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An integrated quality and resilience engineering framework in healthcare with Z-number data envelopment analysis

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Abstract

Supplier selection for medical equipment is a major challenge for hospitals in healthcare supply chains. The primary reason for measuring medical equipment supplier efficiency is to achieve the highest level of overall performance and productivity in healthcare supply chains. This study presents an integrated quality and resilience engineering (QRE) framework for evaluating medical equipment suppliers' performance using structural equation modeling and *Z*-number data envelopment analysis (Z-DEA). Noise analysis is used to select the best α-cut for the Z-DEA model, and fuzzy data are used to handle uncertainties. We show that flexibility, conformance to standards, redundancy, cost, quality certifications, and delivery time significantly affect the medical equipment suppliers' performance. In addition, we demonstrate that the proposed integrated QRE framework is more efficient and informative than stand-alone quality engineering or resiliency engineering. We present a case study in a cardiovascular hospital to illustrate the applicability of the proposed framework for medical equipment supplier evaluation and selection. To the best of our knowledge, this is the first study to integrate QRE and Z-DEA for supplier performance evaluation in healthcare.

Keywords Quality and resilience engineering · Data envelopment analysis · Supplier evaluation · Healthcare · *Z*-number · *F*uzzy set

Highlights

- We propose an integrated quality and resilience engineering framework for supplier selection in healthcare.
- *Z*-numbers and fuzzy data are used in the proposed data envelopment analysis models.
- We show flexibility, standards, redundancy, cost, quality, and delivery time are most important for supplier selection.
- We demonstrate the integrated framework is more efficient than stand-alone quality engineering or resiliency engineering.
- We present a case study in a cardiovascular hospital to exhibit the applicability of the proposed framework.

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1 Introduction

The continuous pressures for reducing costs and improving quality have led organizations to pay considerable attention to their supplier evaluation and selection strategies. Supplier evaluation strategies often focus on finding suppliers who provide products with lower prices and satisfying quality [8, 60]. Supplier evaluation is defined as the process of quantifying the efficiency of the supplier's performance [93]. Supplier evaluation is a pre-defined set of activities employed to evaluate the supplying companies' business practices. Supplier evaluation's central premise is that suppliers with efficient and effective business practices are more likely to deliver high-quality products and services [19, 89, 124].

Healthcare supply chains are complex and interrelated systems with numerous players inside and outside the hospital walls. Hospitals must adapt to the latest technology and provide quality service with low-cost and state-of-the-art medical products and equipment to increase effectiveness and maintain efficiency. Almost half of a hospitals' total operating budget is spent on medical equipment and consumable healthcare products [79]. In addition, technological advances and innovations in medical equipment and devices have resulted in the frequent upgrade of healthcare equipment and services. As a result, hospitals are continually searching for suppliers that can provide low-cost, high-quality medical equipment and supplies [120]. Alshahrani et al. [3] show that hospital-supplier integration positively impacts performance, productivity, and profitability in healthcare. Jørn Juhl et al. [67] studied excellence in hospitals and proposed a new congruence measure to identify and prioritize improvement initiatives. The routine clinical activities have relied heavily on the wide spectrum of medical equipment, and this growing need has significantly increased the competition among the medical equipment suppliers [77]. Failure to choose efficient suppliers is no longer an option in the healthcare industry since it can waste and misuse the equipment and result in irreparable damage to patient welfare and treatment processes [19].

Supplier selection is a difficult task requiring a determination of supplier performance evaluation indicators and the utilization of an effective supplier assessment evaluation method. The literature shows that researchers have studied several traditional indicators for supplier selection. The theoretical basis for supplier selection criteria is originated from the transactional cost theory. According to this theory, the purchasing companies aim to minimize their transactional costs and focus primarily on the cost of the products and services. As a result, less attention is paid to other important factors, including quality, reliability, and equipment maintenance [18]. More recently, growing attention has been paid to supplier quality as a key source of creating value and competitive advantage in healthcare. Consequently, a hospital's medical equipment's quality performance depends largely on its suppliers' quality management effectiveness. Generally, the supplier's quality is affected by the intra-organizational drivers and factors related to the buyer-supplier relationships [78, 97, 98]. In general, the supplier selection process depends heavily on the depth and breadth of the supplier evaluation indicators and processes [116]. Bahadori et al. [19] showed that quality was the most effective factor for medical equipment supplier selection. In this study, the cost and delivery time are considered as traditional indicators for medical equipment supplier evaluation. In addition, we consider a new quality dimension, which includes product quality, service quality, process quality, and organizational quality.

Resilience is at the heart of today's healthcare supply chains. Disruption in the supply chain can occur from internal and external sources. Suppliers are an inevitable source of external risks. Resilient suppliers are those suppliers that can resist the different sources of risk, and in the case of disruptions, can continue with their normal operations. Resiliency is "the intrinsic ability of an organization (system) to maintain or regain a dynamically stable state" ([53]; p.16). Resilience engineering refers to the continuity in system performance at a normal state without disruptions. Resilience engineering also refers to the ability of the system to return quickly to its normal state after a disrupting event [114, 130, 138]. Hence, it can be said that resilience engineering has two positive features: (1) the ability to prevent failure and (2) the ability to return to the normal state. Resilience engineering aims at minimizing those variations that lead to negative results, and at the same time, reinforcing those variations that produce positive results [35, 94]. Interruptions in the supply flow (i.e., delays, backorders, damaged products) can result in irreparable failures for all members of the supply chain [131]. Resilience engineering involves evaluating suppliers for their capabilities to cope with risky conditions and their ability to respond to the disruptions and return to normalcy quickly. Rice and Caniato [111] argue the supply networks need comprehensive processes and procedures in place that are resilient enough to return to normalcy after disruptions. The analysis of the resilience engineering indicators for medical equipment suppliers is extremely important because of the necessity to maintain high-quality and flawless performance. However, research on resilience engineering in the healthcare and hospital supply chains has been limited [100, 112, 113, 135].

This study presents an integrated QRE framework for evaluating and selecting medical equipment suppliers using structural equation modeling and Z-DEA. The distinguishing feature of the proposed framework is the integration of QRE with traditional selection indicators (i.e., cost and delivery time) and a new quality dimension, which includes product quality, service quality, process quality, and organizational quality. We also demonstrate that the proposed integrated framework is more efficient than stand-alone quality engineering or resiliency engineering. We further present a case study to demonstrate the applicability of the proposed framework in a cardiovascular hospital. We believe this is the first study to integrate QRE and Z-DEA for supplier performance evaluation in healthcare.

The remainder of this paper is organized as follows. In Section 3, we present a comprehensive review of supplier selection literature with an emphasis on multi-criteria decision models. Section 4 presents the integrated QRE framework proposed in this study. In Section 5, we present a case study to demonstrate the applicability of the proposed framework. Section 6 presents our computational results. In Section 7, we conclude with our conclusions and future research directions.

2 Literature review

The research on supplier selection indicators in healthcare is inconclusive. For example, Dickson [39] proposed 23 criteria for the supplier selection problem. Ha and Krishnan [45] studied these criteria in detail and proposed 30 indicators for supplier selection. Further analysis of the literature shows that there is no agreement on supplier selection indicators. In the next section, we review the indicators used for medical equipment supplier selection.

A large portion of the supplier evaluation studies has been related to multi-criteria decision-making methods and uncertainty [89, 92, 110]. Benyoucef and Canbolat [21] considered six general categories for classifying hospital products and proposed a fuzzy analytic hierarchy process (AHP) to assess and rank suppliers by using indicators such as product quality, cost, delivery time, warranty, services, and payment program, with a focus on the capability and electronic data exchange between the hospital and the suppliers. However, the suggested indicators were traditional, and AHP has been criticized for rank reversal and consistency. Rank reversal may occur when we add or delete alternative(s) from the existing set of alternatives. The consistency problem refers to maintaining consistency among pairwise comparison judgments in large problems. Wang et al. [134] proposed a fuzzy technique for order of preference by similarity to ideal solution (TOPSIS) approach to evaluate the radio-frequency identification (RFID) system provided by hospital suppliers for tracking, managing, and assessing the supplies provided by the suppliers. Khumpang and Arunyanart [75] applied fuzzy TOPSIS to select the optimal supplier for hospital medical equipment in Thailand. Indicators were quality, price, reliability, agility, compliance, service, benefits/bargaining, and transport/delivery. Recently, Mardani et al. [88] showed the application of decision making and fuzzy sets theory to evaluate the healthcare and medical problems.

Awasthi [9] considered 16 indicators, including product design, environmental considerations, statistical process control, reliability, flexibility, and management commitment, and evaluated the suppliers using the fuzzy TOPSIS method. In another study, Noshad and Awasthi [96] introduced 42 indicators for the supplier quality evaluation in a structured review. They stated that categorizing these indicators in four major dimensions of the product quality, service quality, process quality, and organizational quality leads to more accurate and detailed results about the suppliers. We have adopted this categorization for quality indicators of medical equipment supplier selection. Jenoui and Abouabdellah [66] proposed a three-objective heuristic mathematical model for the evaluation and selection of hospital suppliers. Their proposed model simultaneously maximizes the supplied products and materials, minimizes the total cost related to each supplier, and minimizes the delay in product delivery. The proposed model could not find the optimal solution because the multi-objective solution proposed in the study did not consider uncertainty. A novel fuzzy multi-criteria group decision-making approach was applied by Karsak and Dursun [72] to assess and select the suppliers of the hospital. They presented an integrated solution framework with quality function deployment and data envelopment analysis (DEA) with considering imprecise data. Stević et al. [127] proposed the MARCOS method for sustainable supplier selection in the healthcare industry. Hoseini et al. [57] applied the *Z*-number hierarchy approach for sustainable supplier selection. Although these studies significantly contributed to supplier selection in healthcare, they did not consider resilience and quality indicators essential for medical equipment supplier evaluation.

Many researchers have investigated the resilience concept in supplier evaluation and selection for different industries. Haldar et al. [48] proposed a TOPSIS method based on a group fuzzy decision-making approach for resilient supplier evaluation and selection. They considered evaluation indicators such as product reliability, product performance, and customer satisfaction. Rajesh and Ravi [109] used a gray relational analysis approach for supplier selection in the electronics industry. They evaluated the suppliers by providing a resiliency framework based on the supplier performance indicators, supplier responsiveness indicators, supplier risk-reduction indicators, supplier technical support indicators, and supplier sustainability indicators. Sawik [118] proposed a mixed-integer linear programming model for the selection of supplier portfolios under the resiliency framework taking into account the disruption risks. The model's objective was to minimize the costs related to supplier protection, the pre-defined emergency inventory, shortage, parts ordering, and transportation to diminish the effects of the disruptions. The findings indicated the suppliers with a higher level of protection are more capable of supplying the products. However, the mathematical model was complex and did not consider a disruption management approach. By proposing an integrated approach based on the green, resilient supplier selection, Azadeh et al. [12] evaluated and ranked the suppliers in machine-parts manufacturing. They considered six general dimensions of quality, finance, service, social responsibility, resilience, and environment for the supplier evaluation. They used the fuzzy DEMATEL, ANP, and DEA to rank the suppliers. With an emphasis on the concept of supplier resilience capacity, Hosseini and Al Khaled [58] evaluated the suppliers of a plastic tubes manufacturing company using total effect and AHP. They investigated the resiliency of the suppliers in terms of the shock absorption capacity against the disruptive events, the adaption capacity with the unpredicted changes, and restoration capacity for the incomplete or lost activities. Using the exploratory factor analysis, Yilmaz-Börekçi et al. [141] studied supplier resiliency in the buyer-supplier relationship framework. Accounting for redundancy, diversity, and

process continuity as the resiliency indicators, they evaluated 183 suppliers in different industries. They found that supplier resiliency depends substantially on the satisfaction and commitment of the supplier. Chen et al. [31] considered indicators such as cost, quality, delivery time, service, technology, communications, and risk. They developed two weighted and preemptive goal programming models to address a supplier evaluation problem at an automobile manufacturing company. They showed how the selection of a global supplier could be considered to design a resilient supply chain for reducing unexpected risks. Thus, to support a resilient supply chain, supplier selection should emphasize suppliers' ability to embrace resiliency concepts such as flexibility, redundancy, adaptability, awareness, and commitment.

Hosseini and Barker [59] addressed the supplier selection problem by integrating the primary (traditional) criteria, green criteria, and resilience criteria into a new Bayesian network model. In their proposed model, the resiliency was quantified by considering three concepts of the absorptive capacity, adaptive capacity, and restorative capacity. Their study revealed that "the probability of a disruption" has to be incorporated and modeled as a key issue in resilient supplier selection. However, the development process of a Bayesian network is not straightforward because of a large number of indicators and the causality among them.

Kamalahmadi and Mellat-Parast [69] proposed a two-stage mixed-integer programming model to select suppliers and allocate the demands under disruptions. They indicated that increasing the flexibility of production capacity and supplier reliability in contingency plans is an effective strategy for reducing the probability of disruptions or mitigating their negative effects and increasing the supply chain's resiliency. Therefore, readiness to prevent failure and the ability to return to a stable state should also be embraced as a key strategic concern in supplier selection problems, especially in hospital medical equipment. Parkouhi and Ghadikolaei [99] developed an integrated resiliency framework based on four basic dimensions of benefits, opportunities, costs, and risks (BOCR) and selected and validated the wood and paper industry suppliers. Using the fuzzy analytic network process, they first identified the weights of the criteria and sub-criteria related to each dimension and used gray VIKOR to measure the resiliency level of the suppliers. Azadeh et al. [15] evaluated automobile parts manufacturing company's suppliers using fuzzy DEA with customer trust and resilience engineering indicators. They considered these indicators as the output variables and the cost and delivery time as the input variables. The results showed that the integration of customer trust and resilience engineering indicators increases the suppliers' total efficiency in the supply chain.

To the best of our knowledge, no study has included the concept of resilience engineering in the performance evaluation of the suppliers in healthcare (especially for medical equipment suppliers). Furthermore, the simultaneous effect of QRE indicators on suppliers' performance has not been studied in the literature. Hence, for the first time, we propose an efficient framework for evaluating and ranking medical equipment suppliers for a large cardiovascular hospital under uncertainty by integrating QRE indicators (i.e., product quality, service quality, process quality, and organizational quality) and the traditional indicators (i.e., cost and delivery time). Table 1 shows the main features of our study in comparison to similar studies.

3 Proposed framework

Figure 1 displays the steps and procedures for the integrated framework proposed in this study. In step 1, we conduct a literature review and identify the evaluation indicators. In step 2, we design a questionnaire and collect data concerning the evaluation indicators. In step 3, we evaluate the reliability and validity of the collected data with the Cronbach's alpha and confirmatory factor analysis. In step 4, we use the Z-DEA for different α-cuts and select and calculate the efficiency of the suppliers. In step 5, we validate the optimum Z-DEA model and verify the integrated framework. Finally, in step 6, we perform a sensitivity analysis and suggest solutions for improving supplier performance. It should be noted that this study employs parametric and non-parametric decision-making tools and methods.

3.1 Integration of QRE indicators for supplier performance evaluation

As we have shown in the literature review section, the cost, delivery time, and quality have been considered as the three basic indicators of supplier performance evaluation in different industries [51, 59]. In this study, cost and delivery time are considered as the traditional indicators of supplier performance evaluation, and due to the high importance of quality, it is considered as a dimension by itself extended into four aspects of product quality, service quality, process quality, and organizational quality. We then evaluate the performance of medical equipment suppliers using an integrated framework by adding the resilience engineering indicators, as shown in Fig. 2. The proposed framework with the quality deployment and the integration of the QRE indicators of cost and delivery time provides decision-makers with a comprehensive approach for analyzing different aspects of supplier performance. In the following, the definition of these indicators is given in the context of supplier evaluation and selection.

Table 1 The main features of this study in comparison to similar studies

Study	QRE integration	FDEA	Z-DEA	Noise analysis	Sensitivity analysis	*Z*-numbers concept	Handling uncertainty	Handling reliability	Real case
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓
Amindoust [4]					✓		✓	✓	✓
Azadeh et al. [12]		✓					✓		✓
Azadeh et al. [15]		✓		✓	✓		✓		✓
Awasthi [9]					✓		✓		✓
Benyoucef and Canbolat [21]					✓		✓		
Gan et al. [43]							✓	✓	✓
Haldar et al. [48]					✓		✓		
Hosseini and Al Khaled [58]					✓			✓	✓
Hosseini and Barker [59]					✓				✓
Karsak and Dursun [72]		✓					✓		✓
Kuo et al. [80]				✓	✓				✓
Parkouhi and Ghadikolaei [99]							✓		✓
Pramanik et al. [107]					✓		✓		✓
Rajesh and Ravi [109]					✓				✓

3.1.1 Cost

Supplier costs are divided into two main categories of product cost and communication cost. The purpose of considering the cost indicator is to study the impact of cost and financial transactions between the buyer (the hospital) and the supplier since the supplier financial stability is an important consideration [15, 83, 91, 99].

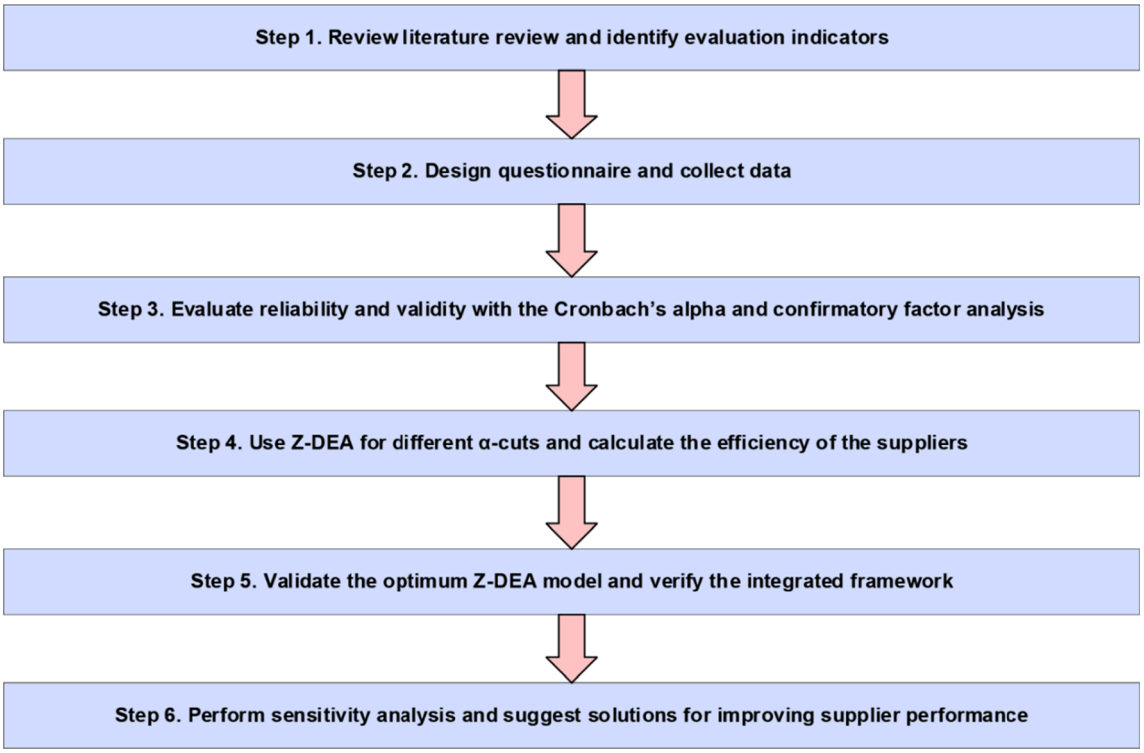

Fig. 1 The methodological structure

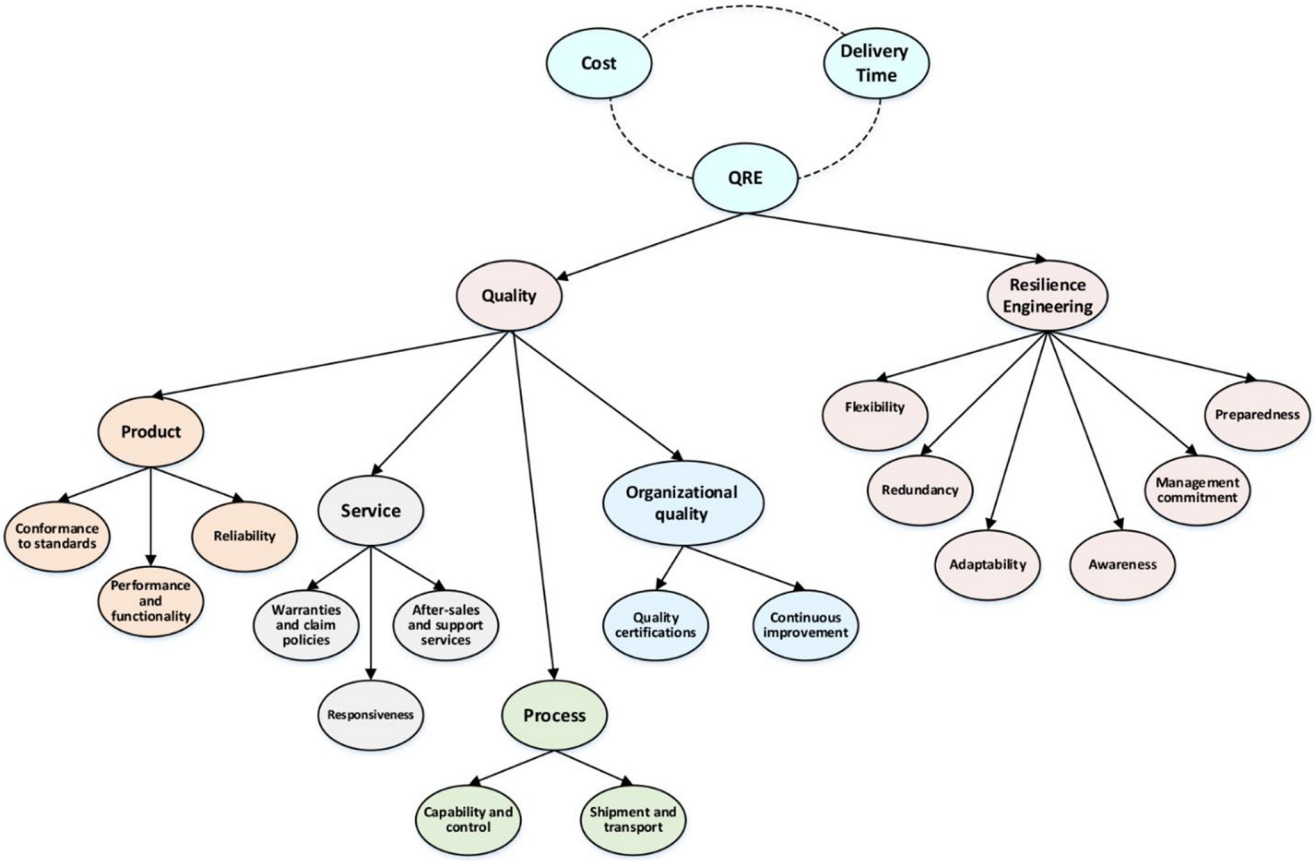

Fig. 2 The proposed integrated QRE framework

3.1.2 Delivery time

Delivery of the orders to the buyer may encounter delays due to operational and disruptive events (human and natural disruptions). These undesirable events, along with out-of-schedule orders, are risks that should be considered in any supplier evaluation framework [15, 91, 109, 131].

3.1.3 Quality

The quality dimension extends into four aspects of product quality, service quality, process quality, and organizational quality, each with several indicators described below:

The product quality indicators

- ***Conformance to standards*:** The conformity of items (medical equipment) characteristics to the pre-specified general and specific quality standards related to the product design and production (such as shape and dimensions), the security and risk management of the product, technical product characteristics, and environmental considerations (such as pollution and recycling). CE Marking (medical equipment safety and environmental standards) is also an important verification of product conformity with the standards [9, 87, 96].
- ***Performance and functionality*:** This indicator considers operational characteristics of the product and includes features such as simplicity, performance accuracy, and proper functionality of the medical equipment and devices [6, 22, 96].
- ***Reliability*:** This indicator reflects the product quality stability and considers the probability that the product does not experience a failure (breakdown) under certain environmental conditions. The medical equipment and devices are expected to operate without failure and error under varying conditions over time. They are also expected to have a long lifespan since their failure or any performance problems may result in irreparable consequences [1, 51, 83, 96].

The service quality indicators

- ***Warranties and claim policies*:** Warranties and claim policies provided by the supplier may include product warranty, price warranty, after-sales service warranty, on-time delivery warranty, and contract warranty. These rights and warranties must be defined clearly and agreed

upon so that the buyer (the hospital) can claim its rights completely if there is any problem with warranties guaranteed by the supplier [96, 119].

- ***Responsiveness***: Accessibility to, permanent presence, and the appropriate reaction of the supplier to resolve problems in the relationship with the buyer, including order completion, support services, and logistics. The on-time and quick responsiveness of the medical equipment suppliers to problems is extremely important in the healthcare industry [9, 52, 56, 80, 96].
- ***After-sales and support services***: This indicator represents the quality level of all after-sales services provided by the supplier to the buyer (the hospital) including setup services, installation, cyclic service, maintenance, repair, and training [62, 90, 96, 119].

The process quality indicators

- ***Process capability and control***: This indicator includes all process capabilities of the supplier in cases like product acceptance at different stages of production and inspection, the production volume, and customer feedback. The acceptance (or non-acceptance) of a product by the buyer, which is based on the conformance (or non-conformance) of its characteristics is an important indicator for supplier evaluation and selection [51, 85, 96, 140].
- ***Shipping and transportation process***: This indicator includes all requirements related to the shipping, transportation, and movement processes of the order delivery to the buyer (the hospital). The most important requirements for this indicator are durable packaging, safe loading, transportation, reliable vehicles, following allowable loading weight, and insurance [51, 96, 119, 132].

The organizational quality indicators

- ***Quality certifications***: The quality of all activities and processes (related to the supplier), including the production, service, administrative, management, and developmental ones conducted at different levels should be evaluated based on defined requirements and standards of quality certifications. The certifications such as ISO 9001, ISO 13485 have emphasized concepts such as process attitude, value creation, organizational environment, integration of medical equipment laws, outsourcing, and effective leadership. It is worth noting that the most quality certifications are only guarantees for the requirements of a quality system in an organization [9, 36, 62, 84, 96].
- ***Continuous improvement***: Implementation of efficient and comprehensive continuous improvement programs designed to increase supplier reliability and sustainable development. This includes policies, internal and external communications, and relationships with the buyer to increase the total supplier efficiency and the products and services quality. It should be noted that continuous improvement programs are implemented after the initial evaluation of the supplier organizational quality and include different concepts and tools that many of them have not been considered in the quality certification requirements [36, 51, 62, 74, 96].

The resilience engineering indicators

- ***Flexibility***: This indicator represents the maximum ability of the system to encounter disruptions and unpredictable crises and resolving them in a timely fashion. This indicator emphasizes that for dealing with unpredictable disruptions, the system must be designed such that the changes which followed by suitable outputs are increased, and the changes that result in undesirable events and crises are decreased. Concerning the suppliers, the flexibility is the supplier ability to handle unexpected changes, encountering possible risks, and quick response in the shortest time and least cost and effort [12, 13, 15, 69, 103].
- ***Redundancy***: This factor implies the existence of surplus and substitute capacity for producing and supplying the items required by the buyer, especially in case of crises and disruptions. This feature makes it possible to quickly compensate for the shortage of resources that become out of reach or out of stock. The measures like adopting multiple suppliers, investing in surplus inventory, and holding strategic inventory are the key approaches for enhancing redundancy [15, 70, 103, 141].
- ***Adaptability***: This factor emphasizes that the components of a supply chain must be completely ready and operational at all times and under all conditions. The supply chain resiliency concentrates on the system adaptability with different conditions to handle the temporary disruptions. The dynamic nature of adaptability provides the suppliers with the possibility to evaluate themselves after the occurrence of disruption and restoring the initial state [13, 15, 101, 126].
- ***Awareness***: Resilient organizations know how to anticipate unpredicted disruptions. A resilient supplier must be aware of risks related to the organizations, assets, processes, competition conditions, and financial fluctuations [54, 73, 109, 117].
- ***Management commitment***: The supplier resiliency heavily depends on the suppliers' long-term commitment towards buyers [14, 24, 106, 141].
- ***Preparedness***: This factor reflects the supplier's activities done before the occurrence of a disruption. The supplier must reinforce the ability to encounter unpredicted and disruptive events. Supplier preparedness has an essential role in the reduction of vulnerability and mitigation of bad effects of the supply chain risks [46, 59, 99, 138].

3.2 Questionnare design

A questionnaire is designed with 18 indicators (53 questions) to evaluate 45 suppliers who have sold cardiovascular medical equipment to the hospital over the past 5 years. These questions coherently cover all evaluation factors (including cost, delivery time, and QRE indicators). A group of 15 employees, including the managers in the medical equipment unit and purchasing staff, with a good knowledge of the medical equipment management system, were selected by the hospital's chief operating officer to participate in the study. The participants included the manager of the medical equipment unit (with 15 years of experience), a supervisor in the medical equipment unit (with 10 years of experience), and 13 purchasing staff (with 5–10 years of experience). The group was instructed to use the questionnaire presented in Appendix A (provided as Electronic Supplementary Material) and evaluate 45 suppliers and assign a score between 1 = very weak to 10 = very strong to 53 questions representing 18 indicators. The participants were also asked to specify the reliability of their responses according to the choices provided in Table 2.

3.3 Fuzzy DEA model

DEA is a non-parametric method using multi-inputs and multi-outputs for performance evaluation comparing DMUs relative to their best peers. The conventional DEA methods require precise measurement of both the inputs and outputs. However, the input and output data's observed values in real-world problems are sometimes imprecise, vague, uncertain, unquantifiable, or incomplete. The supplier evaluation problem in healthcare is not exempt from this vagueness and uncertainty. We use fuzzy DEA as a performance evaluation tool for the following reasons. First, in performance measurement, the use of single measures ignores any interactions among various performance measures. DEA has been proven effective in performance measurement when multiple performance indicators are present [144]. Second, DEA does not require a priori information about the relationship between multiple performance indicators [122, 145]. Third, fuzzy sets are commonly used in DEA to deal with imprecise input and output data [49]. Fourth, the experts' judgments on the indicators can be used directly in the fuzzy DEA models [10]. In this study, the DEA method is used to calculate the efficiency of the suppliers (DMUs). The output-oriented DEA and the Charnes, Cooper, and Rhodes (CCR) model [30] are selected for the implementation of DEA because the increase of the output is proportional to the increase of the inputs in our application, which means the returns-to-scale is constant [34]. Model (1) shows the fuzzy CCR DEA model.

Table 2 Fuzzy values for different degrees of reliability

$Z=(A, B)$	Degree of reliability	Fuzzy value
Bs	Sure	[0.8, 1, 1]
	Usually	[0.65, 0.75, 0.85]
	Likely	[0.5, 0.6, 0.7]

$$\begin{aligned} &\text{Max } \theta = \sum_{k=1}^{16} u_k \tilde{y}_{\text{ki}} \\ &s.t. \\ &\sum_{j=1}^{2} v_j \tilde{x}_{\text{ji}} = 1 \quad i = 1, \ldots, 45 \\ &\sum_{k=1}^{16} u_k \tilde{y}_{\text{ki}} - \sum_{j=1}^{2} v_j \tilde{x}_{\text{ji}} \le 0 \quad i = 1, \ldots, 45 \\ &u_k, v_j \ge 0 \quad j = 1, 2 \ ; \ k = 1, \ldots, 16 \end{aligned} \tag{1}$$

In model (1), θ is the efficiency of the DMUs, and $\widetilde{x\sim}_{\text{ji}}$ and $\widetilde{y\sim}_{\text{ki}}$ are the jth input of the ith DMU and the kth output of the ith DMU in the fuzzy state, respectively. u_k and v_j are respectively the coefficients of the outputs and inputs, and "~" identifies the fuzziness of the outputs and inputs. In this study, 45 DMUs (suppliers) are evaluated according to 2 inputs and 16 outputs. Golany and Roll [44] established a rule of thumb that indicates the number of DMUs in DEA should be at least twice the number of inputs and outputs. In this study, with 2 inputs and 16 outputs, Golany and Roll [44] recommend using at least 36 DMUs. The 45 DMUS used in this study satisfies this requirement.

We utilize triangular fuzzy numbers, which are the most widely used fuzzy numbers in practice. Considering the inputs and outputs as triangular fuzzy numbers and using the α-cut method and applying different α-cuts, the above fuzzy model is converted into a fuzzy linear programming model [65]. The obtained model is then transformed into an interval linear programming model. In this study, we use the method proposed by Chang and Lee [29]. Considering $\widetilde{x\sim}_{\text{ji}} = \left(x_{\text{ji}}^l, x_{\text{ji}}^m, x_{\text{ji}}^u\right)$ and $\widetilde{y\sim}_{\text{ki}} = \left(y_{\text{ki}}^l, y_{\text{ki}}^m, y_{\text{ki}}^u\right)$, model (2) displays the interval programming obtained from model (1) using the α-cut method.

$$\begin{aligned} &\text{Max } \theta = \sum_{k=1}^{16} u_k \left(\alpha y_{\text{ki}}^m + (1-\alpha) y_{\text{ki}}^l, \alpha y_{\text{ki}}^m + (1-\alpha) y_{\text{ki}}^u\right) \\ &s.t. \\ &\sum_{j=1}^{2} v_j \left(\alpha x_{\text{ji}}^m + (1-\alpha) x_{\text{ji}}^l, \alpha x_{\text{ji}}^m + (1-\alpha) x_{\text{ji}}^u\right) = 1 \quad i = 1, \ldots, 45 \\ &\sum_{k=1}^{16} u_k \left(\alpha y_{\text{ki}}^m + (1-\alpha) y_{\text{ki}}^l, \alpha y_{\text{ki}}^m + (1-\alpha) y_{\text{ki}}^u\right) \\ &- \sum_{j=1}^{2} v_j \left(\alpha x_{\text{ji}}^m + (1-\alpha) x_{\text{ji}}^l\right), \alpha x_{\text{ji}}^m + (1-\alpha) x_{\text{ji}}^u \le 0 \ \forall i \\ &u_k, v_j \ge 0 \quad j = 1, 2 \ ; \ k = 1, \ldots, 16 \end{aligned} \tag{2}$$

3.4 *Z*-number DEA model

The *Z*-numbers were first introduced by Zadeh [142]. For a variable *X*, these numbers are defined as an ordered pair like (*A*, *B*) in which *A* is a subset of the variable *X* and *B* is the expert's reliability in identifying the value of *A* (the expert's reliability on its opinion about a certain item or indicator). The value of *B* can be expressed in terms of different concepts like sureness, confidence, the strength of belief, probability, and possibility. Because *A* is a fuzzy subset of *X*, a membership function must be defined for the variable *X*. Due to the calculation simplicity and also high descriptive power, this membership function is usually defined as triangular numbers [2]. If we suppose *m* DMUs each has *n* input and *s* output variables, the input and output variables for each DMU in the form of *Z*-numbers are defined as follows [11]:

$$\widetilde{Z}\sim x_{\mathrm{ji}} = \left(\widetilde{A}\sim x_{\mathrm{ji}}, \widetilde{B}\sim x_{\mathrm{ji}}\right) \quad j = 1, 2, \ldots, n \tag{3}$$

$$\widetilde{Z}\sim y_{\mathrm{ki}} = \left(\widetilde{A}\sim y_{\mathrm{ki}}, \widetilde{B}\sim y_{\mathrm{ki}}\right) \quad k = 1, 2, \ldots, s \tag{4}$$

where $\widetilde{B}\sim x_{\mathrm{ji}}$ and $\widetilde{B}\sim y_{\mathrm{ki}}$ identify the restriction of certainty on $\widetilde{A}\sim x_{\mathrm{ji}}$ and $\widetilde{A}\sim y_{\mathrm{ki}}$, respectively. The Z-DEA model has been designed according to the fuzzy DEA model, supposing a reliability parameter. Hence, by identifying the reliability of the variable's value, this model is converted into a fuzzy DEA model. Model (5) shows the *Z*-number CCR DEA model first introduced by Azadeh and Kokabi [11].

$$\begin{aligned}
&\mathrm{Max}\,\theta = \sum_{k=1}^{16} u_k \widetilde{Z}\sim y_{\mathrm{ki}} \\
&s.t. \\
&\sum_{j=1}^{2} v_j \widetilde{Z}\sim x_{\mathrm{ji}} = 1 \quad i = 1, \ldots, 45 \\
&\sum_{j=k=1}^{16} u_k \widetilde{Z}\sim y_{\mathrm{ki}} - \sum_{j=1}^{2} v_j \widetilde{Z}\sim x_{\mathrm{ji}} \le 0 \quad i = 1, \ldots, 45 \\
&u_k, v_j \ge 0 \quad j = 1, 2\ ;\ k = 1, .., 16
\end{aligned} \tag{5}$$

To linearize the above model, we first convert model (5) into a fuzzy programming model. In this regard, we integrate the reliability values of the decision-making data with the corresponding values of the data. To do this, we first use the defuzzification method to convert the fuzzy reliability values to crisp numbers. Suppose that the membership function of reliability values is as the set of membership functions $\widetilde{B}\sim = \left\{(x, \mu_{\widetilde{B}\sim}(x)) | x \in [0, 1]\right\}$ which, $\mu_{\widetilde{B}\sim}(x)$ is the membership function of the reliability values. Therefore, we suppose that the created classes in the form of linguistic variables are fuzzy sets in the interval [0, 1]. In this study, we use the center of gravity defuzzification method to defuzzify the reliability values with their formula presented by Eq. (6).

$$\alpha = \frac{\int x \mu_{\widetilde{B}\sim}(x) dx}{\int \mu_{\widetilde{B}\sim}(x) dx} \tag{6}$$

Now, supposing that the reliability values are triangular membership functions $\widetilde{B}\sim\sim TFN(a, b, c)$, the above equation is summarized as the Eq. (7).

$$\alpha = \frac{a + b + c}{3} \tag{7}$$

If we suppose that a fuzzy set like $\widetilde{A}\sim$ has been defined in the population *X*, then $\widetilde{A}\sim = \left\{(x, \mu_{\widetilde{A}\sim}(x)) | x \in X\right\}$ where $\mu_{\widetilde{A}\sim}(x)$ is its membership function and identifies the degree of belongingness of *x* to the fuzzy set $\widetilde{A}\sim$. Now, the fuzzy expectation of the fuzzy set $\widetilde{A}\sim$ is calculated according to Eq. (8).

$$E_{\widetilde{A}\sim}(x) = \int x \mu_{\widetilde{A}\sim}(x) dx \tag{8}$$

Eq. (8) is used to provide a mechanism for adding α values to the fuzzy values of decision-making numbers with the help of fuzzy sets expectation. After obtaining the α values, these values are integrated with their corresponding initial values of *Z*-numbers and configure the weighted *Z*-numbers. If $\widetilde{Z}\sim = \left(\widetilde{A}\sim, \widetilde{B}\sim\right)$, its weighted *Z*-number is defined as $\widetilde{Z}_{\alpha} = \left\{(x, \mu^{\alpha}_{\widetilde{A}}(x)) | x \in X\right\}$ in which $\mu^{\alpha}_{\widetilde{A}}(x)$ is the membership function of the abnormal fuzzy set of the weighted *Z*-number. It should be noted that the abnormal fuzzy set is a set whose maximum membership degree is less than 1. In Eq. (9), the relationship between the *Z*-number set and the weighted *Z*-number set has been displayed using the fuzzy set expectation. In addition, the proof of this relation has been given in Eq. (10).

$$\begin{aligned}
&E_{\widetilde{A}^{a}}(x) = \alpha E_{\widetilde{A}}(x) \quad ;\ x \in X \\
&s.t. \quad \mu^{\alpha}_{\widetilde{A}}(x) = \alpha \mu_{\widetilde{A}}(x) \quad ;\ x \in X
\end{aligned} \tag{9}$$

$$E_{\widetilde{A}^{a}}(x) = \int x \mu^{\alpha}_{\widetilde{A}}(x) dx = \int x \alpha \mu_{\widetilde{A}}(x) dx = \alpha \int x \mu_{\widetilde{A}}(x) dx = \alpha E_{\widetilde{A}}(x) \tag{10}$$

Therefore, considering the above equations, the second part of *Z*-numbers is multiplied into the first part, and two normal fuzzy numbers are converted to one abnormal fuzzy number. In Fig. 3, the schematic of the conversion of the triangular set is illustrated.

According to Eq. (9), the input and output values related to DMUs are converted into the *Z*-numbers that have abnormal

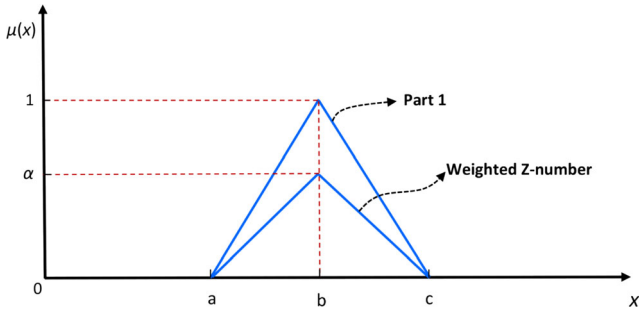

Fig. 3 The *Z*-number after multiplying its corresponding reliability value

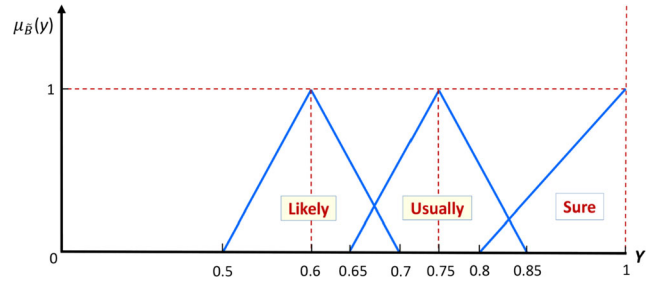

Fig. 4 The fuzzy sets for the reliability values

triangular membership functions. In the following, the approach applied by Azadeh and Kokabi [11] has been used to convert the weighted *Z*-numbers into normal fuzzy numbers and obtain a fuzzy programming model that is equivalent to the Z-DEA model. Finally, using the α-cut method, the parametric linear programming obtained from the *Z*-number CCR DEA model is shown in Model (11).

$$
\begin{aligned}
& Max\theta = \sum_{k=1}^{16} \bar{y}_{ki} \\
& s.t. \\
& \sum_{j=1}^{2} \bar{x}_{ji} = 0 \quad i = 1, \ldots, 45 \\
& \sum_{j=k=1}^{16} \bar{y}_{ki} - \sum_{j=1}^{2} \bar{x}_{ji} \le 0 \qquad i = 1, \ldots, 45 \\
& v_j\left(\alpha x_{ji}^m + (1-\alpha)x_{ji}^l\right) \le \tilde{x}_{ji} \le v_j\left(\alpha x_{ji}^m + (1-\alpha)x_{ji}^u\right) \qquad j = 1, 2; i = 1, \ldots, 45 \\
& u_k\left(\alpha y_{ki}^m + (1-\alpha)y_{ki}^l\right) \le \tilde{y}_{ki} \le u_k\left(\alpha y_{ki}^m + (1-\alpha)y_{ki}^u\right) \qquad k = 1, \ldots, 16; i = 1, \ldots, 45 \\
& u_k, v_j \ge 0 \qquad j = 1, 2; k = 1, .., 16
\end{aligned}
\tag{11}
$$

where $\bar{y}_{ki}$ are the mean characteristics of the normal fuzzy set obtained from the *Z*-number related to the *k*th output of the *i*th DMU and $\bar{x}_{ji}$ are the mean characteristics of the normal fuzzy set obtained from the *Z*-number related to the *j*th input of the *i*th DMU. It should be noted that values related to component *B* in the *Z*-numbers have been obtained from the data presented earlier in Table 2. Figure 4 shows the fuzzy sets related to the corresponding reliability [11].

In this study, the Z-DEA is used to calculate the efficiency of the DMUs (suppliers) and analyze the effects of the indicators. The Z-DEA model runs at 14 levels of α-cut with values 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 to select the best level for the α-cut in the Z-DEA model. It should be noted that the full ranking of DMUs is provided by applying the Z-DEA model.

4 Case study

Hospitals are expected to have a relationship with efficient and high-qualified medical equipment suppliers to improve their performance, increase productivity, and reduce operating costs. The Shahid Rajaei Cardiovascular Hospital is the largest cardiovascular medical center in Iran. This hospital was established in 1974 with a capacity of 270 beds. Thus far, it has made considerable progress in developing specialized departments and clinics, increasing medical and specialized cardiovascular services, using up-to-date science and technology in treatment methods, and utilizing the modern medical equipment and devices to provide specialized medical and treatment services. A wide spectrum of suppliers provides various medical equipment and devices to this hospital. In this study, we evaluate the medical equipment suppliers to this cardiovascular hospital using the integrated framework proposed in this study.

4.1 Data gathering

As described in "Section 4.2," we distributed a questionnaire with 53 questions (representing 18 indicators) to a group of 15 experts in purchasing medical equipment to evaluate 45 suppliers (DMUs) and assign a score between 1 to 10 to each question for each supplier. The average score of the questions for each indicator is used as the baseline evaluation score for each indicator. The average baseline scores and the standard deviations for the 18 indicators are presented in Table 3.

Table 3 The baseline mean and standard deviation for the indicators

Indicator	Mean	Standard deviation
Cost	6.03	0.528
Delivery time	6.57	0.740
Conformance to standards	7.13	1.025
Performance and functionality	6.13	0.992
Reliability	6.65	0.968
Warranties and claim policies	5.92	0.952
Responsiveness	5.63	1.140
After-sales and support services	6.68	1.260
Process capability and control	6.63	0.923
Shipping and transportation	6.40	1.287
Quality certifications	6.44	1.327
Continuous improvement	5.32	0.959
Flexibility	5.55	0.944
Redundancy	6.21	1.108
Adaptability	5.79	0.897
Awareness	5.94	0.948
Management commitment	5.96	0.906
Preparedness	5.60	1.137

4.2 Input and output variables

The selection of input and output variables is an important step in the DEA method. In this study, *cost* and *delivery time* are traditional indicators considered as the input variables. These indicators are undesirable inputs to be minimized in the performance evaluation model. On the other hand, the QRE indicators, including *product quality*, *service quality*, *process quality*, and *organizational quality*, are considered the output variables. These quality indicators are desirable outputs to be maximized in the proposed model (15). The efficiency measure in the DEA is derived as the optimal ratio of the sum of weighted outputs to inputs with no restrictions on the weights.

4.3 Reliability and validity of the questionnaire

Cronbach's alpha test and factor analysis have been used to assess the reliability and validity of the questionnaire data. The reliability of a questionnaire is its ability to reach similar results on different occasions, and the validity implies the measurement of what the questionnaire was supposed to measure [33]. In this study, the Cronbach's alpha values were calculated for each indicator. Values greater than 0.6 are acceptable for reliability [14]. After investigating the questionnaire's reliability, its validity is evaluated by analyzing construct validity and content validity using structural equation modeling. The construct validity identifies whether the evaluative indicators are correctly measured and assessed by the subsidiary components (questions) [41]. Construct validity is studied by confirmatory factor analysis. In this study, each indicator is considered as a distinct construct. The most common decision-making technique for obtaining the factors is to consider factors with eigenvalues greater than 1 as significant. The construct validity of an indicator is verified if all questions related to that indicator are set on one factor and the factor loading values of all questions are greater than 0.4 [47, 61]. The results of the questionnaire's reliability and validity have been given in Table 4. SPSS and Smart-PLS software are utilized for performing the reliability and validity calculations.

5 Computational results and discussion

5.1 Selection of optimum α-cut for Z-DEA model

In this section, first, the efficiency of each DMU is calculated using the Z-DEA model for different levels of α-cut. Then, the normality of the calculated efficiency scores at each level of α-cut is investigated. The normality test results showed that no model is normal. The noise analysis was used to identify the optimum α-cut for the Z-DEA mode by inserting a certain amount of noise (change) into the input data and then investigating the results of the Z-DEA model. We identify the optimum level as the level of α-cut with the least sensitivity to changes [16]. According to the empirical evaluations in this study, inserting about 20% noise to the input data results in a significant change in 11% of DMUs (5 random DMUs). Hence, this amount of noise was inserted into the input data, and then, the sensitivity of the Z-DEA model was investigated at different levels of α-cut. To test the equality of the efficiency means before and after the noise, the Kruskal-Wallis test (with the confidence interval of 95%) and the Spearman's rank–order correlation coefficient are used to test the correlation of the efficiency scores before and after the noise at each level of α-cut. Table 5 shows the results of these analyses. According to the results, the Z-DEA model at the α-cut of 0.5 has the highest correlation coefficient for the efficiency scores of the DMUs before and after the noise, and also the Kruskal-Wallis test confirms the equality of means hypothesis at an acceptable significance level. Therefore, the Z-DEA model with α-cut of 0.5 is selected as the most suitable model for calculating the efficiency and ranking of the suppliers. The efficiency calculation is performed with MATLAB V.2016.

5.2 Calculating the efficiency score and rank of suppliers

Table 6 presents the efficiency scores and their ranking based on the Z-DEA model. As shown in this table, Supplier 26, with an efficiency score of 1.26367, is recognized as the most efficient DMU or the best supplier, and Supplier 7, with an

Table 4 The results of questionnaires' reliability and validity

Indicator (factor)	Reliability (Cronbach's alpha)	Factor analysis	
		Component (question)	Component (factor) loadings
Cost	0.752	1	0.772
		2	0.639
		3	0.780
		4	0.707
Delivery time	0.806	1	0.860
		2	0.797
		3	0.795
Conformance to standards	0.797	1	0.726
		2	0.617
		3	0.551
Performance and functionality	0.849	1	0.743
		2	0.737
		3	0.770
Reliability	0.886	1	0.759
		2	0.731
		3	0.790
		4	0.867
Warranties and claim policies	0.819	1	0.842
		2	0.835
		3	0.809
Responsiveness	0.852	1	0.844
		2	0.801
		3	0.837
After-sales and support services	0.825	1	0.788
		2	0.814
		3	0.737
Process capability and control	0.764	1	0.722
		2	0.791
		3	0.800
Shipping and transportation process	0.672	1	0.594
		2	0.603
Quality certifications	0.695	1	0.729
		2	0.590
Continuous improvement	0.711	1	0.737
		2	0.789
		3	0.812
Flexibility	0.781	1	0.827
		2	0.762
		3	0.815
Redundancy	0.756	1	0.774
		2	0.741
Adaptability	0.775	1	0.722
		2	0.817
		3	0.808
Awareness	0.815	1	0.770
		2	0.783
		3	0.823
Management commitment	0.836	1	0.802
		2	0.846
		3	0.762
		4	0.727
Preparedness	0.862	1	0.888
		2	0.833

efficiency score of 0.98913, is recognized as the most inefficient DMU or the worst supplier. In addition, the mean efficiency of all medical equipment suppliers for this hospital is 1.18617. The primary analysis indicates that about 31% of the suppliers (14 suppliers) have efficiency scores lower than the total mean efficiency. The other 69% (31 suppliers) have efficiency scores higher than the total mean efficiency. The suppliers' performance with efficiency scores lower than the mean efficiency can be improved considerably by appropriate corrective actions, such as reducing costs or delivery time.

5.3 Validation of Z-DEA

In this study, the FDEA method has been used to validate the optimum Z-DEA model results. Because the FDEA method considers only the uncertainty in the input data and does not take into account the reliability concept (component B in the Z-numbers), it is a suitable approach for assessing the validity of the Z-DEA model. First, to identify the suitable FDEA model, similar to the Z-DEA, 20% noise is randomly inserted into the input data for 11% of DMUs (5 DMUs). Then, the correlation of results and change in the mean efficiency before and after the noise insertion at all levels of α-cut in the FDEA model are studied. According to the results presented in Table 7, the FDEA model at α-cut = 0.4 has the highest value of correlation coefficient and p value for the efficiency results before and after the noise insertion; thus, it is selected as the suitable FDEA model to validate the results. Table 8 indicates the efficiency scores and ranking of the suppliers by the optimum FDEA model. The Spearman's correlation coefficient between the efficiency scores and the rank obtained for the suppliers was calculated for the optimum Z-DEA model and the optimum FDEA model to be 0.924 (p value = 0.000), which shows that the results of both models are similar. Thus, the validity of the optimum Z-DEA model is confirmed.

Table 5 The noise analysis results for different α-cuts in the Z-DEA model

α value	Mean efficiency		P value of Kruskal-Wallis test	Spearman's correlation coefficient (p value)
	Before noise insertion	After noise insertion		
0.01	1.42880	1.44886	0.005	0.950 (0.000)
0.05	1.40721	1.43189	0.010	0.971 (0.000)
0.1	1.38071	1.41560	0.005	0.894 (0.000)
0.2	1.32923	1.35668	0.008	0.911 (0.000)
0.3	1.27970	1.29749	0.034	0.964 (0.000)
0.4	1.23204	1.24866	0.089	0.981 (0.000)
0.5	**1.18617**	**1.19159**	**0.368**	**0.991 (0.000)**
0.6	1.14198	1.15993	0.045	0.935 (0.000)
0.7	1.09939	1.13179	0.001	0.838 (0.000)
0.8	1.05838	1.08781	0.000	0.902 (0.000)
0.9	1.01896	1.03818	0.005	0.868 (0.000)
0.95	0.99981	1.02261	0.015	0.876 (0.000)
0.99	0.98900	1.00136	0.156	0.952 (0.000)
1	0.98105	0.99090	0.188	0.975 (0.000)

6 Conclusions and future research directions

In this study, the supplier evaluation and selection problem is studied considering quality, resilience engineering, cost, and delivery time, integrated, for the medical equipment suppliers at a cardiovascular hospital. The principal indicators for performance evaluation are identified, and a questionnaire is designed by reviewing the literature and obtaining expert

Table 6 The Z-DEA results for 45 DMUs with α-cut = 0.5

DMU (supplier no.)	Efficiency score	Rank	DMU (supplier no.)	Efficiency score	Rank
1	1.21195	18	24	1.10775	38
2	1.24269	3	25	1.19065	30
3	1.23215	6	26	1.26367	1
4	1.24130	4	27	1.06959	42
5	1.18496	33	28	1.18164	35
6	1.10328	39	29	1.22360	12
7	0.98913	45	30	1.20267	24
8	1.22805	10	31	1.05259	44
9	1.20766	22	32	1.21236	17
10	1.20270	23	33	1.22852	9
11	1.07839	41	34	1.19144	29
12	1.20193	26	35	1.21079	19
13	1.22501	11	36	1.21069	20
14	1.18497	32	37	1.20003	27
15	1.24324	2	38	1.21838	13
16	1.17804	36	39	1.09877	40
17	1.19206	28	40	1.06147	43
18	1.23007	8	41	1.23197	7
19	1.18645	31	42	1.21703	14
20	1.18167	34	43	1.17742	37
21	1.23865	5	44	1.21625	15
22	1.21350	16	45	1.21029	21
23	1.20231	25	**Mean**	**1.18617**	

Table 7 The noise analysis results for different α-cuts in the FDEA model

α value	Mean efficiency		P value of Kruskal-Wallis test	Spearman's correlation coefficient (p value)
	Before noise insertion	After noise insertion		
0.01	1.29777	1.32852	0.005	0.958 (0.000)
0.05	1.28310	1.31654	0.001	0.944 (0.000)
0.10	1.26499	1.31272	0.000	0.904 (0.000)
0.20	1.22957	1.26109	0.001	0.967 (0.000)
0.30	1.19519	1.21177	0.019	0.971 (0.000)
0.40	**1.16181**	**1.17062**	**0.112**	**0.989 (0.000)**
0.50	1.12840	1.13968	0.102	0.980 (0.000)
0.60	1.09793	1.11393	0.010	0.960 (0.000)
0.70	1.06744	1.07925	0.019	0.968 (0.000)
0.80	1.03775	1.05693	0.005	0.824 (0.000)
0.90	1.00898	1.02120	0.010	0.842 (0.000)
0.95	0.99498	1.04416	0.008	0.816 (0.000)
0.99	0.97584	0.98928	0.079	0.927 (0.000)
1.00	0.96305	0.97690	0.089	0.956 (0.000)

opinions. The questionnaire's reliability and validity are then assessed and confirmed using Cronbach's alpha and factor analysis. The suppliers' efficiencies and rankings are calculated using the Z-DEA method and noise analysis by considering the

Table 8 The FDEA validation results with α-cut = 0.4

DMU (supplier no.)	Efficiency score	Rank	DMU (supplier no.)	Efficiency score	Rank
1	1.20081	6	24	1.08702	38
2	1.20050	7	25	1.17508	29
3	1.20296	5	26	1.23265	1
4	1.21418	3	27	1.04984	42
5	1.17228	31	28	1.17140	32
6	1.08342	40	29	1.19844	9
7	0.97215	45	30	1.18193	20
8	1.21490	2	31	1.04072	44
9	1.18014	24	32	1.18125	21
10	1.18472	18	33	1.18045	23
11	1.05415	41	34	1.17455	30
12	1.17622	28	35	1.18927	12
13	1.18829	13	36	1.18634	14
14	1.16219	34	37	1.18076	22
15	1.21169	4	38	1.19634	11
16	1.15269	37	39	1.08386	39
17	1.17663	27	40	1.04974	43
18	1.18562	15	41	1.17794	26
19	1.16579	33	42	1.18557	16
20	1.15735	35	43	1.15656	36
21	1.19961	8	44	1.19834	10
22	1.18477	17	45	1.17814	25
23	1.18434	19	**Mean**	**1.16181**	
Spearman's correlation coefficient between the results of the optimum Z-DEA and FDEA models				0.924	

reliability concept. The results were also validated through the FDEA method. The type and intensity of the effect of each indicator on the supplier performance were specified using sensitivity analysis. The results of efficiency, ranking suppliers, and the intensity of effect obtained for indicators provide the purchasing managers of the hospital with important insight into different suppliers. The results showed that flexibility, conformance to standards, redundancy, cost, quality certifications, and delivery time have the greatest impact on the performance of suppliers. In addition, the product quality dimension (the quality of medical equipment and devices) is the most important dimension among the quality dimensions. According to the findings of this research, managers in hospital and supplier enterprises must concentrate on improving important indicators to enhance the efficiency of suppliers, improve the hospital-supplier relationships along the supply chain, increase productivity, and promote the overall performance of the hospital. In this regard, the hospital should maintain and reinforce its relationships with the suppliers capable of fulfilling unplanned orders in times of crisis and need. Furthermore, due to the sensitivity of medical equipment and devices, the hospital should have the best relationship with the suppliers whose products meet medical equipment standards such as CE Marking and ISO 17664 (the standards of procurement, consumption, inspection, test, and repair, packaging, sterilize, and maintaining the medical equipment) [63]. To improve the cost components, the price of products and items provided by the suppliers should have adequate stability under different conditions. Also, in the current competitive conditions of the market, providing special offers by the suppliers while maintaining the quality of the products can have a considerable effect on the relationships between the hospital and suppliers.

Future research directions could consider other dimensions such as green (environmental), customer trust, and agility in supplier performance evaluation. In addition, other methods like fuzzy cognitive maps and system dynamics could be used to investigate the cause and effect relations among the indicators. Finally, artificial intelligence methods like neural networks and adaptive neuro-fuzzy inference system (that take into account the complexities and nonlinear relations of the indicators) are other possibilities for future research.

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Declarations

Competing interests 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.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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