ORIGINAL RESEARCH

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An Integrated Data Mining Framework for Organizational Resilience Assessment and Quality Management Optimization in Trauma Centers

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Abstract

Every second counts for patients with life-threatening injuries, and trauma centers deliver timely emergency care to patients with traumatic injuries. Quality assessment and improvement are some of the most fundamental concerns in trauma centers. In this study, a comprehensive organizational resilience approach is proposed to evaluate performance in trauma centers using the European Foundation for Quality Management as a fundamental and strategic approach. We propose a unique intelligent algorithm composed of parametric and non-parametric statistical methods to determine the type and the extent of influence within the organizational resilience and quality management perspectives. We use structural equation modeling to examine the reliability and validity of the input data. The efficiency of each trauma center is then measured using a machine learning method with genetic programming, support vector regression, and Gaussian process regression. The mean absolute percentage error is used to determine the optimal model, and a fuzzy data envelopment analysis model is used to verify and validate the results obtained from the optimal model. The results show that customer results, human capital results, and key performance results have the highest importance weights and positive influence on quality management. Cognitive resources, roles and responsibilities, and self-organization have the highest importance weights and positive influence on organizational resilience.

Keywords Organizational resilience · Quality management · Genetic programming · Support vector regression · Gaussian process regression · Fuzzy data envelopment analysis

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1 Introduction

Evaluating and optimizing the health system is one of the most important concerns of managers and experts active in the health system field. Trauma centers and medical emergency units are among the most critical components of hospitals due to their crucial role in saving lives. Therefore, analysis and evaluation of the performance of these centers are of great importance [1]. Various models have been proposed to improve the performance of the trauma centers and medical emergency units, each of which has its strengths and weaknesses. Some of the most widely used approaches for continuous improvement in trauma centers include the following:

A. Quality management

Healthcare organizations such as hospitals are expected to practice quality management to show their due diligence in taking optimal care of their patients. Assuring quality management in a hospital emergency department or trauma center has become a requirement for various accrediting agencies [2].

Although the roots of quality management date back to the early 1920s when statistical methods were employed in manufacturing for product quality control, quality management, and measurement in healthcare is a relatively new field. The European Foundation of Quality Management (EFQM) model is a commonly used approach to continuous quality management within healthcare facilities such as hospitals and medical clinics. The EFQM model is a non-prescriptive method with four key result criteria [3]. Organizations in different industries try to achieve these results and preserve their accomplishments:

- Customer results: customer results reflect a wide range of issues such as satisfaction, complaints, recommendations, quality, etc. [4, 5].
- Human capital results: human capital results reflect different human resources aspects in organizations such as values, abilities, and trust [6, 7].
- Society results: society results reflect societal concerns such as the unity of the internal structure, mutual relationships, added value, and responsibility [4, 8, 9].
- Key performance results: key performance results reflect performance indicators that contribute to the non-economic reputation of the organization, such as management reputation and capabilities, technological innovations, and organizational reputation [10].

B. Resilience

Resilience is the ability of a system to return to its normal state or move to a more desirable state after a disturbance [11]. Generally, resilience refers to preventing maximum disaster and recovering from a disturbance [12]. Resilience has been adopted in many research domains such as engineering, environment, metallurgy, individual and organizational psychology, safety, economics, and physics [13]. For example, resilience in engineering has proposed a set of diagnostic principles to design secure and compatible working systems [14]. This concept has been

developed in diagnostic systems engineering and safety management [15, 16]. This includes complex and hazardous systems such as air transportation, petrochemicals, and healthcare. Hollnagel et al. [15] identified management commitment, flexibility, awareness, preparedness, learning, and reporting culture as important resilience indicators. Azadeh et al. [17] identified redundancy, fault-tolerant, self-organization, and teamwork as key resilience indicators. In economics, resilience is defined as the ability and adaptability that enables organizations to prevent the maximum probable damage. Glonti et al. [18] conducted several studies on traditional dynamic nonlinear systems and proposed a series of innovative ideas for resilience. Briguglio et al. [19] and Morel et al. [20] adopted the ecological approach to resilience. They suggested that the system tends to self-reorganize and return to the initial state to sustain balance. Richtner and Sodergren [21, 22] showed organizational challenges could be discrete in the form of a sudden disaster and defined resilience as the ability to improve and control the repetitive challenges in the organization. They further identified structural, relational, emotional, and cognitive resources as the necessary resources for resilience.

1.1 Organizational Resilience

Wehbe et al. [23] assert that resilience is necessary not only for sudden shocks (such as storms, earthquakes, tornados) but also for constant environmental changes in organizations. Generally, resilience is a powerful tool for organizations to overcome the continuous disturbances in their business environment [24]. During the past decades, global healthcare systems have faced several crises and shocks [25]. The global economic crisis of 2008 and the Ebola outbreak from 2014 to 2016 resulted in increased attention to the concept of organizational resilience in the healthcare system [26]. More recently, companies are devoting a lot of resources to building organizational resilience against the coronavirus (COVID-19). Over time, this concept entered different fields of study, such as psychology, environmental management, physics, metallurgy, engineering, management, capacity, and supply chain. Organizational resilience is now considered a fundamental approach to maintaining stability [27]. Hamel and Valikangas [28] specified that organizational revolution, resilience, and renewal are three vague states of chaotic times. Resilience is related to the permanent recreation of values, behaviors, and processes. Mallak [29] classified the concept of organizational resilience into six categories: sight, values, resilience, empowerment, opposition, and connection. Different models have been proposed to measure resilience in organizations. McManus et al. [30] summarized organizational resilience into three indicators of situational awareness, adaptive capacity, and management of key vulnerabilities along with 15 sub-indicators. They argued organizational resilience is a necessary element in societal resilience. Lengnick-Hall et al. [31] extended the concept of organizational resilience capacity by using human resources strategy and meritocracy to prevent from instability and incompatibility in organizations. They introduced three indicators of special cognitive abilities, behavioral features, and environmental conditions along with 10 additional sub-indicators.

1.2 Resilience in Healthcare

Resilience is the process of adapting in the face of disaster, disturbance, or other sources of significant stress. The environment of the trauma centers is often stressful, and examining resilience in healthcare has numerous applications in hospital emergency and trauma centers [32]. The most important advantage of resilience in healthcare is customer satisfaction and safety. Healthcare facilities will be better equipped to respond to catastrophes by taking steps and developing concrete disaster preparedness plans [33]. By promoting resilience, hospitals and healthcare systems can recover from disasters and prevent predicted and unpredicted events while providing patients with medical and healthcare services [34, 35].

1.3 A New Organizational Resilience Model

Although different definitions have been proposed for organizational resilience in different contexts and domains, the consensus definition emphasizes returning from disturbance to the initial and balanced state. There is no uniform and comprehensive model for organizational resilience applicable to various fields such as engineering, sciences, business, and government, among others. The model proposed in this study consists of three general features: resources, people, and systems. This model implies that successful organizational resilience is dependent on the resilience of the resources, people, and systems in organizations. Richtner and Sodergren [22] demonstrate that to improve organizational resilience, an organization must improve the resilience of six internal and external resources, including human resources. In addition, it is imperative to enhance the resilience of the processes and the overall system. These four sub-criteria should be present at the soul of the organization. Figure 1 presents a graphical classification of the indicators used in this study.

- Structural resources: an organizational structure can promote or suppress resilience. Richtner and Sodergren [22] emphasize the need to support structural resources for projects that contribute to organizational resilience.
- Cognitive resources: cognitive resources are needed to provide uncommon and creative solutions and responses to difficult and complex organizational problems [22, 36].
- Relational resources: relational resources such as internal or external colleagues, foreign partners, counselors, customers, and politicians are needed to provide suitable remedies to internal and external challenges through a powerful network [22].
- Emotional resources: emotional resources, such as friendship, support, trust, respect, and sympathy, are the most important resources for organizational resilience. These resources also increase the quality of the information exchange and create bases for a culture of learning and creativity [22].
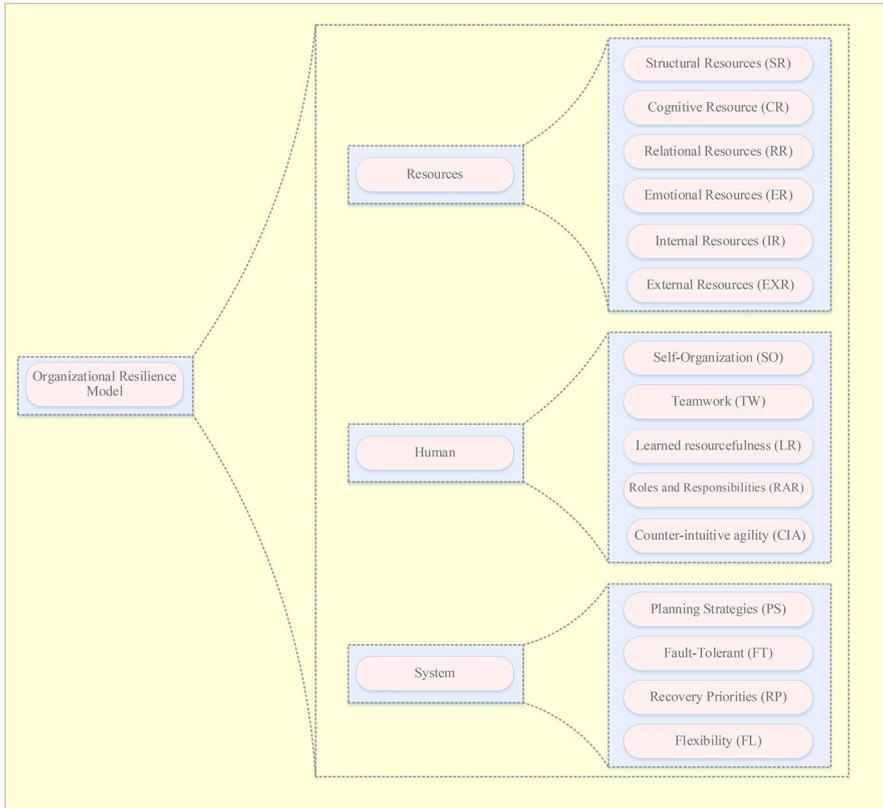
Fig. 1 A graphical classification of the indicators used in this study

- Internal resources: internal resources are physical structures and organizational resources such as buildings, materials, and informational technology equipment, among others. For example, preventing data loss and protecting company databases are vital to information technology resilience [37].
- External resources: external resources such as water, electricity, fuel, transportation, and sewage have a significant impact on organizational resilience during disaster recovery [37].
- Self-organization: self-organization is the manifestation of order in a system by internal forces. Self-organized systems are resilient systems, capable of coping with uncertainty and overcoming undesirable changes without external intervention [38].
- Teamwork: a team is an organizational unit composed of two or more people working together to achieve a shared goal. Teamwork can lessen and diminish organizational stress and pressure through mutual support [39].

- Learned resourcefulness: learned resourcefulness is individual skills that can manage unpredicted and unknown internal challenges. The human force can burgeon in emergencies with these acquired skills [31].
- Roles and responsibilities: redefining organizational roles and responsibilities at the time of disturbance can help an organization overcome the continuous turbulence in its business environment [37].
- Counter-intuitive agility: counter-intuitive agility refers to individual readiness and agility in vulnerable situations. Individuals with counter-intuitive agility are assets during organizational disturbance [12, 37].
- Planning strategies: planning and prospect for business continuity is a fundamental concern at organizations during crises. Contingency plans with specific duties and measures for undesirable events can help organizational resilience [30].
- Fault-tolerant: fault-tolerance represents safety and reliability. Fault-tolerant systems are resilient systems with the ability to recover quickly from total or partial failure [38].
- Recovery priorities: the ability to identify organizational priorities and operational needs during a crisis is an important factor in maintaining organizational resilience [38].
- Flexibility: Organizational changes are often viewed as undesirable events and threats. Flexible organizations can turn organizational changes into opportunities [14].

Figure 2 presents the hierarchical structure of the input and output indicators used in this study. Tables 1 and 2 present a comparison between the indicators and the algorithms utilized in this study compared with the competing methods.

Accordingly, the most important features of this article include:

- Integrating the concepts of quality management and resilience in trauma center evaluation
- Presenting a new model of organizational resilience grounded in the systems theory
- Developing an efficient framework for evaluating and improving quality management in trauma centers using factor analysis, machine learning, and statistical methods
- Developing a new tool to measure organizational resilience and quality management indicators in trauma centers

The remainder of this paper is organized as follows. In Sect. 2, we present the proposed framework. In Sect. 3, we apply the method proposed in this study to measure the performance at eight trauma centers. Section 4 offers our results and practical recommendations. In Sect. 5, we conclude with our conclusions and future research directions.
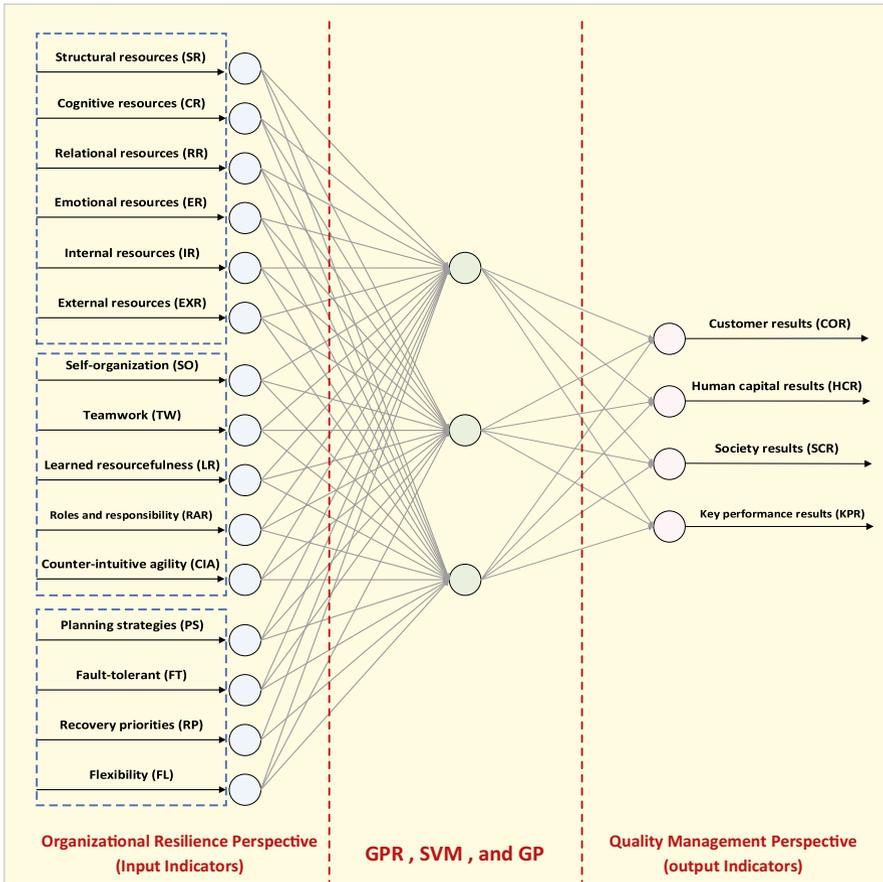
Fig. 2 The hierarchical structure of the input and output indicators

2 The Proposed Algorithm

The proposed algorithm includes six steps, as follows (Fig. 3):

Step 1: In this step, we identify a set of preliminary indicators through a literature review and then assess the relevance of these indicators with the help of experts.
Step 2: In this step, we confirm the indicators and design the basic model. We then design and distribute a questionnaire and determine the input and output variables used in the study.
Step 3: In this step, we test the reliability and validity of the questionnaire through a confirmatory indicator analysis. The rejected variables are removed, and the accepted variables are retained and validated for machine learning in step 4.
Step 4: In this step, we solve the problem with genetic programming (GP), support vector regression (SVR), and Gaussian process regression (GPR) by select-

Table 1 A comparison between the indicators used in this study and competing approaches

Study	Organizational resilience perspective															Quality management perspective			
	SR	CR	RR	ER	IR	EXR	SO	TW	LR	RAR	CIA	PS	FT	RP	FL	COR	SCR	HCR	KPR
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
McManus et al. [30]		✓			✓	✓				✓	✓	✓	✓						
Lengnick-Hall et al. [31]									✓					✓					
Richtner and Sodergren [22]	✓	✓	✓	✓															
Azadeh et al. [38]							✓	✓					✓		✓				
Annarelli and Nonino [27]						✓	✓	✓	✓		✓								✓
Melão et al. [40]		✓		✓		✓	✓	✓	✓							✓		✓	
Back et al. [33]					✓	✓	✓		✓	✓	✓		✓				✓		
Michalska [3]												✓				✓	✓	✓	
Lam and Bai [41]		✓	✓	✓		✓	✓			✓			✓						
Carayannis et al. [42]		✓	✓				✓		✓				✓						
HBO Expert Group [43]	✓	✓	✓				✓	✓					✓						
Hollnagel et al. [15]						✓							✓		✓				
Arsovski et al. [44]		✓	✓	✓	✓						✓		✓						
Chuang et al. [34]	✓		✓	✓	✓				✓			✓							

SR structural resources, *CR* cognitive resources, *RR* relational resources, *ER* emotional resources, *IR* internal resources, *EXR* external resources, *SO* self-organization, *TW* teamwork, *LR* learned resourcefulness, *RAR* roles and responsibilities, *CIA* counter-intuitive agility, *PS* planning strategies, *FT* fault-tolerant, *RP* recovery priorities, *FL* flexibility, *COR* customer results, *SCR* society results, *HCR* human capital results, and *KPR* key performance results

Table 2 A comparison between the methods used in this study and competing approaches

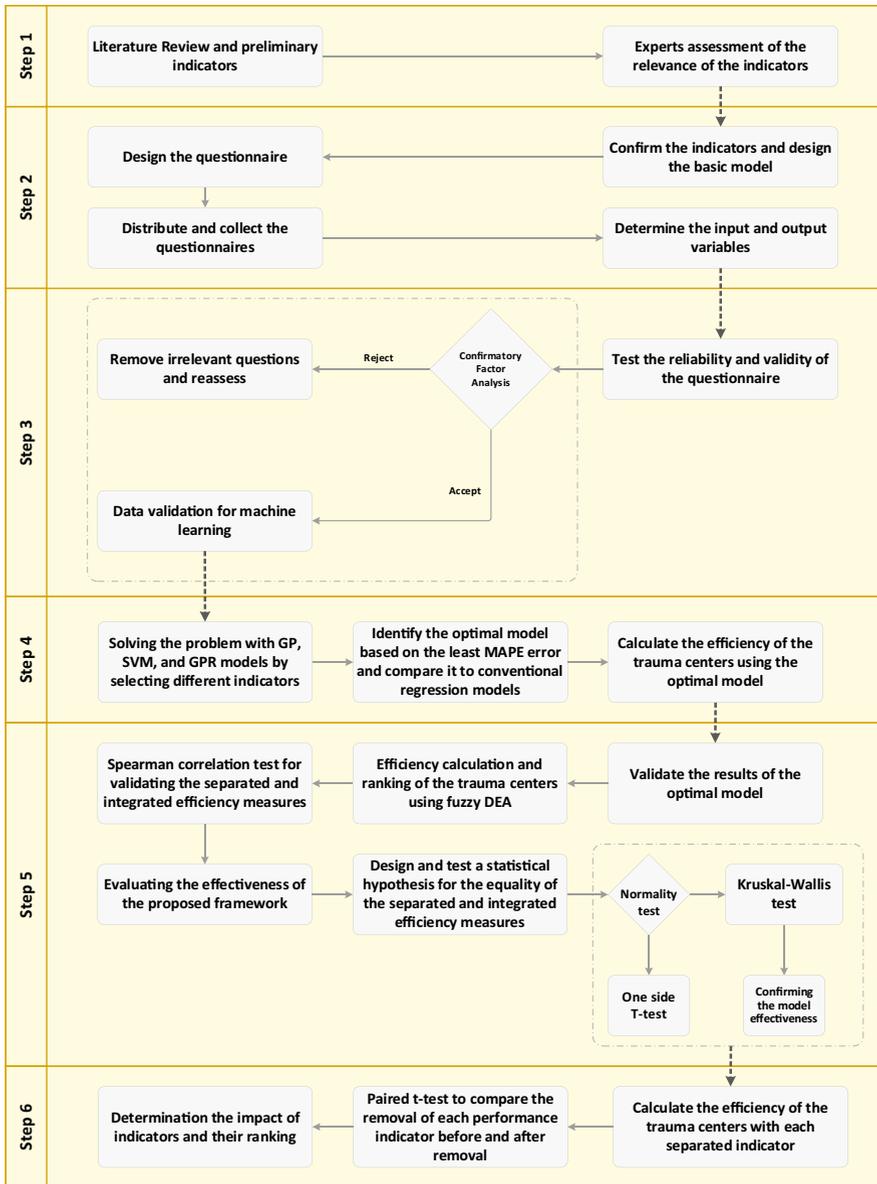| Study	Proposed integrated framework	GP	SVR	GPR	Fuzzy DEA	Noise analysis	Performance evaluation	Sensitivity analysis	Real-life case study
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓
Richtnér and Löfsten [21]				✓					✓
Azadeh et al. [38]					✓	✓	✓	✓	✓
Stephenson [24]						✓	✓		
McDermid et al. [35]						✓	✓	✓	
Morel et al. [20]		✓			✓		✓		✓
Basak et al. [45]		✓	✓			✓			✓
Shenify et al. [46]			✓	✓			✓		✓
Pal and Deswal [47]			✓						✓

Fig. 3 Proposed framework

ing different parameters. Next, we find the optimal model choice based on the lowest mean absolute percentage error (MAPE) error and compare it to the conventional regression models. We then calculate the efficiency of the trauma centers using the optimal model.

Step 5: In this step, we validate the optimal model results and then calculate the efficiency scores and rankings of the decision-making units (DMUs) using the fuzzy data envelopment analysis (DEA) method. The Spearman correlation test is used next to validate separate and integrated variables. We then evaluate the effectiveness of the conceptual framework. Next, we design and test a statistical hypothesis for equality of the separate and integrated efficiency measures. We then perform a normality test with a one-side t-test and Kruskal–Wallis test to confirm the model's effectiveness.

Step 6: In this step, we begin calculating the efficiency of the trauma centers with each separate indicator and use a paired t-test to compare the removal of each performance indicator before and after. The process ends by determining the impact of the indicators and their rankings.

In this paper, machine learning methods and modern data mining methods have been used to calculate the efficiency of DMUs. These methods have been selected according to the existing requirements and various advantages of each method. In this regard, some of the reasons for choosing these methods are the following:

GP method: determining the optimal model structure and coefficients during the training process after defining the block structure (input variables, target, and sum of functions) and using it in domains where the exact form of the answer is not known or the approximate answer is acceptable

GPR method: the comprehensiveness of this method due to the correspondence of the dataset with a Gaussian process

SVR method: used in complex and nonlinear structures to separate data.

2.1 Genetic Programming

GP is an evolutionary approach motivated by biological evolution where computer programs are used to perform a specific task. GP is developed by Koza [48] based on the Darwinian theory [49]. This method is the forerunner of learning, which is the essence of symbolic regression model using the basic natural selection theory proposed by Darwin. GP is different from other machine learning algorithms, such as genetic algorithms and the neural web, because the range of its solutions is not predetermined. GP is a technique for automatic programming in which a population left the improper population to evolve optionally and produce corrected children. Contrary to the genetics algorithm of tree structures of equations, GP uses a series of binary digits [50] by creating a random population from individuals like a tree which consists of two essential parts called functions (operators) and terminals (variables and constants) [51]. The functions and terminals are selected from a set of operators and a set of variables and constants, respectively. For example, the function for set F can consist of mathematical operators, and the terminal for set T can consist of constant numbers, logical constants, and variables. Logical functions are randomly selected and end like a tree model, including root points and branches that are extended from each function. Figure 4 shows how a tree of GP is formed, for example, like Eq. (1).

Fig. 4 Genetic programming
diagram for Eq. (1)
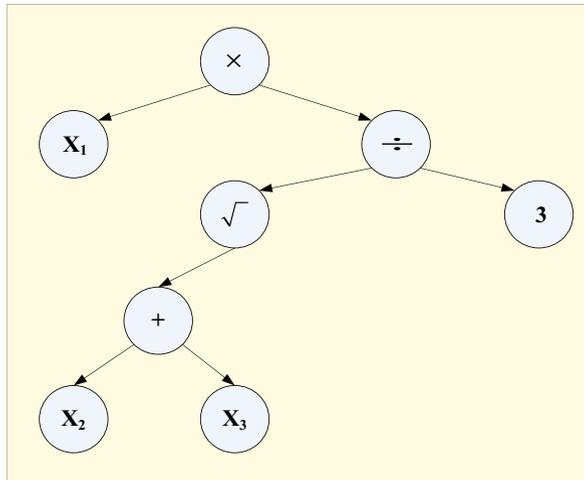
$$x_1 \cdot \frac{\sqrt{(x_2 + x_3)}}{3} \tag{1}$$

2.2 Gaussian Process Regression

The Gaussian process is a useful method for defining the leading distributions for flexible regression models and categorization. The regression of probability functions is not confined to simple parametric forms. One of the attractions of the Gaussian process is the wide variety in its covariance functions, which results in the creation of functions with different degrees or different structures [52]. These models can identify distributions between functions with one or more input parameters. When several average response functions in a regression model with Gaussian errors are defined, these matrices can be used to deduce [53]. This is possible for datasets with more than 1000 samples. The Gaussian process is an important statistical model with normal features. It is possible to consider n observations in an arbitrary dataset like a sampled single point of multiple variable Gaussian distributions so that the datasets can be correspondent using a Gaussian process. Although Gaussian processes are simple, they are pervasive. The average of the correspondent Gaussian limit process is often assumed zero at every point. It is the covariance function $k(x, x')$ that connects one observation to another in such cases. Each y observation can be connected to the main function through the Gaussian noise model:

$$y = f(x) + N(0, \sigma_f{}^2) \tag{2}$$

where $N(0, \sigma_f^2)$ is the noise of normal distribution function with an average of zero and sigma2 variance. Regression is a search for $f(x)$. The new method of combining noise in $k(x, x')$ is used to simplify the process and develop Eq. (3):

$$k(x, x') = \sigma_f{}^2 \exp\left[\frac{-(x - x')^2}{2\tau^2}\right] + \sigma_n{}^2 \delta(x, x') \tag{3}$$

where $\delta(x, x')$ is the function of Kernel delta. Therefore, n observations are considered as y, and the goal is to predict y_0, but not the real f_*. According to Eq. (3), the predicted values are the same, but variances differ because of the observations. To prepare the GPR of the covariance function, Eq. (3) will be calculated between all possible combinations of two points, and the findings will be explained briefly in two matrices (4) and (5):

$$k = \begin{bmatrix} k(x_1, x_1) & k(x_1, x_2) & \dots & k(x_1, x_n) \\ k(x_2, x_1) & k(x_2, x_2) & \dots & k(x_2, x_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(x_n, x_1) & k(x_n, x_2) & \dots & k(x_n, x_n) \end{bmatrix} \tag{4}$$

$$k_* = \begin{bmatrix} k(x_*, x_1) & k(x_*, x_2) & k(x_*, x_n) \end{bmatrix}, \quad k_{ij} = k(x_i, x_j) \tag{5}$$

where the k diagonal elements are in the form of σ_f^2. Whenever x chooses an approximately large range, the diagonal elements tend to be zero.

2.3 Support Vector Regression

The machines of support vector consist of two groups: support vector classification and SVR. A support vector machine is one of the learning methods with supervision. Vapnik (1995) introduced a support vector machine based on the statistical learning theory, where complex and nonlinear structures are used to separate the data. This is done by using a set of mathematical functions called Kernel support vector machine maps and recovers the main data [46, 54]. This activity is called converting the map. An algorithm of support vector machine searches for a hyperplane with a maximum margin. From a geometrical point of view, the margin is the distance between the hyperplane and the closest educational samples [55]. The shortest distance from the hyperplane to samples with label $+1$ is equal to the shortest distance from the same hyperplane to samples with label -1 [45]. The margin is calculated by doubling this distance. Figure 5 demonstrates a scheme of the SVR model. A separating hyperplane can be defined as Eq. (6):
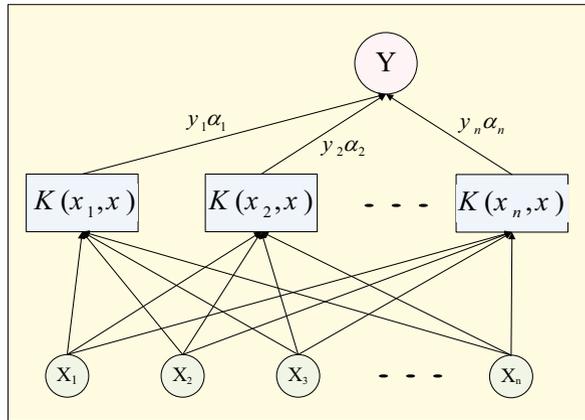
$$W.X + b = 0 \tag{6}$$

where $W = [w_1, w_2, \dots, w_n]$ is a vector that the number of members existing in it is equal to the specific features and b is considered a constant value.

In two-dimensional space where datasets are defined by two specific features and one class label, if we assume $b = w0$, Eq. (6) can be rewritten as Eq. (7):

$$w_0 + w_1 x_1 + w_2 x_2 = 0 \tag{7}$$

Fig. 5 Support vector machine process

Thus, samples that are placed in the space above this hyperplane, and samples that are placed in the space below this hyperplane, complete the inequalities (8) and (9), respectively.

$$w_0 + w_1 x_1 + w_2 x_2 > 0 \tag{8}$$

$$w_0 + w_1 x_1 + w_2 x_2 < 0 \tag{9}$$

$$w_0 + w_1 x_1 + w_2 x_2 \geq 1 \quad if \quad y_1 = +1 \tag{10}$$

$$w_0 + w_1 x_1 + w_2 x_2 \leq -1 \quad if \quad y_1 = -1 \tag{11}$$

By adjusting the values of *w* and b in Eqs. (10) and (11), we will have:

This means, every sample placed on the hyperplane H1 belongs to class + 1, and every sample placed on or below hyperplane H2 belongs to class − 1. Each sample that is placed exactly on hyperplane H1 and H2 is called "support vector."

2.3.1 Kernel Function

One of the common methods to solve nonlinear problems is to use Kernel functions. These functions are defined based on the internal multiplication of the assumed data. Designing Gaussian process-based regression methods also involves the usage of the Kernel function concept. The problems can become separable in a linear manner using a nonlinear conversion from input space into feature space with more dimensions. The nonlinear separator will become linear by converting samples form input space into feature space. Each of these kernel functions has some parameters in their structure known as hyper-parameter [47]. For example, the radial basis function (RBF) has gamma and C hyper-parameter, and Pearson function has sigma and omega hyper-parameter. Determining the optimal value of parameters related to each function is very important when applying the optimal Kernel function-based methods. The equation is shown in Eq. (12):

Table 3 Kernel functions used in this study

Kernel name	Kernel function
Polynomial	$k(x_i, x_j) = (x_i.x_j + 1)^d$
Radial basis function (RBF)	$k(x_i, x_j) = \exp\left(-\gamma||x_i - x_j||\right)$
Sigmoid	$k(x, y) = \tanh\left(\alpha x^T y + c\right)$
Pearson	$k(x_i, x_j) = \dfrac{1}{\left[1 + \left(2\sqrt{x_i.x_j^2}\sqrt{2^{\frac{1}{w}} - \frac{1}{\sigma}}\right)^2\right]^w}$

$$w^T \varphi(x_j) + b = 0 \tag{12}$$

While the primary and the dual cases form a special space, the difference is that $k(x_i), x_j = \phi^T(x_i).\phi(x_j)$ has been used instead of (x_i^T, x_j). $k(x_i, x_j)$ as the kernel function to linearize the nonlinear problem. Table 3 shows the names and kernel functions used in this study. The codes used for GPR, SVR, and GP are presented in Tables 16, 17, and 18 in Appendix 2.

3 Case Study

This study was conducted for the Department of Health in Iran to study the efficiency of eight trauma centers in Tehran Province (see Table 4 for the participating centers). These centers are located in Tehran and have affiliated facilities such as pharmacy, operating room, emergency center, and specialized clinics. Also, some features like admission capacity, number of beds, and number of specialists are different. Due to access restrictions during the coronavirus disease pandemic, these eight centers have been selected to cover the necessary support throughout the city of Tehran.

We distributed 240 questionnaires to the medical staff in these eight trauma centers. The first part of the questionnaire asked for general and background information about the respondents. The second part focused on 15 organizational resilience indicators and formed the input segment of the algorithm. The third part focused

Table 4 Trauma centers

DMU	Trauma centers
1	Imam Khomeini Hospital
2	Bahonar Hospital
3	Shariati Hospital
4	Rajair Hospital
5	Kosar Hospital
6	Kasra Hospital
7	Sadegh Hospital
8	Takhte Jamshid Hospital

on the EFQM results concerning four quality management indicators and formed the output segment of the algorithm. A Likert scale ranging from 1 (very little) to 5 (very much) was used for scoring purposes. With a 67% return rate, we received 160 usable responses. The questionnaire used in this study is presented in Table 5 in Appendix 1.

3.1 Questionnaire Reliability and Validity

The validity and reliability of the questionnaire were tested using confirmatory factor analysis (CFA), Cronbach's alpha, and composite reliability (CR). Cronbach's alpha and CR are the most widely used methods for internal consistency and reliability, with a threshold value of over 0.70 Hair et al. [56]. The average variance extracted (AVE) was used for the convergent validity of each construct, and the recommended threshold values are above 0.50. A structural equation modeling based on partial least squares was adopted for the validity and reliability of the questionnaire through SmartPLS 2.0 software. As shown in Table 5, all 19 constructs had a Cronbach's alpha and CR greater than 0.75 and AVE greater than 0.5. All factor loadings for the CFA were also significant and greater than 0.7.

Table 5 Data reliability

Perspective	Indicator	Cronbach's alpha	CR	AVE*
Organizational resilience	**Structural resources (SR)**	0.818	0.893	0.550
	Cognitive resources (CR)	0.863	0.892	0.725
	Relational resources (RR)	0.862	0.907	0.735
	Emotional resources (ER)	0.882	0.918	0.777
	Internal resources (IR)	0.875	0.944	0.751
	External resources (EXR)	0.891	0.905	0.794
	Self-organization (SO)	0.843	0.924	0.831
	Teamwork (TW)	0.876	0.954	0.830
	Learned resourcefulness (LR)	0.904	0.914	0.780
	Roles and responsibilities (RAR)	0.852	0.923	0.856
	Counterintuitive agility (CIA)	0.831	0.815	0.869
	Planning strategies (PS)	0.864	0.901	0.761
	Fault-tolerant (FT)	0.894	0.865	0.802
	Recovery priorities (RP)	0.921	0.974	0.867
	Flexibility (FL)	0.810	0.832	0.723
Quality management	**Customer results (COR)**	0.831	0.865	0.733
	Human capital results (HCR)	0.759	0.908	0.709
	Society results (SCR)	0.762	0.965	0.865
	Key performance results (KPR)	0.821	0.892	0.696

*Average variance extracted

3.2 Efficiency Score Estimation

The efficiency score estimation is conducted by considering the 15 organizational resilience indicators as the inputs and four quality management indicators (EFQM results) as the outputs. GP, GPR, and SVR are used to calculate the efficiency scores of the DMUs. A comparative MAPE error is used to analyze the results and select the optimal model. For the Gaussian model process, sigmoid, polynomial, quadratic, and RFB kernels were used due to their high fitness ability. Details of the parameters used in the models are shown in Tables 6 to 7. Next, certain levels of noise were applied to the input data for each model to find the exact amount of noise needed in the input data to make a significant change in the results. We determined a 20% noise applied a significant change in the results. This value was selected as an indicator for the selection of optimal model before and after noise. After that, we examined the results to find the level of parameters that show the minimum sensitivity to the created noise in each model. Thus, the 20% noise was applied to the input data, and then the extent of sensitivity of the model at a different level of parameters to the created noise was examined. Tables 6, 8, and 7 show the outputs of the estimation of quality indicators using different parameters and MAPE error for the GPR, SVR, and GP models, respectively. Table 6 shows the MAPE error of the GPR model with specified kernels of sigmoid, polynomial, quadratic, and RBF and also specified parameters of N Restarts Optimizer (NRO) by values 6, 12, and 20 on their kernels in estimating the output indicators. Table 8 shows the MAPE error of the SVR model with specified kernels of sigmoid, polynomial, quadratic, and RBF and also specified parameters of gamma and C on their kernels in estimating the output indicators. Table 7 shows the MAPE error of the GP model with different population sizes and also specified parameter of link function and mutation rate on their population in estimating the output indicators. The collective results from Tables 6,

Table 6 Different GPR structures and their related MAPE	Model No.	Kernel	NRO*	MAPE			
				COR	HCR	SOR	KPR
	1	Quadratic	6	0.141	0.178	0.228	0.138
	2	Quadratic	12	0.131	0.138	0.164	0.182
	3	Quadratic	20	0.185	0.170	0.155	0.147
	4	Polynomial	20	0.133	0.127	0.186	0.132
	5	Polynomial	6	0.167	0.159	0.161	0.194
	6	Polynomial	12	0.164	0.166	0.126	0.134
	7	RBF	9	0.123	0.134	0.175	0.152
	8	RBF	15	0.111	0.227	0.222	0.166
	9	RBF	20	0.144	0.129	0.217	0.119
	10	Sigmoid	12	0.184	0.157	0.128	0.140
	11	Sigmoid	9	0.157	0.210	0.164	0.129
	12	Sigmoid	18	0.119	0.115	0.177	0.133

*N Restarts Optimizer

Table 7 Different SVR structures and their related MAPE

Model no.	Kernel	Gamma	C	MAPE			
				COR	HCR	SOR	KPR
1	Quadratic	0.01	e^1	0.196	0.202	0.207	0.261
2	Quadratic	0.1	12	0.218	0.193	0.179	0.289
3	Quadratic	0.9	e^3	0.223	0.197	0.209	0.243
4	Polynomial	0.01	15	0.211	0.211	0.211	0.255
5	Polynomial	0.1	e^3-e^1	0.169	0.199	0.205	0.239
6	Polynomial	0.9	9	0.211	0.192	0.226	0.246
7	RBF	0.01	12	0.200	0.219	0.197	0.267
8	RBF	0.1	e^2	0.201	0.197	0.158	0.219
9	RBF	0.9	20	0.219	0.188	0.219	0.204
10	Sigmoid	0.01	6	0.209	0.224	0.211	0.229
11	Sigmoid	0	e^3	0.188	0.187	0.206	0.259
12	Sigmoid	0.9	18	0.196	0.177	0.179	0.267

8, and 7 show that the average MAPE error of GP on output indicators is lower than SVR and GPR models, and it is selected as the optimal model for calculating the efficiency of the DMUs.

A comparison between the optimal model and the conventional regression methods presented in Table 9 shows the average MAPE error in the GP model is lower than the average MAPE error in the conventional regression methods. This confirms the performance of the GPI model as the optimal model. The efficiency values of all the departments (DMUs) and their rankings using Python 3.6 software are reported in Table 10.

Table 8 Different GP structures and their related MAPE

Model no.	Population size	Link function	Mutation rate	MAPE			
				COR	HCR	SOR	KPR
1	30	Addition	0.01	0.100	0.127	0.180	0.113
2	40	Subtraction	0.01	0.137	0.142	0.143	0.121
3	60	Multiplication	0.02	0.121	0.124	0.153	0.116
4	90	Subtraction	0.06	0.147	0.110	0.148	0.103
5	35	Division	0.05	0.114	0.142	0.152	0.131
6	50	Addition	0.02	0.162	0.125	0.138	0.102
7	55	Division	0.05	0.139	0.109	0.169	0.116
8	85	Addition	0.04	0.116	0.113	0.142	0.097
9	80	Subtraction	0.07	0.153	0.108	0.171	0.129
10	45	Division	0.01	0.119	0.129	0.125	0.120
11	70	Multiplication	0.06	0.149	0.131	0.137	0.114
12	95	Multiplication	0.03	0.129	0.127	0.119	0.131

Table 9 A comparison between the optimal model and the conventional regression methods

Model	MAPE			
	COR	**HCR**	**SOR**	**KPR**
Linear regression	0.141	0.139	0.176	0.124
Quadratic regression	0.139	0.134	0.168	0.119
Logistic regression	0.143	0.141	0.151	0.135
Optimal model	0.132	0.123	0.148	0.116

3.3 Verification and Validation

DEA is a non-parametric mathematical programming approach for estimating the relative efficiency of homogeneous DMUs performing with multiple inputs and multiple outputs. The conventional DEA requires precise measurement of the input and output data. However, previse data is often not available in real-world problems with uncertain or ambiguous input and output data. Fuzzy DEA has been used to handle uncertain or imprecise values for the input and output data [57]. Model (13) shows the fuzzy CCR model.

$$Max \ \theta_p = \sum_{r=1}^{s} u_r \tilde{y}_{rp}$$

$$s.t.$$

$$\sum_{i=1}^{m} v_i \tilde{x}_{ip} = 1 \tag{13}$$

$$\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} \leq 0 \qquad j = 1, ..., n$$

Table 10 Efficiency and ranking of the DMUs with full indicators

DMU	Efficiency	Rank
1	0.75708	4
2	0.78744	3
6	0.73083	3
4	0.79349	2
5	0.67835	5
6	0.86835	1
7	0.58348	8
8	0.64238	7
Mean	0.72017	-

$$u_r, v_i \geq 0 \qquad r = 1, ..., m \; ; \, r = 1, ..., s$$

In this model, the efficiency of the DMUp is equal to θ_p, and v_i and u_r are the weight coefficients for the inputs and outputs, respectively. "~" represents the fuzziness of the input and output data in the model. Triangular and trapezoidal fuzzy numbers are two functions and fuzzy numbers widely used in DEA. It is necessary to convert the input data into fuzzy numbers to implement the fuzzy DEA model. In this paper, the mean and standard deviation have been used to construct the left and the right boundaries of the triangular fuzzy numbers (the input of the FDEA model).

The α-cut approach is used to change Model (13) into the interval linear programming Model (14) as follows:

$$Max \; \theta_p = \sum_{r=1}^{s} u_r (\alpha y_{rp}^m + (1 - \alpha) y_{rp}^l, \alpha y_{rp}^m + (1 - \alpha) y_{rp}^u)$$

$$s.t.$$

$$\sum_{i=1}^{m} v_i (\alpha x_{ip}^m + (1 - \alpha) x_{ip}^l, \alpha x_{ip}^m + (1 - \alpha) x_{ip}^u) = 1 \qquad (14)$$

$$\sum_{r=1}^{s} u_r (\alpha y_{rj}^m + (1 - \alpha) y_{rj}^l, \alpha y_{rj}^m + (1 - \alpha) y_{rj}^u)$$
$$- \sum_{i=1}^{m} v_i (\alpha x_{ij}^m + (1 - \alpha) x_{ij}^l), \alpha x_{ij}^m + (1 - \alpha) x_{ij}^u \leq 0 \quad \forall j = 1, ..., n$$

$$u_r, v_i \geq 0 \qquad i = 1, ..., m \; ; \, r = 1, ..., s$$

4 Results and Discussion

Based on the obtained results, DMU 6, with an efficiency score of 0.86835, is selected as the most efficient trauma center. DMU 7, with an efficiency score of 0.58348, is selected as the least efficient (most inefficient) trauma center. In addition, the average efficiency of all eight trauma centers is 0.72017. The primary analyses show that about 37% of trauma centers (three trauma centers) have an efficiency score of lower than the average efficiency, and the other 63% (five trauma centers) have an efficiency score of higher than the average efficiency. Therefore, according to the primary analyses, a relatively considerable proportion of the performance of the trauma centers is generally acceptable. Furthermore, the performance of those trauma centers that showed an efficiency score of lower than the average efficiency

could be improved to a large extent if the hospitals adopt the proper and corrective measures. For example, by correcting the managerial and relational methods and improving the evaluated indicators, the efficiency score of DMU 5 can be increased by 15%, moving this trauma center to the list of efficient centers.

4.1 Verification and Validation of the Results

In this section, the results obtained from the efficiency score of the trauma centers are verified and validated using the fuzzy DEA model. Noise analysis has been applied to calculate the efficiency of the trauma centers due to different alpha-cut in the FDEA model. In this regard, the alpha level at which the model has the least sensitivity to generating noise is selected as the optimal alpha level. Noise analysis is performed based on changes in input data and examines the sensitivity of the model to these changes. Therefore, an acceptable alpha level is the one with the least sensitivity to data change.

In this study, noise analysis was used to determine the alpha level showing the least sensitivity to the introduced noise (optimal model). A 20% noise (change) was applied to the input data for 10% of DMUs to examine the sensitivity of the fuzzy DEA model at different alpha-cuts. The noise analysis and correlation results of the efficiency scores before and after the noise are reported in Table 11 for each alpha-cut. As shown in Table 11, the fuzzy DEA model at the alpha level of 0.6 has the highest correlation coefficient for the efficiency values before and after applying the noise and the lowest amount of sensitivity. Furthermore, the Kruskal–Wallis test confirms the assumption of the equality of efficiency value averages before and after noise at this alpha level of 0.051. In addition, the fuzzy DEA model with the alpha level of 0.6 is selected as the optimal performance measurement model. Table 12

Table 11 Results before and after noise analysis

Alpha-cut	Efficiency before noise	Efficiency after noise	Kruskal–Wallis (*p*-value)
$\alpha=0.01$	0.61745	0.81232	0.003
$\alpha=0.05$	0.55848	0.71624	0.001
$\alpha=0.1$	0.70238	0.89615	0.002
$\alpha=0.2$	0.82835	0.84105	0.001
0.019	0.77119	0.75708	$\alpha=0.3$
$\alpha=0.4$	0.79340	0.71011	0.049
$\alpha=0.5$	0.69344	0.72148	0.079
$\alpha=0.6$	0.86954	0.87168	0.087
$\alpha=0.7$	0.75781	0.77159	0.019
$\alpha=0.8$	0.68348	0.78216	0.003
$\alpha=0.9$	0.74495	0.76110	0.005
$\alpha=0.95$	0.52855	0.64585	0.008
$\alpha=0.99$	0.69325	0.79364	0.802
$\alpha=1$	0.70238	0.72774	0.712

Table 12 A comparison between the optimal model and fuzzy DEA efficiency (at $\alpha = 0.06$)

DMU	Efficiency		Ranking	
	Optimal model	Fuzzy DEA	Optimal model	Fuzzy DEA
1	0.75708	0.65480	4	5
2	0.78744	0.80125	3	1
3	0.73083	0.74215	6	3
4	0.79349	0.78452	2	2
5	0.67835	0.64213	5	6
6	0.86835	0.72365	1	4
7	0.58348	0.45144	8	8
8	0.64238	0.59235	7	7

presents efficiency scores, rankings, and the correlation test (ranked Spearman correlation coefficient) results for the optimal model. The high value of the correlation coefficients between the results of the optimal model and the fuzzy DEA confirms the validity of the obtained results.

4.2 Sensitivity Analysis

The effectiveness (confirmation) of the proposed conceptual model, including the indicators of the comprehensive organizational resilience model and quality management indicators, was determined after ensuring the validity of the obtained results. In this regard, first, the unit efficiency values were calculated for each category of organizational resilience indicators separately using the optimal programmatic model, and then the results of each of them were compared with the results of the comprehensive model including all indicators. The Kruskal–Wallis nonparametric test has been used to statistically investigate this issue and evaluate the differences between the obtained results. According to this, the hypothesis of equality of the mean of the groups (results) is tested as the null hypothesis.

Here, the null hypothesis $\mu_{\text{Integrated}} = \mu_i$ and the opposite hypothesis $\mu_{\text{Integrated}} > \mu_i$ or $\mu_{\text{Integrated}} < \mu_i$ are considered for the paired t-test, in which $\mu_{\text{Integrated}}$ the means average values of the unit performance in the initial state (in the presence of all indices) and μ_i the mean values obtained by deleting the i index. The mean of the efficiency values was obtained by removing the ith index.

The results obtained in Table 13 show a significant difference between the values of efficiency obtained by considering each category of indicators separately and the results of the integrated model. Therefore, simultaneous consideration of comprehensive indicators in organizational resilience leads to higher performance values for the trauma centers under consideration. Hence, the effectiveness of the integrated conceptual model presented in this study is confirmed. Furthermore, in this section, we evaluate the influence of the organizational resilience indicators on the performance of the trauma centers. Indicators are weighted according to their

Table 13 Comparison of the results obtained from the integrated concept model with the results of each category of indicators separately

| Indicators | Average efficiency | Kruskal–Wallis test | | Comparison of average efficiency values |
		Null hypothesis	*p*-value	
Integrated	$\mu_{\text{Integrated}} = 0.8842$	–	–	–
Quality management	$\mu_{QM} = 0.72542$	$\mu_{\text{Integrated}} = \mu_{QM}$	0.000	$\mu_{Integrated} > \mu_{QM}$
Organizational resilience	$\mu_{OR} = 0.7856$	$\mu_{\text{Integrated}} = \mu_{OR}$	0.000	$\mu_{Integrated} > \mu_{OR}$

influence, and the most influencing (important) indicators are identified. To this end, the evaluation indicators are removed one by one, and the efficiency scores are recalculated using machine learning and the optimal model for each removal case. This task is accomplished by calculating the average efficiency scores for each removal step and comparing them to the average efficiency scores in the presence of all indicators. The paired t-test is used to compare the efficiency results before and after each removal case. The efficiency scores calculated with the optimal model for all removal cases are presented in Table 14.

According to the results, the equality assumption of averages in the t-test for the teamwork indicators, explored ability, visual agility, error tolerance, and society results are not rejected. This finding shows that these indicators do not have a significant influence on the performance of the trauma centers. Furthermore, the results reject the equality assumption of averages for the remaining indicators because the removal of each remaining indicator causes a noticeable change in the calculated efficiency scores. Next, the efficiency score average of all trauma centers is compared before and after each indicator removal to determine the direction of the influence. If the efficiency score average after the removal of an indicator is increased, it means the removed indicator has a negative influence on the system as a whole. On the other hand, if the efficiency score average after the removal of an indicator is decreased, it means the removed indicator has a positive influence on the system as a whole. The results show that the efficiency score averages of the trauma centers after the removal of the customer results, cognitive resources, roles and responsibilities, human capital results, self-organization, relational resources, external resources, performance key results, internal resources, recovery priorities, and programming strategies have decreased compared to the all-inclusive case. The obtained indicator weight values (influence percentages) show that customer results, cognitive resources, and roles and responsibilities have the strongest positive influence on the performance of the trauma centers, while the society results indicator has the least positive influence on the performance. The weight (influence percentage) of each indicator is also achieved through the calculation of the percentage difference between the efficiency averages before and after each removal case (see Fig. 6) (Table 15).

Table 14 Efficiency score results for the one-by-one indicator removal cases

DMU	KPR	SCR	HCR	COR	FL	RP	FT	PS	CIA	RAR	LR	TW	SO	EXR	IR	ER	RR	CR	SR
	Removed indicator																		
1	0.6925	0.8121	0.7156	0.6954	0.7145	0.7074	0.6825	0.6927	0.7231	0.6542	0.6947	0.6521	0.7495	0.6820	0.8027	0.7548	0.6845	0.7091	0.6785
2	0.7328	0.7529	0.7128	0.7155	0.6585	0.7862	0.6931	0.6936	0.8064	0.6952	0.7124	0.7212	0.7825	0.6918	0.7646	0.6874	0.7288	0.7221	0.7641
3	0.7209	0.7427	0.7245	0.6825	0.7625	0.7936	0.7529	0.7572	0.6634	0.6714	0.7452	0.7549	0.7265	0.7258	0.7264	0.7259	0.7347	0.7127	0.6967
4	0.6873	0.6854	0.7411	0.7311	0.7420	0.7021	0.7020	0.7138	0.7950	0.6825	0.7365	0.7698	0.6914	0.7169	0.7370	0.7120	0.6958	0.6852	0.7152
5	0.6925	0.7123	0.7052	0.7114	0.6621	0.7552	0.7519	0.7079	0.7547	0.6917	0.7664	0.8029	0.6826	0.7049	0.6845	0.7254	0.7442	0.6456	0.7564
6	0.6875	0.7224	0.6913	0.6420	0.7774	0.6725	0.7846	0.7446	0.6728	0.7214	0.7124	0.7317	0.6722	0.7519	0.6752	0.6856	0.6785	0.6793	0.6849
7	0.7239	0.7151	0.7917	0.6719	0.7625	0.694	0.7637	0.7530	0.7129	0.7521	0.7718	0.7119	0.7018	0.7836	0.6930	0.7749	0.7656	0.7364	0.7567
8	0.7529	0.6856	0.6995	0.6991	0.7193	0.6982	0.6982	0.7196	0.7036	0.7634	0.7026	0.6814	0.7164	0.7039	07,125	0.6998	0.7147	0.6895	0.7199
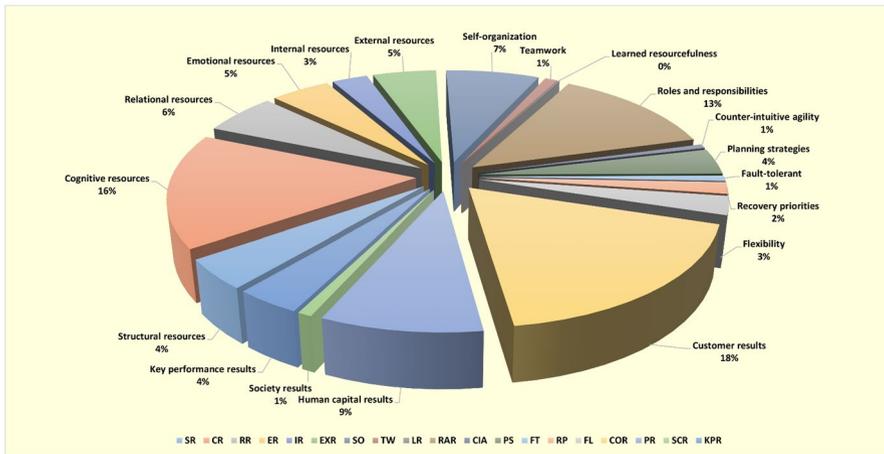
Fig. 6 Importance weights of indicators

5 Managerial Implications

Given the importance of quality management in the health sector, especially trauma centers, evaluating the quality performance of these centers is significant. In addition, due to the specific, sensitive, and complex circumstances, these centers may encounter various risks and disruptions that directly impact the importance of the resiliency approach. The resiliency approach is a relatively new concept that refers to organizations' ability to deal with predicted and unpredictable risks. Therefore, in this study, by integrating quality management indicators and a comprehensive model of organizational resilience, trauma centers were evaluated, and the impact of each of these indicators on the quality of these units was examined and analyzed. In this regard, the following measures were taken:

- Designing and defining a new and comprehensive model for organizational resilience
- Designing a standard questionnaire based on the basic indicators of EFQM results and organizational resilience to evaluate and improve quality
- Applying exploratory and confirmatory factor analysis methods to evaluate the reliability and validity of the questionnaire
- Using correlation matrix to determine the type and extent of each of the indicators of quality management and organizational resilience to each other
- Determining the efficiency of trauma centers through the use of machine learning algorithms including genetic programming models GP, SVR, and GPR
- Selecting the optimal model by measuring the MAPE error
- Validating the proposed model using two methods of fuzzy DEA and PCA in both indefinite and definite cases
- Calculating the effectiveness by using the correlation test between the performance results obtained from the integrated framework and the performance results

- Evaluating the effect of the studied indicators on the performance of trauma centers using statistical tests

In addition, some suggestions are recommended to increase the applicability of the proposed framework. Recommendations based on features such as geographical locations and capacity. Accordingly, the implications of this study are as follows:

- Since hospitals and trauma centers are considered one of the most critical and sensitive service centers, the safety and satisfaction of patients are essential.
- Hospital and trauma center managers can use the results of this framework as an effective tool to monitor quality management and improve its outcomes as a comprehensive and effective decision support framework.
- Managers can expand the number of centers by increasing resources (time, workforce, and cost).

6 Conclusion

In this study, we introduced an integrated data mining framework for organizational resilience assessment and quality management optimization in trauma centers. We used EFQM and proposed a unique intelligent algorithm composed of parametric and non-parametric statistical methods to determine the type and the extent of influence within the organizational resilience and quality management perspectives. Structural equation modeling was used to examine the reliability and validity of the input data. The efficiency of the trauma centers was then measured using machine learning with GP, SVR, and GPR. The MAPE was used to determine the optimal model. Finally, a fuzzy DEA model was used to verify and validate the results obtained from the optimal model. The results show that customer, human capital, and critical performance results had the highest weight and positive influence among the quality management indicators. This finding supports the importance of customer satisfaction in trauma centers. Cognitive resources, roles and responsibilities, and self-organization have the highest weight and positive influence among the organizational resilience indicators. The framework proposed in this study is applicable to other industries besides healthcare. Furthermore, the model proposed in this study is confined by two dimensions (quality management and resiliency) for evaluating the performance of trauma centers. Future studies can incorporate other dimensions in the model, including but not limited to environmental (green), customer trust, agility, and lean in their evaluation process. It is also suggested to use fuzzy cognitive map (FCM) methods or system dynamics to study and analyze the cause and effect relationships between indicators. It should be noted that artificial intelligence approaches such as artificial neural networks and adaptive neural-fuzzy inference systems are efficient methods for considering the complexities and non-linear relationships between indices. Therefore we suggest using these methods and techniques to obtain the efficiency and ranking of trauma centers and optimize them.

Appendix 1

Table 15 The data collection questionnaire

Organizational resilience perspective	**Structural resources (SR)**	• Trauma center organizational rules are explicit and understandable. • My authority in decision making is apparent. • This trauma center has enough financial resources and equipment. • The trauma center organizational structure makes the works more accessible. • I think I know about all the events and news in my department in the trauma center at the moment.
	Cognitive resources (CR)	• I can easily use the knowledge of my colleagues in the department where I work. • The held education courses have had a positive impact on my performance. • The experts and experienced people have been used in this department. • In this unit, job training is essential for interns. • In this department, different people are responsible for various problems.
	Relational resources (RR)	• I use my colleagues' assistance in other hospitals and have excellent communication with them. • The trauma center has excellent communication with stakeholders, well known, and talented people. • The network of teams and persons in this trauma center is robust. • To better communicate with the trauma center with other departments, some replacements happen periodically.
	Emotional resources (ER)	• I would like to try more than all that is expected of me to achieve the hospital's success and excellence. • There is a being a benevolent atmosphere among staff in this department. • Everyone in this department is doing the best. • In this trauma center, good ideas are heard and encouraged without any criticism. • I have confidence in my colleagues in the trauma center.
	Internal resources (IR)	• When it occurs a problem in the trauma center, internal resources are readily available in the short run. • How much do you think the current building can handle crises. • All equipment used in the trauma center meets the required standards. • If senior executives are not present, employees can make decisions. • In part I work, I make necessary decisions in times of emergency.
	External resources (EXR)	• What do you think the hospital is successful concerning suppliers? • In times of crisis, the trauma center always arranges contracts to provide equipment with other companies. • I believe that this hospital can quickly access foreign resources with its external connections • How much can the trauma center in critical situations still provide excellent service? • I believe this trauma center has enough resources for its daily activities
	Self-organization (SO)	• Organizational structure has given me specific powers to decide to deal with sudden accidents and critical situations, without going through the hierarchy. • The hospital is collaborating with other organizations to handle other economic shocks. • The hospital is continuously communicating with patients to manage critical situations and events.
	Teamwork (TW)	• There is a spirit of partnership and cooperation among the employees in the trauma center. • Creativity is a job requirement in the trauma center. • Originality and initiative are required skills for success in a trauma center.
	Learned resourcefulness (LR)	• The trauma center has a challenging work environment with unpredictable circumstances. • I am prepared to take on accidents and critical situations. • The trauma center can handle disturbance and crisis.
	Roles and responsibilities (RAR)	• If key people are absent in the trauma center during a crisis, replacements are available to take charge • In critical situations, the organization can quickly switch from regular to critical mode. • Priorities are clear during and after the crisis • I believe that the current emergency priorities are sufficient and affordable to overcome any crisis.
	Counter-intuitive agility (CIA)	• The hospital has a variety of competitive actions to make unexpected responses • The hospital is trying to create similar environments to cope with a crisis, • My duties in the hospital are quite clear • I am aware of the roles and duties of my colleagues
	Planning strategies (PS)	• The hospital is always looking to strengthen three parts of risk management, crisis management, and emergency planning • The organization has planned for major events and incidents such as fire, explosion, flood, earthquake, etc. • The hospital has taken the necessary measures for major diseases such as COVID19, influenza, and other diseases.
	Fault-tolerant (FT)	• In a crowded trauma center, a non-specialized doctor may deal with different conditions of patients. • When there are not enough resources in the hospital, the trauma center will provide its services at an acceptable level. • If some parts of the hospital are not able to do an activity, it won't hurt to other parts. • Maybe sometimes there is no specific doctor in the trauma center in some patient's conditions.
	Recovery priorities (RP)	• The trauma center has a minimum level of resources to succeed • The organization always respects the priority in the use of resources and equipment • Hospital draws emergency planning and business strategy for all departments. • Importance to stakeholders is a good policy for the organization
	Flexibility (FL)	• After determining the patient's condition, if the patient's condition is fatal, the patient is prioritized. • The patients in the hospital are not local and come from all over the country. • There is no limitation in resources during crises and disasters. • During the crisis, all patients' information is accessible and available.
Quality management perspective	**Customer results (COR)**	• There are indicators for patient performance monitoring (speed, quality, service quality). • There are clear indicators for monitoring patient satisfaction in the organization. • There are indicators for monitoring complaints and patient suggestions in the organization
	Human capital results (HCR)	• I feel that my salary is fair. • My manager is fully qualified in the organization. • The organization appreciates me when my work is well. • There is a clear job promotion path for my position.
	Society results (SCR)	• The organization is aware of the responsibility of each employee. • The organization annually evaluates its progress and current status. • The organization annually evaluates the progress of each employee.
	Key performance results (KPR)	• The organization has financial indicators for its health assessment. • The organization has indicators for evaluating innovation performance. • The organization's performance is always compared to superior patterns.

Appendix 2

Table 16 Gaussian process regression (Python code)

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import sklearn
from sklearn.gaussian_process import GaussianProcessRegressor
from sklearn.gaussian_process.kernels import RBF as C
from sklearn.gaussian_process.kernels import poly as P
from sklearn.gaussian_process.kernels import sigmoid as S
from sklearn.gaussian_process.kernels import pearson as Pe
w=pd.read_excel('DT.xlsx')
w=pd.DataFrame(w)
x=w.iloc[:,:-4].values
y=w.iloc[:,15:19].values
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size=0.3,random_state = 0)
kernel = C(1, (1e-3, 1e3)) * C(10, (1e-4, 1e4))
gp=GaussianProcessRegressor(kernel=kernel, n_restarts_optimizer=9)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain = sc.fit_transform(xtrain)
xtest = sc.transform(xtest)
gp.fit(xtrain,ytrain)
Y=gp.predict(xtest)
MAPE=np.abs((Y-ytest))/ytest
MAPE=np.average(MAPE)
print(MAPE)
plt.plot(ytest,Y, 'r.', markersize=10, label=u'Observations')
```

Table 17 Support vector machine (Python code)

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import xlrd
pd.ExcelWriter('df3.xlsx')
from sklearn.preprocessing import MinMaxScaler
m=range(15,19)
# Importing the dataset
dataset = pd.read_excel('DT.xlsx')
value=[]
reall=[]
for i in m:
    X = dataset.iloc[:,:-4].values
    y = dataset.iloc[:,i:i+1].values
    # Splitting the dataset into the Training set and Test set
    from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

    # Feature Scaling
    from sklearn.preprocessing import StandardScaler
    sc=StandardScaler()
    X_train = sc.fit_transform(X_train)
    X_test = sc.transform(X_test)

    # Fitting SVM to the Training set
    from sklearn.svm import SVR
    from sklearn.linear_model import Ridge
    from sklearn.preprocessing import PolynomialFeatures
    poly=PolynomialFeatures(degree=2)
    svr_rbf = SVR(kernel='sigmoid', C=1e3, gamma=0.1)
    svr_rbf.fit(X_train, y_train)
    y_rbf=svr_rbf.predict(X_test)
    ytest=y_test
    value+=[y_rbf]
    reall+=[ytest]
value=np.transpose(value)
reall=np.transpose(reall)
MAPE=np.abs(value-reall)/reall
MAPE=np.average(MAPE)
print(MAPE)
```

Table 18 Genetic programming (Python code)

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from gplearn import *
import pydotplus as ptp
from IPython.display import Image
from sklearn.tree import export_graphviz
from mpl_toolkits.mplot3d import Axes3D
w=pd.read_excel('DT.xlsx')
w=pd.DataFrame(w)
x=w.iloc[:,:-4].values
y=w.iloc[:,15:16].values
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size=0.3,random_state = 0)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain = sc.fit_transform(xtrain)
xtest = sc.transform(xtest)
est_gp=genetic.SymbolicRegressor(population_size=200,
stopping_criteria=0.01,p_crossover=0.7,p_subtree_mutation=0.1,p_hoist_mutation=0.05,
p_point_mutation=0.1,max_samples=0.9,verbose=1,parsimony_coefficient=0.01, random_state=0)
est_gp.fit(xtrain, ytrain)
Y=est_gp.predict(xtest)
MAPE=np.abs((Y-ytest))/ytest
MAPE=np.average(MAPE)
print(MAPE)
plt.plot(ytest,Y, 'r.', markersize=10, label=u'Observations')
```

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

Declarations

Conflict of Interest The authors declare no competing interests.

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