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Measuring the sustainability and resilience of blood supply chains

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ABSTRACT

Blood supply chains (BSCs) play a strategic and crucial role in healthcare systems especially in unexpected situations such as earthquakes and pandemic outbreaks. Nevertheless, measuring the sustainability and resilience of BSCs is a major challenge for many decision-makers in healthcare systems. To this end, this paper presents an advanced network data envelopment analysis (NDEA) method to evaluate the sustainability and resilience of BSCs. We deal with BSCs, including blood collection centers (BCCs), blood production centers (BPCs), and blood distribution centers (BDCs). A new directional distance function (DDF) is also developed for evaluating both the overall and stage efficiency scores. Our proposed model can deal with different types of data, including integers, undesirable outputs, negative, zero, and positive. The undesirable outputs are the outputs that adversely impact the performance of DMUs. Moreover, the developed method addresses the sustainability and resilience of BSCs. A case study is provided to demonstrate the usefulness of the proposed model.

1. Introduction

Disasters such as floods, earthquakes, fire, and the Covid-19 epidemic affect human beings in many aspects [1]. As disasters are unpredictable, some measures need to be taken for minimizing the related consequences [2]. There have been several catastrophic disasters with devastating impacts around the world over the last two decades. The 2003 Bam earthquake struck Iran with a death toll of over 26,000 people and injured almost 30,000. The earthquake hurt Haiti in 2010 and Japan in 2011 with a death toll of 182,000 people. Most recently, the Covid-19 pandemic with 1,274,311 death tolls by 11 November 2020.

Blood supply chains (BSCs) are essential parts of healthcare systems to save people's lives and prevent irreparable damages to society [3]. As blood and its sub-products cannot be replaced by any alternatives, they are considered vital commodities in any healthcare system [4]. Moreover, despite many people being eligible to donate blood, only a small percentage of people donate. The rate can also be lower in developing and underdeveloping countries [5]. Furthermore, the supply and demand for blood and its sub-products are irregular and can be changed significantly especially in emergencies. In addition, the nature of the perishability of blood can raise issues in satisfying demands [3]. Therefore, to address emergencies, a sustainable and resilient BSC is of great significance [2]. A BSC includes three main components such as blood collection centers (BCCs), blood production centers (BPCs), and blood distribution centers (BDCs) [6]. As Samani et al. [4] and Haeri et al. [7] discussed, BCC is the first stage in a BSC and is responsible for collecting blood from donors. The BPC is the second stage of BCC, which decomposes and tests the blood. While business supply chains (SCs) are profit-oriented, BSCs are service-oriented. Additionally, blood is the most vital product in healthcare systems and the shortage of it may result in people's death [8].

As Heidari-Fathian and Pasandideh [9] discussed, due to the transportations among different stages of BSCs, environmental pollutions are unavoidable. Sustainable SCs play a key role in many organizations [10]. Over the last decade, considerable attention has been paid to sustainability aspects of SCs such as economic, environmental, and social factors [11,12,13]. Nevertheless, the sustainability of BSCs has not been addressed well in the literature. Furthermore, SCs particularly BSCs deal with uncertain environments, which can create considerable disruptions across the SC. Environmental uncertainty in BSCs refers to different factors that can adversely impact the performance of the SC in crises such as the Covid-19 pandemic and SARS outbreak [14]. For example, owing to preventive measures by governments such as mass lockdowns to control the COVID-19 outbreak many BCCs have been suspended [15]. In the BSCs, the stochastic behavior of donors imposes

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considerable uncertainty and complexity in the SC [16]. To address the uncertainty in BSCs some approaches have been proposed (e.g., [17,7,18,3,5,19]).

As a working definition for the current paper, resilient SC is defined as an ability to recover rapidly and efficiently from a disruption in SC. Resilient SC has a high capability to adapt decisions and restore the performance under disruptions using recovery measures. Resilience is so essential especially for SCs with perishable products [20]. Thus, an effective SC needs to address resilience aspects for mitigating unexpected disruptions [21].

Efficiency assessment of SCs is a key factor for enhancing the organizations' performance [22]. Nevertheless, a few studies have addressed the performance assessment of BSCs to date. Data envelopment analysis (DEA) is considered an effective tool for measuring the performance of decision making units (DMUs) [23]. DEA is a nonparametric method for measuring the efficiency of a set of DMUs in the presence of multiple inputs and outputs (Shao et al. [24]; [25]).

The main objective of the current paper is to gauge the sustainability and resilience of BSCs. In this paper, a novel network DEA (NDEA) model is developed to deal with different types of data such as integer, negative, undesirable outputs, and zero data. In summary, this study has significant contributions, which are as follows:

- To measure the sustainability and resilience of BSCs, a new NDEA model is developed.
- A directional distance function (DDF) is developed for evaluating both overall and stage scores.
- The proposed NDEA model can deal with several types of data, including integer, undesirable, negative, and zero.
- A case study is presented.

The rest of this paper is organized as follows: In Section 2, we present the literature review. The proposed method is given in Section 3. In Section 4, a case study is presented. Finally, conclusions and future research directions are presented in Section 5.

2. Literature review

2.1. Blood supply chains (BSCs)

Lowalekar & Ravichandran [26] introduced a simulation model for assessing blood collection policies. Alfonso, Augusto & Xie [27] presented mathematical programming models for planning annual blood collection. Elalouf et al. [28] proposed a dynamic programming algorithm to minimize operational costs through reforming blood sampling. Şahinyazan, Kara & Taner [29] presented a bi-objective method to minimize transportation costs and maximize the collected blood. Ramezanian & Behboodi [3], to design BSCs, considered social aspects, and stochastic demand. Haijema, van der Wal & van Dijk [30] presented a method using Markov dynamic programming for producing blood. Ghandforoush & Sen [31] developed a decision support system (DSS) for platelet production and bloodmobile scheduling. Cetin & Sarul [32] developed a method for blood inventory in BSCs through integrating discrete and continuous location models. The proposed method can minimize the travel time for providing blood in healthcare centers. Abdulwahab & Wahab [33] utilized dynamic programming for dealing with the inventory problem of blood platelets in uncertain situations. They utilized the criteria such as inventory level and blood platelet to evaluate the proposed model. To minimize the total cost, shortage, and wastes of blood products, Gunpinar & Centeno [34] used integer programming. Dillon, Oliveira & Abbasi [35] presented an approach to optimize blood inventory replenishments. They applied a stochastic programming model for representing the uncertain demand for blood. Rajendran & Ravindran [36] proposed an integer stochastic programming model for platelet ordering policies in BSCs.

Hemmelmayr et al. [37] developed a delivery method of blood products based on integer programming. Kamp et al. [38] examined the management of red blood cells (RBCs) in hospitals using simulation. Hosseini-Motlagh, Samani & Homaei [39] developed a two-stage stochastic programming model to plan blood supply. Sönmezoglu et al. [40] examined the effect of the earthquake on blood donor types in BSCs. To design BSCs in natural and anthropogenic disasters, Fahimnia et al. [17] developed a stochastic bi-objective approach. Zahiri & Pishvaee [5] introduced a bi-objective method for optimizing effective factors on BSCs. Haghjoo et al. [41] presented a dynamic robust allocation model for designing BSCs in the existence of disruption risks in unexpected situations such as natural disasters.

2.2. Sustainability and resilience in SCs

Sustainable SCs have recently received substantial attention from both academia and industry [42]. The adoption of sustainability aspects in SCs contributes organizations to improve their performance in competitive markets [43]. Moreover, it assists organizations to decrease pressures from stakeholders and media [25]. In addition to sustainability, adopting the resilience concept needs to be addressed to mitigate disruptions in SCs [44]. Incorporating the sustainability and resilience concepts into the SCs can optimize SCs [45]. However, the sustainability and resilience aspects in SCs especially BSCs have not been explored adequately. Kumar & Kumar [46] proposed a genetic algorithm to generate and compare the routes in sustainable BSCs. Hosseinifard & Abbasi [16] presented an optimization method for centralizing the inventory of hospitals in sustainable and resilient BSCs. Ramezankhani, Torabi & Vahidi [47] discussed that if organizational efficiency is not measured well, sustainable and resilient SCs cannot be realized.

2.3. Data envelopment analysis (DEA)

DEA is one of the most popular tools to evaluate the relative efficiency of a set of DMUs in which multiple inputs produce multiple outputs [48]. Due to the numerous advantages of DEA, it has been utilized in many settings [49]. DEA assumes that the more output with less input, the better performance. However, there might be some undesirable outputs in the performance measurement of DMUs [50]. The undesirable outputs are the outputs that adversely impact the performance of DMUs [51]. For example, CO_2 emissions and industrial wastewaters are undesirable outputs [52,53]. It is obvious that the undesirable outputs should be decreased [54]. Färe et al. [55] proposed an efficiency criterion, which considers the undesirable outputs and good outputs. Seiford & Zhu [56] developed a DEA model to increase efficiency by decreasing the bad outputs and increasing the desirable outputs. Jahanshahloo et al.[57] proposed a non-radial DEA model to deal with undesirable outputs in the efficiency measurement of DMUs. Leleu [58] proposed a hybrid model for ensuring the economically significant jointness of desirable and undesirable outputs while limiting shadow prices of undesirable outputs. Cherchye, De Rock & Walheer [59] characterized the undesirable outputs based on their production technologies for multi-output efficiency measurements. For more discussions on DEA and undesirable outputs, see Cecchini et al. [60], Halkos & Petrou [52], Liu et al. [61], Pishgar-Komleh et al. [62], and Zhou et al. [53].

In the traditional DEA models, it is assumed that all variables are real values. However, there might be some integer data. Lozano & Villa [63] addressed the integer data in DEA by proposing mixed-integer linear programming (MILP). Kazemi Matin & Kuosmanen [64] enhanced Lozano and Villa's model using returns to scale assumptions. Kazemi Matin & Emrouznejad [65] developed the axiomatic foundation of integer DEA for considering bounded outputs. To estimate the efficiency of city bus systems, Chen et al. [66] proposed a DEA model with both integer-valued data and undesirable outputs. To determine the performance of suppliers, Azadi & Saen [67] developed an integer-stochastic DEA model. Taleb, Ramli & Khalid [68] developed a slacks-based measure (SBM) model to assess two-stage production units with both integer data and non-discretionary data. Ajirlo, Amirteimoori & Kordrostami [69] proposed an integer-valued slacks model to appraise the efficiency of a two-stage structure. To tackle some pitfalls of integer DEA models, Khoveyni et al. [70] proposed an integer-valued SBM. Kordrostami, Amirteimoori & Noveiri [71] presented a method for evaluating the performance of firms with dual-role and integer data.

On the other hand, conventional DEA models can only deal with positive data. Nevertheless, many problems in the real world deal with negative data. For the first time, Scheel [72] addressed negative data in DEA. His model considers negative inputs as outputs and negative outputs as inputs. Sharp, Meng & Liu [73] proposed a modified SBM model for overcoming the lack of translation invariance in the SBM model and addressed negative inputs and outputs. Portela, Thanassoulis & Simpson [74] proposed a directional distance method to tackle negative data in DEA and measured the efficiency of bank branches. To address both positive and negative data in DEA models, Emrouznejad, Anouze & Thanassoulis [75] presented a semi-oriented radial measure (SORM). Based on the additive DEA model, Kazemi Matin & Azizi [76] developed a two-stage method in the existence of negative data. Tavana et al. [77] proposed a dynamic range directional measure (RDM) for two-stage DEA models with negative data. Tavana et al. [78] developed a non-radial directional distance model for DEA problems in the presence of dual-role factors and negative data.

Apart from negative and positive data, there might be zero data to compute the efficiency of DMUs. Lee & Zhu [79] proposed a super-efficiency DEA model in the presence of zero data. Tavassoli, Farzipoor Saen & Faramarzi [80] developed a super-efficiency model in the existence of zero data and undesirable outputs. Over the last few years, several scholars have addressed zero data in DEA (e.g., [81,82,83]).

Ignoring the internal components of DMUs is another pitfall of traditional DEA models. However, many DMUs have network structures and there is a need to consider internal components of DMUs. To estimate the efficiency of network structures, for the first time, Färe & Grosskopf [84] proposed NDEA. Liang, Cook & Zhu [85] proposed a two-stage DEA model using game theory assumptions. Kao & Hwang [86] proposed an NDEA model to investigate system inefficiency in the banking industry. Mirhedayatian, Azadi & Saen [87] proposed an NDEA model in the existence of flexible factors, undesirable outputs, and fuzzy data. Kalantary & Saen [88] introduced an inverse network dynamic DEA model to evaluate sustainable SCs in multiple periods. Izadikhah et al. [25] developed a chance-constrained NDEA model for measuring the sustainability of SCs.

2.4. Knowledge gap

The above discussions show that there is limited research on the sustainability and resilience of BSCs. Moreover, the performance assessment of BSCs has not been addressed well. Furthermore, integer-valued data has not been paid attention in NDEA structures. Last but not least, current NDEA models are unable to deal with undesirable outputs, integer-valued data, negative, zero, and positive data, simultaneously. In this paper, these research gaps are addressed by proposing a new NDEA model and applying it to assess the sustainability and resilience of BSCs.

3. Proposed model

BSCs play a strategic and crucial role in unexpected situations such as earthquakes and pandemic Covid-19. Here, an advanced NDEA model is introduced to evaluate the sustainability and resilience of BSCs. A new DDF is developed to assess the overall and stage efficiency scores. As is seen in Section 4, our proposed model can deal with different types of data, including integers, undesirable outputs, negative, zero, and positive.

Suppose there are n DMUs, which DMU_j $(j = 1, \ldots, n)$ consumes m inputs $x_{ij} \geq 0$, $(x_{ij} \neq 0, i = 1, \ldots, m)$ to produce s final outputs $y_{rj} \geq 0$, $(y_{rj} \neq 0, r = 1, \ldots, s)$. Under variable returns to scale (VRS) assumption, the underlying production possibility set (technology) is stared as follows (Banker, Charnes & Cooper [89]):

$$T_{DEA} = \left\{ (\boldsymbol{xy}) \in \Re_+^{m+s} \mid \boldsymbol{x} \geq \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} \lambda_j \boldsymbol{x}_j, \boldsymbol{y} \leq \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} \lambda_j \boldsymbol{y}_j, \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} \lambda_j = 1, \forall \mathrm{j} : \ \lambda_\mathrm{j} \geq 0 \right\}$$

Traditional DEA models consider the DMUs as black-boxes without taking into account the internal structure of DMUs. This may lead to an over-estimate of efficiency scores. To overcome this issue, NDEA models are introduced, which take the internal operations of sub-processes into account. Now, consider a network production system, including p sub-processes. Let $x_{ij}^{(k)}$ and $y_{rj}^{(k)}$ denote the ith input and rth final output of kth sub-process of DMU_j for $i = 1, \ldots, m$; $r = 1, \ldots, s$; $k = 1, \ldots, p$; and $j = 1, \ldots, n$, respectively. Following the standard notation of inputs and outputs, we may write $x_{ij} = \sum_{k=1}^{p} x_{ij}^{(k)}$ and $y_{rj} = \sum_{k=1}^{p} y_{rj}^{(k)}$.

The key feature, which distinguishes NDEA from the traditional ones is considering the intermediate products. The intermediate products are produced in the sub-processes and are consumed within the production units. In the traditional DEA models, the intermediate products are ignored and DMUs are treated as black-boxes. Further, let $z_{gj}^{(l,t)}$ denotes the gth intermediate product, which is produced by sub-processes s for consuming in sub-processes t for $g = 1, \ldots, h$. Therefore, $\sum_{t=1}^{p} z_{gj}^{(k,t)}$ shows the total amount of the gth intermediate product, which is produced by sub-process k for being consumed in other sub-processes. Similarly, $\sum_{l=1}^{p} z_{fj}^{(l,k)}$ shows the total amount of the fth intermediate product, which is produced by other sub-processes for being consumed in sub-process k. In real-world applications, a sub-process may consume only a subset of inputs and intermediates to produce a subset of intermediates and final outputs. A typical network DMU is depicted in Fig. 1. See Kao [90] for more details.

The associated production possibility set under VRS assumption is as follows:

$$T_{Network} = \left\{ (\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{y}) \middle| \sum\nolimits_{j=1}^{n} \lambda_j^{(k)} x_{ij}^{(k)} \leq x_i^{(k)}, \sum\nolimits_{j=1}^{n} \lambda_j^{(k)} \left(\sum\nolimits_{l=1}^{p} z_{fj}^{(lk)} \right) \leq z_f^{(k)}, z_g^{(k)} \leq \sum\nolimits_{j=1}^{n} \lambda_j^{(k)} \left(\sum\nolimits_{t=1}^{p} z_{gj}^{(kt)} \right), y_r^{(k)} \leq \sum\nolimits_{j=1}^{n} \lambda_j^{(k)} y_{rj}^{(k)}, \sum\nolimits_{j=1}^{n} \lambda_j^{(k)} = 1, k = 1, \ldots, p, \forall k, \forall j : \lambda_j^{(k)} \geq 0,, \right\}$$

Note that the intermediate products appear in two different roles; i.e. output of the tth sub-process and input of the $t + 1$th sub-process. Therefore, two different types of constraints are used for the intermediates. In this modeling, the sub-processes are connected via the intermediate products and thus the formulation is known as the connected model in NDEA literature [91]. Traditional DEA models rely on some basic assumptions, including homogeneity of activities, continuity, and non-negativity of inputs and outputs. However, in the real world, DMUs might be non-homogenous, data may be integer-valued, negative, and/or undesirable. Here, we introduce a novel NDEA model to address negative, integer-valued, and undesirable data.

Several approaches have been proposed to deal with negative data in DEA literature. Kaffash et al. [92] summarized the DEA models with negative data. The SORM model, proposed by Emrouznejad et al. [93], is one of the popular techniques in dealing with negative data in DEA. A modified version of the SORM model was introduced by Kazemi Matin et al. [94]. Their introduced model has an important feature that considers positive and negative-valued data in all inputs and outputs.

To deal with the negative outputs, using SORM, consider DMUs as $(\boldsymbol{x}, \boldsymbol{y}^P, \boldsymbol{y}^N)$; where $\boldsymbol{y}^p$ indicates the positive outputs, i.e., $y_{rj}^p \geq 0$ for all $r =$

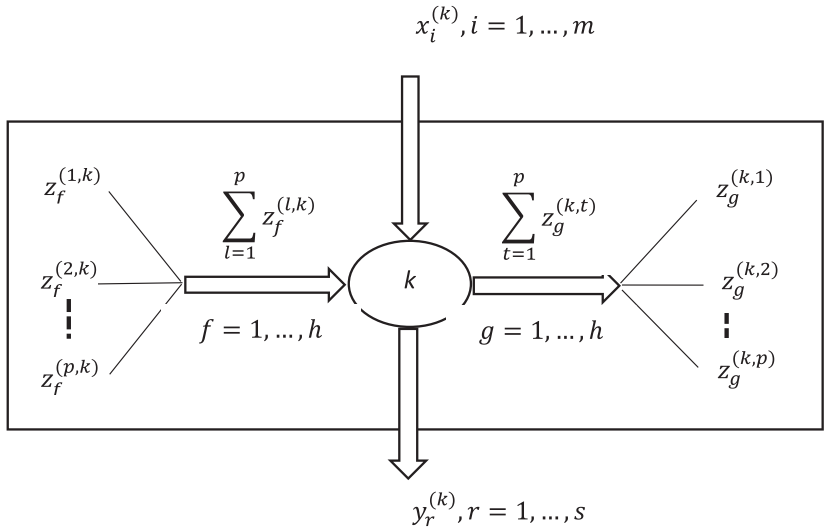

Fig. 1. A sub-process in network DMU.

1, …, s, $j = 1$, …, n, and $\boldsymbol{y}^N$ shows the negative outputs. According to Emrouznejad et al. [93], we may write $\boldsymbol{y}^N = \boldsymbol{y}^1 - \boldsymbol{y}^2$, where non-negative vectors $\boldsymbol{y}^1$ and $\boldsymbol{y}^2$ are defined as follows:

$$y_{rj}^1 = \begin{cases} y_{rj} \text{ if } y_{rj} \geq 0 \\ 0 \text{ otherwise} \end{cases} \text{ and } y_{rj}^2 = \begin{cases} -y_{rj} \text{ if } y_{rj} < 0 \\ 0 \text{ otherwise.} \end{cases}$$

Under these settings, SORM production technology can be represented as follows:

$$T_{DEA-SORM} = \left\{ \left(\boldsymbol{x}, \boldsymbol{y}^P, \boldsymbol{y}^1, \boldsymbol{y}^2\right) \mid \boldsymbol{x} \geq \sum_{i=1}^{n} \lambda_j \boldsymbol{x}_j, \boldsymbol{y}^p \leq \sum_{i=1}^{n} \lambda_j \boldsymbol{y}_j^p, \boldsymbol{y}^1 \leq \sum_{i=1}^{n} \lambda_j \boldsymbol{y}_j^1, \boldsymbol{y}^2 \geq \sum_{i=1}^{n} \lambda_j \boldsymbol{y}_j^2, \sum_{i=1}^{n} \lambda_j = 1, \forall j: \ \lambda_j \geq 0 \right\}$$

Given the linear structure of $T_{DEA-SORM}$, the DEA models can be modified to deal with the negative outputs. For network DMUs with negative outputs, we suggest a modified production possibility set based on the SORM approach. To this end, let I and O denote the inputs and outputs, respectively. Also, O' and O'' represent a set of outputs associated with $\boldsymbol{y}^P$ and $\boldsymbol{y}^N$, respectively; where $O' \cap O'' = \varnothing$ and $O' \cup O'' = O$. Under the VRS assumption, the SORM production possibility set with network structure for dealing with negative outputs is as follows:

$$\begin{aligned} T_{Network-SORM} = \Bigg\{ & \left(\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{y}^P, \boldsymbol{y}^1, \boldsymbol{y}^2\right) \Big| \sum_{j=1}^{n} \lambda_j^{(k)} x_{ij}^{(k)} \\ & \leq x_i^{(k)}, \sum_{j=1}^{n} \lambda_j^{(k)} \left(\sum_{l=1}^{p} z_{fj}^{(lk)} \right) \leq z_f^{(k)}, z_g^{(k)} \\ & \leq \sum_{j=1}^{n} \lambda_j^{(k)} \left(\sum_{t=1}^{p} z_{gj}^{(kt)} \right), y_r^{(k)} \leq \sum_{j=1}^{n} \lambda_j^{(k)} y_{rj}^{(k)} \forall r \in O', y_r^{1(k)} \\ & \leq \sum_{j=1}^{n} \lambda_j^{(k)} y_{rj}^{1(k)} \forall r \in O'', y_r^{2(k)} \geq \sum_{j=1}^{n} \lambda_j^{(k)} y_{rj}^{2(k)} \forall r \\ & \in O, \sum_{j=1}^{n} \lambda_j^{(k)} = 1, k = 1, \ldots, p, \forall k \ \forall j: \ \lambda_j^{(k)} \geq 0,, \Bigg\} \end{aligned}$$

In addition to the negative outputs, suppose that there are integer-valued inputs and undesirable outputs. For simplicity, assume that all

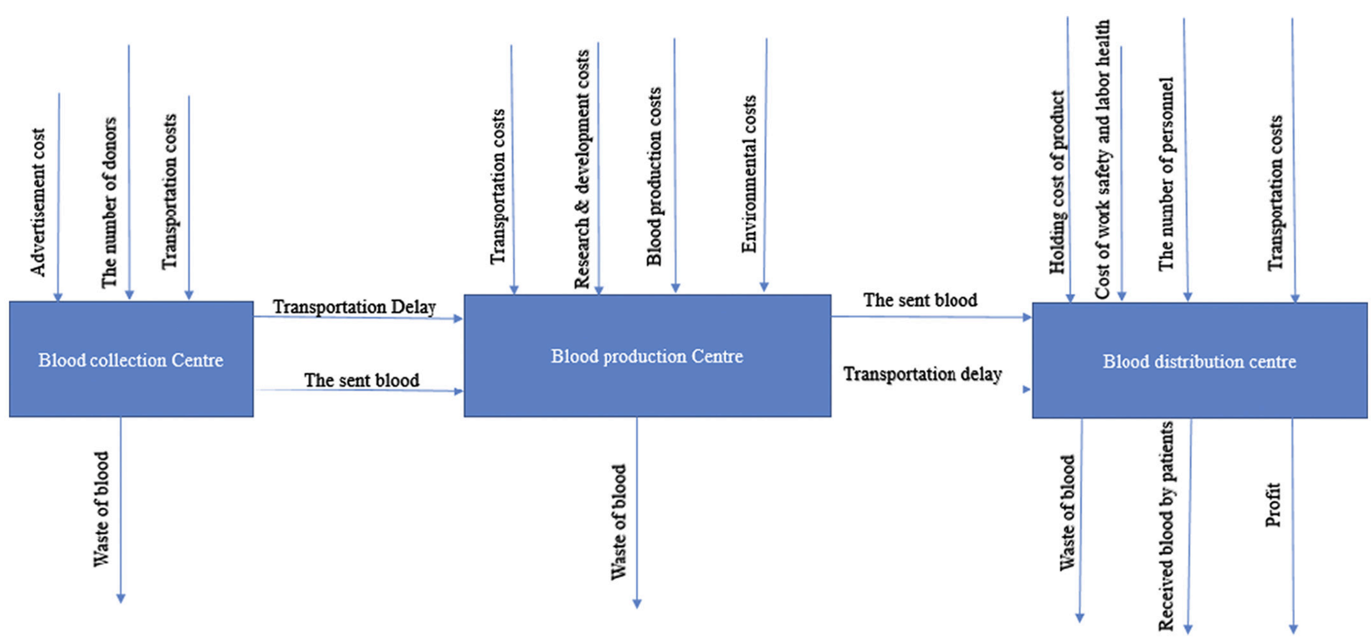

Fig. 2. The BSC of IBTO.

Table 1
The used factors for evaluating the sustainability and resilience of BSCs.

Stages	Factors	Factor type	Data type	Notation	Sustainability/resilience dimension	Measurement unit
Blood collection centers (BCCs)	Advertisement cost	Input	Real	$x_1^{(1)}$	Economic	Rial
	The number of donors	Input	Integer	$x_2^{I(1)}$	Economic	Person
	Transportation costs	Input	Real	$x_3^{(1)}$	Economic	Rial
	Waste of blood	Output	Undesirable	$y_1^{UD(1)}$	Economic	Litre
	Transportation delay	Intermediate	Real	$z_1^{(1,2)}$	Resilience	Minute
	The sent blood	Intermediate	Real	$z_2^{(1,2)}$	Economic	Litre
Blood production centers (BPCs)	Transportation costs	Input	Real	$x_1^{(2)}$	Economic	Rial
	Research and development costs	Input	Real	$x_2^{(2)}$	Economic	Rial
	Blood production costs	Input	Real	$x_3^{(2)}$	Economic	Rial
	Environmental costs	Input	Real	$x_4^{(2)}$	Environmental	Rial
	Waste of blood	Output	Undesirable	$y_1^{UD(2)}$	Economic	Litre
	The sent blood	Intermediate	Real	$z_1^{(2,3)}$	Economic	Litre
	Transportation delay	Intermediate	Real	$z_2^{(2,3)}$	Resilience	Minute
Blood distribution centers (BDCs)	Holding cost of the product	Input	Real	$x_1^{(3)}$	Economic	Rial
	Cost of work safety and labor health	Input	Real	$x_2^{(3)}$	Social	Rial
	The number of personnel	Input	Integer	$x_3^{I(3)}$	Economic	Person
	Transportation costs	Input	Real	$x_4^{(3)}$	Economic	Rial
	Waste of blood	Output	Undesirable	$y_1^{UD(3)}$	Economic	Litre
	Received blood by patients	Output	Real	$y_2^{(3)}$	Economic	Person
	Profit	Output	Real	$y_3^{N(3)}$	Economic	Rial

the divisions have the same integer inputs and undesirable outputs. Extending for the case of a hybrid index in which integer and/or undesirable outputs coexist in a subset of divisions is straightforward. The non-negative outputs can be classified into two categories of desirable (D) and undesirable (UD) outputs; i.e., $O' = D \cup UD$ in which $D \cap UD = \phi$. Therefore, we have $\boldsymbol{y}^p = (\boldsymbol{y}^D, \boldsymbol{y}^{UD})$. The inputs also can be classified into two disjoint categories, including integer (I) and real (NI), where $i \in I \cup NI$, $I \cap NI = \phi$ and we use $\boldsymbol{x} = (\boldsymbol{x}^I, \boldsymbol{x}^{NI})$.

To address the undesirable outputs, the axiom of weak disposability (WD) is used. The axiom provides possible tradeoffs between the good and undesirable outputs in the production possibility set. Given the production possibility set $T_{Network}$, WD axiom can be stated as follows:

Definition: The outputs $(\boldsymbol{y}^D, \boldsymbol{y}^{UD})$ are weakly disposable if and only if $(\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{y}^D, \boldsymbol{y}^{UD}) \in T_{Network}$, which implies that $(\boldsymbol{x}, \boldsymbol{z}, \alpha \boldsymbol{y}^D, \alpha \boldsymbol{y}^{UD}) \in T_{Network}$ for all $\alpha \in [0, 1]$.

Kuosmanen [95] introduced the production possibility set given

Table 2
Explanations about the used factors.

Factors	Explanations
Advertisement cost	Cost of publishing brochures and advertising in media to donate blood [3].
The number of donors	The number of persons who voluntarily donate their blood for humanitarian purposes [18].
Transportation costs	Costs associated with transportation such as repair and maintenance and fuel ([99]; [17])
Waste of blood	The amount of wasted blood due to human error or defective equipment ([100]; [101]).
The sent blood	The amount of sent blood among stages of BSCs ([28]; [31]).
Transportation delay	The delay in transportation ([17]; [102]).
Research and development costs	Costs associated with improving blood sub-products and preventing waste of blood [103].
Blood production costs	Costs associated with processing blood and its sub-products [104].
Environmental costs	Costs associated with preventing greenhouse gas emissions and fuel consumption [9].
Cost of work safety and labor health	Costs associated with increasing personnel work safety and enhancing labor health [23].
The number of personnel	The number of technical and non-technical staff [105].
Holding cost of the product	Costs associated with storing blood and its sub-products such as personnel costs and utilities' costs [106].
Received blood by patients	The amount of received blood by patients [107].
Profit	The amount of profit by providing blood and its sub-products to patients [108].

axioms, including convexity, free disposability of inputs and desirable outputs, and weak disposability of desirable and undesirable outputs. See Kuosmanen and Kazemi Matin [96] for details. The associated production possibility set for a general network, including integer-valued inputs and negative and undesirable outputs under WD assumption can be presented as follows:

$$T^{WD-Integer}_{Network-SORM} = \Bigg\{ (\boldsymbol{x}^I, \boldsymbol{x}^{NI}, \boldsymbol{z}, \boldsymbol{y}^D, \boldsymbol{y}^{UD}, \boldsymbol{y}^1, \boldsymbol{y}^2) | \sum_{j=1}^{n} \lambda_j^{(k)} x_{ij}^{(k)} \le x_i^{I(k)}, \sum_{j=1}^{n} \lambda_j^{(k)} x_{ij}^{NI(k)} \le x_i^{NI(k)}, \sum_{j=1}^{n} \lambda_j^{(k)} \left(\sum_{l=1}^{p} z_{fj}^{(l,k)} \right) \le z_f^{(k)}, z_g^{(k)} \le \sum_{j=1}^{n} \lambda_j^{(k)} \left(\sum_{t=1}^{p} z_{gj}^{(k,t)} \right),$$
$$y_r^{D(k)} \le \sum_{j=1}^{n} \alpha_j \lambda_j^{(k)} y_{rj}^{(k)} \ \forall\ r \in O',\ y_r^{UD(k)} = \sum_{j=1}^{n} \alpha_j \lambda_j^{(k)} y_{rj}^{(k)} \ \forall\ r \in O',\ y_r^{1(k)} \le \sum_{j=1}^{n} \alpha_j \lambda_j^{(k)} y_{rj}^{1(k)} \forall r \in O'',\ y_r^{2(k)} \ge \sum_{j=1}^{n} \alpha_j \lambda_j^{(k)} y_{rj}^{2(k)} \forall r \in O, \sum_{j=1}^{n} \lambda_j^{(k)} = 1,\ \forall k\ \forall j : \lambda_j^{(k)} \ge 0, 0 \le \alpha_j \le 1 \Bigg\}$$

Here, α_j is used to denote the abatement factor associated with the WD axiom for the undesirable output of DMU_j. Note that these factors should be considered for all the outputs, including both positive and negative outputs. Due to the multiplication of abatement factors α_j by the intensity weights $\lambda_j^{(k)}$, the new production possibility set $T^{-WD}_{NetworkSORM}$ has non-linear constraints. To overcome this issue, we use the following variable substitutions (see Kuosmanen [95] for more details):

$\forall j, \forall\ k : \alpha_j \lambda_j^{(k)} = \delta_j^{(k)}, (1 - \alpha_j) \lambda_j^{(k)} = \mu_j^{(k)}, \lambda_j^{(k)} = \delta_j^{(k)} + \mu_j^{(k)}$.

Therefore, the linear version of the production possibility set $T^{SORM-WD}_{Network}$ is as follows:

$$T^{WD-Integer}_{Network-SORM} = \{ (\boldsymbol{x}^I, \boldsymbol{x}^{NI}, \boldsymbol{z}, \boldsymbol{y}^D, \boldsymbol{y}^{UD}, \boldsymbol{y}^1, \boldsymbol{y}^2) \mid \sum_{j=1}^{n} (\delta_j^{(k)} + \mu_j^{(k)}) x_{ij}^{I(k)} \le x_i^{I(k)}, \sum_{j=1}^{n} (\delta_j^{(k)} + \mu_j^{(k)}) x_{ij}^{NI(k)} \le x_i^{NI(k)}, \sum_{j=1}^{n} (\delta_j^{(k)} + \mu_j^{(k)}) (\sum_{l=1}^{p} z_{fj}^{(l,k)}) \le z_f^{(k)}, z_g^{(k)} \le \sum_{j=1}^{n} (\delta_j^{(k)} + \mu_j^{(k)}) (\sum_{t=1}^{p} z_{gj}^{(k,t)}), y_r^{D(k)} \le \sum_{j=1}^{n} \delta_j^{(k)} y_{rj}^{(k)} \ \forall\ r \in O',\ y_r^{UD(k)} = \sum_{j=1}^{n} \delta_j^{(k)} y_{rj}^{(k)} \ \forall\ r \in O',\ y_r^{1(k)} \le \sum_{j=1}^{n} \delta_j^{(k)} y_{rj}^{1(k)} \forall r \in O'',\ y_r^{2(k)} \ge \sum_{j=1}^{n} \delta_j^{(k)} y_{rj}^{2(k)} \forall r \in O, \sum_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)} \right) = 1, \forall k, \forall j : \ \delta_j^{(k)} \ge 0, \mu_j^{(k)} \ge 0 \Big\}$$

Now, based on the introduced production possibility set $T^{WD-Integer}_{Network-SORM}$, the efficiency scores of DMUs are assessed. The traditional DDF for performance evaluation of DMU_o (the DMU under evaluation) for the known production possibility set, T, can be represented as *Max*

Table 3
The dataset.

BSCs (DMUs)	Blood collection centers (BCC)						Blood production centers (BPC)		
	Inputs			Output	Intermediates		Inputs		
	Advertisement cost (1000 Rial)	The number of donors (Integer)	Transportation costs (1000 Rial)	Waste of blood (Undesirable)	Transportation delay (minute)	The sent blood (Litre)	Transportation costs (1000 Rial)	Research & Development costs (1000 Rial)	Blood production costs (1000 Rial)
1	1,401,000	25,318	4,125,000	51	935	12,015	5,317,000	2,150,000	7,019,000
2	3,259,000	39,615	6,941,000	64.5	1019	18,310	7,819,000	3,347,000	8,542,000
3	1,135,000	24,917	3,940,000	59	992	12,134	4,550,000	2,940,000	6,374,000
4	2,047,000	27,965	4,275,000	43	1247	13,078	4,917,000	3,541,000	6,918,000
5	1,517,000	29,174	3,941,000	55	1139	12,193	4,193,000	2,682,000	6,018,000
6	1,638,000	25,615	4,463,000	32	1175	11,847	4,817,000	1,749,000	6,494,000
7	3,741,000	34,170	7,901,000	67	1482	16,172	7,714,000	2,481,000	7,805,000
8	2,652,000	31,435	6,047,000	39.4	1037	14,560	6,286,000	3,726,000	6,397,000
9	3,415,000	33,241	5,972,000	55	1274	15,825	7,119,000	3,910,000	7,151,000
10	1,797,000	27,947	5,122,000	41	1197	13,728	5,468,000	3,270,000	7,409,000
11	1,345,000	23,650	4,576,000	37	872	11,910	5,085,000	1,748,000	4,937,000
12	2,939,000	38,171	6,245,000	62	1546	17,596	6,973,000	4,168,000	8,412,000
13	1,720,000	24,389	4,016,000	35.4	910	10,401	3,857,000	2,340,000	5,730,000
14	3,320,000	34,860	6,581,000	42	1413	15,358	7,198,000	2,368,000	6,490,000
15	1,489,000	21,527	2,052,000	30	759	8714	2,610,000	1,743,000	4,513,000
16	1,835,000	23,943	4,718,000	53	1268	11,037	4,342,000	1,418,000	5,176,000
17	1,371,000	19,781	2,950,000	37	916	8350	3,830,000	1,773,000	4,495,000
18	2,842,000	31,177	6,572,000	21.5	1571	15,064	6,187,000	2,728,000	5,972,000
19	1,187,000	18,635	3,276,000	34	1049	7928	4,028,000	1,951,000	4,810,000
20	1,352,000	23,287	4,017,000	46	1476	10,517	4,542,000	3,275,000	6,492,000
21	3,987,000	34,715	6,519,000	52	1182	16,254	7,092,000	2,628,000	7,139,000
22	3,524,000	30,824	6,217,000	29	1319	14,381	5,938,000	1,833,000	5,725,000
23	1,920,000	21,389	3,281,000	37	1051	9155	3,917,000	1,425,000	4,927,000
24	2,371,000	28,671	5,019,000	44	1232	12,227	5,938,000	2,718,000	6,735,000
25	1,682,000	22,324	3,956,000	31	993	9819	4,513,000	1,758,000	5,514,000
26	1,435,000	18,257	3,591,000	25	1146	8328	3,715,000	2,310,000	5,596,000
27	2,981,000	31,141	7,126,000	56	1374	13,921	6,820,000	2,587,000	7,825,000

$\{\varphi \mid (\boldsymbol{x_o}, \boldsymbol{z_o}, \boldsymbol{y_o}) + \varphi(\mathbf{g^x}, \mathbf{g^z}, \mathbf{g^y}) \in T\}$, where the uniform distance parameter φ is used. Note that the natural directional vector $(\mathbf{g^x}, \mathbf{g^z}, \mathbf{g^y}) = (-\boldsymbol{x_o}, \mathbf{0}, \boldsymbol{y_o})$ can be chosen in which the DDF takes the form $Max\{\varphi \mid ((\mathbf{1}-\varphi)\boldsymbol{x_o}, \boldsymbol{z_o}, (\mathbf{1}+\varphi)\boldsymbol{y_o}) \in T\}$. For more details, see Färe and Grosskopf [97].

To provide both the overall and stage efficiency scores in $T^{WD-Integer}_{Network-SORM}$, we introduce a modified version of DDF in which the natural improvement direction $(\mathbf{g^{xI}}, \mathbf{g^{xNI}}, \mathbf{g^{z}}, \mathbf{g^{yD}}, \mathbf{g^{yUD}}, \mathbf{g^{y1}}, \mathbf{g^{y2}}) = (-\boldsymbol{x}_o^I, -\boldsymbol{x}_o^{NI}, \boldsymbol{z}_o, \boldsymbol{y}_o^D, -\boldsymbol{y}_o^{UD}, \boldsymbol{y}_o^1, -\boldsymbol{y}_o^2)$ is used for the evaluation and different distance parameters are applied for different stages. Let $\varphi^{(k)}$ denotes the inputs and output distance parameters. Also, let $w^{(k)}$ denotes the associated predefined positive weights corresponding to the kth division in which $\sum_{k=1}^{p} w^{(k)} = 1$. For the performance assessment of $DMU_o: (\boldsymbol{x}_o^I, \boldsymbol{x}_o^{NI}, \boldsymbol{z}_o, \boldsymbol{y}_o^D, \boldsymbol{y}_o^{UD}, \boldsymbol{y}_o^1, \boldsymbol{y}_o^2)$, we suggest the following modified DDF model:

$$\max_{\varphi,\delta,\mu} \sum_{k=1}^{p} w^{(k)} \varphi_o^{(k)} \tag{1}$$

Subject to

$$\sum\nolimits_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) x_{ij}^{I(k)} \le \overline{x_i}^{(k)} \le \left(1 - \varphi_o^{(k)}\right) x_i^{I(k)}, i \in I$$

$$\sum\nolimits_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) x_{ij}^{NI(k)} \le \left(1 - \varphi_o^{(k)}\right) x_i^{NI(k)}, i \in NI$$

$$\sum\nolimits_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) \left(\sum\nolimits_{l=1}^{p} z_{fj}^{(l,k)}\right) \le z_f^{(k)}, \forall k$$

$$z_g^{(k)} \le \sum\nolimits_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) \left(\sum\nolimits_{t=1}^{p} z_{gj}^{(k,t)}\right), \quad \forall k$$

$$\sum\nolimits_{j=1}^{n} \delta_j^{(k)} y_{rj}^{(k)} \ge \left(1 + \varphi_o^{(k)}\right) y_r^{D(k)}, \forall r \in O',$$

$$\sum\nolimits_{j=1}^{n} \delta_j^{(k)} y_{rj}^{(k)} = \left(1 - \varphi_o^{(k)}\right) y_r^{UD(k)}, \forall r \in O',$$

$$\sum\nolimits_{j=1}^{n} \delta_j^{(k)} y_{rj}^{1(k)} \ge \left(1 + \varphi_o^{(k)}\right) y_r^{1(k)}, \forall r \in O",$$

$$\sum\nolimits_{j=1}^{n} \delta_j^{(k)} y_{rj}^{2(k)} \le \left(1 - \varphi_o^{(k)}\right) y_r^{2(k)}, \forall r \in O,$$

$$\sum_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) = 1, \forall k,$$

$$\forall i \in I, \forall k, \forall j: \quad \overline{x}_i^{(k)} \in \mathbb{Z}_+, \theta_o^{(k)}, \varphi_o^{(k)} \ge 0, \delta_j^{(k)} \ge 0, \mu_j^{(k)} \ge 0.$$

To avoid non-integer targets for integer-valued inputs, $i \in I$, new integer variables $\overline{x}_i$ are used in Model (1) (see Kuosmanen, Keshvari & Matin [98]). This is a mixed-integer linear programming model in which the objective function and all the constraints are linear and just a small subset of variables are restricted to integer values, which can be easily solved by any optimization solver.

In optimality, the overall and stage efficiency score of DMU_o are suggested as follows:

$$Eff_{Overall}\left(\boldsymbol{x}_o^I, \boldsymbol{x}_o^{NI}, \boldsymbol{z}_o, \boldsymbol{y}_o^D, \boldsymbol{y}_o^{UD}, \boldsymbol{y}_o^1, \boldsymbol{y}_o^2\right) = \frac{1 - \sum_{k=1}^{p} w^{(k)} \varphi_o^{*(k)}}{1 + \sum_{k=1}^{p} w^{(k)} \varphi_o^{*(k)}}$$

$$Eff_k\left(\boldsymbol{x}_o^I, \boldsymbol{x}_o^{NI}, \boldsymbol{z}_o, \boldsymbol{y}_o^D, \boldsymbol{y}_o^{UD}, \boldsymbol{y}_o^1, \boldsymbol{y}_o^2\right) = \frac{1 - \varphi_o^{(k)}}{1 + \varphi_o^{*(k)}} \; (k = 1, \dots, p)$$

where $\varphi_o{*}^{(k)}$ shows the maximum percentage of proportional improvements of inputs and outputs of division k.

Blood production centers (BPC)				Blood distribution centers (BDS)						
Inputs	Output	Intermediates		Inputs				Outputs		
Environmental costs (1000 Rial)	Waste of blood (Undesirable)	The sent blood (Litre)	Transportation delay (minute)	Holding cost of product (1000 Rial)	Cost of work safety and labor health cost (1000 Rial)	The number of personnel (Integer)	Transportation costs (1000 Rial)	Waste of blood (Undesirable) (Litre)	Received blood by patients (Litre)	Profit (1000 Rial)
1,158,000	434	11,375	1316	1,521,000	164,250	16	5,941,000	357	10,918	11,930,000
1,418,000	421	17,632	1874	2,335,000	301,980	25	8,146,000	592	16,840	16,785,000
1,053,000	331	11,510	1512	1,492,000	151,740	17	5,012,000	336	11,074	13,172,000
1,734,000	457	12,431	1348	845,700	193,200	19	4,573,000	459	11,972	14,590,000
1,390,000	305	11,715	1119	1,217,000	243,140	17	4,958,000	527	11,188	6,170,000
1,042,000	491	11,137	1671	2,249,000	257,590	21	5,617,000	835	10,302	0
915,200	343	15,679	1354	2,027,000	281,120	23	7,281,000	565	15,114	9,148,000
1,179,000	285	14,112	1028	1,847,000	267,970	20	7,190,000	522	13,590	6,875,000
1,068,000	212	15,490	1313	1,798,000	318,310	27	6,745,000	479	15,011	11,380,000
2,287,000	367	13,239	1065	1,624,000	143,590	19	6,010,000	393	12,856	19,250,000
937,000	351	11,405	1591	1,738,000	245,100	21	4,917,000	583	10,822	9,957,000
1,570,000	293	17,029	1439	2,014,000	349,780	24	6,245,000	402	16,627	1,083,000
892,000	387	9872	995	1,017,000	99,350	16	7,219,000	279	9593	10,079,000
1,308,000	272	14,913	1125	2,104,000	298,400	24	7,745,000	547	14,366	−172,435
845,000	249	8315	811	1,248,000	75,300	11	2,916,000	215	8100	7,820,000
1,173,000	305	10,554	1124	1,387,000	101,072	18	5,012,000	230	10,324	10,520,000
1,280,000	372	7801	943	1,244,000	126,500	15	3,215,000	192	7609	9,227,000
1,193,000	319	14,546	1431	1,847,000	314,180	27	7193,000	643	13,903	−356,455
1,257,000	197	7614	737	1,035,000	128,000	14	3,915,000	206	7408	7,287,000
1,625,000	203	10,148	1095	1,638,000	103,500	16	4,953,000	185	9963	10,972,000
1,935,000	328	15,709	1321	1,497,000	216,270	23	6,947,000	313	15,396	11,510,000
1,622,000	251	13,981	1184	1,273,000	158,210	19	7,074,000	346	13,635	9,367,000
1,238,000	194	8805	783	1,035,000	126,400	17	4,253,000	241	8564	8,928,000
1482,000	275	11,796	1018	1,416,000	172,100	21	6,219,000	193	11,603	7,514,000
1,729,000	178	9537	1215	1,158,000	153,350	19	5,401,000	207	9330	10,717,000
1,043,000	214	7965	1074	1,193,000	197,800	16	4,318,000	154	7811	8,543,000
1,539,000	317	13,489	1397	1247,000	141,230	21	6,652,000	319	13,170	9,321,000

Theorem 1. Model (1) is always feasible and bounded.

Proof. Let $\varphi_o^{(k)} = 0\ (\forall k)$, $\delta_o^{(k)}=1$, $\delta_j^{(k)} = 0\ (\forall j \neq o)$, and also $\mu_j^{(k)} = 0\ (\forall k\ \forall j)$. Furthermore, let $\overline{x}_i^{(k)} = x_{io}^{I(k)} (\forall i \in I)$. It is easy to verify that these values satisfy all the constraints of Model (1). Therefore, the model is feasible. For the boundedness part, given the constraints of inputs, undesirable, and second part of negative outputs, we conclude that $\varphi_o^{(k)} \leq 1$. From the constraints of the desirable outputs, based on $\sum_{j=1}^{n} \delta_j^{(k)} \leq 1$, we have $0 \leq \varphi_o^{(k)} \leq \frac{\max_j \left\{ y_{rj}^{D(k)} \right\}}{y_{ro}^{D(k)}} - 1$. A similar relation can be repeated for the first part of negative outputs. Thus, we have $\forall k : 0 \leq \varphi_o^{(k)} \leq 1$, which shows the objective value is bounded. ■

Theorem 2. The following statements are true:

i. $0 < Eff_{Overall} \leq 1$ and $0 < Eff_k \leq 1$ for all k.
ii. $Eff_{Overall} = 1$ if and only if $Eff_k = 1$ for all k.
iii. $Eff_{Overall}$ and $Eff_k (k = 1, \ldots, p)$ are unit invariant.
iv. $Eff_{Overall}$ and $Eff_k (k = 1, \ldots, p)$ are monotonic in inputs and outputs.

Proof:

i. From Theorem (1), we have $\forall k : \varphi_o{}^{*(k)} \in [0,1]$. First, we show that $\forall k : \varphi_o{}^{*(k)} \neq 1$. Otherwise, if for any k, $\varphi_o{}^{*(k)} = 1$, then from the first constraint we have $\sum_{j=1}^{n} (\delta_j^{(k)} + \mu_j^{(k)})\ x_{ij}^{I(k)} = 0$, which based on at least one positive value in any $i \in I$, leads to $\sum_{j=1}^{n} (\delta_j^{(k)} + \mu_j^{(k)}) = 0$, which is a contradiction. This leads to $0 < Eff_k = \frac{1-\varphi_o^{*(k)}}{1+\varphi_o^{*(k)}} \leq 1$. To complete the proof, note that $\forall k : w^{(k)} > 0$ and $\sum_{k=1}^{p} w^{(k)} = 1$, so we have $\sum_{k=1}^{p} w^{(k)} \left(1 - \varphi_o^{*(k)}\right) \leq \sum_{k=1}^{p} w^{(k)} \left(1 + \varphi_o^{*(k)}\right)$. Therefore, $0 < \frac{\sum_{k=1}^{p} w^{(k)} \left(1-\varphi_o^{*(k)}\right)}{\sum_{k=1}^{p} w^{(k)} \left(1+\varphi_o^{*(k)}\right)} \leq 1$. This shows that $0 < Eff_{Overall} \leq 1$.
ii. Note that $Eff_{Overall}(\boldsymbol{x}_o^I, \boldsymbol{x}_o^{NI}, \boldsymbol{z}_o, \boldsymbol{y}_o^D, \boldsymbol{y}_o^{UD}, \boldsymbol{y}_o^1, \boldsymbol{y}_o^2) = 1$ leads to $\forall k : \varphi_o{}^{*(k)} = 0$, which shows no input and output improvements are possible in any stage. This is equal to $\forall k : Eff_k(\boldsymbol{x}_o^I, \boldsymbol{x}_o^{NI}, \boldsymbol{z}_o, \boldsymbol{y}_o^D, \boldsymbol{y}_o^{UD}, \boldsymbol{y}_o^1, \boldsymbol{y}_o^2) = 1$.
iii. Note that all inputs, intermediates, and outputs' constraints are linear. Without any change in the optimal values of $\varphi_o^{(k)}$, any change in units of measurement affects both sides of constraints in Model (1). Therefore, both $Eff_{Overall}$ and Eff_k are unit invariant.
iv. It is enough to show that $Eff_k (k = 1, \ldots, p)$ are monotonic in inputs and outputs. Then, based on the assumption $\forall k : w^{(k)} > 0$ and $\sum_{k=1}^{p} w^{(k)} = 1$, monotonicity of $Eff_{Overall}$ achieves immediately. To do so, we first consider the case that only one input of DMU_o is changed by a positive a in any division k; i.e. $i \in I \cup NI : x_{io}^{I(k)^{new}} = x_{io}^{I(k)} + a$. We show that, at optimality, $Eff_k^{new} \leq Eff_k^{old}$. For $i \in I$, we have $a \in \mathbb{Z}_+$. By putting this value on the ith input constraint, we get

$$\sum_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) \left(x_{ij}^{I(k)} + a\right) \leq \overline{x}_i^{(k)} \leq \left(1 - \varphi_o^{(k)}\right) \left(x_{io}^{I(k)} + a\right)$$

Since $\sum_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) = 1$, we have

Table 4
The sustainability and resilience of BSCs.

BSCs	Overall and stage sustainability and resilience							Integer input targets	
	$\varphi_o^{(1)}$	$\varphi_o^{(2)}$	$\varphi_o^{(3)}$	Overall	Stage 1	Stage 2	Stage 3	$\hat{x}_2^{I(1)}$	$\hat{x}_3^{I(3)}$
1	0.02824078	0	0	0.9813484	0.9450697	1	1	24,603	16
2	0	0	0	1	1	1	1	39,615	25
3	0	0	0.005296280	0.9964754	1	1	0.9894632	24,917	16
4	0	0	0	1	1	1	1	27,965	19
5	0	0	0	1	1	1	1	29,174	17
6	0.03517416	0	0	0.9768223	0.9320421	1	1	24,714	21
7	0	0	0	1	1	1	1	34,170	23
8	0.04555432	0	0	0.9700847	0.9128609	1	1	30,003	20
9	0	0	0	1	1	1	1	33,241	27
10	0	0	0	1	1	1	1	27,947	19
11	0	0	0	1	1	1	1	23,650	21
12	0	0	0	1	1	1	1	38,171	24
13	0.09323876	0	0	0.9397145	0.8294265	1	1	22,115	16
14	0.07971888	0	0	0.9482298	0.8523340	1	1	32,081	24
15	0	0	0	1	1	1	1	21,527	11
16	0	0	0	1	1	1	1	23,943	18
17	0	0	0	1	1	1	1	19,781	15
18	0	0	0	1	1	1	1	31,177	27
19	0	0	0	1	1	1	1	18,635	14
20	0	0.1005226	0	0.9351576	1	0.8173184	1	23,287	16
21	0.1056575	0.01175043	0	0.9246759	0.8088784	0.9767721	1	31,047	23
22	0.1748962	0	0	0.8898256	0.7022781	1	1	25,433	19
23	0.07677900	0	0	0.9500913	0.8573913	1	1	19,746	17
24	0.1739641	0.2125386	0	0.7717393	0.7036295	0.6494320	1	23,683	21
25	0.1751959	0	0	0.8896472	0.7018439	1	1	18,412	19
26	0.02747283	0	0	0.9818510	0.9465235	1	1	17,755	16
27	0.2242703	0	0	0.8608862	0.6336262	1	1	24,157	21

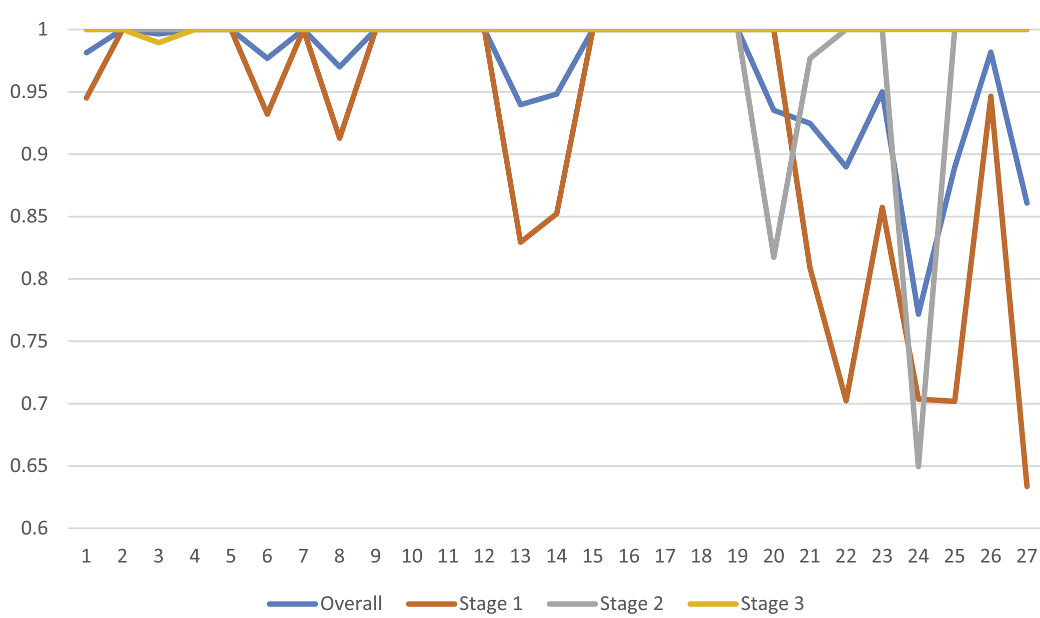

Fig. 3. Summary of the results.

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)x_{ij}^{I(k)} \le \overline{x_i}^{(k)} - a \le x_{io}^{I(k)} - \varphi_o^{(k)}\left(x_{io}^{I(k)}+a\right)$$

Therefore, $\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)x_{ij}^{I(k)} \le \overline{x_i}^{(k)} - a \le \left(1-\varphi_o^{(k)}\left(1+\frac{a}{x_{io}^{I(k)}}\right)\right)x_{io}^{I(k)}$. This shows that $\varphi_o^{\prime(k)} = \varphi_o^{(k)}\left(1+\frac{a}{x_{io}^{I(k)}}\right)$ is a feasible distance parameter for evaluating the ith input of the second observation; i.e. after changing $x_{io}^{I(k)}$ to $x_{io}^{I(k)}+a$ in which we have $\varphi_o^{\prime(k)} > \varphi_o^{(k)}$. Thus, if $\varphi_o^{\prime(k)} \in \left[\varphi_o^{*(k)}, \varphi_o^{*(k)}\left(1+\frac{a}{x_{io}^{I(k)}}\right)\right]$ and subject to feasibility of this distance parameter for other inputs/outputs of DMU_o, this immediately shows that $\frac{1-\varphi_o^{\prime(k)}}{1+\varphi_o^{\prime(k)}} \le \frac{1-\varphi_o^{*(k)}}{1+\varphi_o^{*(k)}}$ and at optimality, we can state $Eff_k^{new} \le Eff_k^{old}$. In case of changes in any other input/output components, similar proof can be provided.

These properties are the four basic properties of an efficiency score. The first two properties imply that the new proposed overall and stage efficiency scores are bounded by 0 and 1, reaching the efficient states if and only if $\forall k: {\varphi_o}^{*(k)} = 0$. This means that, in no stage, no improvement in the input/output vector of the DMU under evaluation is possible. Property (iii) guarantees that the values of $Eff_{Overall}$and $Eff_k$are independent of the unit of measurement of inputs, intermediates, and outputs. Property (iv) states that the introduced overall and stage measures are monotonic decreasing (increasing) functions in terms of inputs (outputs).

Based on the optimal value of model (1), the feasible vector $\left(\widehat{x}_o^{I}, \widehat{x}_o^{NI}, z_o, \widehat{y}_o^{D}, \widehat{y}_o^{UD}, y_o^{N} = \widehat{y}_o^{1} - \widehat{y}_o^{2}\right)$ is introduced as the target point for the DMU under evaluation:

$$\widehat{x}_i^{I(k)} = \overline{x_i}^{*(k)} \text{ for } i \in I, k = 1, \ldots, p$$

$$\widehat{x}_i^{NI(k)} = \left(1 - \varphi_o^{*(k)}\right) x_i^{NI(k)} \text{ for } i \in NI, k = 1, \ldots, p$$

$$\widehat{y}_r^{D(k)} = \left(1 + \varphi_o^{*(k)}\right) y_r^{D(k)} \text{ for } r \in O', k = 1, \ldots, p$$

$$\widehat{y}_r^{UD(k)} = \left(1 - \varphi_o^{*(k)}\right) y_r^{UD(k)} \text{ for } r \in O', k = 1, \ldots, p$$

$$\widehat{y}_3^{N(3)} = \left(1 + \varphi_o^{*(k)}\right) y_r^{1(k)} - \left(1 - \varphi_o^{*(k)}\right) y_r^{2(k)} = y_r^{N(k)} + \varphi_o^{*(k)} \left(\frac{\underbrace{y_r^{1(k)} + y_r^{2(k)}}}{\left| y_r^{N(k)} \right|} \right) \text{ for } r \in O'', k = 1, \ldots, p$$

Note that the obtained target vector shows a strict improvement in the inputs, desirable, undesirable, and negative parts of the outputs of the DMU under evaluation.

4. Case study

To demonstrate the usefulness and validity of the proposed model, a case study is presented. Here, the proposed NDEA model is applied to measure the sustainability and resilience of BSCs. Iran Blood Transfusion Organization (IBTO) was founded in 1970. Iran with more than 200 blood transfusion centers is one of the most active countries in blood products in the Middle East. The BSC (DMU) of our case study consists of three stages; BCCs (stage 1), BPCs (stage 2), and BDCs (stage 3). Fig. 2 shows the BSC of IBTO.

Through meetings with managers and experts of IBTO, we identified the indicators to assess the performance of sustainability and resilience of BSCs. The inputs of stage 1 are advertisement cost $x_1^{(1)}$, the number of donors $x_2^{I(1)}$,and transportation costs $x_3^{(1)}$. The output of stage 1 is waste of blood $y_1^{UD(1)}$. Transportation delay $z_1^{(1,2)}$ and the sent blood $z_2^{(1,2)}$ are the intermediate measures between stage 1 and stage 2. The inputs of stage 2 are transportation costs $x_1^{(2)}$, research and development costs $x_2^{(2)}$, blood production costs $x_3^{(2)}$, and environmental costs $x_4^{(2)}$. The output of stage 2 is the waste of blood $y_1^{UD(2)}$. The sent blood $z_1^{(2,3)}$ and transportation delay $z_2^{(2,3)}$ are the intermediate measures between stage 2 and stage 3. The external inputs of stage 3 are the holding cost of the product $x_1^{(3)}$, the cost of work safety and labor health $x_2^{(3)}$, the number of personnel $x_3^{I(3)}$, and transportation costs $x_4^{(3)}$. The outputs are waste of blood $y_1^{UD(3)}$, received blood from patients $y_2^{(3)}$, and profit $y_3^{N(3)}$. Table 1 summarizes the information related to the inputs, outputs, and intermediate measures. Table 2 presents some explanations about the used factors in the case study. Table 3 provides the dataset of 27 BSCs across Iran. The dataset is related to July 2020 to November 2020, which is obtained by analyzing the documents and archives of IBTO.

The customized version of Model (1) for the case study is as follows:

$$\max_{\varphi,\delta,\mu} \sum_{k=1}^{3} w^{(k)} \varphi_o^{(k)}$$

$$s.t. \ \sum_{j=1}^{27} \left(\delta_j^{(1)} + \mu_j^{(1)}\right) x_{ij}^{(1)} \le \left(1 - \varphi_o^{(1)}\right) x_{io}^{(1)}, \ i = 1, 3$$

$$\sum_{j=1}^{27} \left(\delta_j^{(1)} + \mu_j^{(1)}\right) x_{1j}^{I(1)} \le \overline{x_2}^{(1)} \le \left(1 - \varphi_o^{(1)}\right) x_2^{I(1)},$$

$$\sum_{j=1}^{27} \left(\delta_j^{(2)} + \mu_j^{(2)}\right) x_{ij}^{(2)} \le \left(1 - \varphi_o^{(2)}\right) x_{io}^{(2)}, \quad i = 1, 2, 3, 4,$$

$$\sum_{j=1}^{27} \left(\delta_j^{(3)} + \mu_j^{(3)}\right) x_{ij}^{(3)} \le \left(1 - \varphi_o^{(3)}\right) x_{io}^{(3)}, \quad i = 1, 2, 4,$$

$$\sum_{j=1}^{27} \left(\delta_j^{(3)} + \mu_j^{(3)}\right) x_{3j}^{I(1)} \le \overline{x_3}^{(3)} \le \left(1 - \varphi_o^{(3)}\right) x_3^{I(3)},$$

$$\sum_{j=1}^{27} \left(\delta_j^{(1)} + \mu_j^{(1)}\right) z_{ij}^{(1,2)} \ge z_{io}^{(1,2)}, \quad i = 1, 2,$$

$$z_{io}^{(1,2)} \ge \sum_{j=1}^{27} \left(\delta_j^{(2)} + \mu_j^{(2)}\right) z_{ij}^{(1,2)}, \quad i = 1, 2,$$

$$\sum_{j=1}^{27} \left(\delta_j^{(2)} + \mu_j^{(2)}\right) z_{ij}^{(2,3)} \ge z_{io}^{(2,3)}, \quad i = 1, 2,$$

$$z_{io}^{(2,3)} \ge \sum_{j=1}^{27} \left(\delta_j^{(3)} + \mu_j^{(3)}\right) z_{ij}^{(2,3)}, \quad i = 1, 2,$$

$$\sum_{j=1}^{27} \delta_j^{(1)} y_{1j}^{UD(1)} = \left(1 - \varphi_o^{(1)}\right), \quad y_{1o}^{UD(1)}$$

$$\sum_{j=1}^{27} \delta_j^{(2)} y_{1j}^{UD(2)} = \left(1 - \varphi_o^{(2)}\right), \quad y_{1o}^{UD(2)}$$

$$\sum_{j=1}^{27} \delta_j^{(3)} y_{1j}^{UD(3)} = \left(1 - \varphi_o^{(3)}\right), \quad y_{1o}^{UD(3)}$$

$$\sum_{j=1}^{27} \delta_j^{(3)} y_{2j}^{(3)} \ge \left(1 + \varphi_o^{(3)}\right) y_{2o}^{(3)}$$

$$\sum_{j=1}^{27} \delta_j^{(3)} y_{3j}^{(3)} \ge \left(1 + \varphi_o^{(3)}\right) y_{3o}^{1(3)}$$

$$\sum_{j=1}^{27} \delta_j^{(3)} y_{3j}^{(3)} \le \left(1 - \varphi_o^{(3)}\right) y_{3o}^{2(3)}$$

$$\sum_{j=1}^{27} \left(\delta_j^{(k)} + \mu_j^{(k)}\right) = 1, \ k = 1, \ldots, 3,$$

$$\delta_j^{(k)}, \mu_j^{(2)} \ge 0, j = 1, \ldots, 27, k = 1, \ldots, 3,$$

$$\overline{x_2}^{(1)}, \overline{x_3}^{(3)} \in \mathbb{Z}_+, \theta_o^{(k)}, \varphi_o^{(k)} \ge 0, k = 1, \ldots, 3.$$

5. Results and discussions

To analyze the dataset, Lingo 18.0 software is used. Table 4 shows that 13 out of 27 BSCs are overall sustainable and resilient with a score of 1. The overall sustainable and resilient BSCs have sustainable and resilient stages as well. Note that there is at least one sustainable and resilient BSC in each stage. BSC #24 has the lowest overall sustainability and resilience. As is shown in Table 4, 15 BSCs are unsustainable and not resilient in stage 1. Also, there are 3 unsustainable and not resilient BSCs in stage 2 and only one BSC is unsustainable and not resilient in stage 3. The targets for integer-valued inputs are reported in the last two columns of Table 4. As is seen, 13 out of 27 BSCs get different sustainability and resilience scores when integer assumption is taken into account. This indicates that the integer assumption plays important role in evaluating the BSCs.

Fig. 3 shows the results. As is seen, in stage 3, all the BSCs (except for

BSC #3) are relatively sustainable and resilient. However, in stages 1 and 2 there are many relatively unsustainable and not resilient BSCs. As is seen, whenever the overall sustainability and resilience of BSCs relatively become 1, all the stages are also relatively sustainable and resilient. Note that in the real world there is no 100% sustainable and resilient BSC. Since DEA compares DMUs relatively, a couple of BSCs are determined relatively sustainable and resilient.

5.1. Managerial implications

BSCs are vital in every healthcare system [3]. To address emergencies, a sustainable and resilient BSC is important [2]. Blood shortage leads to people's death [8]. Since the proposed approach measures the resilience and sustainability aspects of BSCs, it can help managers and decision-makers to mitigate pressures from beneficiaries such as patients and media. Furthermore, the proposed approach not only can calculate the sustainability and resilience of each stage of BSC but also can measure the overall sustainability and resilience of BSCs. This, in turn, helps decision-makers to have a better insight into the performance of BSCs. In addition, the proposed approach considers different types of data.

6. Conclusions and future researches

The supply and demand for blood and its sub-products are essential for humankind. Blood is a perishable commodity and its shortage particularly in unexpected situations such as natural and man-made disasters may lead to human death. Furthermore, human blood and its sub-products are a scarce and valuable resource that is produced only by human beings. Therefore, measuring the sustainability and resilience of BSCs is of great importance in any healthcare [109,110,41].

Given the importance of blood in saving people's lives, for the first time, we proposed a novel NDEA model for evaluating and analyzing the sustainability and resilience of BSCs. The BSCs, in this study, consist of three stages, including BCCs, BPCs, and BDCs. Furthermore, we developed a new DDF based measure to evaluate both overall and stage scores. Also, for the first time, we modeled integer data, negative data, positive data, zero data, and undesirable outputs in the network structure.

One of the limitations of our model is that it cannot take into account stochastic data. However, in the real world, there might be stochastic data. Also, our proposed model assesses DMUs in a static setting and cannot deal with DMUs in dynamic settings. Some future research directions can be derived based on the developed method. In this paper, we proposed an NDEA model in the existence of undesirable outputs, integer, negative, zero, and positive data. Proposing an NDEA model to address stochastic data can be an interesting topic for future researchers. Also, developing a dynamic NDEA model to evaluate BSCs in several periods can be another future research avenue.

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