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A hybrid approach using Z-number DEA model and Artificial Neural Network for Resilient supplier Selection

Salman Nazari-Shirkouhi [a], Mahdokht Tavakoli [b], Kannan Govindan [c,d,e,f,*], Saeed Mousakhani [b]

[a] Department of Industrial and Systems Engineering, Fouman Faculty of Engineering, College of Engineering, University of Tehran, Tehran, Iran
[b] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[c] China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai 201306, China
[d] Center for Sustainable Supply Chain Engineering, Department of Technology and Innovation, Danish Institute for Advanced Study, University of Southern Denmark, Campusvej 55, Odense M, Denmark
[e] Yonsei Frontier Lab, Yonsei University, Seoul, Korea
[f] School of Business, Woxsen University, Sadasivpet, Telangana, India

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ABSTRACT

Today's business environment has created a high level of uncertainty and disturbed procedures in supply chains. Suppliers have been often identified as the main source of risks in creating the massive levels of disruptions in supply chains. That is why resilient supplier selection can greatly reduce purchase costs and time delays and can create stability in business practices, thereby increasing competitiveness and customer satisfaction. Pharmaceutical companies play an important key role in the health of society, and these companies are frequently exposed to this disorder. Hence, this paper tries to propose a new integrated approach based on traditional (delivery, quality, price, technology level) and resilient criteria for supplier selection in pharmaceutical companies using the Z-number data envelopment analysis (Z-DEA) model and artificial neural network (ANN). In the proposed approach, expert opinions have been provided based on Z-numbers due to the inherent ambiguity and uncertainty in the evaluation process. This is the first study that evaluates the pharmaceutical industry based on traditional and resilience factors by presenting a methodological structure under the uncertainty environment. Here, a fuzzy mathematical model is used. A real case study is utilized to indicate the applicability of the proposed approach to resilient supplier selection in the pharmaceutical industry. Finally, the suppliers are ranked and the best supplier is selected regarding the reliable level of α. To indicate the features and capabilities of the selected approach, the performance analysis is presented in three parts. First, the obtained results are compared with a fuzzy DEA (FDEA) method in the form of validation and verification. Second, a sensitivity analysis is executed to show the effects of different criteria on ranking results, and the price index is identified as the most important evaluation criteria. Third, a predictive model is presented based on ANN that is able to detect the efficiency or inefficiency of suppliers with an 83% accuracy.

1. Introduction

Globalization and increased volatility in demand have created a range of actions and behaviors that disturb the smooth operation of supply chains (Altan et al., 2019; Hosseini et al., 2019; Sharma et al., 2022; Tavana et al., 2021). In addition to the two elements mentioned, events such as natural disasters (earthquakes, floods, etc), widespread infectious diseases such as COVID-19, or other unanticipated conditions represent critical occurrences that lead to supply chain disruptions (Altan & Karasu, 2020). Thus, organizations may face many types of threats and unwanted happenings that could yield a fundamental loss in productivity, competitive advantage, revenue, profitability, etc. (Torabi et al., 2015).

To address the issue, the supply chain design is required to be able to provide an efficient and effective reaction, one that is also capable of rapidly recovering the initial state or achieving an improvement over the past disruptive event (Altan et al., 2021; Hollnagel, 2011). Sheffi (2005) introduced the term resilience for the first time. In other words,

* Corresponding author at: China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai 201306, China.
E-mail addresses: snnazari@ut.ac.ir (S. Nazari-Shirkouhi), mahdokht.tavakoli@ut.ac.ir (M. Tavakoli), kgov@iti.sdu.dk (K. Govindan), s.moosakhani@ut.ac.ir (S. Mousakhani).

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supply chain resilience is the ability of the supply chain to prepare against unexpected risks, to enact a response and rapid recovery of potential disruptions, and to return to the original status or even to demonstrate growth by moving towards a new and more favorable situation (Pramanik et al., 2020). Therefore, many companies considered resilience approach to deal with market volatility and disruptions in the supply chain processes (Parkouhi et al., 2019). In recent years, the concept of resilience has become important to cope with unwanted happenings in organizations (Aslan et al., 2017; Belge et al., 2021).

Meanwhile, suppliers are considered as the main sources of risks that cause massive levels of disturbances in supply chains (Pramanik et al., 2017). Furthermore, many supply chain processes are dependent on the supplier. For the reasons mentioned above, choosing resilient suppliers can significantly reduce purchase costs, delay time, and increase a company's competitiveness and its customer satisfaction (Davoudabadi et al., 2020). Hence, companies must consider a number of factors and criteria to select the best resilient suppliers.

Multiple criteria decision-making or multiple attributes decision-making (MCDM/MADM) is the approach to deal with the selection of the best supplier (Mousakhani et al., 2017; Nazari-Shirkouhi et al., 2013). The data envelopment analysis (DEA) method is one of the most important techniques in the decision-making problem. This method uses multiple outputs and inputs for ranking and measuring the efficiency of decision-making units (DMUs) (Fallahpour et al., 2016). For the first time, Charnes et al. (1984) presented the DEA method to assess the DMUs.

Furthermore, experts play a major role in decision-making problems and provide essential information. Assigning crisp numerical values to the evaluation of alternatives and criteria is not always possible and has ambiguity (Nazari-Shirkouhi et al., 2020; Xu et al., 2023). Hence, fuzzy approaches have been introduced. The Z-number is one of these approaches that, in addition to the uncertainty in the value of a parameter, also considers the reliability of this uncertain value. The Z-number is intended to perform calculations based on numbers that are not completely reliable. Accordingly, each Z-number is expressed based on a pair of fuzzy numbers (A, B) (Chutia, 2021). The first factor (A) is a constraint for the real value of the variable. The second factor (B) also indicates the reliability of the first factor (Zadeh, 2011).

All of the definitions and items mentioned above are among the topics that are doubly important in the pharmaceutical industry because medicine is a primary item of general necessity. Proper and timely production and distribution of these products are issues that should be considered by governments in all circumstances. Accordingly, this paper aims to propose an integrated framework for evaluation and selection of the resilient supplier based on a Z-number DEA model in the pharmaceutical industry. To implement this, a case study has been used in the pharmaceutical industry. The desired company is exposed to a variety of disruptions due to rapid technological changes, uncertainties, and fluctuations in its demands that can lead to reduced competitiveness and customer satisfaction and, consequently, to reduced profitability.

In addition, in the section of sensitivity analysis using ANN method and dividing the data into two types of testing and training, a predictive model was presented that can divide suppliers with 83% accuracy into two categories of efficient and inefficient.

The rest of the paper is organized as follows: Section 2 provides a comprehensive literature survey of supplier selection. Section 3 introduces the Z-number data envelopment analysis (Z-DEA) approach for obtaining efficiency and ranking the supplier. The proposed approach is provided in Section 4. In Section 5 a real case study is illustrated in a pharmaceutical company. In Section 6 the performance analysis is given which includes validation, verification, and sensitivity analysis. Several managerial implications are explored in Section 7. A discussion of the results is provided in Section 8. Finally, some concluding remarks and future directions are suggested in Section 9.

2. Literature review

There are various techniques to evaluate suitable suppliers in the literature. Chan (2003) proposed an analytic hierarchy process (AHP) method to select the most suitable suppliers. Wang et al. (2009) utilized the technique for order of preference by similarity to ideal solution (TOPSIS) to determine the priority of partnerships in selecting manufacturing. They proved the validity of their model by comparing their model with other models by solving a numerical example. Gencer and Gürpinar (2007) applied the analytic network process (ANP) to assess the relative importance of supplier criteria in an electronic company. Also, in this paper, evaluation criteria were prepared according to the structure of the business scenario. Aditi et al. (2022) proposed a novel four-stage integrated multi-criteria decision-making (MCDM) sustainable supplier selection model using sustainable key performance indicators. Yang et al. (2010) determined five evaluation criteria through a questionnaire and proposed integrated AHP and TOPSIS methods for ranking the suppliers of nuclear power plant (NPP) equipment. Kannan (2021) and Kannan et al. (2022) proposed a hybrid method to analyse the sustainable procurement. Zarbakhshnia et al. (2023) proposed a new fuzzy decision-making approach to assess outsourcing logistics in a circular economy.

In addition to the works above, many studies have applied the DEA method for assessing performance or used a DEA-based approach for ranking alternatives in the multi-criteria decision-making problems (Liu et al., 2000). These papers were published in many fields, such as agriculture, education, energy and environment, banking, economics, insurance, healthcare, transportation, manufacturing, etc. In this regard, Weber et al. (2000) utilized the DEA and multi-objective programming (MOP) to assess the number of vendors for employment. Also, different scenarios, based on the number of vendors, were used to illustrate the solution method. Ross et al. (2006) focused on action research (AR) based on the DEA method for the assessment of suppliers in a telecommunication company. They showed a reciprocal dependence on the impact of changes in buyer performance characteristics on the capacity of each supplier. Wu et al. (2007) proposed a novel DEA method based on augmented imprecise factors to evaluate suppliers and then to rank the efficient suppliers. The model used in their paper solved the DEA's traditional inability to rank efficient suppliers and, further, they showed it was possible to solve the model with inaccurate data. Falagario et al. (2012) used cross-DEA method to assess appropriate suppliers with the ability to evaluate quantitative data related to vendor selection and to retain features requested in the tender of an Italian public agency. Lim and Zhang (2016) applied an integrated DEA and AHP method to choose the appropriate supplier using six criteria of Quality, Service, Reputation, Management, Environment, and Risks.

On the other hand, decision-making in today's complex world has become a challenge for managers and organizations. In the real world, assigning crisp numerical values to assess potential candidates and their criteria is not always possible due to inherent ambiguity. The fuzzy sets theory approach could help us solve decision-making problems in such cases of uncertainty (Büyüközkan & Çifçi, 2012). Hence, decision-makers use fuzzy values to express their judgment preferences. For instance, Z-numbers, intuitionistic fuzzy sets, and interval-valued intuitionistic fuzzy sets are employed to deal with uncertain conditions. Furthermore, some researchers have used the fuzzy information to solve supplier selection problems.

Chen et al. (2006) applied the TOPSIS method based on fuzzy set theory to choose the best supplier in supply chain management. In their study, linguistic values are used for the rankings and weights. Boran et al. (2009) proposed a fuzzy group decision making based on the TOPSIS and Intuitionistic Fuzzy Weighted Averaging (IFWA) methods to evaluate the supplier performance. In this paper, the scores of each alternative were calculated according to each criterion and the weight of each criterion based on the Euclidean distance. You et al. (2015) extended VIKOR (*vlsekriterijumska optimizacija i kompromisno resenje* in

Serbian) method based on interval 2-tuples fuzzy environment for ranking the suitable suppliers. In the environment of ambiguous, vague, and incomplete information, this method is more appropriate and effective than similar previous methods. Heidarzade et al. (2016) concentrated on clustering method due to average linkage clustering, to identify the suitable supplier based on interval type-2 fuzzy sets. Büyüközkan and Göçer (2017) suggested a hybrid method based on axiomatic design (AD) and AHP methods due to the fuzzy group decision-making to select the suitable supplier in international sporting goods group operating. Kang et al. (2016) proposed a novel MCDM model based on Z-number and genetic algorithm to select suppliers. First, Z-numbers were converted to classic fuzzy numbers, and then alternatives were ranked based on GA method. Zhong and Yao (2017) applied ELECTRE method under interval type-2 fuzzy numbers and introduced an entropy weight model to determine the criteria weights. The proposed model was then utilized to select and rank alternatives. Fazlollahtabar (2016) implemented a hybrid model based on fuzzy PROMETHEE, fuzzy linear program models, and FAHP methodology to evaluate suppliers. The results obtained in this research are useful for achieving competitive advantage and maximizing profit in business plans and business roadmap.

Kuo et al. (2010) presented integrated DEA and AHP methods under fuzzy environment to assess suppliers in an auto lighting company. The weight of the indicators was calculated through a questionnaire and used the fuzzy AHP method, then the suppliers were ranked using the fDEA method. Azadi et al. (2015) developed the DEA model based on fuzzy sets and determined the most suitable sustainable suppliers; this model helped DMs to select suppliers based on economic, social, and environmental factors. Dotoli et al. (2016) proposed a new hybrid cross-DEA and Monte Carlo approach based on uncertain inputs and outputs. In this paper, the authors have identified an indicator of the robustness of the ranking provided. Karsak and Dursun (2015) provided a new integrated DEA and quality function deployment (QFD) method based on group decision-making. In the study, the supplier evaluation criteria are computed regarding fuzzy weighted average (FWA) technique. Amindoust and Saghafinia (2014) concentrated on Affinity Diagram to obtain criteria and presented FDEA technique based on α- cut method to evaluate suppliers.

Despite numerous researches and a rich background in the field of supplier selection, as seen in the previous section, research in the field of resilient supplier selection is very limited. In the following, some of the most important studies are discussed. Torabi et al. (2015) proposed a bi-objective mixed possibilistic model to select the supplier and order allocation problem based on operational and disruption risks. The authors presented a five-step method to solve the problem; their computational results show the effect of considering disruptive events on supplier selection. Sawik (2013) suggested an approach based on disruption risks for order quantity allocation and supplier selection in a supply chain with a mixed-integer programming approach. Also, the risk-neutral and risk-averse solutions were compared for both single and multiple sourcing strategies. Haldar et al. (2014) developed an integrated fuzzy group decision-making approach based on TOPSIS for supplier selection under a disaster environment. In addition, the authors used the weight of suppliers in an overall strategy and a resilient strategy to analyze the sensitivity of the proposed model. Shyur and Shih (2006) applied a hybrid MCDM model based on ANP and TOPSIS methods to evaluate vendors in new task situations. In this method, ANP was used to determine the relative weight of multiple evaluation criteria. Rajesh and Ravi (2015) implemented the grey relational analysis method to evaluate resilient suppliers in electronic supply chain. Also, by changing the weighting to each of the resilience criteria, how the suppliers' priorities changed was analyzed. Pramanik et al. (2017) proposed integrated modeling based on AHP, TOPSIS, and QFD methods to evaluate resilient suppliers considering fuzzy environment. The proposed model has a more realistic level of desirability than previous models and solves the problem of information loss to some extent. Foroozesh et al. (2017) presented a new group decision-making model to select a resilient supplier based on interval-valued fuzzy and possibilistic statistics. In this model, the weight of decision-makers and evaluation criteria were computed under the uncertainty using entropy method. Davoudabadi et al. (2020) presented an integrated model based on DEA and principal components analysis (PCA) methods so that correlation between the criteria was reduced using the PCA method and criteria weights, and supplier ranking was performed by DEA method. Zarei et al. (2021) developed a hybrid MCDM model based on AHP and VIKOR in a fuzzy environment. The performance level of a gas refinery was measured based on six resilience indices. Tsai et al. (2021), by categorizing the supplier evaluation criteria into two categories of cost and income criteria, presented the fDEA model in the supplier selection problem. In addition, this paper helps managers identify the most appropriate suppliers by differentiating between efficient and inefficient suppliers.

As seen above, many studies have considered resilient supplier selection, but so far there has been no study dealing with the importance of resilient suppliers in the pharmaceutical sector (pharmaceutical industry). Moreover, we make the following contributions:

- Developing a resilient supplier selection based on traditional (delivery, quality, price, technology level) and resilient categories. To our knowledge, this paper pioneers in the consideration of a resilience approach in the pharmaceutical industry.
- Proposing a Z-DEA approach to solve the resilient supplier problem.
- Applying noise analysis to find the optimal alpha level in problem-solving using the Z-DEA method.
- Considering the uncertainty and reliability in data simultaneously.
- Identifying the most important influencing factors for supplier evaluation in the pharmaceutical industry
- Determining the type and severity of each of the traditional resilience criteria on supplier performance.
- Providing a forecasting model with 83% accuracy to identify the efficiency or inefficiency of a supplier.

Furthermore, the features of our proposed approach and other methods of assessing the suppliers of pharmaceutical companies are summarized in Table 1. Accordingly, the proposed model is compared with the previous studies to illustrate its superiorities and advantages.

According to the literature review and selected papers in Table 1, the use of the Z-DEA model to evaluate suppliers is one of the most practical and important methods in the literature. Therefore, applying the Z-DEA method along with other methods in order to enhance the capability of the supplier evaluation model is one of the salient features of this paper, which distinguishes it from other papers. These methods include using the fuzzy approach (based on Z-numbers), noise analysis, and ANN in order to perform analysis and forecasting.

2.1. Motivation and significance

Pharmaceutical companies are recognized as one of the most important industries that play an especially vital role in the community's health. Moreover, the processes of these companies depend on a large number of suppliers. Hence, disruptions in the process of each supplier can cause irreparable damage to society. Therefore, this paper aims to reduce disturbances and risks in the supply chain by selecting a suitable resilient supplier.

One of the most useful and practical tools to evaluate and select an appropriate supplier is the DEA method. The priority of each supplier is computed by considering the inputs and outputs. Furthermore, the possibility of using fuzzy sets approach regarding uncertainty and complexity in data evaluation is another advantage of this method. In addition, considering the reliability of experts is significant in providing information due to the collection of uncertain data by experts. In this paper, fuzzy Z-numbers are used to consider the reliability of information, and the developed Z-DEA model is applied to evaluate suppliers.

Table 1
Features of the proposed model versus other methods for assessing the suppliers of pharmaceutical companies.

	Features					
Author (s)	Multiple inputs and outputs	Uncertainty in the data	Reliability in the data	Sensitivity analysis	Application of a forecasting model	Applicability in the real world
Mehralian et al. (2012)						
Alinezad et al. (2013)		✓				
Pourghahreman and Qhatari (2015)						
Cabrita and Frade (2016)						✓
Vörösmarty and Dobos (2019)	✓					
Davoudabadi et al. (2020)	✓	✓		✓		✓
The proposed approach	✓	✓	✓	✓	✓	✓

(Abbasi et al., 2020; Ghoushchi et al., 2021; Hosseini et al., 2022).

Moreover, by exact literature study, several important criteria are considered to assess resilient suppliers. In this paper, we divide these criteria into two categories: traditional and resilient categories. Delivery, quality, price, and technology level have been considered as the traditional indicators because of the importance of these criteria in literature. The resilient category, such as risk awareness, is applied to enhance the organization's flexibility in the event of disruption.

In addition, the performance analysis is provided for validation and verification of the proposed approach, specification of the most important evaluation criteria, and supplier performance prediction based on ANN in the form of DEA model.

3. Data envelopment analysis (DEA)

DEA is a non-parametric mathematical programming approach for evaluating the efficiency of DMUs that have multiple inputs and multiple outputs. Also, there are two kinds of DEA models included: Charnes–Cooper–Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models. The CCR models are created based on the assumption of constant returns to scale (CRS) of activities, but the BCC models are provided based on the assumption of variable returns to scale (VRS) of activities. The efficiency of the weighted sums of the input–output ratio is evaluated by the CCR model and the assumption that constant returns to scale. Unlike the CCR model, BCC models consider variable returns of the scale of DMUs (Azadeh & Kokabi, 2016).

In addition, the DEA method can be classified into two categories: input-oriented and output-oriented. In input-oriented models, inputs are minimized while outputs are constant, but in output-oriented models, outputs are maximized while inputs are constant.

3.1. Basic models of DEA

Consider n DMUs, where each amount of m has different inputs to produce s different outputs. DMU_ρ consumes amount $x_{j\rho}$ of input ($j = 1, 2, \cdots, m$) and produces amount $y_{r\sigma}$ of output ($r = 1, 2, \cdots, s$). Assume that $x_{ij} \geq 0$ and $y_{rj} \geq 0$. In the standard CCR models, try to maximize the ratio of weighted sum of output to the weighted sum of inputs. Therefore, the model can be represented as:

$$Max\theta = \sum\nolimits_{r=1}^{s} \mu_r y_{r\rho} / \sum\nolimits_{i=1}^{m} \omega_j x_{j\rho} \quad (1)$$

Subject to:

$$\sum\nolimits_{r=1}^{s} \mu_r y_{r\rho} / \sum\nolimits_{i=1}^{m} \omega_j x_{ji} \leq 1, i = 1, 2, \cdots, n$$

$$\omega_j.\mu_r \geq 0, j = 1, 2, \cdots, m.r = 1, 2, \cdots, s$$

where θ_ρ, ω_i and μ_r represent the efficiency of DMU_ρ and the factor weights, respectively. However, this model is non-linear due to the division operator in the objective function. Furthermore, the standard input-oriented CCR linear model is defined as follows:

$$Max \sum_{r=1}^{s} \mu_r y_{r\rho} \quad (2)$$

Subject to:

$$\sum_{r=1}^{s} \mu_r y_{ri} - \sum_{j=1}^{m} \omega_i x_{ji} = 1, i = 1, 2, \cdots, n$$

$$\sum_{i=1}^{m} \omega_i x_{j\rho} = 1$$

$$\omega_i.\mu_r \geq \varepsilon, j = 1, 2, \cdots, m.r = 1, 2, \cdots, s$$

To ensure that all the factor weights will have positive values in the solution, the small value ε is introduced. In CCR model, DMUs can get the best weights and efficiencies. Also, the output-oriented CCR model is defined as below:

$$Max\theta \quad (3)$$

Subject to:

$$x_{j\rho} \geq \sum_{i=1}^{n} \lambda_i x_{ji}, j = 1, 2, \cdots, m$$

$$\theta y_{r\rho} \leq \sum_{i=1}^{n} \lambda_i y_{ri}, r = 1, 2, \cdots, s$$

$$\lambda_i \geq 0, ..i = 1,\ 2,\ \cdots,\ n$$

On the other hand, for the applicability of the above model, it is modified by Andersen and Petersen, as follows:

$$Max\theta \quad (4)$$

Subject to:

$$x_{j\rho} \geq \sum_{j=1}^{n} \lambda_j x_{ji} j = 1, 2, \cdots, m$$

$$\theta y_{r\rho} \leq \sum_{j=1}^{n} \lambda_i y_{ri} r = 1, 2, \cdots, s$$

$$\lambda_i \geq 0, ..i = 1,\ 2,\ \cdots,\ n$$

3.2. Z-number DEA

The Z-numbers were introduced by Zadeh (2011) and associated with the value and reliability of a number as follows: $Z = (\widetilde{A}, \widetilde{B})$. $\widetilde{A}$ includes fuzzy set related to variable X and $\widetilde{B}$ is reliability and certainty on selected $\widetilde{A}$. In this regard, the triangular fuzzy number (Fig. 1) is shown as follows:

If X is a random variable, then X is equal to $\widetilde{A}$ of a fuzzy event in the set of real numbers, the probability of which is calculated in Eq. (5).

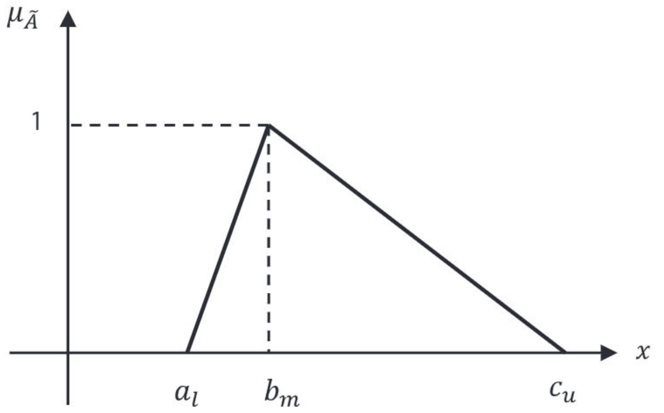

Fig. 1. The triangle fuzzy number $\widetilde{A} = (a_l, b_m, c_u)$

$$\rho = \int \mu_A(u)\rho_x(u)du \tag{5}$$

In the above equation, the density function is the unknown probability X. So a Z-number with a triple (X, A, B) is the general case of the above case in which the value of ρ_x is unknown. What is clear is the fuzzy constraint on the values it can adopt, known as reliability. Thus the membership function μ_B plays the role of certainty with respect to the values of X. Fig. 2 shows the membership function A along with the probability density function.

The Z-number can be expressed in the form in $Z^+ = (A, R)$ which R is the probability distribution of a random variable in which the distribution function is not known; what is known is the size of probability A. Therefore, the relationship between Z-number and Z^+-number is shown in Eq. (6), which expresses the relationship between fuzzy constraints related to certainty and possible reliability function.

$$\mu_A.\rho_X = \rho_A = \int \mu_A(u)\rho_X(u)du \tag{6}$$

$$Z(A, B) = Z^+(A, \mu_A.\rho_X)$$

This equation states that $\mu.\rho$ is the probability size for A and B is the probability and fuzzy constraint for $\mu_A.\rho_X$. Therefore, Z-numbers can cover random numbers with a specific distribution function for values. Azadeh and Kokabi (2016) developed the DEA model based on Z-numbers and solved a case study to practically illustrate the proposed model. In the following, the CCR model is shown based on Z-numbers and then, the linear form of this model is presented. Hence, for the $\mathrm{DMU_i}$ the input and output amounts of decision-making criteria are respectively $\widetilde{Zx}_{ji} = (\widetilde{Ax}_{ji}, \widetilde{Bx}_{ji})$ and $\widetilde{Zy}_{ri} = (\widetilde{Ay}_{ri}, \widetilde{By}_{ri})$. The amount of $\widetilde{Ax}_{ji}$ is the fuzzy value that the j^{th} input related to the $\mathrm{DMU_i}$. Also, the amount of $\widetilde{Bx}_{ji}$ is the fuzzy set containing uncertainty for the $\widetilde{Ax}_{ji}$. In a similar way, the $\widetilde{Ay}_{ri}$ is the fuzzy value that the r^{th} output related to the $\mathrm{DMU_i}$ and the $\widetilde{By}_{ri}$ is the reliability of this number. The CCR model is represented as:

$$Max\theta = \sum_{r=1}^{s} U_r \widetilde{Zy}_{r\rho} \tag{7}$$

Subject to:

$$\sum_{j=1}^{m} v_j \widetilde{Zx}_{j\rho} = 1$$

$$\sum_{r=1}^{s} u_r \widetilde{Zy}_{ri} \leq \sum_{j=1}^{m} v_j \widetilde{Zx}_{ji}, i = 1, 2, \cdots, n$$

$u_r, v_j \geq 0, \quad r = 1, 2, \cdots, s, .. j = 1, 2, \cdots, m$

However, the models are not linear. For this purpose, the models offered were converted to fuzzy mathematical programming; then, using one of the methods of fuzzy linear, they were converted to a linear mathematical model. Accordingly, for the j^{th} input related to the $\mathrm{DMU_i}$ we have: $\widetilde{Zx}_{ji} = (\widetilde{Ax}_{ji}, \widetilde{Bx}_{ji})$ in which $\widetilde{Ax}_{ji} = (ax^l_{ji}, ax^m_{ji}, ax^u_{ji})$ and $\widetilde{Bx}_{ji} = (bx^l_{ji}, bx^m_{ji}, bx^u_{ji})$ expressed in the form of triangular fuzzy numbers.

$\widetilde{Bx}_{ji}$ is defused by the Center of Gravity (COG) method and the definite value of reliability, βx_{ji} is obtained. This value is added to the first pair, $\widetilde{Ax}_{ji}$ and then Eqs. (8) and (9) are executed to convert the weighted Z-number into triangular fuzzy numbers. The converted Z-number is illustrated in Fig. 3.

Also, the Z-number values are obtained by using the following equations:

$$\beta x_{ji} = (bx^l_{ji} + bx^m_{ji} + bx^u_{ji})/3 \tag{8}$$

$$x^m_{ji} = ax^m_{ji}$$

$$x^l_{ji} = (\beta x_{ji} ax^m_{ji} - ax^m_{ji} + ax^l_{ji})/\beta x_{ji}$$

$$x^u_{ji} = (\beta x_{ji} ax^m_{ji} - ax^m_{ji} + ax^u_{ji})/\beta x_{ji}$$

Also, for the r^{th} output related to the $\mathrm{DMU_i}$ $\widetilde{Zy}_{ri} = (\widetilde{Ay}_{ri}, \widetilde{By}_{ri})$ in which $\widetilde{Ay}_{ri} = (ay^l_{ri}, ay^m_{ri}, ay^u_{ri})$ and $\widetilde{By}_{ri} = (by^l_{ri}, by^m_{ri}, by^u_{ri})$ and in the same way we have:

$$\beta y_{ri} = (by^l_{ri} + by^m_{ri} + by^u_{ri})/3 \tag{9}$$

$$y^m_{ji} = ay^m_{ji}$$

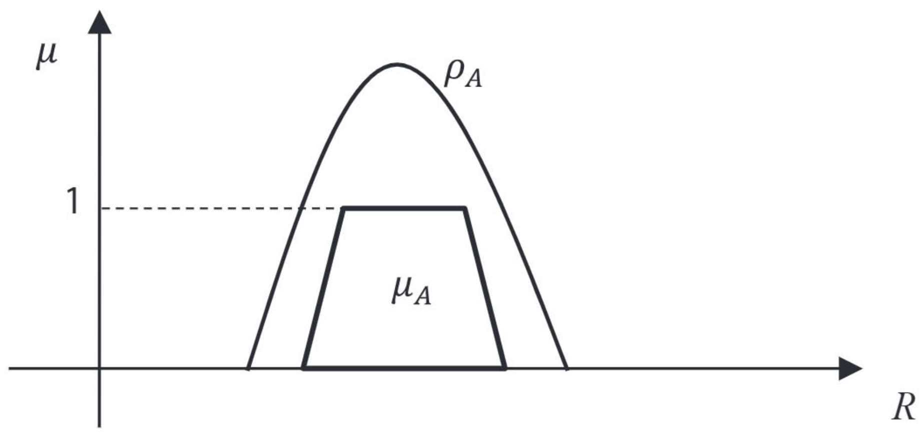

Fig. 2. Membership function A with probability density function ρ

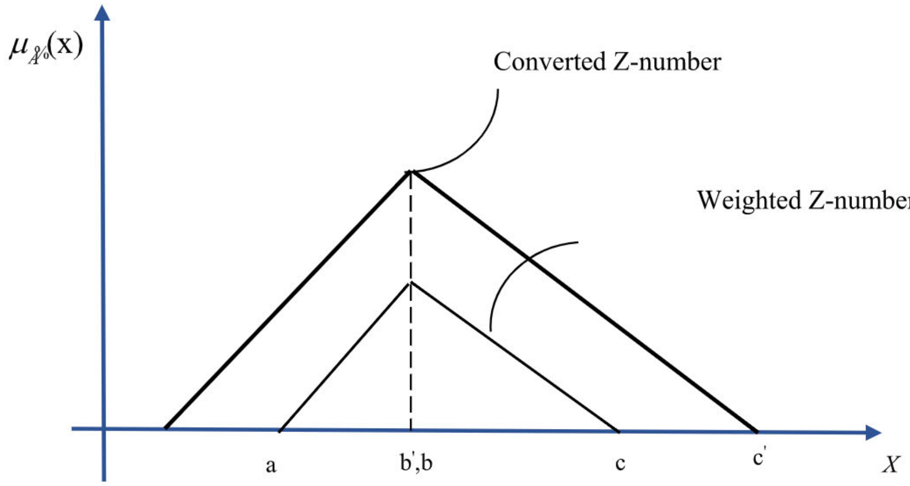

Fig. 3. The converted Z-number.

$$y^l_{ri} = (\beta y_{ri} a y^m_{ri} - a y^m_{ri} + a y^l_{ri})/\beta x_{ri}$$

$$y^u_{ri} = (\beta y_{ri} a y^m_{ri} - a y^m_{ri} + a y^u_{ri})/\beta y_{ri}$$

The above equations are defined to provide a mechanism by which βx_{ji} and βy_{ri} values can be added to the fuzzy values of decision numbers. Once βx_{ji} and βy_{ri} values are obtained, they merge with the first values of the corresponding Z-numbers to form weighted Z-numbers. If $\widetilde{Zx}_{ji} = (\widetilde{Ax}_{ji}, \widetilde{Bx}_{ji})$, its weighted Z-number is defined as the set $\widetilde{Z}^{\alpha} = \{(x, \mu^{\alpha}_{A}(x)) | x \in X\}$ in which the membership function of the unnormal fuzzy set Z-number is weighted.

According to the above equation, the fuzzy model corresponding to Z-DEA model in the CCR was obtained as follows:

$$Max\theta_{\rho} = \sum_{r=1}^{s} U_r(y^l_{r\rho}, y^m_{r\rho}, y^u_{r\rho}) \tag{10}$$

Subject to:

$$\sum_{j=1}^{m} v_j\left(a^l_{j\rho}, x^m_{j\rho}, x^u_{j\rho}\right) = (1^l, 1, 1^u)$$

$$\sum_{r=1}^{s} u_r(y^l_{ri}, y^m_{ri}, y^u_{ri}) \le \sum_{j=1}^{m} v_j\left(a^l_{ji}, x^m_{ji}, x^u_{ji}\right), i = 1, 2, \cdots, n$$

$u_r, v_j \ge 0, \quad r = 1, 2, \cdots, s, .j = 1, 2, \cdots, m$

In the end, by using the α-cut method, the Z-DEA linear model was achieved.

$$Max\theta_{\rho} = \sum_{r=1}^{s} \overline{y}_{r\rho} \tag{11}$$

Subject to:

$$\sum_{j=1}^{m} \overline{x}_{j\rho} = 1$$

$$\sum_{r=1}^{s} \overline{y}_{ri} \le \sum_{j=1}^{m} \overline{x}_{ji}, i = 1, 2, \cdots, n$$

$$v_j\left(\alpha x^m_{ji} + (1-\alpha)x^l_{ji}\right) \le \overline{x}_{ji} \le v_j\left(\alpha x^m_{ji} + (1-\alpha)x^u_{ji}\right), i = 1, 2, \cdots, n, j = 1, 2, \cdots, m$$

$$u_r\left(\alpha y^m_{ri} + (1-\alpha)y^l_{ri}\right) \le \overline{y}_{ri} \le u_r\left(\alpha y^m_{ri} + (1-\alpha)y^u_{ri}\right), i = 1, 2, \cdots, n, r = 1, 2, \cdots, s$$

$u_r, v_j \ge 0, \quad r = 1, 2, \cdots, s, .j = 1, 2, \cdots, m$

In the above model, the α value represents a satisfaction degree.

3.3. Noise analysis

Given that the Z-DEA model is a fuzzy and uncertain model, it must be adjusted by α -cut. In this regard, the reliable α -cut should be determined before evaluating the performance of suppliers. In order to determine the reliable α -cut in this type of model, there are several methods, and noise analysis is one of the methods to determine the reliable α-cut in the Z-DEA model. For this purpose, the most reliable α value of the α available was selected by disrupting some data. The steps of noise analysis are shown as below:

Step 1: Obtaining initial efficiency by the Z-DEA model in a specific level of α.
Step 2: About 15 percent of the data in the table is multiplied by 10, randomly and repeatedly. This is performed five times (noise creation).
Step 3: Obtaining efficiency of the new data in the specific level of α.
Step 4: Calculating the value of the average initial efficiency and the average efficiency of noisy data.
Step 5: Calculating the correlation between the average initial efficiency and the average noisy data efficiency.
Step 6: The process is performed for the various levels of α.
Step 7: The level of α related to the maximum amount of correlation has the greatest reliability.

4. Proposed approach

The proposed approach for selecting a resilient supplier in the pharmaceutical industry consists of two parts: (1) conducting initial studies and (2) implementing mode and evaluation of the potential candidate. In the first section, appropriate alternatives distinguished by experts' opinion and the criteria utilized in this issue are determined based on resilience approach and review literature. In the second section, Z-DEA model is implemented at various levels of α. Afterward, the reliable level of α is selected and the resilient suppliers are ranked. The process of resilient supplier selection in the pharmaceutical industry based on the Z-DEA method is depicted in Fig. 4.

5. A real case study

In this study, a new assessment model has been proposed to evaluate the suppliers of a pharmaceutical company in Iran. To do so, an MCDM

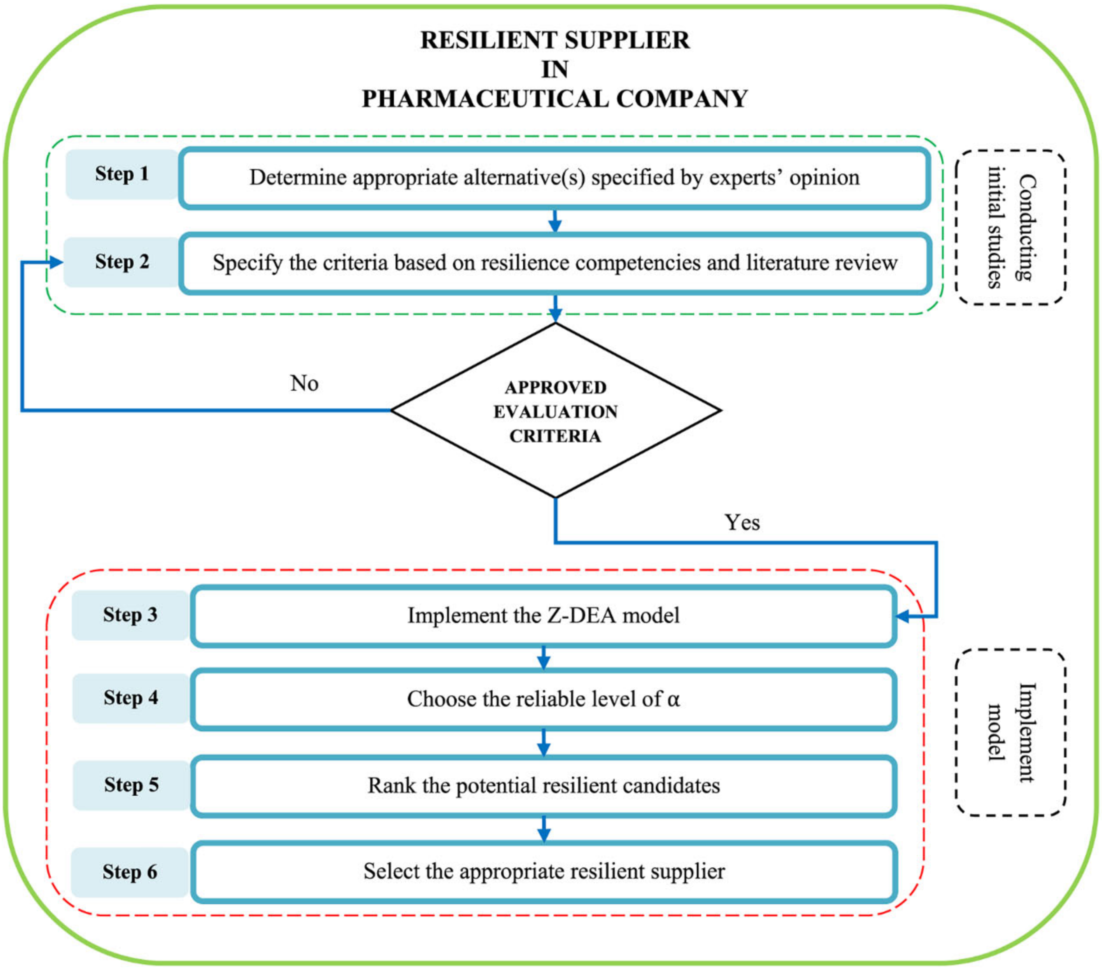

Fig. 4. The schematic structure of resilient supplier selection process based on Z-DEA method.

methodology based on DEA model is suggested under Z-numbers environment. The Z-numbers, as a new tool, are recognized to handle uncertainty due to the reliability of the numbers in experts' preferences. Applying this method has some advantages such as reliability and flexibility to compare and assess criteria in the decision-making process.

Also, in this study, suppliers were evaluated based on resilience and traditional criteria and, then, the suitable supplier was selected. In addition to having attractive competitive metrics in the supply chain, the designated supplier has resilient features that will allow a return to the original status or even surpass the previous status in the event of a disruption. Accordingly, real case data have been applied in the pharmaceutical company in Iran to implement the proposed model (more effectively, more precisely).

The XYZ company (the company's name is kept anonymous due to confidentiality) is one of Iran's major pharmaceutical companies. This company is currently able to produce a variety of medicines such as tablets, coated tablets, hard gelatin capsules, soft-gel capsules, oral drops, syrups, edible suspensions, topical solutions, topical gels, topical creams, and ointments. The activities of this company are always exposed to a wide variety of disturbances which may lead to a reduction of competitiveness and customer satisfaction and, ultimately, to a reduction in the company's profitability. These disorders include international sanctions, changes in currency exchange rates, changes in demand and customer expectations, rapid changes in technology, dysfunction of suppliers, lack of supplier flexibility, etc.

One of the major issues the company is facing today is the use of new science and technology that creates new needs and requirements in the market. Therefore, it is exposed to rapid changes in technology, which has to satisfy these requirements in their products in the shortest time possible. Another issue facing the company is that because of international sanctions against Iran, the global suppliers who provide materials needed for the production of pharmaceuticals are disturbed. Thus, evaluating and selecting resilient suppliers can be identified as the first and most critical step to assist this company in augmenting the resilience of the supply chain. For this purpose, it is necessary to recognize the evaluation criteria of resilience in suppliers in the company.

In this study, the main criteria for assessing resilient suppliers have been identified using the literature and experts' opinions. Finally, the Z-DEA method was used for ranking resilient suppliers. Accordingly, thirty-six potential suppliers for the manufacture of products listed in the company (DMU_1, DMU_2, DMU_3, and DMU_{36}) were evaluated based on eight criteria in Table 2.

Also, for evaluating suppliers, the triangular fuzzy number was used in this study. In Tables 3 and 4, the linguistic variables for the parameter $\widetilde{A}$ and $\widetilde{B}$ are shown respectively. In this case, $\widetilde{A}$ is a fuzzy limit that refers to criteria value and $\widetilde{B}$ is reliability value of the amount of $\widetilde{A}$.

In the following, the relative importance of evaluation criteria was determined for each resilient candidate supplier based on experts' judgments and Tables 3 and 4. The results of the experts' judgment per supplier based on Z-numbers are shown in Table 5. Also, the linguistic terms are converted into the triangular fuzzy number and represented in Tables 6 and 7, respectively.

Accordingly, the criteria should be divided into two parts: input and output due to the nature of the DEA method in supplier selection issues. As previously mentioned, each alternative is considered as one DMU. Accordingly, if a criterion is increased while other criteria are assumed

Table 2
Criteria considered for supplier selection based on literature review and experts' opinions.

Category	Attribute	Remarks	Relevant literature
Traditional	Delivery (G_1)	The ability to obtain the features in the product (quality characteristics) that respond to customer needs.	(Büyüközkan & Çifçi, 2012; Karsak & Dursun, 2015)
	Quality (G_2)	The ability to deliver the orders to the customer at the time promised.	(Büyüközkan & Çifçi, 2012; Kuo et al., 2010)
	Price (G_3)	It is defined as the total cost of the providing services or production.	(Büyüközkan & Çifçi, 2012; Mehralian et al., 2012)
	Technology level (G_4)	The ability to produce products to meet company demand.	(Mehralian et al., 2012)
Resiliency	Risk awareness (R_1)	Risk awareness helps the organizations to the appropriate correction when an emergency arises.	(Cabrita & Frade, 2016; Torabi et al., 2015)
	Adaptive capability (R_2)	The system's ability to adapt to complex problems or new activities so its ability to solve problems without disturbing the overall performance is maximized.	(Parkouhi et al., 2019; Pramanik et al., 2020)
	Vulnerability (R_3)	The system's ability to resist the vulnerability of various sources of risk.	(Foroozesh et al., 2017; Haldar et al., 2014; Sheffi, 2005)
	Responsiveness (R_4)	The system's ability to respond quickly to clients' requirements.	(Haldar et al., 2014; Pramanik et al., 2017)

Table 3
Linguistic scales for the parameter...$\widetilde{A}$

Linguistic variable	Triangular fuzzy number
Very poor (VP)	(0,1,3)
Poor (P)	(1,3,5)
Fair (F)	(3,5,7)
Good (G)	(5,7,9)
Very good (VG)	(7,9,10)

constant, the performance of a supplier (DMU) is reduced, that is a criterion input. The vice versa is also valid: if a criterion is increased while other criteria are assumed constant, the performance of a supplier (DMU) is increased, that is a criterion output.

According to this point, the delivery and price are inputs of DMUs, and vulnerability, technology level, quality, risk awareness, adaptive capability, and responsiveness are outputs of DMUs.

Then, the Z-DEA model is implemented due to the issue data and the efficiency of each supplier was obtained based on various levels of α. These results are shown in Table 8.

In the following, Noise analysis is performed based on the mentioned steps to determine the reliable levels of α. Accordingly, the noise anal-

Table 4
Linguistic scales for reliability values ($\widetilde{B}$).

Linguistic variable	Membership functions parameters
Sure (S)	(0.8,1,1)
Usually (U)	(0.65,0.75,0.85)
Likely (L)	(0.5,0.6,0.7)

Table 5
The linguistic variable to the criteria based on experts' judgments for each supplier in the form of pairs...$(\widetilde{A},\widetilde{B})$

DMUs	Criteria							
	Inputs		Outputs					
	G_1	G_3	R_1	R_2	R_3	R_4	G_2	G_4
Supplier 1	(G,S)	(F,U)	(G,U)	(F,S)	(F,S)	(P,U)	(VG,S)	(G,U)
Supplier 2	(F,L)	(P,S)	(VG,S)	(G,S)	(F,U)	(G,U)	(F,L)	(F,U)
Supplier 3	(G,S)	(F,U)	(VG,U)	(G,U)	(F,U)	(P,U)	(G,U)	(VG,L)
Supplier 4	(G,U)	(F,U)	(F,L)	(G,L)	(P,L)	(F,U)	(F,S)	(G,U)
Supplier 5	(VG,L)	(G,S)	(G,U)	(F,U)	(F,U)	(G,U)	(VG,U)	(G,S)
Supplier 6	(G,S)	(F,U)	(P,U)	(P,L)	(G,U)	(F,U)	(VG,S)	(F,S)
Supplier 7	(F,S)	(G,S)	(VG,L)	(G,S)	(G,L)	(G,U)	(G,S)	(G,U)
Supplier 8	(G,S)	(F,L)	(G,L)	(G,U)	(P,U)	(P,U)	(G,S)	(F,U)
Supplier 9	(VG,U)	(G,S)	(G,S)	(F,L)	(F,U)	(F,U)	(F,L)	(F,S)
Supplier 10	(G,S)	(G,U)	(F,U)	(G,U)	(G,S)	(G,U)	(F,U)	(G,S)
Supplier 11	(F,L)	(G,S)	(G,U)	(VG,L)	(F,U)	(G,L)	(G,U)	(F,L)
Supplier 12	(G,L)	(F,S)	(F,U)	(G,S)	(P,U)	(G,U)	(F,S)	(G,U)
Supplier 13	(G,U)	(G,S)	(G,S)	(G,L)	(G,S)	(F,U)	(G,L)	(F,S)
Supplier 14	(G,S)	(G,U)	(G,L)	(G,U)	(P,U)	(G,L)	(F,U)	(VG,S)
Supplier 15	(F,L)	(F,L)	(G,S)	(VG,U)	(G,L)	(P,U)	(G,U)	(G,S)
Supplier 16	(G,U)	(G,S)	(P,S)	(G,U)	(F,S)	(G,L)	(VG,L)	(F,U)
Supplier 17	(G,S)	(G,S)	(F,U)	(F,U)	(P,U)	(F,U)	(F,U)	(G,U)
Supplier 18	(G,L)	(G,L)	(F,L)	(F,S)	(F,U)	(G,L)	(G,U)	(VG,L)
Supplier 19	(G,U)	(VG,S)	(G,S)	(F,L)	(G,U)	(F,U)	(G,S)	(G,U)
Supplier 20	(G,U)	(F,U)	(P,U)	(G,L)	(F,S)	(G,L)	(F,U)	(G,L)
Supplier 21	(F,L)	(G,U)	(G,U)	(G,L)	(F,S)	(P,U)	(F,U)	(F,S)
Supplier 22	(G,U)	(P,S)	(P,U)	(G,S)	(G,S)	(F,U)	(G,L)	(G,S)
Supplier 23	(F,L)	(G,S)	(G,L)	(VG,L)	(F,U)	(F,U)	(F,U)	(G,U)
Supplier 24	(G,S)	(G,L)	(P,U)	(G,L)	(F,S)	(G,L)	(VG,L)	(VG,L)
Supplier 25	(F,S)	(VG,S)	(F,L)	(G,L)	(F,U)	(F,U)	(F,U)	(F,S)
Supplier 26	(G,U)	(F,U)	(G,S)	(F,L)	(G,S)	(F,U)	(VG,S)	(G,L)
Supplier 27	(F,U)	(F,L)	(F,L)	(VG,S)	(P,U)	(G,U)	(G,U)	(G,S)
Supplier 28	(VG,S)	(G,U)	(P,U)	(G,U)	(F,S)	(P,U)	(G,S)	(F,S)
Supplier 29	(F,L)	(G,S)	(G,L)	(G,S)	(F,U)	(G,L)	(VG,L)	(G,U)
Supplier 30	(G,U)	(F,U)	(G,U)	(F,U)	(P,U)	(P,U)	(G,L)	(G,S)
Supplier 31	(G,S)	(VG,S)	(P,L)	(G,L)	(F,S)	(G,U)	(F,U)	(VG,L)
Supplier 32	(F,U)	(G,S)	(F,L)	(G,U)	(F,U)	(P,U)	(G,L)	(VG,L)
Supplier 33	(G,S)	(F,L)	(G,U)	(F,U)	(G,L)	(P,U)	(VG,S)	(G,U)
Supplier 34	(G,S)	(G,L)	(G,L)	(F,L)	(P,U)	(F,U)	(G,S)	(G,L)
Supplier 35	(G,S)	(F,L)	(G,S)	(G,L)	(P,U)	(P,U)	(F,U)	(VG,L)
Supplier 36	(G,U)	(G,S)	(F,U)	(VG,S)	(F,U)	(F,U)	(G,U)	(G,U)

Table 6
Triangular fuzzy values assigned to the parameter...$\widetilde{A}$

DMUs	Criteria							
	Inputs		Outputs					
	G_1	G_3	R_1	R_2	R_3	R_4	G_2	G_4
S_1	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(1,3,5)	(7,9,10)	(5,7,9)
S_2	(3,5,7)	(1,3,5)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)
S_3	(5,7,9)	(3,5,7)	(7,9,10)	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(7,9,10)
S_4	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(1,3,5)	(3,5,7)	(3,5,7)	(5,7,9)
S_5	(7,9,10)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,10)	(5,7,9)
S_6	(5,7,9)	(3,5,7)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)
S_7	(3,5,7)	(5,7,9)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)
S_8	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)
S_9	(7,9,10)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)
S_{10}	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
S_{11}	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
S_{12}	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)
S_{13}	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S_{14}	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(7,9,10)
S_{15}	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,10)	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)
S_{16}	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,10)	(3,5,7)
S_{17}	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(1,3,5)	(3,5,7)	(3,5,7)	(5,7,9)
S_{18}	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)
S_{19}	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)
S_{20}	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)
S_{21}	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(3,5,7)
S_{22}	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)
S_{23}	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)
S_{24}	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,10)	(7,9,10)
S_{25}	(3,5,7)	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)
S_{26}	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)	(5,7,9)
S_{27}	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,10)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)
S_{28}	(7,9,10)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(3,5,7)
S_{29}	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,10)	(5,7,9)
S_{30}	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)
S_{31}	(5,7,9)	(7,9,10)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)
S_{32}	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(7,9,10)
S_{33}	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,10)	(5,7,9)
S_{34}	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)
S_{35}	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(3,5,7)	(7,9,10)
S_{36}	(5,7,9)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)

ysis shows the value of standard α is 0.95 in this issue and this amount is the lowest deviation against disorders. Therefore, it is defined as the level of reliability in this study. The average correlation coefficients obtained between the initial and average noisy data are presented in Table 9.

According to the results obtained in Table 9, the amount of reliable α is 0.95 in the Z-DEA model. Therefore, the amount of performance calculated in Table 8 at the level of $\alpha = 0.95$ is introduced as an acceptable result. In this regard, supplier 2 and supplier 29 were recognized as the best and worst resilient suppliers in this company, respectively. Table 10 shows the results of efficiency and ranking resilient suppliers based on the proposed structure.

6. Performance analysis

In this section, performance analysis is presented to validate and verify Z-DEA model and sensitivity analysis to distinguish the effect of the importance of criteria on ranking supplier. Moreover, ANN method was used to predict the performance of suppliers.

6.1. Validation and verification

For Z-DEA model validation and verification, the results of this model were compared with those of FDEA model. In this study, the FDEA method was used to confirm the optimal results of the Z-DEA model. Because the FDEA method only considers uncertainty in the input data and does not consider the concept of reliability (except for component B in Z-numbers), it is a suitable method for evaluating the validity of the Z-DEA model. In this regard, as in the noise analysis performed in the previous section, this time the FDEA model was implemented. Thus, first, the reliable levels of α for the FDEA model are determined, and secondly, the correlation coefficient is calculated between the two Z-DEA and FDEA models at the specified levels of α. If the calculated correlation coefficient is more than 0.7, it can be claimed that the results obtained from Z-DEA are validated.

Hence, after determining reliable levels of α for FDEA model ($\alpha = 0.01$), the correlation coefficient was calculated between the ranking results obtained in Z-DEA and FDEA models. In this regard, the value of the correlation coefficient was calculated to be 0.85, which is more than 0.7. Therefore, it can be said that the results obtained from the efficiency of suppliers based on the Z-DEA model are confirmed by the FDEA model. These results are presented in Table 11.

6.2. Sensitivity analysis

In this section, the type and extent of the impact of each of the resilience and traditional criteria is evaluated on the calculated performance for supplier selection. The main purpose of this evaluation is to identify the factors that have the greatest impact on supplier efficiency, which makes the managers of the organization capable of identifying the most effective factor(s) in their performance; the result is that focusing and spending more money to strengthen those factors can, directly and indirectly, improve performance.

For this purpose, the data related to each of the input and output factors are deleted one by one from the main data set and the efficiency of the suppliers is recalculated. The results of the initial model in which all the factors are taken into account must be compared with the results of the model in which each of the factors has been removed from the

Table 7
Membership functions parameters assigned to the parameter... $\widetilde{\boldsymbol{B}}$

DMUs	Criteria							
	Inputs		Outputs					
	G_1	G_3	R_1	R_2	R_3	R_4	G_2	G_4
S_1	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_2	(0.5,0.6,0.7)	(0.8,1,1)	(0.8,1,1)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)
S_3	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)
S_4	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_5	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)
S_6	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)
S_7	(0.8,1,1)	(0.8,1,1)	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_8	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_9	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)
S_{10}	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)
S_{11}	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.5,0.6,0.7)
S_{12}	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_{13}	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)
S_{14}	(0.8,1,1)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.8,1,1)
S_{15}	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)
S_{16}	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)
S_{17}	(0.8,1,1)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)
S_{18}	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.5,0.6,0.7)
S_{19}	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_{20}	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.5,0.6,0.7)
S_{21}	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)
S_{22}	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)
S_{23}	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)
S_{24}	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.5,0.6,0.7)
S_{25}	(0.8,1,1)	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)
S_{26}	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.5,0.6,0.7)
S_{27}	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)
S_{28}	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.8,1,1)
S_{29}	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)
S_{30}	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.8,1,1)
S_{31}	(0.8,1,1)	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)
S_{32}	(0.65,0.75,0.85)	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.5,0.6,0.7)
S_{33}	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)
S_{34}	(0.8,1,1)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.8,1,1)	(0.5,0.6,0.7)
S_{35}	(0.8,1,1)	(0.5,0.6,0.7)	(0.8,1,1)	(0.5,0.6,0.7)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.5,0.6,0.7)
S_{36}	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)	(0.8,1,1)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)	(0.65,0.75,0.85)

data set in order to determine how the factors perform. Next, a paired *t*-test is performed between the performance of the original model and the model with the deleted factor. The results of this analysis are reported in Table 12. In all analyses, the average confidence level is 95%.

Based on the results of the analysis, the price factor has the greatest impact on the performance of suppliers. After deleting the data related to this factor, the calculated efficiency has had the largest possible change, which indicates the greatest impact on the efficiency of suppliers. In this analysis, it was found that the technology level factor has the least impact on the efficiency of suppliers because by deleting the data related to this principle, the least amount of changes in the efficiency of suppliers was observed. This conclusion testifies to the importance of this principle and the managers of the study unit can adjust future plans of organization in order to improve the efficiency of suppliers.

Furthermore, weight of criteria calculated regarding differences between values of performance average after and before elimination of each criterion was divided by the total difference weight of criteria. The results are indicated in Fig. 5.

6.3. Performance prediction

In this paper, the ANN method and its ability to predict and approximate relationships are used and the efficiency of suppliers is analyzed. For this purpose, the simple ANN method (perceptron of sequential type) has been used to predict the efficiency and inefficiency of suppliers. The input and output of the designed model include eight evaluation criteria and the efficiency of suppliers, respectively. In addition, due to the definition of two classes of one and zero (efficiency and inefficiency), the activator function in this model is sigmoid.

The architecture of ANN model is in the form of rhythmic directional graphs in which the artificial neurons are nodes and the directional arrows, together with the weights, show the relationship between the output and the inputs of the neurons. The perceptron ANN algorithm used in this paper is shown in Fig. 6.

In order to implement the model, a neural network predicting performance and learning algorithm has been used. Here the data is taught to the network after defuzzification and normalization with the efficiency calculated by DEA method. After a few iterations, the network learns the performance pattern of the suppliers with a small error and establishes a mapping between inputs and outputs.

The evaluation of the model is calculated in such a way that the accuracy is equal to 83%. As it turns out, this assessment is based on test data that the model has never seen before. Therefore, if new data is given to the (neural network) model, it can determine with 83% accuracy whether the supplier in question is efficient or inefficient. Besides, the cost function and the accuracy diagram per repetition are shown in Figs. 7 and 8, respectively.

As shown in Fig. 7, after 50 iterations, the cost function diagram fits well into the data. Moreover, first, the designed model is not able to categorize suppliers well in the accuracy diagram (Fig. 8). After the 50th repetition, the model is fit before the 70th repetition, and then before the 90th repetition, the model is underfit, and again the model is fit until the 150th repetition. After this, until the 200th repetition of the model, it goes well and the train diagram is higher than the test.

As mentioned, the results calculated through the predictive neural network are very close to the calculated efficiency of suppliers using the DEA method. The results are shown in Table 13. Also, the rank of each

Table 8
The efficiency of each supplier based on the Z-DEA model.

DMUs	Levels of α													
	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95	0.99	1
S_1	6.03	5.46	4.85	3.86	3.08	2.46	1.97	1.60	1.29	1.06	0.89	0.81	0.76	0.74
S_2	16.42	14.03	11.66	8.30	6.12	4.61	3.53	2.72	2.12	1.65	1.29	1.14	1.03	1.00
S_3	6.14	5.57	4.99	4.03	3.30	2.73	2.27	1.91	1.61	1.37	1.17	1.07	1.00	0.98
S_4	6.96	6.36	5.71	4.63	3.78	3.10	2.55	2.10	1.73	1.44	1.19	1.09	1.02	1.00
S_5	3.68	3.45	3.17	2.68	2.27	1.94	1.66	1.43	1.23	1.06	0.92	0.85	0.81	0.80
S_6	5.58	5.02	4.41	3.44	2.71	2.15	1.73	1.39	1.17	1.00	0.86	0.80	0.75	0.74
S_7	4.24	3.97	3.66	3.11	2.65	2.26	1.93	1.65	1.41	1.20	1.02	0.94	0.88	0.86
S_8	8.51	7.47	6.41	4.83	3.67	2.82	2.24	1.81	1.48	1.23	1.02	0.93	0.86	0.85
S_9	10.42	9.20	7.93	6.01	4.66	3.66	2.91	2.34	1.88	1.52	1.23	1.11	1.02	1.00
S_{10}	7.32	6.65	5.92	4.74	3.83	3.12	2.56	2.11	1.74	1.45	1.20	1.10	1.02	1.00
S_{11}	4.24	3.92	3.57	3.00	2.53	2.15	1.82	1.55	1.32	1.13	0.96	0.89	0.83	0.82
S_{12}	6.54	6.04	5.46	4.47	3.68	3.04	2.51	2.09	1.73	1.44	1.20	1.09	1.02	1.00
S_{13}	5.03	4.62	4.16	3.39	2.79	2.30	1.92	1.61	1.36	1.15	0.98	0.90	0.84	0.83
S_{14}	8.12	7.37	6.54	5.20	4.16	3.36	2.73	2.23	1.82	1.49	1.22	1.11	1.02	1.00
S_{15}	8.30	7.28	6.23	4.66	3.56	2.85	2.35	1.94	1.62	1.36	1.13	1.03	0.96	0.94
S_{16}	3.69	3.43	3.13	2.59	2.16	1.80	1.51	1.27	1.07	0.90	0.76	0.69	0.65	0.64
S_{17}	6.64	6.02	5.35	4.25	3.41	2.75	2.24	1.86	1.55	1.29	1.09	1.00	0.93	0.91
S_{18}	5.05	4.64	4.18	3.42	2.82	2.35	1.98	1.67	1.42	1.20	1.01	0.93	0.86	0.85
S_{19}	3.86	3.62	3.33	2.82	2.40	2.05	1.75	1.49	1.27	1.09	0.93	0.86	0.80	0.79
S_{20}	8.02	7.29	6.48	5.17	4.17	3.39	2.77	2.26	1.84	1.50	1.22	1.11	1.02	1.00
S_{21}	7.54	6.85	6.09	4.84	3.89	3.14	2.55	2.08	1.70	1.38	1.13	1.02	0.94	0.92
S_{22}	15.44	13.20	10.99	7.86	5.79	4.36	3.34	2.59	2.03	1.60	1.26	1.12	1.02	1.00
S_{23}	7.85	7.15	6.37	5.10	4.11	3.33	2.72	2.22	1.82	1.49	1.22	1.10	1.02	1.00
S_{24}	4.34	3.96	3.57	2.92	2.42	2.02	1.70	1.44	1.23	1.05	0.88	0.81	0.75	0.74
S_{25}	7.10	6.44	5.71	4.53	3.62	2.91	2.35	1.91	1.56	1.27	1.04	0.95	0.87	0.86
S_{26}	6.31	5.69	5.02	3.96	3.13	2.50	2.00	1.62	1.31	1.07	0.90	0.83	0.77	0.76
S_{27}	8.22	7.15	6.11	4.56	3.48	2.72	2.20	1.79	1.50	1.25	1.05	0.97	0.91	0.89
S_{28}	3.78	3.55	3.28	2.81	2.42	2.09	1.79	1.55	1.34	1.16	1.02	0.95	0.90	0.89
S_{29}	3.57	3.32	3.04	2.54	2.13	1.79	1.51	1.27	1.07	0.89	0.75	0.68	0.63	0.62
S_{30}	6.27	5.68	5.05	4.03	3.27	2.67	2.20	1.82	1.50	1.24	1.03	0.93	0.87	0.85
S_{31}	7.23	6.57	5.86	4.71	3.84	3.15	2.60	2.14	1.77	1.46	1.21	1.10	1.02	1.00
S_{32}	4.71	4.33	3.90	3.18	2.61	2.19	1.85	1.58	1.34	1.14	0.97	0.89	0.84	0.82
S_{33}	8.65	7.57	6.45	4.78	3.61	2.79	2.18	1.73	1.37	1.09	0.91	0.83	0.77	0.76
S_{34}	4.32	3.99	3.61	2.97	2.47	2.05	1.71	1.42	1.19	1.00	0.85	0.78	0.73	0.71
S_{35}	8.75	7.80	6.84	5.41	4.30	3.45	2.79	2.27	1.85	1.50	1.23	1.11	1.02	1.00
S_{36}	4.00	3.72	3.42	2.90	2.46	2.11	1.82	1.56	1.34	1.15	0.99	0.92	0.86	0.85

Table 9
Results of the carried out calculations to select the reliable α.

Levels of α	Average correlation	Levels of α	Average correlation
0.01	0.8197	0.6	0.8402
0.05	0.87	0.7	0.8749
0.1	0.8446	0.8	0.8372
0.2	0.8467	0.9	0.8009
0.3	0.8414	0.95	0.8953
0.4	0.7957	0.99	0.811
0.5	0.8468	1	0.8436

supplier in real mode (DEA method) and after repetition and model training (ANN method) are compared in Fig. 9.

The comparison of the calculated results (efficiency) of DEA and ANN methods shows the proper power separability of the neural network. The calculated network results with ANN algorithm consider about 14 suppliers as efficient suppliers, which is almost equal to 13 suppliers in the DEA model. Therefore, it can be said that the proposed model has good power separability.

Table 10
The ranking of the potential suppliers for the resilient supplier.

Supplier	Efficient	Rank	Supplier	Efficient	Rank
Supplier 1	0.81	31	Supplier 19	0.86	27
Supplier 2	1.14	1	Supplier 20	1.11	3
Supplier 3	1.07	12	Supplier 21	1.02	14
Supplier 4	1.09	10	Supplier 22	1.12	2
Supplier 5	0.85	28	Supplier 23	1.1	7
Supplier 6	0.8	33	Supplier 24	0.81	31
Supplier 7	0.94	19	Supplier 25	0.95	17
Supplier 8	0.93	20	Supplier 26	0.83	29
Supplier 9	1.11	3	Supplier 27	0.97	16
Supplier 10	1.1	7	Supplier 28	0.95	17
Supplier 11	0.89	25	Supplier 29	0.68	36
Supplier 12	1.09	10	Supplier 30	0.93	20
Supplier 13	0.9	24	Supplier 31	1.1	7
Supplier 14	1.11	3	Supplier 32	0.89	25
Supplier 15	1.03	13	Supplier 33	0.83	29
Supplier 16	0.69	35	Supplier 34	0.78	34
Supplier 17	1	15	Supplier 35	1.11	3
Supplier 18	0.93	20	Supplier 36	0.92	23

7. Managerial implications

Crises, environmental hazards, recessions, and other problems that the economy and society face each affect organizations and their internal environment. Organizations need to increase organizational resilience or their ability to cope with adverse environmental conditions. Organizational resilience is important because the organization and the community are interconnected in a complex environment and can create a competitive advantage.

However, there are organizations that lack the ability to deal with these problems and are normally forced to close down. According to statistics provided by the Statistics Center of Iran, 2816 medium and large factories were closed or went bankrupt between 2007 and 2012. 5100 industrial units were closed from 2012 to 2017 (Zadeh, 2011).

On the other hand, considering that organizational resilience is defined as the capacity to resist and recover from accidents and shocks, it shows that organizations that went bankrupt had little resilience because resilient organizations can adapt to a changing environment. Therefore, it can be said that the bankruptcy rate in resilient

Table 11
Results of the comparative analysis between FDEA and Z-DEA.

Supplier	Rank-Z-DEA (α = 0.95)	Rank-FDEA (α = 0.01)	Supplier	Rank-Z-DEA (α = 0.95)	Rank-FDEA (α = 0.01)
Supplier 1	31	16	Supplier 19	27	27
Supplier 2	1	1	Supplier 20	3	26
Supplier 3	12	15	Supplier 21	14	3
Supplier 4	10	10	Supplier 22	2	12
Supplier 5	28	33	Supplier 23	7	1
Supplier 6	33	23	Supplier 24	31	6
Supplier 7	19	24	Supplier 25	17	34
Supplier 8	20	16	Supplier 26	29	14
Supplier 9	3	8	Supplier 27	16	16
Supplier 10	7	4	Supplier 28	17	16
Supplier 11	25	31	Supplier 29	36	29
Supplier 12	10	4	Supplier 30	20	35
Supplier 13	24	25	Supplier 31	7	16
Supplier 14	3	9	Supplier 32	25	11
Supplier 15	13	16	Supplier 33	29	30
Supplier 16	35	35	Supplier 34	34	16
Supplier 17	15	13	Supplier 35	3	31
Supplier 18	20	16	Supplier 36	23	6
Correlation Coefficient				**0.85**	

organizations is very low.

Choosing a resilient supplier is one of the examples of creating a resilient organization. In view of the above, this paper seeks to move towards a resilient organization by providing a model to select a resilient supplier.

For this purpose and to increase the applicability of the proposed approach, some managerial implications are explored. These implications help the managers of organizations in the process of implementing the proposed model and increasing the efficiency of the model. The implications are as below:

- The model presented in this paper can be implemented in all organizations that seek to evaluate suppliers based on resilient and traditional criteria.
- Given the importance of quality and responsiveness indicators, recommended in the supplier selection and also orders allocating to them, those suppliers have a higher priority that will be able to respond quickly to unanticipated changes and disruptions and have a clear and transparent system.
- Suggested workshops will be held to enhance awareness of managers and supervisors on the resilience supply chains and how to use resilience indicators in their decisions.
- It is suggested that suppliers should be assessed and ranked periodically regarding certain resilience criteria to retain effectiveness. External audits should also be conducted periodically, and recommendations should be provided to improve their resilience.

8. Discussion

Natural and man-made disasters impose various types of damages, injuries, and deaths on affected communities. These disasters can disrupt various infrastructures and facilities, including hospitals, schools, transportation systems, and emergency services. The absence of, or unpreparedness for, the continuation of services in emergencies caused by accidents has destructive and adverse effects on the response of these centers. One of the scourges that is spreading around the world today and affecting all countries of the world is the corona virus. The global conflict with this virus as an unpredictable event has led to problems in providing services to all centers, especially in medical centers and related industries. One of the most important of these industries, due to the importance of resilience, is the pharmaceutical industry, which has witnessed double the amount of readiness after the development of vaccines. If these companies and their suppliers are not prepared, irreparable damage will be inflicted on the body of the medical system and society.

Given the importance of assessment, monitoring, and planning to improve the resilience of these industries to such accidents, a comprehensive framework for assessing the resilience of pharmaceutical industry suppliers against natural disasters is necessary. For this purpose, in the present study, the effective factors in evaluating suppliers were identified and collected. Then, a model was developed to evaluate the suppliers.

According to the perspectives described in the research background, research conducted in the field of supplier evaluation in a resilient supply chain can be divided into two general categories. The first category is research that has been done with a managerial approach. These studies include the studies of Haldar et al. (2012, 2014), Azadeh et al. (2014), and Rajesh and Ravi (2015). These studies have focused on single source sourcing in resilient chains and, for this purpose, they have extracted suppliers' resilience indicators. They evaluated the resilience of suppliers using MCDM methods and introduced the best supplier. On the other hand, some studies have evaluated the resilience of suppliers and the allocation of orders to them in multiple source sourcing with a mathematical modeling approach. These researches include Torabi et al. (2015) and Kamalahmadi and Parast (2016).

The present study aimed to combine the two approaches to demonstrate the benefits of each approach. In this regard, first by extracting

Table 12
Results of analysis and evaluation of the effects of individual factors on efficiency.

Criterion removed	Average efficiency	Two-tailed t-test p-value	Relationship between means	Type of impact	Correlation coefficient
Quality	0.9567	0.0632	$\mu_1 > \mu_2$	Positive	0.9993
Price	0.9386	0.0557	$\mu_1 > \mu_2$	Positive	0.999253
Risk awareness	0.9275	0.001	$\mu_1 = \mu_2$	Insignificant	0.999371
Adaptive capability	0.9388	0.001	$\mu_1 = \mu_2$	Insignificant	0.999388
Vulnerability	0.9394	0.001	$\mu_1 = \mu_2$	Insignificant	0.999389
Responsiveness	0.9494	0.0650	$\mu_1 > \mu_2$	Positive	0.999372
Delivery	0.9361	0.001	$\mu_1 = \mu_2$	Insignificant	0.999305
Technology level	0.9326	0.001	$\mu_1 = \mu_2$	Insignificant	0.999398

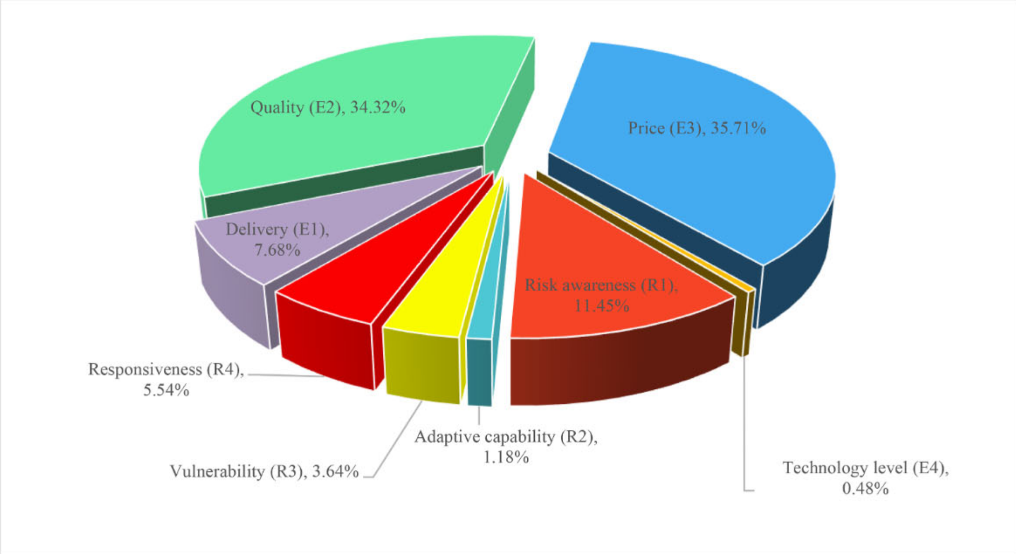

Fig. 5. Results of criteria weight calculations.

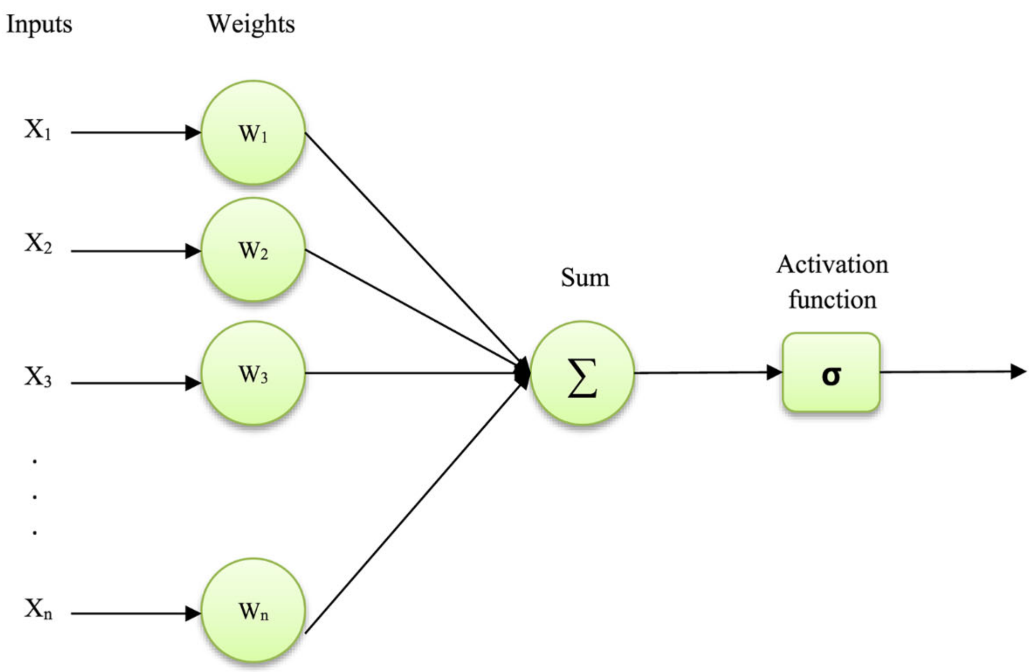

Fig. 6. The perceptron ANN algorithm.

suppliers' indicators, the weakness of not considering them by the researchers of the second approach is covered and, by using the DEA model to evaluate these indicators, the weaknesses of the first approach will be eliminated.

The most important indicators of supplier evaluation (resilience and traditional indicators) were identified using past studies and expert opinions. Then, by visiting the studied pharmaceutical company, preparing questionnaires, and sending them to different sections of the company (selecting individuals such as sales and marketing manager, support manager and production manager, etc.), a database was prepared. The database contained valuable information about the status of the company's suppliers. According to the main purpose of this research, an integrated framework of the mathematical model based on DEA method was presented that considers both reliability and uncertainty in the information based on the fuzzy Z-number.

Applying the fuzzy Z-number approach in solving problems has two major problems that require more studies. The first case is the conversion of fuzzy Z-numbers into crisp or fuzzy numbers, which, despite the computational simplicity, may lead to information loss. However, many researchers believe that missing information does not have much effect on the output and final results (Kang et al., 2012). The second case is the use of an ordered pair of Z-numbers in the calculations, which is quite clear and leads to computational difficulty and an increase in entropy. This means that calculations on fuzzy numbers will eventually lead to a fuzzy number. Hence, the results obtained in this case have become unreliable (Abdullahi et al., 2020). The authors of this article have chosen the first approach to solve this problem by understanding and accepting all the mentioned points and also considering the existing limitations.

The proposed structure has many capabilities in terms of

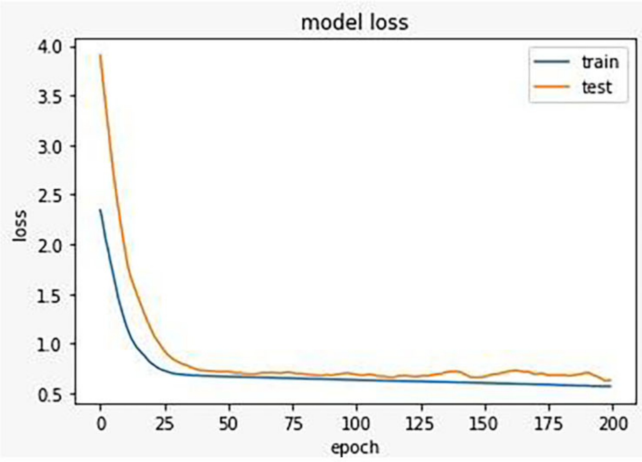

Fig. 7. The Cost function diagram per iteration.

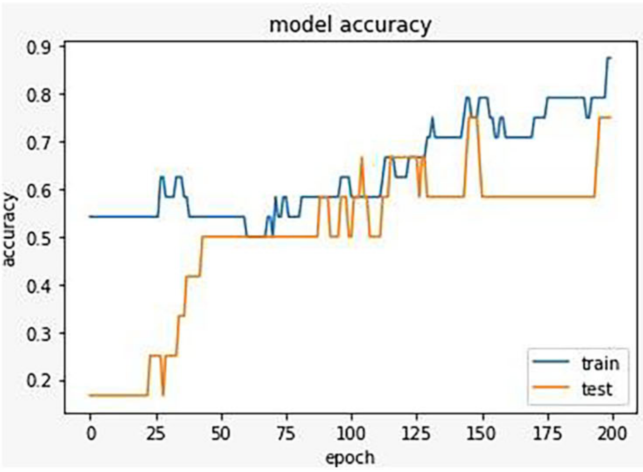

Fig. 8. Accuracy of evaluation model based on test and training data.

performance analysis and supplier ranking as a support algorithm. In addition, this framework is applicable to other industries that deal in some way with supplier evaluations.

The research findings against each of the research gaps obtained from the literature review can now be identified based on the three main contributions of this paper.

1. In this study, the performance of suppliers of a pharmaceutical company was evaluated based on traditional and resilient indicators using DEA method as an optimization method. In addition to the advantages such as simultaneous consideration of multiple inputs and outputs for the system, there is no need for prerequisite weighting of criteria, and simultaneous consideration of uncertainty and reliability in the input data are the main advantages of this method.
2. In order to validate and verify Z-DEA model and sensitivity analysis, the performance analysis is presented. In this regard, noise analysis was used, which step by step determines the acceptable α level to specify the optimal model between FDEA and Z-DEA model. Moreover, the effect of the importance of criteria on ranking supplier is computed in format of sensitivity analysis.
3. A perceptron network is used to predict the performance of DMUs (suppliers) that as a simulator can simulate the performance of suppliers and use it to analyze the sensitivity of suppliers. Due to the power separability of the proposed model, if a new supplier is added to the previous suppliers, the model will be able to detect the efficiency or inefficiency of the new supplier with 83% accuracy.

Table 13
The comparison of the actual and predicted efficient values based on DEA and ANN.

Supplier	DEA-Efficient	ANN-Efficient	Supplier	DEA-Efficient	ANN-Efficient
Supplier 1	0.81	0.84	Supplier 19	0.86	0.88
Supplier 2	1.14	1.1	Supplier 20	1.11	1.07
Supplier 3	1.07	1.09	Supplier 21	1.02	1
Supplier 4	1.09	1.09	Supplier 22	1.12	1.11
Supplier 5	0.85	0.08	Supplier 23	1.1	1.07
Supplier 6	0.8	0.81	Supplier 24	0.81	0.8
Supplier 7	0.94	0.98	Supplier 25	0.95	0.94
Supplier 8	0.93	0.92	Supplier 26	0.83	0.8
Supplier 9	1.11	1.09	Supplier 27	0.97	92
Supplier 10	1.1	1.1	Supplier 28	0.95	0.9
Supplier 11	0.89	0.85	Supplier 29	0.68	0.69
Supplier 12	1.09	1.01	Supplier 30	0.93	0.96
Supplier 13	0.9	0.92	Supplier 31	1.1	1.08
Supplier 14	1.11	1.05	Supplier 32	0.89	0.87
Supplier 15	1.03	1.02	Supplier 33	0.83	0.8
Supplier 16	0.69	0.71	Supplier 34	0.78	0.81
Supplier 17	1	0.98	Supplier 35	1.11	1.13
Supplier 18	0.93	0.93	Supplier 36	0.92	0.9

9. Conclusions and future directions

In general, the ultimate goal of the assessment and selection supplier in the resilience supply chain is to select the appropriate suppliers which possess high compliance with the resilience capabilities of the company. Assessing the resilience of suppliers is one of the most important ways to enter the supply chain resilience world since suppliers are one of the main sources of vulnerability in supply chains. Pharmaceutical companies, as vital organizations, play an important role in the health of society and have faced numerous risks and vulnerabilities. In this paper, a new approach for assessing suppliers of pharmaceutical companies has been proposed based on the Z-DEA model. Accordingly, the preferences of decision makers' were collected based on Z-number. A real case study regarding the paper structure and defined criteria about the traditional (delivery, quality, price, and technology level) and resilient categories in supplier selection is considered. The Z-DEA model was generated in various levels of α; a reliable level of α was obtained and the suppliers were ranked based on their level of specified α. The results of the applied Z-DEA model showed that supplier 2 maintains the best performance and it is selected. In addition, the obtained results from the Z-DEA model have been compared with FDEA method. The comparisons of the computational results indicate Z-DEA model is practical; further, in dealing with noisy data (existence of outgoing data) it has a more appropriate function. Finally, performance analysis is provided to represent the power and features of the proposed approach. In this part, the model used was validated. Then, the importance of each of the

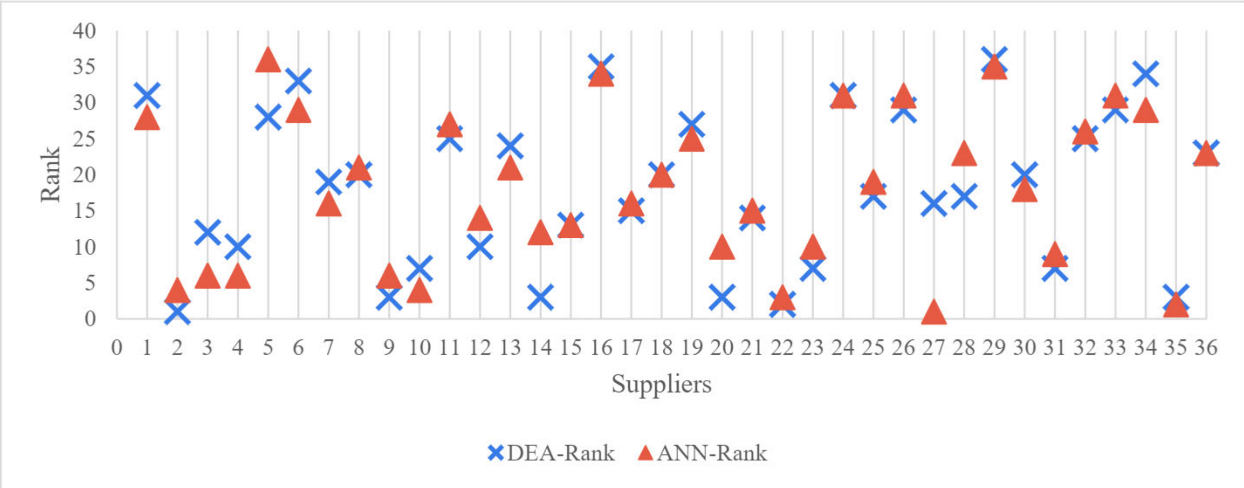

Fig. 9. Comparison of supplier ranking results.

supplier evaluation criteria was determined. Finally, the forecast model was presented with 83% accuracy, which is able to detect the efficiency or inefficiency of suppliers. Managerial implications are suggested in order to develop and to increase the applicability of the proposed approach. The presented methodology and approach can still incorporate hidden probability distributions of Z-numbers in DEA models and the ANN method in a resilient supplier selection problem. For future research, researchers can develop other types of DEA models by using Z-numbers without an aggregation of reliability into uncertainty and compare the results of these methods with current methods in this paper. Also integrating sustainable criteria for supplier selection will be another direction for future research.

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.

Data availability

Data will be made available on request.

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Data Availability statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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