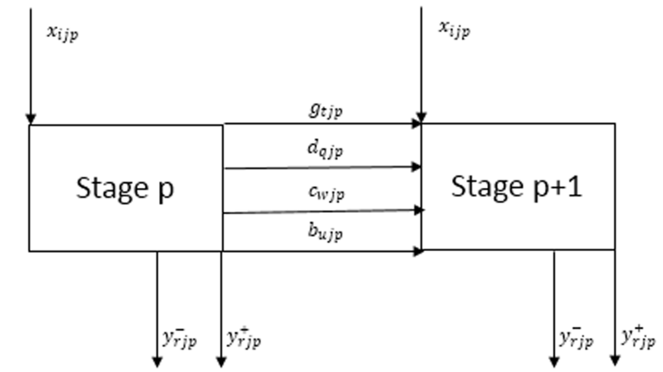

Fig. 3. Network structure.

the proposed model, we try to minimize these sorts of criteria.

At this juncture, we define the variables. Let's consider each "DMU" as a "network" in the proposed network model. The networks are represented by the index *j* (*j* = *1,…, J*). The number of stages of each network is shown by *p* (*p* = *1,…, P*). The connection is in a way that leaves stage *p* and enters stage *p* + *1*. Let's show the bounded connections by *d* (*q* = *1,…,Q*), the dual-role connections by *w* (*w* = *1,…,W*), the desirable connections by *g* (*t* = *1,…,T*), and undesirable connections by *b* (*u* = *1,…, U*). Table 1 describes the notations used in this study.

As is shown in Fig. 3, in the proposed model, each stage has four types of connections. Also, each stage has desirable and undesirable connections.

The following constraints describe the inputs and outputs of DMUs. Here, o depicts the network under evaluation. The desirable and undesirable outputs are defined, separately. Hence, we have.

$$\sum_{j=1}^{J} y^{+}_{rjp}\lambda^{p}_{j} \leq y^{+}_{rOp}(r = 1, \cdots, R; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} y^{-}_{rjp}\lambda^{p}_{j} \geq y^{-}_{rOp}(r^{-} = 1, \cdots, R^{-}; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} x_{ijp}\lambda^{p}_{j} \geq x_{iop}(i = 1, \cdots, I; p = 1, \cdots, P) \tag{1}$$

In addition, after exiting the *p*th stage, the desirable and undesirable connections are considered as inputs of *the p* + *1* stage. The proposed model can be applied in series, parallel, and series–parallel networks. Here, the weighted sum of the desirable connection is considered smaller or equal to the desirable connection in the *p*th stage of the network. Also, the weighted sum of the undesirable connection is considered larger or equal to the undesirable connection in the *p*th stage of the network.

$$\sum_{j=1}^{J} g_{tjp}\lambda^{p}_{j} \leq g_{top}(t = 1, \cdots, T; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} b_{ujp}\lambda^{p}_{j} \geq b_{uop}(u = 1, \cdots, U; p = 1, \cdots, P) \tag{2}$$

Now, we define the constraints of "bounded" and "dual-role" connections as follows:

$$d^{-}_{qop} \leq \sum_{j=1}^{J} d_{qjp}\lambda^{p}_{j} \leq d^{+}_{qop}(q = 1, \cdots, Q; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} c_{wjp} : c_{wop}(w = 1, \cdots, W; p = 1, \cdots, P) \tag{3}$$

Besides, to determine the nature of the dual-role connection, η and α are included in the following equations. Thus, we have.

$$\sum_{j=1}^{J} c_{wjp}\eta^{p}_{w} \leq \eta^{p}_{w}c_{wop}(w = 1, \cdots, W; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} c_{wjp}\alpha^{p}_{w} \leq \alpha^{p}_{w}c_{wop}(w = 1, \cdots, W; p = 1, \cdots, P)$$

$$c_{wop} = \eta^{p}_{w}c_{wop} + \alpha^{p}_{w}c_{wop}$$

$$1 = \eta^{p}_{w} + \alpha^{p}_{w} \tag{4}$$

Since constraints (4) are linear, η and α are considered to be either 0 or 1 so the sum of them should be equal to 1. Here, if the dual-role connection is recognized as 'desirable', then η equals 1 and α equals 0. Otherwise, it is recognized as 'undesirable'. In other words, if η becomes 1; then α will be 0 and a dual-role connection will be desirable. In contrast, if α becomes 1, then η will be 0 and the connection plays an undesirable role. To standardize constraints and the inequalities, we add slacks and define the following constraints:

$$\sum_{j=1}^{J} y_{rjp}\lambda^{p}_{j} - s^{y}_{r} = y_{rop}(r = 1, \cdots, R; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} y^{-}_{rjp}\lambda^{p}_{j} + s^{y-}_{r} = y^{-}_{rOp}(r^{-} = 1, \cdots, R^{-}; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} x_{ijp}\lambda^{p}_{j} + s^{x}_{i} = x_{iop}(i = 1, \cdots, I; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} g_{tjp}\lambda^{p}_{j} - s^{g}_{t} = g_{top}(t = 1, \cdots, T; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} b_{ujp}\lambda^{p}_{j} + s^{b}_{u} = b_{uop}(u = 1, \cdots, U; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} d_{qjp}\lambda^{p}_{j} - s^{+d}_{q} = d^{+}_{qop}(q = 1, \cdots, Q; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} d_{qjp}\lambda^{p}_{j} + s^{-d}_{q} = d^{-}_{qop}(q = 1, \cdots, Q; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} c_{wjp}\eta^{p}_{w} - s^{+c}_{w} = \eta^{p}_{j}c_{wop}(w = 1, \cdots, W; p = 1, \cdots, P)$$

$$\sum_{j=1}^{J} c_{wjp}\alpha^{p}_{w} + s^{-c}_{w} = \alpha^{p}_{j}c_{wop}(w = 1, \cdots, W; p = 1, \cdots, P)$$

$$c_{wop} = \eta^{p}_{w}c_{wop} + \alpha^{p}_{w}c_{wop}(w = 1, \cdots, W; p = 1, \cdots, P)$$

$$1 = \eta^{p}_{w} + \alpha^{p}_{w}$$

$$s^{y}_{i} \geq 0, s^{x}_{r} \geq 0, s^{g}_{t} \geq 0, s^{b}_{u} \geq 0, s^{+d}_{q} \geq 0, s^{-d}_{q} \geq 0, s^{c}_{w} \geq 0, \lambda^{p}_{j} \geq 0, \eta^{p}_{w} \geq 0, \alpha^{p}_{w} \geq 0 \tag{5}$$

Given the inputs, outputs, and connections, the production possibility set (PPS) is defined for the stages of the network. Hence, using η and α, two objective functions are described based on input-oriented and output-oriented approaches.

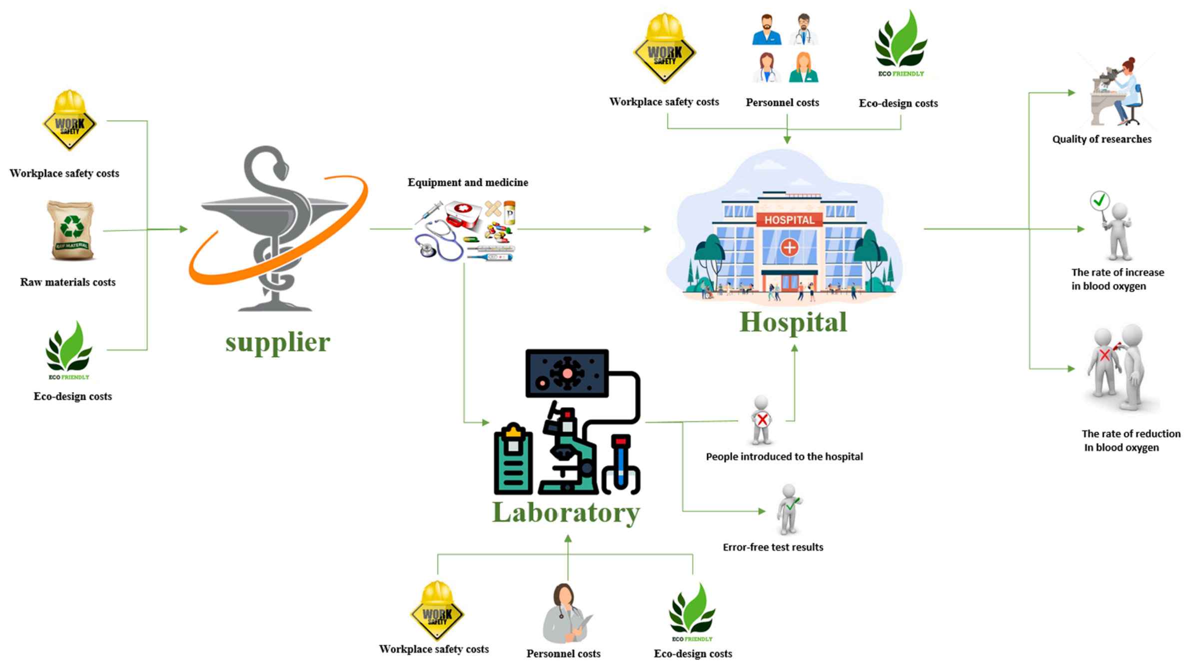

Fig. 4. Healthcare supply chain.

3.2. *Objective function and efficiency*

The overall efficiency is defined in terms of input-oriented, output-oriented, and hybrid models. Note that in input-oriented models, inputs are reduced and outputs are unchanged while in output-oriented models, outputs are maximized and inputs are unchanged.

3.2.1. *Input-oriented model*

Let's define the input-oriented model to calculate the efficiency of the *p*th stage of the *j*th network. Hence, the objective function is as follows:

$$\theta_j^p = \left\{ \min = 1 - \frac{\left(\sum_{i=1}^{I} s_i^x x_{iop} + \sum_{u=1}^{U} s_u^b b_{uop} + \sum_{q=1}^{Q} s_q^{-d} d_{qop}^{-} + \sum_{w=1}^{W} \alpha_w^p c_{wop} + \sum_{r=1}^{R} s_r^{y-} y_{rjp}^{-}\right)}{I + U + Q + W + R^{-}} \right\} \tag{6}$$

The objective function (6) along with standard constraints creates an input-oriented model. Since the model is based on the SBM approach, the infeasible solution in the objective function fades away. Therefore, if each of the parameters becomes zero, the model can still work. Besides, the result of this input-oriented objective function is obtained given the sum of the following variables; (1) a weighted combination of criteria and standardizing slacks; (2) the inputs, undesirable connections, and dual-role connections with undesirable roles; (3) lower bound in bounded connections. To force the efficiency scores to be between 0 and 1, the sum of all aforementioned variables is divided by their values.

3.2.2. *Output-oriented model*

The objective function (7) alongside the standard constraints creates an output-oriented model. To develop the objective function, we utilize outputs and desirable connections, the dual-role connections with the desirable role, and the upper bound in bounded connections. As a result, the efficiency score of the *p*th stage of the *j*th network in the output-oriented objective function is as follows:

$$\theta_j^p = \left\{ \max = \frac{\left(\sum_{r=1}^{R} s_r^{y+} y_{rjp}^{+} + \sum_{t=1}^{T} s_t^g g_{top} + \sum_{q=1}^{Q} s_q^{+d} d_{qop}^{+} + \sum_{w=1}^{W} \eta_w^p c_{wop}\right)}{R^{+} + T + Q + W} \right\} \tag{7}$$

3.2.3. *Hybrid model*

Now, we obtain the efficiency of the hybrid model. Accordingly, we have.

$$\theta_j^p = max = \frac{\frac{\left(\sum_{r=1}^{R} s_r^{y+} y_{rjp}^{+} + \sum_{t=1}^{T} s_t^g g_{top} + \sum_{q=1}^{Q} s_q^{+d} d_{qop}^{+} + \sum_{w=1}^{W} \eta_w^p c_{wop}\right)}{R^{+}+T+Q+W}}{\frac{\left(\sum_{i=1}^{I} s_i^x x_{iop} + \sum_{u=1}^{U} s_u^b b_{uop} + \sum_{q=1}^{Q} s_q^{-d} d_{qop}^{-} + \sum_{w=1}^{W} \alpha_w^p c_{wop} + \sum_{r=1}^{R} s_r^{y-} y_{rjp}^{-}\right)}{I+U+Q+W+R^{-}}} \tag{8}$$

Since objective function (8) is non-linear, we run the Charnes-Cooper approach (Charnes & Cooper, 1962) to transform it into a linear model. Therefore, we have.

$$\max = \frac{\left(\sum_{j=1}^{J} s_r^{y+} y_{rjp}^{+} + \sum_{t=1}^{T} s_t^g g_{top} + \sum_{q=1}^{Q} s_q^{+d} d_{qop}^{+} + \sum_{w=1}^{W} \eta_w^p c_{wop}\right)}{R^{+} + U + Q + W} \tag{9}$$

S.t.

$$\frac{\left(\sum_{i=1}^{I} s_i^x x_{iop} + \sum_{u=1}^{U} s_u^b b_{uop} + \sum_{q=1}^{Q} s_q^{-d} d_{qop}^{-} + \sum_{w=1}^{W} \alpha_w^p c_{wop} + \sum_{r=1}^{R} s_r^{y-} y_{rop}^{-}\right)}{I + U + Q + W + R^{-}} = 1$$

Other constraints.

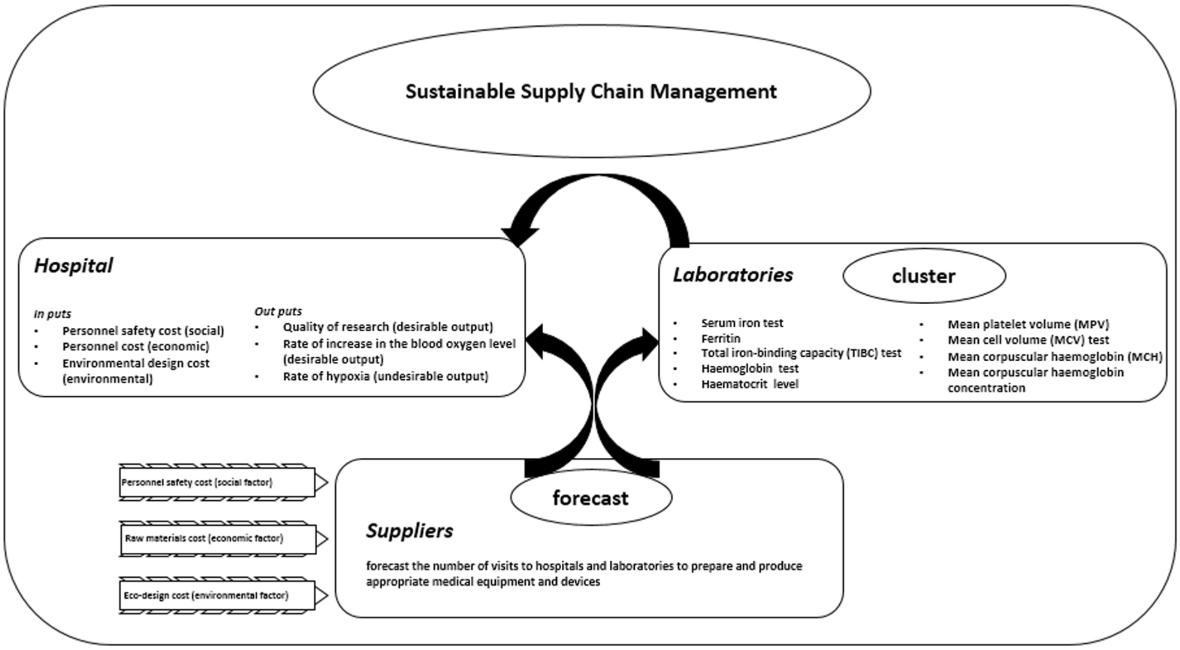

Fig. 5. The input–output framework of the healthcare supply chain.

Overall efficiency *(β)* of the *j*th network in both input and output-oriented models is as below:

$$\frac{\sum_{p=1}^{P} v_p \theta_j^p}{P} = \beta_j \tag{10}$$

Note that in the proposed model we can allocate appropriate weights given the degree of importance of each stage. Thus, v_p depicts the importance of the *p*th stage.

4. Case study

In this section, we evaluate the sustainability of HSCs in different parts of Iran. The main purpose of this study is to evaluate the sustainability of medical operations for Covid-19 patients. To do so, we use secondary data extracted from the documents recorded in the archive of the Ministry of Health and Iranian Universities of Medical Sciences. Besides, the evaluation criteria are the extracted criteria from similar previous papers. We finalize and select the ultimate criteria based on the opinions of medical experts. We further discuss and improve the data evaluation and analysis process by providing various graphs in the paper. Fig. 4 shows the HSCs.

We use the sustainability criteria (economic, social, and environmental factors) for evaluating HSCs (DMUs). As is shown in Fig. 4, the HSC consists of three stages.

4.1. Evaluation criteria for the first stage of the HSCs (suppliers)

The suppliers provide the medicines and equipment needed for Covid-19 patients. At this stage, using deep learning, the needs of hospitals and laboratories are forecasted. The evaluation criteria of the first stage are as follows:

Inputs:

Personnel safety cost (social factor) (1000-Dollars): It refers to the cost that laboratories pay for the safety of their personnel.

Raw materials cost (economic factor) (1000-Dollars): It is the cost of purchasing raw materials.

Eco-design cost (environmental factor) (1000-Dollars): The cost that each supplier pays to design products to protect the environment.

Output:

Equipment and medicine (1000-Dollars): It indicates the values of equipment and medicine that are supplied to hospitals and laboratories.

4.2. Evaluation criteria for the second stage of the HSCs (laboratories)

The second stage includes laboratories that test patients and provide necessary advice for them. At this stage, patients are divided into two groups infected and non-infected people. Then, we use the following factors to classify the infected people into three clusters. The clustering factors are as follows:

- **Serum iron test:** This test measures the amount of circulating iron in the form of transferrin (WHO, 2020).
- **Ferritin:** It is a measure of the iron stored in the body (WHO, 2020).
- **Total iron-binding capacity (TIBC) test:** This test measures the amount of transferrin in the blood. The iron-carrier protein receives the metals from the intestines, where it is absorbed from food, delivering them to the blood (The Lancet, 2020).
- **Hemoglobin test:** This test measures the total hemoglobin level, a reliable parameter for evaluating the blood's capacity to deliver oxygen to tissues and organs (Villagonzalo et al., 2019).
- **Hematocrit level:** It is the ratio of the volume of red blood cells to the total volume of blood. This factor rises in conditions that blood plasma reduces (The Lancet, 2020; WHO, 2021).
- **Mean platelet volume (MPV):** This factor shows the dimensions of platelets. It also provides valuable information about platelet production in bone marrow (WHO, 2021).
- **Mean cell volume (MCV) test:** This test measures the mean size of red blood cells (WHO 2021).
- **Mean corpuscular hemoglobin (MCH):** This factor calculates the hemoglobin content of red blood cells (Villagonzalo et al., 2019).
- **Mean corpuscular hemoglobin concentration (MCHC)**: MCHC shows the mean concentration of hemoglobin in red blood cells (WHO, 2020).

By taking these micro-factors into account, patients are categorized into the following clusters:

- **The first cluster:** The Covid-19 patients who are in emergency conditions and must be hospitalized in hospital.

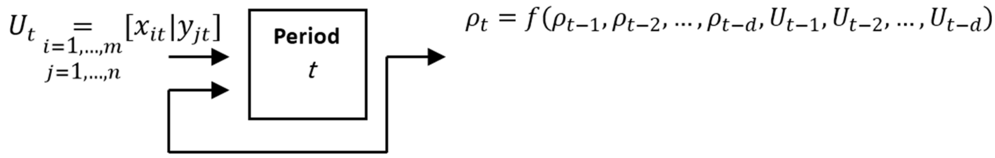

Fig. 6. Nonlinear autoregressive (NARX) model for each period.

- **The second cluster:** The Patients with a positive Covid-19 test who can be treated at home.
- **The third cluster:** The patients who have a positive Covid-19 test, but can be treated by going to a clinic periodically, using medical equipment, and taking medicines.

Now, we define the inputs and outputs criteria for the second stage.

Inputs:

Personnel safety cost (social) (1000-Dollars)**:** It refers to the cost that laboratories pay for the safety of their personnel.

Personnel cost (economic) (1000-Dollars): It is the cost that is paid in a certain period to personnel.

Environmental design cost (environmental**)** (1000-Dollars)**:** The cost paid by each laboratory to reduce medical waste.

Outputs:

Correct results (desirable output): It is the percentage of people who have been correctly identified as Covid-19 patients and referred to the hospital.

Incorrect results (Undesirable output): It is the percentage of people who have been incorrectly identified by the Covid-19 test. In other words, the incorrect test results include people who have not been infected by the virus but have been identified as infected or vice versa.

4.3. Defining evaluation criteria for the third stage of the HSCs (hospital)

Hospital is considered the last stage in the HSCs. At this stage, patients are treated in the hospital. Inputs and outputs of this stage are as follows:

Inputs.

Personnel safety cost (social) (1000-Dollars)**:** It is the cost that a hospital pays for the safety of its personnel.

Personnel cost (economic) (1000-Dollars)**:** It is the cost paid in a certain period to personnel.

Environmental design cost (environmental) (1000-Dollars)**:** It is the cost paid by each hospital to reduce medical waste.

Outputs.

Quality of research (desirable output): It includes high-quality research conducted in each hospital. This quality is based on publishing valid reports and books as well as published articles in reputed journals.

Rate of increase in the blood oxygen level (desirable output): The rate of improvement in the status of patients under medical care because of increasing positive micro factors.

Rate of hypoxia (undesirable output): It indicates a decrease in the general condition of patients owing to increasing negative micro factors and decreasing positive micro factors for patients.

Fig. 5 displays the whole input–output framework of the three-stage HSC.

4.4. . Applying deep learning and artificial neural networks (ANN) models in the stages of the HSCs

4.4.1. Suppliers

As mentioned earlier, in this study each supplier uses deep learning to forecast the number of visits to hospitals and laboratories to prepare and produce appropriate medical equipment and devices. It is important as the shortage of the required medical equipment and medicine results in some major problems in treating the patients. As such, this prediction can prevent an excess of the required items in one hospital and a shortage in another hospital. Applying deep learning and ANN can be considered an effective approach to do so. To forecast the required level of each hospital and laboratory to medicine and medical equipment, it is necessary to forecast the next periods based on past information. Accordingly, in this study periods are considered weekly. Given the

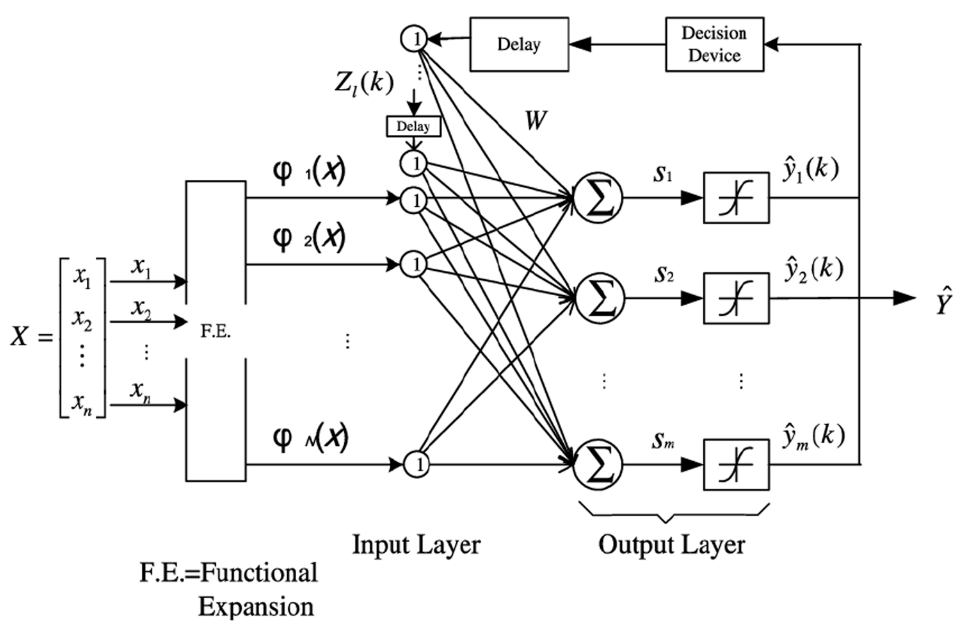

Fig. 7. Overview of the feedback network with the feedback-delay connection.

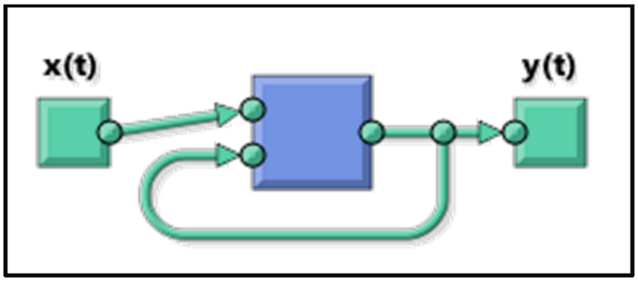

Fig. 8. Schematic model of neural network based on NARX time series.

available information, from the beginning of October 2019 to the beginning of January 2021, we gathered the data for 60 time periods.

Considering the above explanations, a time series model can be created for future forecasting. Given the distinctive features of deep learning, we apply the deep learning network structure to create the proposed model. The generated model is a non-linear model with recursive relations that is defined for each time step as follows:

$$\rho_t = f(\rho_{t-1}, \rho_{t-2}, \cdots, \rho_{t-d}, U_{t-1}, U_{t-2}, \cdots, U_{t-d}) \tag{11}$$

where ρt is the amount of equipment required for period t, and Ut is the set of input vectors x_i and y_j for period t. The value of d is equal to the number of lag steps (Lag) to influence the forecasted value. Considering the return relations and the effects of the values of this equipment (as time series output) on future values, the above model can be shown in Fig. 6.

This model is a NARX model with recursive connections, which is calculated in this study using the perceptron ANN. To implement the above time series with the neural network, the feedback perceptron neural network has been used. By doing so, both the nonlinear computational connections of the model and the recursive connections of the model can be implemented.

To implement our time series network, different architectures and training methods are considered, and based on their combination the best output is calculated. Different regions have been expanded to determine the number of neurons and the number of hidden layers. One of them is the Enke approach (Enke & Thawornwong, 2005), which considers the existence of one or two layers to be sufficient for processing most of the information. Selecting the right number of neurons of the hidden layer (s) can prevent over-occurrence in the network (Yousefi et al., 2019, 2021). In this study, the number of layers is considered equal to one and two, and neurons are determined in the mentioned interval. The simple structure of a feedback ANN with a hidden layer is shown in Fig. 7.

According to Fig. 7, the output values are incorporated into the network along with the input values considering the delay steps to make the return connections meaningful. Fig. 7 shows three parts of the feedback network separately indicating (1) the weights of the synapses; (2) the creation of the bias for the equilibrium of the equations; as well as (3) the sum and transfer functions of each layer.

In conventional perceptron networks, the output layer transfer function is considered linear and the latent layer transfer function (s) is considered a hyperbolic or sigmoid tangent. This network uses a post-publication algorithm to correct errors.

Various indicators can be applied to evaluate the network results and select the appropriate neural network architecture (network structure). We may apply the indicators such as mean absolute error (MAE), mean squared error (MSE), the root mean squared error (RMSE), and/or mean absolute percentage error (MAPE). In this study, we utilize the MSE index. The index is calculated as follows:

$$\mathrm{MSE} = \frac{1}{N_T}\sum_{t=1}^{N_T}(\rho_t - \widehat{\rho}_t)^2 \tag{12}$$

Here, ρ_t and $\widehat{\rho}_t$ are the actual and forecasted values of the equipment used, respectively, and N_T represents the total number of observations. Based on the minimum value of MSE, the corresponding architecture is selected and the results are analyzed. In addition, the correlation between the results of the neural network output is evaluated in this study.

This is a widely-used professional word. Based on the values obtained for the equipment sent to each ward of the hospital and laboratories in each period and using these values as the output of the ANN as well as applying the real inputs of each of these centers in periods, this time series model can be implemented through feedback neural network method. In this research, the implementation of the proposed network is tested using MATLAB 2019 software. Fig. 8 shows the schematic model of the neural network based on the NARX time series. In this Figure, *x (t)* means the set of input vectors to the neural network and is presented *U (t)* hereafter, and that *y (t)* means the output vectors of the equipment needed to be sent to the centers and are denoted by ρ.

To train the proportional neural network, the data obtained from the 60-month performance calculation were divided into three groups of training, validation, and test data, with ratios of 70%, 15%, and 15%, respectively. This segmentation is done randomly and is the same as all the neural network performances with different structures.

Considering the above model and the data defined for it, the training process of the feedback neural network with different permutations was performed based on the training algorithm, the number of layers and neurons, and the number of delay steps. Here the structure of a neural network consisted of one and two hidden layers with 10 and 15 neurons, Levenberg-Marquardt, Bayesian Regularization, Scaled Conjugate Gradient, post-propagation training algorithms, and delay steps 2 and 3 create different permutations. Among them, the best MSE and R values for the structure of a single-layer feedback perceptron network (with 10 neurons in the hidden layer) were observed with the Bayesian error post-diffusion training algorithm, which is 0.000053 and 0.997912, respectively. These values indicate a low error and high correlation of network output. Also, the reported correlation for test data is equal to 0.925942, which provides a high level of reliability. A schematic view of this structure with an open loop is shown in Fig. 9.

The neural network fitting obtained from the implementation of the ANN is shown in Fig. 10. Here, the difference between the performance prediction and its actual value for each time step is depicted separately

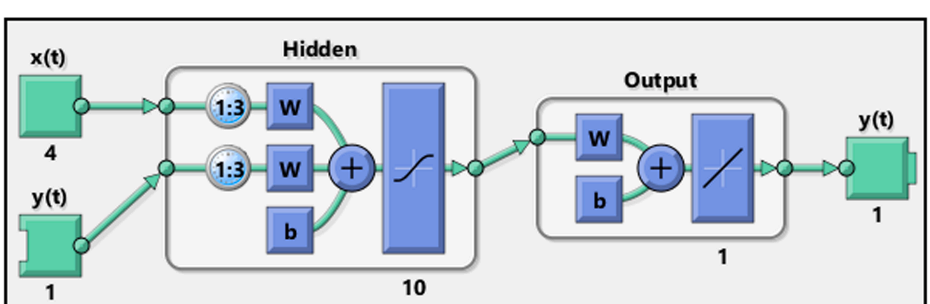

Fig. 9. Schematic view of the selected structure.

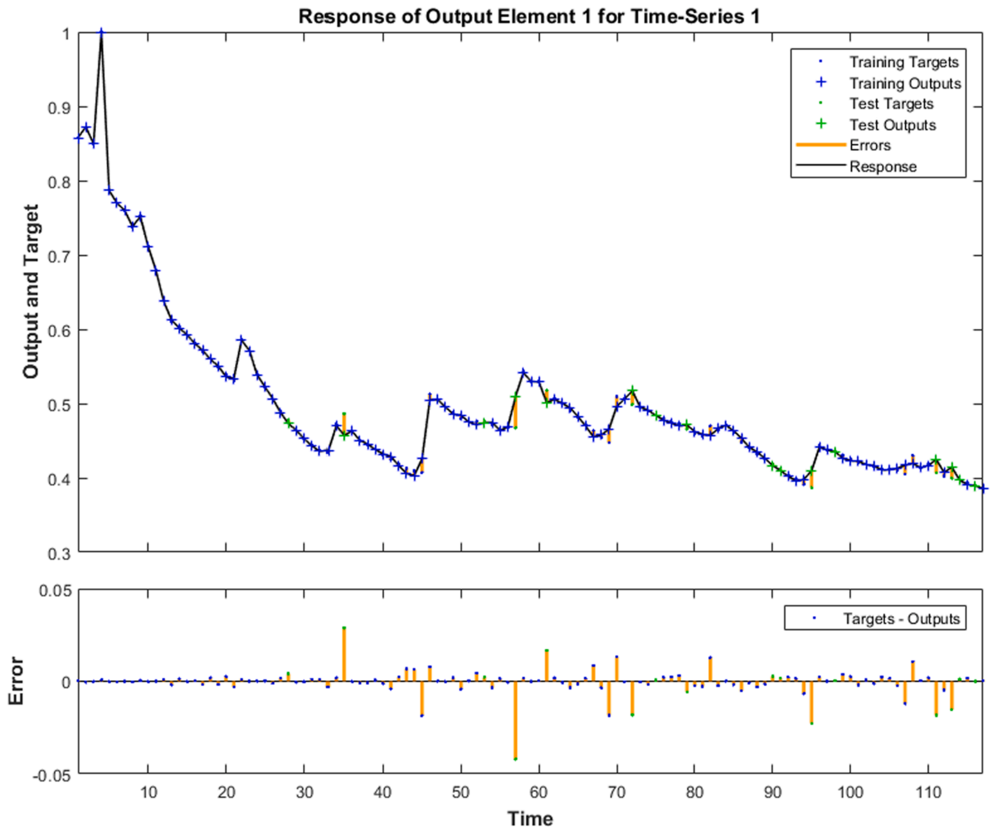

Fig. 10. Neural network fitting and error values.

for the data sets. This difference indicates the amount of forecast error.

4.4.2. Laboratories

As mentioned earlier, the laboratories' test results are obtained using the micro-factors to cluster Covid-19 patients. In this research, we use a deep learning algorithm to analyze the initial cluster and find the centers of the clusters. It is also worth mentioning that we use the micro-factors to classify patients into the following three clusters:

- The first cluster: The Covid-19 patients who are in emergency conditions and must be hospitalized in hospital.

- The second cluster: The Patients with a positive Covid-19 test who can be treated at home.

- The third cluster: The patients who have a positive Covid-19 test, but can be treated by going to a clinic periodically, using medical equipment, and taking medicines.

To analyze the initial cluster and find the centers of the clusters, the deep learning algorithm is applied using the growing neural gas network (GNGN) model. According to Fritzk's (1995) model, the GNGN algorithm includes the following steps:

1) Start by creating two random neurons w_a and w_b ,

2) Generate an input signal ξ based on *P (ξ)* ,

3) Find the nearest neuron s_1 and the nearest next neuron s_2,

4) Increase the age of all edges resulting from s_1,

5) Calculate the square of the distance between the input signal and the nearest neuron in the input space.

$$\Delta(s_1) = \|w_{s_1} - \xi\| \tag{13}$$

6) Transfer s_1 and its direct neighbors to ξ, with ratios $\in_b$ and $\in_n$, respectively.

$$\Delta w_{s_1} = \in_b(\xi + w_{s_1})$$

$$\Delta w_n = \in_n(\xi + w_n) \tag{14}$$

7) If s_1 and s_2 are connected by an edge, the age of the edge is set to zero and if such an edge does not exist, it is created.

8) Remove all edges that are older than α_{max}. If no edge is generated, all of them will be removed.

9) If all the input signals generated are integers of the λ parameter, a new neuron is generated as follows:

- Determine neuron q with maximum accumulated error.
- Place r neurons between q and its neighbor with the largest error *(f)*.

$$w_r = \frac{1}{2}(w_q + w_f) \tag{15}$$

10) Reduce all error values by constant multiplication of d.

11) If the stop index (network size or some performance indicators) still does not apply, continue the process from step one once again.

Assuming that the centers of the clusters are calculated by the GNGN algorithm, the following proposed model can be used to determine the membership of each sample in each cluster. This model is based on the linear allocation model and the logic of its objective function is to minimize the distances between the samples and the centers of the corresponding clusters. In this model, two sets are considered. The *Pnt* set includes demand points and the *Cls* set includes cluster centers. These sets are obtained using the implementation of the GNGN. In other words, assuming n samples and k clusters, then we have:

$$\text{Pnt} = \{k_1, k_2, \cdots, k_n\}, \text{Cls} = \{v_1, v_2, \cdots, v_n\} \tag{16}$$

$$\min \sum_i \sum_j d_{ij} x_{ij}$$

s.t.

$$\sum_j x_{ij} = 1 \forall j \in \text{Pnt}$$

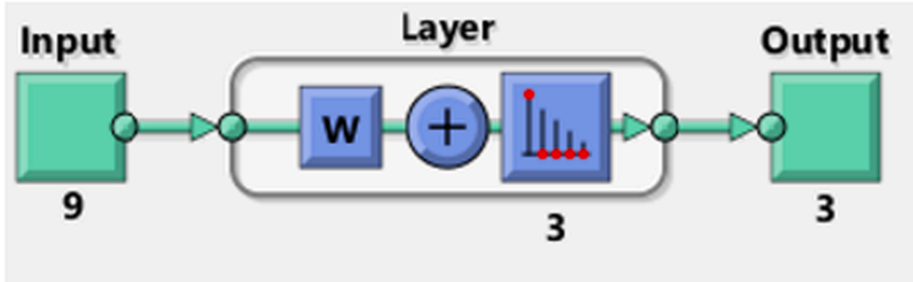

Fig. 11. The network topology for clustering.

$$\sum_{i} x_{ij} \leq n \forall i \in \text{Cls}$$

$$\sum_{j}\sum_{i} w_i x_{ij} \leq w \forall i \in \text{Cls}$$

$$\sum_{j}\sum_{i} u_i x_{ij} \leq u \forall i \in \text{Cls}$$

$$x_{ij} \in \{0,1\}, \forall i \in \{k_1, k_2, \cdots, k_n\}, \forall i \in \{v_1, v_2, \cdots, v_n\}$$

where d_{bh} is the distance between sample b from the center of cluster h and it is used for determining the cost of allocating the sample to a given cluster. Equations (13), (14), and (15) show the limitations of the optimization. Constraint (2) in Model 16 ensures that each sample is assigned to only one cluster. The third and fourth constraints are repeated for each of the micro-factors presented in the medical experiment.

Note that the above model is an integer linear programming model. By solving it, the assignment of each sample (new patients) to each of the clusters will be obtained. In other words, using this model in the laboratory, the status of each patient is determined and allocated to one of three clusters. Fig. 11 shows that the network used for clustering uses 9 micro factors to determine the patient membership in the three clusters.

At this juncture, based on the information provided by 38 HSCs, we evaluate and rank them in 2020. Table 2 presents the dataset. The data has been extracted from the available documents and information archives of each SC as well as the information available on the website.[11]

Looking at Table 2, the first row presents each of the three stages of the HSC including suppliers, laboratories, and hospitals. In the first column from the left, the number of each SC is presented, and in the next columns, the inputs and outputs of each stage are presented, respectively. The final evaluation and ranking were performed using the objective function and constraint 9 along with the constraint set 5 and the data in Table 2. The evaluation results are presented in Table 3.

In Table 3, the first column from the left shows the specific number of each SC. The second column shows the efficiency scores and the last column demonstrates the ranks obtained from the evaluation. Using the model presented in this study, HSC 2 with an efficiency score of 1 is the most efficient DMU followed by HSCs 8 and 27. Accordingly, SCs that use the least facilities, and have the most desirable output, as well as the least undesirable output, are in the top ranks. Using the results of Table 3, the efficient SCs are identified as benchmarks for inefficient ones. Here, the benchmarks are proposed for all the inefficient HSCs based on the position of the efficient DMUs on the efficiency frontier.

In this study, we evaluated Iranian HSCs using different connections between the stages. For this purpose, we considered two types of desirable and undesirable outputs as the outputs of each stage. We also used the deep learning approach in different stages for predicting and clustering DMUs. The prediction and clustering have led the HSCs to be balanced not only in sending equipment and medicine but also in allocating patients to hospitals. This has also led to a significant number of SCs having acceptable incremental performance. Furthermore, even the rest of the SCs which are in lower ranks, have had a significant increase in performance compared to the same past period. The superior SC in 2019, compared to SCs in 2020 did not rank better than 36. It is noteworthy that in 2019, deep learning was not used to deliver medicine and equipment and send patients to the hospital.

It should be noted that the significant reduction in undesirable outputs in some SCs compared to 2019 has been because of the reduction in medicine and equipment inputs in some hospitals. This achievement has been obtained in forecasting the requirements of each hospital based on deep learning. Moreover, by using the clustering approach carried out in laboratories, the patients are referred to hospitals correctly. This has led to the optimal and fair use of hospital equipment and services by patients, which has played an important role in controlling the epidemic.

One of the outcomes of this study, in addition to ranking HSCs, is to provide an improvement solution (benchmark). For this purpose, for inefficient SCs, benchmarks are introduced. Also, a sensitivity analysis is performed for benchmarks. Table 4 shows, the sensitivity analysis results. The sensitivity analysis specifies the degree of fluctuation in inputs and outputs of each SC that improves the efficiency of an inefficient SC. Table 4 provides benchmarks for all SCs. As is shown in Table 4, to push the SCs on the efficiency frontier, the amount of decrease in inputs is presented in the form of a negative value, and also the amount of increase in the desirable outputs is presented in the form of positive values. Note that SC #2 has an efficiency score of 1 and is the benchmark. For this reason, no improvement is provided for SC #2. Therefore, we provide an improvement benchmark for other SCs based on the efficiency frontier derived from SC #2. SC #2 (as a benchmark) can provide an improvement solution for all inefficient HSCs. For example, if SC #34 wants to be efficient in the next period, it should reduce its first input by 59 units (i.e., the cost of raw materials). Likewise, it shows how much SC #34 should reduce its inputs and increase its desirable outputs in each stage of the SC. In addition, the reductions that should be made in the undesirable outputs are presented in Table 4. The approach presented in this paper can provide a precautionary benchmark for SCs that may become inefficient next period.

Table 5 shows the sensitivity analysis based on the elimination of the inputs and outputs. Table 5 signifies how much the efficiency of each SC will change if we remove the value of a specific criterion. Each column provides a performance value. The average column also presents the average efficiency.

Evaluation, analysis, and prediction of sustainability of SCs based on powerful tools, including NDEA and deep learning can be an effective way for improving the performance of organizations in many areas. As such, instead of using traditional performance evaluation tools and techniques, we developed a new NDEA model. To do so, we modeled the whole SC containing all inputs, outputs, and intermediate variables in an integrated model and obtained the results. Moreover, to mitigate the effect of the type of data on performance evaluation results, we incorporated desirable, undesirable, and dual-role data as well as lower

[1] https://www.research.ac.ir/.

Table 2
The dataset for the HSCs in 2020.

SCs	Supplier				Laboratory					Hospital					
	Inputs			Output	Inputs			Outputs		Inputs			Outputs		
	Raw materials costs	Eco-design costs	Workplace safety costs	Equipment and medicine	Eco-design costs	Personnel costs	Workplace safety costs	Error-free test results	People introduced to the hospital	Eco-design costs	Personnel costs	Workplace safety costs	Quality of researches	The rate of increase in blood oxygen	The rate of reduction In blood oxygen
1	321	52	23	538	47	154	7	3	81	22	243	5	159	44	56
2	219	38	14	515	52	230	16	1	97	9	395	25	180	36	67
3	282	20	11	422	53	172	29	1	99	8	309	19	137	25	81
4	257	14	13	488	27	232	14	5	95	21	203	7	97	39	37
5	152	7	12	435	87	237	24	3	84	19	341	15	128	10	68
6	318	35	21	487	64	110	12	2	83	29	327	21	161	38	64
7	270	47	3	414	78	246	22	5	98	20	401	23	114	29	54
8	298	48	16	372	36	214	10	6	89	7	261	23	189	34	50
9	150	24	21	519	72	151	5	9	90	7	304	20	130	33	68
10	352	36	10	413	88	100	13	3	80	13	236	19	87	23	71
11	135	40	22	366	61	250	26	5	96	16	418	7	176	28	72
12	140	52	10	560	78	143	6	10	93	22	376	10	143	31	63
13	139	51	10	385	35	220	14	3	89	19	370	8	162	31	31
14	233	54	15	369	69	133	6	7	87	25	312	21	133	25	39
15	262	24	20	528	75	185	17	9	93	22	329	18	120	21	84
16	150	13	18	381	82	213	5	3	81	13	319	20	186	13	41
17	177	44	16	513	34	186	15	10	83	16	355	20	108	40	57
18	197	33	22	420	30	125	21	3	82	24	309	21	110	33	82
19	243	25	18	467	20	149	10	4	94	14	219	5	129	37	56
20	276	26	23	431	20	216	13	5	92	16	469	23	107	30	54
21	121	15	21	465	88	169	20	3	99	15	315	5	108	33	36
22	195	23	24	407	40	141	15	2	97	17	432	21	172	16	58
23	182	54	20	448	60	116	20	1	85	23	218	12	80	31	39
24	250	15	18	525	80	257	17	5	87	23	427	25	150	29	46
25	216	19	4	413	48	102	6	7	98	29	451	10	105	29	33
26	345	52	14	550	42	113	8	3	91	19	464	19	106	35	60
27	193	43	6	498	20	160	24	9	89	17	404	14	189	27	80
28	309	14	2	544	31	121	10	9	89	16	259	5	149	45	70
29	156	45	24	473	38	166	27	9	87	18	270	14	83	30	68
30	220	44	3	510	46	184	24	6	86	19	305	22	180	11	84
31	202	44	16	395	76	112	14	3	87	11	208	14	125	10	38
32	284	10	6	448	57	102	6	10	85	21	250	26	123	26	75
33	288	49	11	529	72	207	25	8	88	23	415	15	166	30	54
34	164	25	12	529	34	127	7	4	89	8	432	10	168	20	76
35	222	12	5	484	65	201	24	10	84	5	223	10	162	24	66
36	184	40	11	356	42	163	26	10	85	19	267	29	137	10	50
37	228	23	1	479	26	199	5	7	82	25	259	18	118	38	58
38	315	7	5	375	75	244	11	9	92	24	340	25	116	38	46

Table 3
The HSCs ranking results in 2020.

SCs	Efficiency	Rank
The best SC	0.778	36
1	0.97	6
2	1	1
3	0.87	17
4	0.801	30
5	0.78	35
6	0.946	10
7	0.824	22
8	0.986	2
9	0.849	19
10	0.728	39
11	0.976	4
12	0.894	15
13	0.959	9
14	0.828	21
15	0.81	26
16	0.916	11
17	0.8	31
18	0.789	33
19	0.865	18
20	0.791	32
21	0.821	23
22	0.971	5
23	0.756	38
24	0.891	16
25	0.806	28
26	0.804	29
27	0.981	3
28	0.965	7
29	0.775	37
30	0.901	13
31	0.785	34
32	0.816	25
33	0.965	8
34	0.912	12
35	0.897	14
36	0.807	27
37	0.819	24
38	0.841	20

bound and upper bound in bounded connections in the model. By doing so, we presented more accurate results that can be used for better decision-making. Additionally, we addressed the infeasibility in the case study using the developed NDEA model so that all DMUs provide efficiency scores between 0 and 1. Furthermore, the results show that our developed model has more discrimination power, which can support management in making better decisions.

5. Conclusion and research directions

5.1. Methodological implications

The advent of advanced digital technologies in different areas has been a hot topic over the last few years. Recent studies show that these technologies provide organizations with several benefits (Toorajipour et al., 2021). The increased demand for digital technologies in healthcare systems aimed at enhancing performance and satisfying stockholders demonstrates the significance of such technologies. Furthermore, the recent Covid-19 outbreak has emphasized how the performance of healthcare systems can be affected by unexpected events if such systems are not designed, planned, and equipped using advanced digital technologies (Secundo, Shams, & Nucci, 2021). As well as applying advanced digital technologies in complicated systems such as healthcare SCs, state-of-the-art performance measurement approaches need to be used in such systems (Yasmin, Tatoglu, Kilic, Zaim, & Delen, 2020). While deep learning and NDEA are recognized as state-of-the-art methods, there is no research on using deep learning in NDEA for evaluating sustainable HSCs. The literature demonstrates that the optimal threshold of each variable and the nature of dual-role connections in sustainable HSCs have not been addressed so far. Furthermore, the current studies illustrate that the applied methods cannot forecast the need of each stage for receiving equipment and medications considering significant indicators.

In this paper, we presented an NDEA model and applied deep learning for predicting the sustainability of healthcare SCs. Our NDEA model is compatible with different topologies. We addressed the threshold of each bounded connection for maximizing the performance of DMUs. Furthermore, we used bounded connections and identified the optimal threshold for each variable and dual-role connections, and identified the role of each dual-role connection. We also applied our novel approach to the sustainability assessment of HSCs in face of the Covid-19 pandemic.

5.2. Managerial and theoretical implications

Using the proposed model, we not only forecasted future performance and ranking of HSCs but also identified the drawbacks of inefficient SCs and put forward a proportionate improvement solution (benchmark). In other words, first, we identified the cause of future inefficiencies in healthcare SCs. By so doing, the decision-maker already knows what stage of each inefficient SC will face a deficiency, and how it will cause the entire SC to have relatively low efficiency.

From the optimal facility allocation point of view, the implementation of this forecasting approach will lead to the delivery of pharmaceutical equipment and items to each of the hospitals and laboratories per the real needs, so that there will be no shortage, depot, or waste of medicine and equipment in medical centers. Furthermore, clustering patients using the deep learning technique may lead to providing medical services according to the needs of each patient. In this case, if the patient needs special care, they will be hospitalized immediately. If the disease can be treated on an outpatient basis, medical equipment will not be unnecessarily suspended somewhere else. Finally, a proportionate improvement solution (benchmark) is provided for inefficient SCs.

To the best of our knowledge, despite the significance of the healthcare sector particularly in crises such as the COVID-19 pandemic and Severe Acute Respiratory Syndrome (SARS), no research has been conducted on predicating sustainability of HSCs using advanced techniques such as deep learning and NDEA. As such, these state-of-the-art techniques deal with a key challenge in the healthcare sector so that scholars can develop their approaches. Moreover, using the NDEA model proposed in this study, scholars can have a better understanding of the performance measurement of network structures by defining the existing relationships among inputs, outputs, and intermediate variables. Furthermore, based on the developed NDEA model, scholars can model other network structures that deal with desirable, undesirable, and dual-role connections, simultaneously. This, in turn, also assists them to obtain more reliable results in investigating the sustainability of SCs. In addition, the deep learning technique presented in this study shows how well the sustainability of SCs can be forecasted.

5.3. Future research directions

Our proposed approach can be developed for similar HSCs evaluations. A future research direction is to develop new NDEA models based on range-adjusted measures (RAM) and bounded-adjusted measures (BAM). In addition, the sustainability performance of HSCs can be assessed by some dissimilar types of data such as shared inputs, fuzzy data, and ordinal data. Novel NDEA models can be developed to address these types of data in HSCs. Finally, robust data also may be suggested for future research projects on the performance evaluation of HSCs.

Table 4
Improvement solutions (benchmarks) for inefficient healthcare SCs.

Hospital						Laboratory					Supplier				SCs
Outputs			Inputs			Outputs		Inputs			Output	Inputs			
The rate of reduction In blood oxygen	The rate of increase in blood oxygen	Quality of researches	Workplace safety costs	Personnel costs	Eco-design costs	People introduced to the hospital	Error-free test results	Workplace safety costs	Personnel costs	Eco-design costs	Equipment and medicine	Workplace safety costs	Eco-design costs	Raw materials costs	
−13	11	25	−23	−166	−14	19	−8	−10	−81	−6	25	−19	−29	−45	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
−16	14	47	−9	−100	−2	5	0	−16	−63	−4	95	−4	−20	−30	3
−32	6	87	−21	−206	−13	5	−5	−3	−9	−26	29	−2	−26	−58	4
−3	29	56	−13	−68	−11	16	−3	−10	−12	−22	82	−3	−33	−26	5
−5	5	23	−7	−82	−21	17	−12	−5	−125	−18	30	−9	−5	−102	6
−15	10	70	−5	−8	−12	4	−12	−7	−22	−19	103	−12	−18	−69	7
−19	5	13	−5	−148	−3	11	−14	−7	−21	−17	145	−11	−16	−22	8
−3	6	54	−8	−105	−3	10	−11	−12	−84	−22	6	−6	−16	−73	9
−6	16	97	−9	−173	−5	20	−4	−4	−135	−35	104	−5	−4	−36	10
−7	11	8	−21	−9	−8	4	−5	−9	−27	−9	151	−15	−9	−88	11
−6	8	41	−18	−33	−14	7	−11	−11	−92	−27	47	−5	−26	−89	12
−38	8	22	−20	−39	−11	11	−6	−3	−15	−18	132	−5	−19	−73	13
−30	14	51	−7	−97	−17	13	−6	−11	−102	−22	148	−16	−26	−47	14
15	18	64	−10	−80	−14	7	−7	0	−50	−23	15	−17	−16	−34	15
−28	26	10	−8	−90	−5	19	−7	−12	−22	−36	136	−18	−27	−73	16
−12	7	76	−8	−54	−8	17	−11	−2	−49	−19	4	−4	−7	−46	17
−13	6	74	−7	−100	−16	18	−6	0	−110	−23	97	−9	−7	−26	18
−13	4	55	−23	−190	−6	6	−6	−7	−86	−33	50	−6	−15	−37	19
−15	9	77	−5	−60	−8	8	−6	−4	−19	−33	86	−17	−14	−34	20
−33	6	76	−23	−94	−7	5	−4	0	−66	−37	52	−7	−25	−74	21
−11	23	12	−7	−23	−9	3	−4	−2	−94	−13	87	−14	−17	−28	22
−30	8	53	−16	−191	−15	15	−1	−5	−105	−6	19	−7	−23	−41	23
−23	10	34	−3	−18	−15	13	0	−2	−35	−28	12	−5	−25	−39	24
−36	10	79	−18	−42	−21	4	−7	−11	−133	−5	77	−11	−21	−7	25
−9	4	78	−9	−55	−11	9	−6	−9	−122	−11	37	−1	−19	−68	26
−15	12	13	−14	−5	−9	11	−7	0	−75	−33	25	−9	−6	−30	27
−5	12	35	−23	−150	−8	11	−7	−7	−114	−22	31	−13	−26	−59	28
−3	9	101	−14	−139	−10	13	−9	−15	−69	−15	61	−11	−10	−67	29
−19	28	4	−6	−104	−11	14	−6	−19	−51	−7	2	−12	−7	−18	30
−31	29	59	−14	−201	−3	13	−3	−3	−123	−28	2	−6	−12	−21	31
−10	13	61	−2	−159	−13	15	−14	−11	−133	−9	31	−9	−30	−63	32
−15	9	18	−13	−6	−48	12	−7	−14	−28	−21	16	−4	−18	−27	33
−11	19	16	−18	−23	−2	11	−7	−10	−108	−19	16	−3	−15	−59	34
−3	15	22	−18	−186	−5	16	0	−7	−34	−14	66	−10	−28	−19	35
−19	29	−39	−1	−142	−11	15	−10	−11	−72	−11	371	−4	−6	−39	36
−11	5	66	−10	−150	−17	18	−7	−12	−36	−27	24	−14	−17	−29	37
−23	5	68	−3	−69	−16	8	−9	−6	−10	−26	31	−10	−33	−79	38

Table 5
Sensitivity analysis according to the elimination of the criteria.

Hospital						Laboratory					Supplier				Average efficiency	SCs
Outputs			Inputs			Outputs		Inputs			Output	Inputs				
The rate of reduction In blood oxygen	The rate of increase In blood oxygen	Quality of researches	Workplace safety costs	Personnel costs	Eco-design costs	People introduced to the hospital	Error-free test results	Workplace safety costs	Personnel costs	Eco-design costs	Equipment and medicine	Workplace safety costs	Eco-design costs	Raw materials costs		
1	1	0.919	0.928	0.987	1	0.963	0.928	0.918	1	0.949	0.939	0.948	0.948	0.97	0.960	1
0.98	0.987	0.989	0.976	0.959	0.97	1	1	1	0.909	1	1	0.941	1	1	0.981	2
0.826	0.864	0.833	0.846	0.84	0.859	0.839	0.89	0.879	0.818	0.809	0.86	0.0.839	0.9	0.88	0.853	3
0.825	0.836	0.801	0.819	0.824	0.836	0.814	0.798	0.84	0.816	0.836	0.809	0.814	0.798	0.8	0.818	4
0.823	0.809	0.795	0.758	0.779	0.789	0.801	0.793	0.759	0.816	0.819	0.801	0.798	0.8	0.831	0.798	5
0.894	0.9	0.905	0.869	0.889	0.879	0.896	0.88	0.879	0.901	0.903	0.896	0.916	0.936	0.991	0.902	6
0.846	0.859	0.869	0.839	0.897	0.839	0.864	0.879	0.894	0.88	0.894	0.859	0.851	0.844	0.809	0.862	7
0.901	0.921	0.934	0.916	0.896	0.898	0.91	0.924	0.952	0.91	0.915	0.932	0.902	0.957	0.96	0.922	8
0.876	0.869	0.895	0.859	0.809	0.849	0.91	0.897	0.882	0.89	0.896	0.869	0.881	0.891	0.84	0.874	9
0.789	0.709	0.769	0.769	0.769	0.749	0.789	0.794	0.769	0.779	0.777	0.809	0.757	0.754	0.754	0.769	10
0.936	0.949	0.969	0.974	1	0.949	0.95	0.969	0.973	0.989	0.946	0.936	0.964	0.95	0.969	0.962	11
0.89	0.893	0.879	0.896	0.89	0.904	0.921	0.936	0.928	0.899	0.924	0.916	0.905	0.9	0.914	0.906	12
0.899	0.936	1	0.964	0.978	0.939	0.967	0.989	0.964	0.959	0.994	0.964	0.945	0.963	0.969	0.962	13
0.816	0.822	0.831	0.808	0.816	0.831	0.946	0.829	0.846	0.839	0.849	0.864	0.825	0.814	0.839	0.838	14
0.869	0.879	0.819	0.864	0.829	0.894	0.839	0.859	0.88	0.864	0.893	0.874	0.859	0.846	0.819	0.859	15
0.916	0.934	0.9936	0.94	0.93	0.92	0.934	0.96	0.919	0.896	0.89	0.811	0.923	0.925	0.923	0.921	16
0.813	0.823	0.903	0.846	0.813	0.813	0.824	0.863	0.859	0.816	0.836	0.834	0.822	0.805	0.794	0.831	17
0.736	0.734	0.739	0.746	0.801	0.784	0.701	0.739	0.874	0.796	0.73	0.752	0.749	0.769	0.81	0.764	18
0.855	0.869	0.849	0.839	0.891	0.878	0.869	0.839	0.88	0.91	0.85	0.858	0.871	0.859	0.889	0.867	19
798	0.824	0.836	0.811	831	0.821	0.82	0.85	0.83	0.833	0.874	0.854	0.81	0.801	0.828	109.319	20
0.829	0.831	0.861	0.834	0.831	0.814	0.839	0.836	0.804	0.836	0.84	0.8	0.836	0.822	0.836	0.830	21
0.964	0.958	0.934	0.997	0.93	0.964	0.975	0.966	0.98	0.964	0.974	0.98	1	0.981	0.981	0.970	22
0.775	0.79	0.769	0.764	0.791	0.81	0.739	0.824	0.823	0.815	0.805	0.799	0.798	0.754	0.801	0.790	23
0.923	0.964	0.94	0.894	0.858	0.903	0.909	0.915	1922	0.937	0.961	0.9	0.91	0.88	0.901	128.986	24
0.864	0.869	0.894	0.839	0.864	0.9	0.864	0.874	0.87	0.911	0.869	0.89	0.846	0.825	0.799	0.865	25
0.85	0.864	0.809	0.864	0.891	0.841	0.809	8.32	0.799	0.882	0.864	0.894	0.836	0.815	0.815	1.344	26
0.965	0.97	0.985	0.934	0.968	0.989	0.96	0.949	95	0.964	0.99	0.907	0.978	0.96	0.985	7.234	27
0.931	0.934	0.964	0.95	0.981	0.964	0.909	0.956	0.938	0.931	946	0.922	0.969	0.934	0.978	63.951	28
0.921	0.858	0.864	0.849	0.877	0.839	0.894	0.827	0.849	0.864	0.828	0.839	0.834	0.81	0.759	0.847	29
0.92	0.934	0.928	0.936	0.946	0.928	0.92	0.919	0.896	0.879	0.934	0.902	0.926	0.89	0.9	0.917	30
0.823	0.869	0.894	0.839	0.809	864	0.839	0.849	0.809	0.874	0.839	0.882	0.845	0.861	0.779	58.387	31
805	0.836	0.812	0.834	0.836	0.849	0.824	0.82	0.834	0.819	0.824	0.855	0.819	0.825	0.809	54.440	32
0.9	0.934	0.905	0.911	0.9934	0.937	0.969	0.946	0.927	0.934	0.922	967	0.977	0.969	0.936	65.344	33
0.959	0.964	928	0.934	0.964	0.92	0.967	0.939	0.949	0.972	0.966	0.971	0.969	0.935	0.915	62.755	34
0.89	0.841	0.869	0.852	0.836	0.864	0.895	0.809	0.866	0.829	0.864	0.86	0.889	0.905	0.884	0.864	35
901	891	0.864	0.8745	0.898	0.869	0.849	0.822	0.798	0.895	0.839	0.86	0.869	0.859	0.901	120.213	36
0.881	0.839	0.901	0.912	0.946	0.823	0.9	0.887	0.814	0.866	0.839	0.855	0.879	0.836	0.789	0.864	37
0.819	0.859	0.864	0.874	0.88	0.856	0.859	0.836	0.824	0.839	0.849	0.829	0.884	0.919	824	55.733	38

CRediT authorship contribution statement

Majid Azadi: Conceptualization. **Saeed Yousefi:** Formal analysis, Data curation. **Reza Farzipoor Saen:** Writing – review & editing, Supervision, Investigation. **Hadi Shabanpour:** Resources, Writing - original draft, Writing - review & editing. **Fauzia Jabeen:** Project administration, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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