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Performance assessment and improvement of a care unit for COVID-19 patients with resilience engineering and motivational factors: An artificial neural network method

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ARTICLE INFO

Keywords:

Resilience engineering
COVID-19
Performance evaluation
Job satisfaction
Artificial neural network
Data envelopment analysis

ABSTRACT

The global conflict with the new coronavirus disease (COVID-19) has led to frequent visits to hospitals and medical centers. This significant increase in visits can be severely detrimental to the body of the healthcare system and society if the physical space and hospital staff are not prepared. Given the significance of this issue, this study investigated the performance of a hospital COVID-19 care unit (COCU) in terms of the resilience and motivation of healthcare providers. This paper used a combination of artificial neural networks and statistical methods, in which resilience engineering (RE) and work motivational factors (WMF) were the input and output data of the network, respectively. To collect the required data, we asked the COCU staff to complete a standard questionnaire, after which the best neural network configuration was determined. According to each indicator, sensitivity analysis and statistical tests were performed to evaluate the center's performance. The results indicated that the COCU had the best and worst performance with respect to self-organization and teamwork indicators, respectively. A data envelopment analysis (DEA) method was also used to validate the algorithm, and the SWOT (strengths, weaknesses, opportunities, threats) matrix was eventually presented to recommend appropriate strategies and improve the performance of the studied COCU.

1. Motivation and significance

The spread of coronavirus disease (COVID-19), an advanced species of the SARS (Severe acute respiratory syndrome) virus, has brought about devastating and sometimes irreversible socio-economic consequences, especially in the healthcare sector. The outbreak of the virus has led to rising mortality rates worldwide. Indeed, the World Health Organization (WHO) refers to this disease as a significant crisis for the world. Accordingly, the high resilience of health centers, especially the wards involved more in this challenge than other wards and centers, is critical in addressing this crisis.

On the other hand, organizations need to improve the performance of their staff as a prerequisite for overall improved performance and attainment of positive changes and goals. Among the factors affecting staff performance and consequently the organization's performance are mental factors, such as stress, motivation, reward, job pressures, job

satisfaction, and burnout. A work environment that fails to consider motivational factors leads to physical and psychological pressures, reduced productivity, and poor working conditions. In this area, resilience and motivational factors have not been studied concurrently in a COVID-19 care unit (COCU) yet. Simultaneous inclusion of these two indicators can improve the performance of healthcare centers by reducing risks and increasing employee safety and motivation. The joint use of these two factors can establish the correct balance between employee efficiency and motivation. Given the importance of these two factors, this study examines for the first time the integrated system of staff resilience and motivation in the COCU of a hospital located in Tehran.

The remainder of the paper is as follows. An introduction and literature review are provided in Section 2. Section 3 presents the research methodology in sequential steps. Sections 4 and 5 present the computational results and improvement strategies, respectively. Finally,

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<https://doi.org/10.1016/j.combiomed.2022.106025>

Received 3 May 2022; Received in revised form 9 August 2022; Accepted 20 August 2022

Available online 31 August 2022

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Section 6 draws some conclusions and provides suggestions for future research.

2. Introduction and literature review

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. The majority of individuals who are infected with this virus undergo mild to moderate respiratory problems and recover without special treatment; however, some people become seriously ill and need medical attention. Older adults and people with underlying diseases (e.g., chronic respiratory disease, cardiovascular disease, cancer, and diabetes) are more prone to experience serious illness. Nevertheless, anyone can become infected with COVID-19 and consequently get seriously ill or die at any age. When an infected person coughs, sneezes, speaks, sings, or even breathes, the virus could spread from their mouth or nose in small particles. The best approach to avoid and decrease transmission is to keep well informed about the disease and how it spreads [1].

The healthcare staff, especially COVID-19 care providers, are prone to infection because of their proximity to inflicted patients, which can endanger their health and life [2]. Thus far, many researchers have explored the problems associated with this epidemic in varying disciplines. For example, Bragatto et al. [3] designed a 25-item questionnaire to assess the resilience of the immune management system, and thus, control significant accident hazards in the context of the COVID-19 pandemic. Geng et al. [4] examined the effects of COVID-19 on park visits on regional, national, and global scales by collecting the required data from Google and Oxford reports. In another study, using a food system resilience ‘action cycle’ framework and based on past experiences, Love et al. [5] examined COVID-19-associated disruptions, effects, and responses to the seafood supply cycle. During the COVID-19 pandemic, Tavakoli et al. [6] simulated the flow of patients and predicted their future hospital admissions by considering a real case on a 30-day time horizon. Last but not least, Das et al. [7] built on a multi-criteria decision-making approach to analyze the criteria that affected supply chain network resilience during the COVID-19 outbreak.

As mentioned, COVID-19 is an emerging disease, and experts and scientists have no conclusive evidence concerning the end of the pandemic. This study draws on resilience and motivational factors in the context of the COVID-19 pandemic to evaluate a COCU’s performance. In the following section, we introduce the indicators used in this study.

2.1. Resilience engineering (RE)

One of the critical stages of crisis management in the healthcare sector is the empowerment of the healthcare system to promote resilience in service provision [8]. In crisis management, it is mandatory to have a regular process of applying executive and organizational decisions and other capacities in order to implement policies and strategies, improve the community’s adaptive capacity, and consequently reduce the negative impact and outcomes of new hazards. In other words, the ultimate goal of crisis management is to eliminate and reduce the adverse outcomes of hazards to human health. In addition to harming the general population and infrastructure, the coronavirus outbreak has also affected patient care systems in a context where health care networks are at the forefront of service provision to patients with COVID-19. Evidently, in this situation, healthcare providers are under more pressure. However, resilience factors can enhance their satisfaction, self-confidence, and motivation at work, all of which lead to improved performance in medical centers. Therefore, it is beneficial, even necessary, to address motivational factors when measuring the resilience of the staff in COCU.

Resilience engineering (RE) represents a new concept of safety, reliability, and improved performance in various organizations. It aims to monitor and control various risks and crises and create methods that increase organizations’ stability and flexibility [9]. Put another way,

resilience means remaining stable or returning to a stable state in the face of accidents to survive and prevent changes in human factors [10]. Indeed, a resilient organization can predict and deal with accidents, survive them, and learn from them [11].

The significance of resilience has attracted the attention of many researchers, and they have explored several associated factors in their studies. Arcuri et al. [12] conducted two studies in Brazil to predict the performance of mobile emergency medical services along rivers and coastal areas during the COVID-19 pandemic. Using the data envelopment analysis (DEA) method, Azizi et al. [8] presented a novel framework to assess the performance of operating rooms from both quantitative and qualitative aspects. Haghghi and Torabi [13] presented a resilience-based framework for ranking information systems by using fuzzy DEA. Azadeh et al. [10] investigated the effects of RE on job satisfaction and safety and aimed to enhance these factors. Morel et al. [14] built on a system’s financial performance to present a model for demonstrating the complex links between resilience and safety in the system. Shirali et al. [15] explored the challenges of developing RE and adaptive capacity and categorized these challenges in a chemical plant. Last but not least, Costella et al. [16] evaluated health and safety management systems by using RE and the four primary principles of flexibility, learning, awareness, and top management commitment.

The following is a brief description of the resilience indicators studied in the current article for evaluating the performance of a COCU:

2.1.1. Top management commitment

In an organization, the management is deemed to detect problems and risks and overcome them by proper fulfillment of the tasks. This principle represents the management’s willingness to invest and allocate resources and improve RE effectively [17].

2.1.2. Reporting culture

One of the crucial indicators that improve the organization’s performance in critical situations is the reporting culture. This indicator proposes solutions to errors made during accidents and incidents (e.g., COVID-19). Accident feedback through a reporting system plays a substantial role in health care and can make the organization resilient to new unexpected situations.

2.1.3. Learning

Pre-accident training is essential for staff to be aware of potential hazards and establish a resilient system. Every system must learn from past events and must implement this principle effectively in its structure.

2.1.4. Preparedness

The preparedness indicator means that the system is ready for serious problems. Accordingly, systems must anticipate hazards and accidents and take preventive measures by preparing their components.

2.1.5. Flexibility

If systems are flexible, they will adapt to the current situation in the face of any daunting event or accident.

The other four principles of RE postulated by Azadeh et al. [18] are called integrated resilience engineering (IRE). These four principles are as follows:

2.1.6. Awareness

Managers of organizations need to be aware of the status quo of their organization. This awareness is essential for predicting and evaluating fundamental changes that can influence the ability of the system to maintain its stability in the face of hazards and accidents [19].

2.1.7. Self-organization

Self-organization delegates authority to employees and decentralizes tasks in the organization. A self-organizing system has more control over various errors and changes. As no one dominates the activities

performed by other employees, self-organization facilitates managing and overcoming various complexities and situations.

2.1.8. Teamwork

Teamwork means the cooperation of employees with one another, despite their varying tasks in the organization. This collaboration causes the pressure to be distributed among individuals in times of increased workload, hence higher efficiency and fewer human errors.

2.1.9. Fault-tolerance

This feature is also one of the contributors to enhanced reliability. When any failure occurs in the system, fault-tolerance maintains the system's operation in a stable and appropriate state and prevents the system from being affected by any error or mistake [18].

2.1.10. Redundancy

In case of the breakdown or failure of any important constituent or resource, one needs to consider a suitable substitute. This feature will be a copy of the system components and an essential factor in increasing reliability and flexibility and reducing staff overwork [20].

2.2. Work motivational factors (WMFs)

In the current situation, healthcare providers, especially nurses, are busy working in healthcare centers to fight the COVID-19 pandemic. They are experiencing an increasing number of referrals and more challenging work conditions. The prevalence of COVID-19 has put extra stress and strain on the healthcare staff and nurses, resulting in their fatigue and physical and mental exhaustion. They need to take care of themselves while also providing medical services and care to patients. Therefore, their activities in medical centers should be supported, and a safe and secure environment should be prepared for them to deliver higher-quality service and patient care. Indeed, the current evidence indicates lower staff motivation and capacity in inpatient COCUs.

WMFs play an essential role in increasing employee job satisfaction. Employees can best help improve the organization's performance when they feel satisfied. Burtcher and Manser [21] studied the links between motivational factors in nurses' work environments. They examined the links between job satisfaction, stress, and fatigue, and found that enhanced job satisfaction and social interaction in nurses strengthen motivation and affect patients' recovery process. Aworemi et al. [22] described the importance of seven ranking indicators, namely, job security, interesting work, personal loyalty to employees, working conditions, wages, promotions in the organization, and complete appreciation of the work performed among the staff of 15 Nigerian companies. Schiefer and Hoffmann [23] examined the relationship between work motivation and aging. It was found that older employees differ from younger peers in terms of work motivation and training. The purpose of another study was to examine workplace factors affecting employee motivation. The required data were obtained by distributing a questionnaire among employees of Vietnamese firms. The authors explored the work environment, salaries, extensible opportunities, and employee empowerment [24]. Also, Ahmed et al. [25] analyzed the impact of motivational factors on employee job satisfaction and concluded that intrinsic motivational factors had a significant relationship with employees' job satisfaction.

In the present study, the following factors are utilized to evaluate the performance of the inpatient COCU in question-based on WMFs.

2.2.1. Job satisfaction

Job satisfaction represents employees' satisfaction with their job and significantly impacts their performance [26]. Also, it is introduced as an individual reaction to work experiences [27].

2.2.2. Job security

Job security means that employees maintain their jobs without the

risk of becoming unemployed. When employees feel insecure, they will not perform their responsibilities with the required quality and precision. Numerous studies indicate that job insecurity is detrimental to job satisfaction, organizational commitment, and organizational performance in general [28].

2.2.3. Work stress

Work stress affects our mind and body in several ways. As a vital indicator of employees' motivation, work stress reduces the employees' efficiency and consequently lowers the organization's profit margin. Efficient and timely stress management improves employee productivity, decision-making, and motivation [29].

2.2.4. Overall workload

This indicator shows the amount of work that each employee must perform. Workload assessment plays a notable role in designing new human-machine systems. Evaluating the staff's workload when designing a new system or replicating an existing one contributes to identifying concerns (e.g., bottlenecks and overtime); and addressing these concerns requires the efficient and safe operation of the system [30].

2.3. Proposed RE-WMF framework

As mentioned, in addition to increased resilience, higher levels of staff motivation contribute to the quality of services delivered to patients and thus improve the center's performance. Accordingly, for the first time, this study utilizes RE and WMF to evaluate the performance of a COCU in a hospital in Tehran. Therefore, a questionnaire assessing RE and WMF was designed and distributed among the staff of this unit, and its performance was examined accordingly. The main contributions of this study are as follows:

- Evaluating the performance of a COCU from the perspectives of RE and WMFs in Tehran;
- Using an artificial neural network (ANN)-based approach to specify and rank the efficiency of decision-making units (DMUs);
- Identifying the strengths and weaknesses of the coronavirus unit of the hospital through sensitivity analysis;
- Building on SWOT analysis to present appropriate improvement strategies as well as improvement measures for the studied organization to enhance the current situation in terms of resilience and motivational factors; and
- Using quantitative and qualitative modeling methods for the center.

3. Methodology

Many studies have underlined the advantages of the ANN over other methods. Unlike other conventional algorithms, neural networks can learn the complex relationships between inputs and outputs and yield good results [31,32]. Many studies have been conducted in this field in recent years, some of which will be mentioned here. Using a combination of resilience and lean production approaches, Azadeh et al. [33] optimized the performance of a pipe manufacturer in Iran. They employed an ANN to evaluate and execute the algorithm. Another study presented a flexible fuzzy neural network algorithm for forecasting oil prices in complex environments [34]. To estimate the real-time of a single-step change, Ghazizadeh et al. [35] studied the change point problem by proposing a method based on ANN in the area of non-linear profiles. Ünlü [36] implemented a weighting strategy combined with ANNs and examined the performance of weighted ANNs for several atypical patterns. The results showed that the weighting policy could improve the forecasting process more than the single use of ANNs. Sudarshan et al. [37] evaluated an emergency department via forecasting models. They developed models for forecasting ED patient arrivals and concluded deep neural network (DNN)-based models

outperform machine learning(ML)-based models.

We use two well-known models, MLP and RBF, in the present study. While these two models are different in computational steps, they ultimately have the same application [38]. The definitions of ANNs, MLP, and RBF are detailed in Supplementary Material.

Similar to the related literature, we use a flexible approach to evaluate the performance of COCU patients according to RE and WMF indicators. The steps of this study are described below and illustrated in

Fig. 1.

Step 1. Based on expert opinions and previous research, we first identified RE indicators as input and WMFs as output. Since the nature of the input variables should be the smaller the better (STB), and at the same time the output data should be the larger the better (LTB), Equations (1) and (2) were used to normalize and homogenize the input and output data, respectively [39].

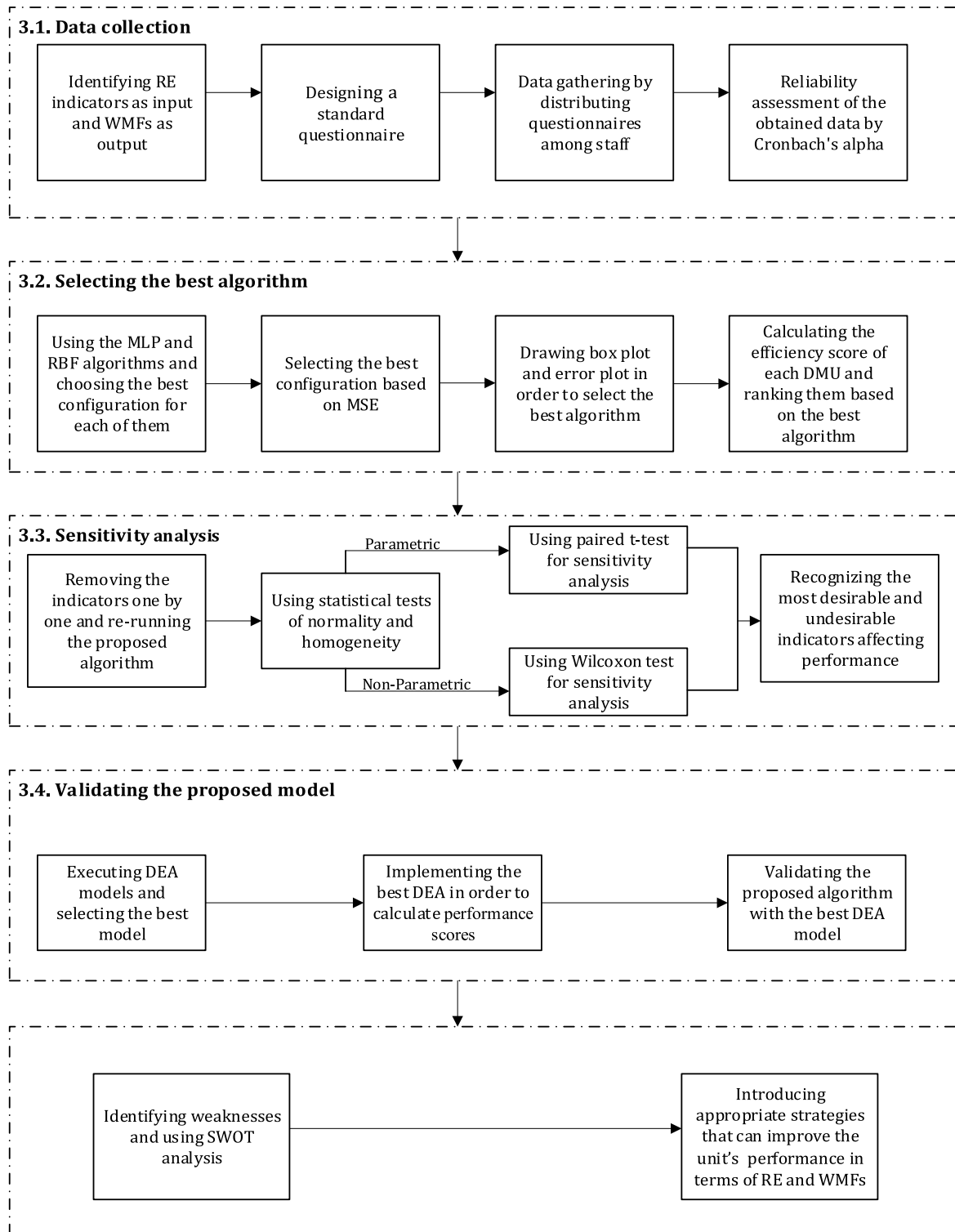


Fig. 1. Flowchart of the proposed approach.

$$V_{ij} = \frac{\text{Max}(x_{ij}) - x_{kj}}{\text{Max}(x_{ij}) - \text{Min}(x_{kj})} \quad (1)$$

$$V_{kj} = \frac{y_{kj} - \text{Min}(y_{kj})}{\text{Max}(y_{kj}) - \text{Min}(y_{kj})} \quad (2)$$

where V_{ij} is the normalized value of the input variable i for DMU j , and V_{kj} is the value of the output variable k for DMU j . These are the normalized values of the input variables x_{ij} and y_{kj} , respectively.

Step 2. In this step, a standard questionnaire was designed based on expert opinions and RE and WMF indicators to obtain the required data. The questionnaire was completed by 122 staff members of the COCU, and the options were arranged on a continuous scale from 1 to 10 (where 1 and 10 are the lowest and highest rates, respectively). This questionnaire is presented in Supplementary Material.

Step 3. Before using the obtained data, the reliability and accuracy of the questionnaire were checked using Cronbach's alpha [40], which showed good internal consistency between the items (Equation (3)). In this equation, the number of headings associated with each indicator is denoted by n , and σ_i^2 and σ^2 represent the variance of each indicator and the total variance, respectively.

$$\alpha = \frac{n}{n-1} \left(1 - \frac{\sum_{i=1}^n \sigma_i^2}{\sigma^2} \right) \quad (3)$$

Notably, the minimum acceptable value of Cronbach's alpha is 0.7 [41–43].

Step 4. As mentioned, RE and WMF factors are considered input and output in this study, respectively. A data set had to be specified as network training and testing data to use ANNs. For this purpose, 30% of the total data were considered testing and validation data (15% each), and the rest were considered training data.

Step 5. To determine the best ANN configuration, we carried out the following steps in order:

- Executing RBF and MLP algorithms to select the best configuration for each of them; and
- Calculating the mean squared error (MSE) for each MLP and RBF configuration.

As a measure to prevent noise, each configuration was run 1000 times, and the error and box plots were drawn at a confidence interval of 95% for the MSE values obtained from the algorithm.

Step 6. To calculate the optimal model performance, we used the steps presented by Azadeh et al. [44]. These steps are described in detail in the "Results" section.

Step 7. To evaluate the impact of each of the indicators on the performance of the target unit, we removed the indicators one by one to observe the change occurring in the results. The optimized algorithm was re-run, and the performance results were compared with those of a situation where all factors are taken into account. Before this comparison, the data distribution normality test was performed to use an appropriate statistical test. Normality and homogeneity are the two conditions considered for the parametric nature of the data. As a general rule, if both conditions are met, the paired t -test is used as a parametric statistical test [42]. Otherwise, the Wilcoxon signed-rank test is employed [45]. These statistical tests examine whether the mean scores of the initial performance obtained by the optimal algorithm (before indicator removal) are similar to the mean scores of the second performance (after indicator removal). The null hypothesis (H_0) assumes the equality of the mean scores ($\mu_1 = \mu_2$), which is tested at a confidence interval of 95%. If the p -value obtained for each H_0 is less than 0.05, the hypothesis is rejected. It can be claimed that the omitted indicator is

effective because its omission can change the mean performance score. To evaluate the desirability of performance of the studied unit in terms of the omitted indicators, we compared the average performance scores before and after the removal of each indicator. If the mean value decreased, it was inferred that the unit would perform well in terms of the removed indicator because eliminating this indicator would reduce the average performance scores. Conversely, if the average performance scores increased after removing the indicator, it was concluded that the unit had a weak performance as far as that indicator was concerned. Lastly, if the calculated p -value was bigger than 0.05, it was assumed that statistically that there was no reason to reject the null hypothesis ($\mu_1 = \mu_2$).

Step 8. In this step, we attempted to validate the obtained results. The data envelopment analysis (DEA) method was conducted to calculate the efficiency of DMUs. It was for the first time developed to evaluate the performance of multifaceted decision-making units [43,46–49]. Later, more models of this method were proposed. The DEA method is based on non-parametric linear programming. It seeks to measure and improve the relative efficiency of a number of DMUs. This method operates by dividing the total weight of the outputs by the total weight of the inputs. It has many advantages that have made it one of the most widely used analysis methods for research purposes. For example, this method does not require a relationship between the inputs and outputs. The input and output units can be very different. This data analysis method has been used in various fields such as safety, health systems, and production and scheduling [43,48,50–53]. Considering the measured evaluation standards makes it more effective [46,48,54]. More explanation about DEA and their employed models are presented in the Supplementary Materials.

The results of the proposed optimization algorithm determined in Step 6 were compared with the DEA results. If the results matched, they were confirmed. For this purpose, the optimal DEA model was determined first. Thus, input-oriented CCR, output-oriented CCR, input-oriented BCC, and output-oriented BCC models were executed and compared with each other. We randomly selected 5% of the data and exposed them to 20% noise. The results of each of the four models before and after noise were compared using the Spearman rank correlation coefficient. The model with the lowest sensitivity was selected as the optimal model. Subsequently, the model was run based on the proposed algorithm, and a high correlation was found between the performance scores obtained from the DEA model and the proposed framework. Hence, the results obtained from the algorithm were confirmed.

After the optimal DEA model was determined, it was executed and the performance scores were calculated. The high consistency between the performance scores calculated from the optimal DEA model and the proposed approach confirmed the results.

Step 9. When the impact of each indicator on the performance of the COCU was determined by detecting weaknesses via SWOT analysis, a strategic balance was established between strengths and opportunities. Moreover, corrective measures were proposed in accordance with the WO (weakness-opportunities) strategy.

All the mentioned steps, especially the parts of the work that are done automatically, are graphically displayed in Fig. 2. In the following, we refer to the steps of the work that are performed automatically in the proposed system:

- I. Various configurations are randomly defined in the proposed system. The system selects the best configuration of neural networks based on the lowest MSE value. This process is automatically executed by the user.
- II. As stated in the text of the paper, the approach provided by Azadeh et al. [44] was used to calculate efficiency. According to the coding done in the paper, these calculation steps can be implemented automatically by the code.

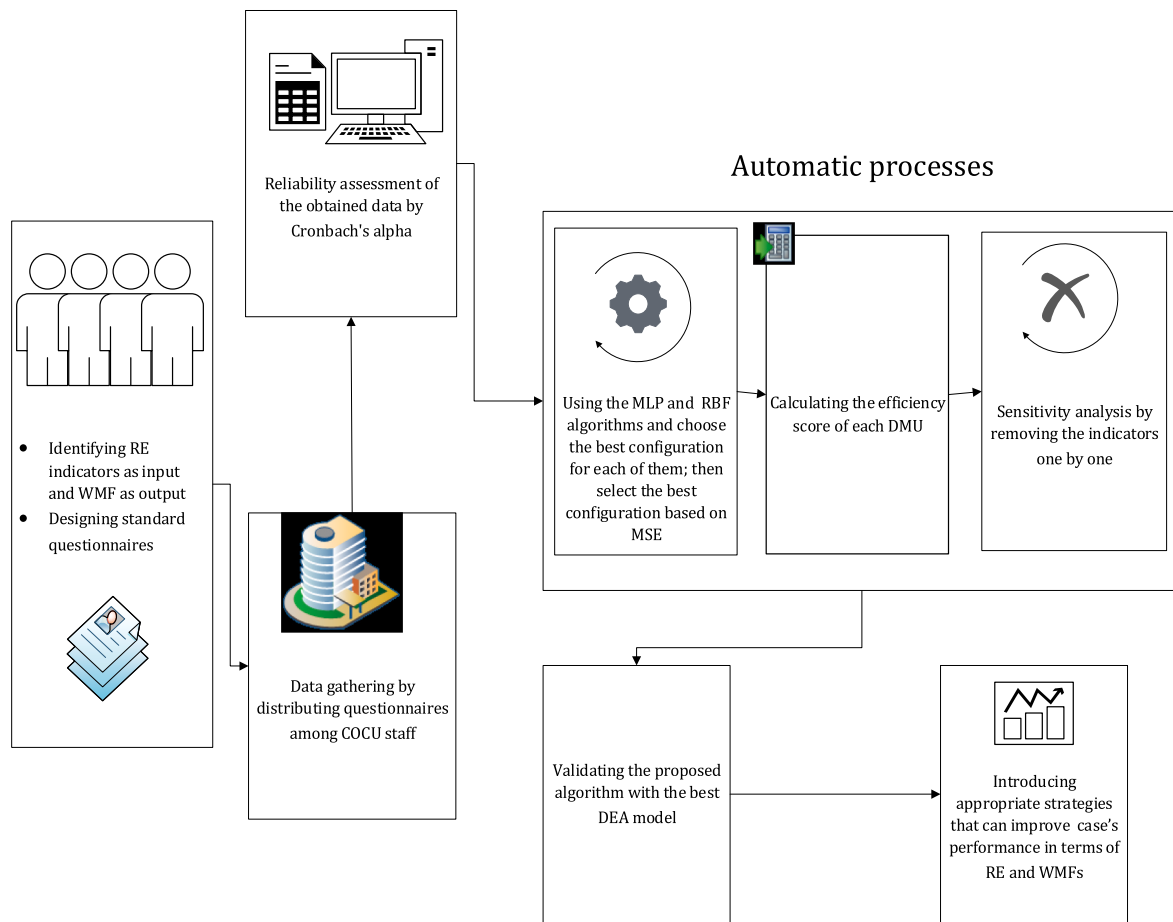


Fig. 2. The graphical chart of this research.

III. After calculating the efficiencies according to Step II, to check the effect of indicators on the performance of the case study, one indicator is removed and the model is run again. The operation of removing each indicator for $i = 1, \dots, n$ (where i is the index of the selected indicators) and evaluating its effect is coded using the iterative process in MATLAB. The results can be obtained by running this code automatically.

4. Computational results

First, a standard questionnaire was designed according to previous research and expert opinions in order to collect the required data for the present study. The questionnaire was completed by 122 COCU staff and is available in Supplementary Material.

4.1. Checking the validity and reliability of the questionnaire

The reliability of the required data obtained through the standard questionnaire was assessed using Cronbach's alpha (Table 1) in SPSS software. All values were above 0.7, indicating acceptable reliability of the questionnaire and data.

4.2. Best configuration results

In the present study, two different neural networks were used to evaluate the performance of the COCU. For this purpose, different configurations of each of these two algorithms were executed 100 times, and their MSE values were compared with each other. The results are given in Tables 2 and 3. Finally, the best configuration with the lowest

Table 1
Reliability of the collected data and outputs.

Indicator	Cronbach's alpha	Indicator	Cronbach's alpha
Resilience engineering	0.725	Redundancy	0.856
Management commitment	0.873	Fault tolerance	0.837
Learning	0.823	Self-organization	0.859
Reporting culture	0.770	Work motivational factors	0.973
Preparedness	0.775	Job satisfaction	0.966
Awareness	0.866	Job security	0.924
Flexibility	0.920	Work stress	0.915
Teamwork	0.865	overall workload	0.951

MSE was selected. In short, this process of examining different configurations automatically selects the best structure. In Tables 2 and 3, the best configurations are highlighted in bold.

For each algorithm, to prevent noise, we determined the best configuration and ran it 1000 times; Besides, box and error plots were drawn at a confidence interval of 95% for the MSE values of each algorithm. The algorithm with the shortest distance between the first and third quartiles and the least scatter in MSE values was considered the optimal and more accurate algorithm.

Figs. 3 and 4 depict each algorithm's accuracy, sensitivity, and specificity. Considering the obtained MSE values and the graphic diagrams of the error plot and box plot, the RBF algorithm had the lowest scatter in MSE values, which indicates the greater accuracy and sensitivity of this algorithm. Therefore, we used it as the optimal algorithm to

Table 2
MLP results.

Row	No. of neurons		Transfer function	Learning rule	MSE	
	No. of hidden layers	Layer 1				Layer 2
1	1	2	0	Sig	LM	0.0912
2	1	4	0	Sig	LM	0.0849
3	1	6	0	Sig	LM	0.0822
4	1	8	0	Sig	LM	0.0603
5	2	12	0	Sig	LM	0.0622
6	2	2	4	Sig	LM	0.0989
7	2	2	8	Sig	LM	0.0996
8	2	2	12	Sig	LM	0.0987
9	2	4	2	Sig	LM	0.0734
10	2	4	4	Sig	LM	0.0859
11	2	4	8	Sig	LM	0.0837
12	2	4	12	Sig	LM	0.0790
13	2	8	2	Sig	LM	0.0689
14	2	8	4	Sig	LM	0.1044
15	2	8	8	Sig	LM	0.0513
16	2	8	12	Sig	LM	0.0979
17	2	12	2	Sig	LM	0.1091
18	2	12	4	Sig	LM	0.0561
19	2	12	8	Sig	LM	0.0801
20	2	12	12	Sig	LM	0.1113

Table 3
RBF results.

Row	Spread	Maximum neurons	MSE
1	5	10	0.0462
2	10	15	0.0827
3	15	20	0.0398
4	20	25	0.0613
5	25	30	0.0763
6	30	35	0.1017
7	35	40	0.0353
8	40	45	0.0767
9	45	50	0.0519
10	50	55	0.0372

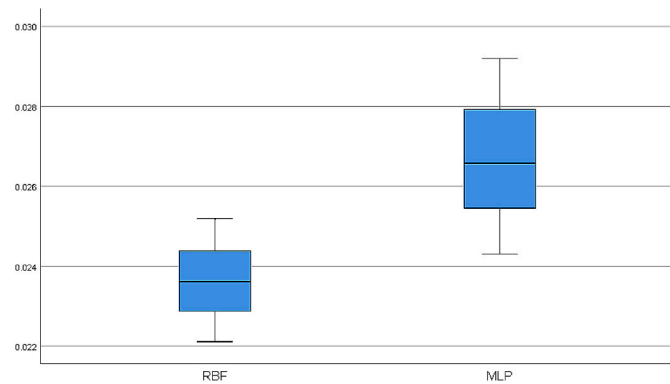


Fig. 3. Box plot diagram for the results obtained from 1000 executions of the best ANN.

implement the proposed approach. According to Fig. 5, the RBF neural network with 40 neurons can find the appropriate solution. The graphs related to the test data are also shown in Fig. 6. The error size, mean and standard deviation, correlation, and scatter of this neural network are seen in this figure.

4.3. Results of calculating the efficiency scores

To calculate the efficiency of the COCU, we modeled the relationship

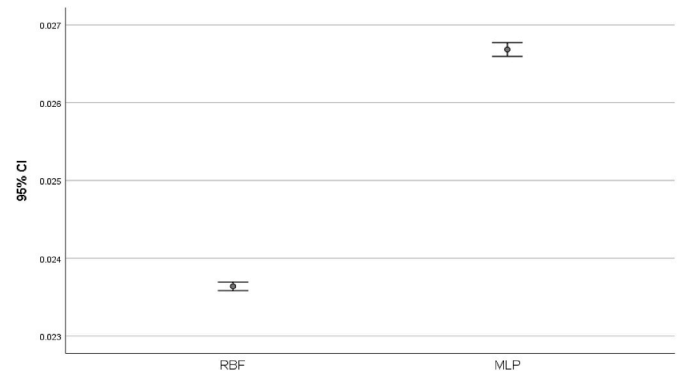


Fig. 4. Error plot diagram for the results obtained from 1000 executions of the best ANN.

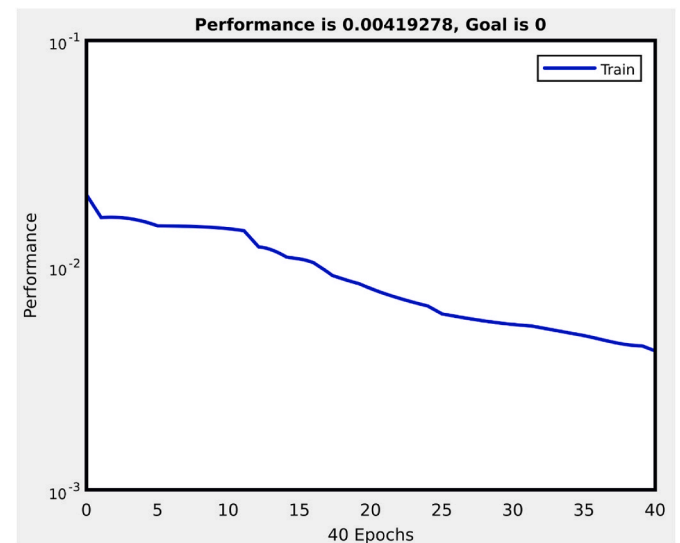


Fig. 5. Performance diagram of the best configuration of the training data.

between input factors (RE) and output factors (WMF) by using the most appropriate algorithm determined in the previous section. For this purpose, we applied the following algorithm introduced by Azadeh et al. [44]. This procedure has been coded and is automatically run with one click by the user. Using Equation (4), the error value between the observed output and the output value of the optimal model (i.e., Z_j and O_j) was calculated for the output variable DMU j .

$$ER_j = Z_j - O_j \quad j = 1, \dots, n \tag{4}$$

ER'_j represents the effect of the large positive error calculated in Equation (5).

$$ER'_j = \frac{ER_j}{O_j} \quad j = 1, \dots, n \tag{5}$$

Equation (6) presents the maximum frontier function shift value between all DMUs and ER_m .

$$ER_m = \max(ER'_j) \quad j = 1, \dots, n \tag{6}$$

According to Equation (7), Sh_j is the shift value for each DMU j .

$$Sh_j = \frac{ER_m * O_j}{O_m} \quad j = 1, \dots, n \tag{7}$$

where O_j introduces the optimal model value for DMU j . Also, O_m indicates the optimal value of the model for DMU m (i.e., the DMU

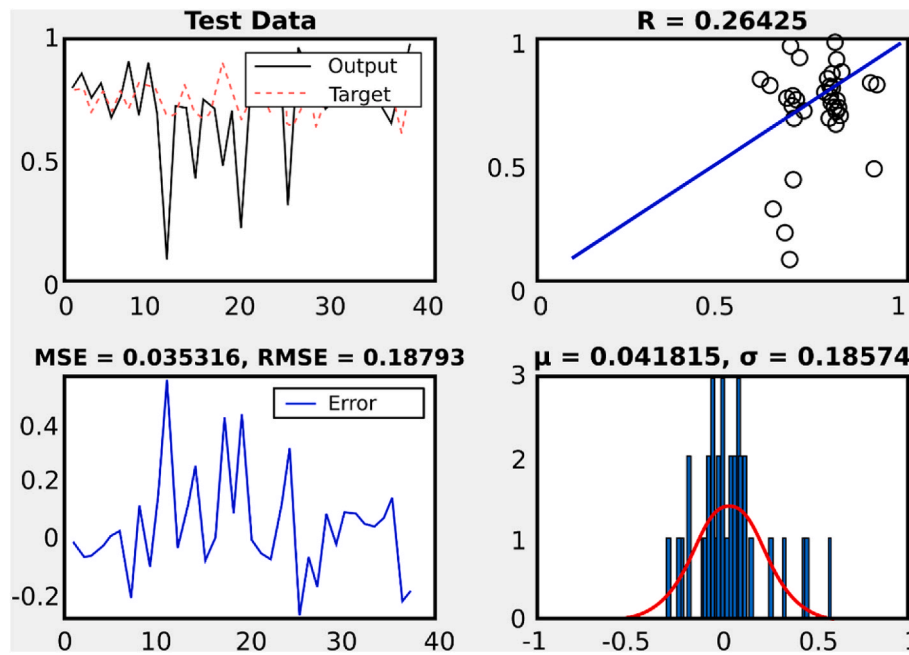


Fig. 6. Analysis of the best configuration of the testing data.

characterized by the maximum frontier function shift).

Lastly, the efficiency score τ_j for DMU j is obtained according to Equation (8).

$$\tau_j = \frac{Z_j}{O_j + Sh_j} \quad j = 1, \dots, n \quad (8)$$

4.4. Sensitivity analysis

After the efficiency score of each of the DMUs mentioned in the previous step was calculated, the input and output indicators were removed one by one, and the performance of the studied COCU was recalculated using the selected algorithm. This was carried out to understand the impact of each indicator on performance. Statistical tests were used at this stage. Hence, the data were examined to see if they were parametric or non-parametric so that appropriate statistics could be used to describe them. Typically, normality and homogeneity conditions are considered for this purpose. If both conditions are met, the paired t -test is used to compare the statistics; otherwise, the non-parametric Wilcoxon test is used for comparison [45].

These tests evaluate the mean performance scores before and after each indicator is removed. In principle, the Null Hypothesis (H_0) is a hypothesis of equality of means ($\mu_1 = \mu_2$), evaluated at a 95% confidence level. If the value of p is smaller than 0.05, the null hypothesis is rejected, and it is claimed that the removed variable can statistically change the performance score of DMUs. Moreover, if the value of p is greater than 0.05, it can be statistically concluded that there is no reason to reject the null hypothesis. The p -value results of normality and homogeneity tests are reported in Table 4.

Since the p -value was smaller than 0.05 after deleting all the indicators, H_0 was rejected. It could be concluded that the mean performance score changed significantly after removing these indicators. To determine the desirability of the unit's performance, we compared the mean performance scores before and after removing indicators. If the mean efficiency score decreased after removing a particular indicator, it was assumed that the presence of that specific indicator would contribute positively to the performance of the COVID-19 care unit. In contrast, a higher mean score after removing a certain indicator implied its negative impact on the unit's performance. Therefore, given the reduced mean performance scores after removing the indicators of

Table 4
Results of normality and homogeneity tests.

Omitted indicator	p -value (normality)	p -value (homogeneity)
None	0.00	
Resilience engineering	0.00	0.065
Management commitment	0.00	0.053
Learning	0.00	0.058
Reporting culture	0.00	0.054
Preparedness	0.00	0.069
Awareness	0.00	0.063
Flexibility	0.00	0.171
Teamwork	0.00	0.077
Redundancy	0.00	0.073
Fault tolerance	0.00	0.051
Self-organization	0.00	0.064
Work motivational factors	0.00	0.055
Job satisfaction	0.00	0.059
Job security	0.00	0.037
Work stress	0.00	0.050
Overall workload	0.00	0.041

management commitment, learning, reporting culture, awareness, flexibility, fault tolerance, self-organization, job satisfaction, job security, overall workload, resilience engineering, and work motivational factors, it seems these indicators are the strengths of the studied COCU. On the other hand, the mean performance score increased after removing the indicators of preparedness, teamwork, redundancy, and work stress, suggesting the poor performance of the COCU in terms of these indicators. Indeed, the DMUs need to take corrective measures to increase their efficiency score with regard to these indicators. According to Table 5, the unit under study demonstrated the highest and lowest performance in the areas of self-organization and teamwork, respectively.

It should be noted that, in addition to evaluating the performance of COCU based on each sub-indicator stated in this research, it is possible to investigate the overall effect of RE and WMF. For this purpose, the sensitivity analysis was carried out on these two main indicators and the impact of each indicator on the COCU performance was evaluated. In this analysis, the RE indicators were first removed all at once. Considering the WMF indicators, we followed all the steps mentioned in the removal of sub-indicators, including efficiency calculation (using the

Table 5
Results of sensitivity analysis.

Omitted indicator	$\mu_1 - \mu_2$	Hypothesis test	p-value (Wilcoxon)
Resilience engineering	0.01523	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Management commitment	0.01706	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Learning	0.02357	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Reporting culture	0.00994	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Preparedness	-0.03681	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.001
Awareness	0.02955	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Flexibility	0.00306	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Teamwork	-0.11094	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Redundancy	-0.09427	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Fault tolerance	0.02411	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Self-organization	0.05864	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Work motivational factors	0.03442	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.0014
Job satisfaction	0.02619	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.0023
Job security	0.00318	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Work stress	-0.01247	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Overall workload	0.05781	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.0015

algorithm described in Section 4.3), statistical tests, and the like. Then, the same process was done by removing all WMF indicators and considering RE. The results are given in Table 5, which shows that the average efficiency of DMUs decreased after removing RE. This means that its implementation increased the performance of the center. Also, when all the WMF indicators were removed, the average efficiency decreased to a greater extent compared to the average efficiency when the RE indicators were removed. It could be inferred the WMF indicators had a greater effect on the performance of the COCU. The indicator removal operation is done automatically using a repetitive process in MATLAB.

4.5. Validation results

In this section, the performance of a COVID-19 care unit is evaluated using the DEA method based on the opinions of 122 employees (DMUs) of this unit. The DEA is a non-parametric method based on linear programming. Its advantage over other evaluation methods is the existence of decision support tools to calculate the efficiency score of DMUs [44]. Besides, this method has a more convenient approach to handling problem inputs and outputs to measure performance scores. For the proposed approach to be validated, we utilize the performance score of each indicator calculated for each DMU in Section 4.3. First, four different DEA models (i.e., CCR input-oriented, CCR output-oriented, BCC input-oriented, and BCC output-oriented [46]) are calculated by the CPLEX solver in GAMS software to validate the performance scores of DMUs. Afterward, the results obtained by these models are reviewed, and the best model is selected as the optimal model to validate the proposed framework. For this purpose, 20% noise is generated in 5% of the data, and the model with minimum noise sensitivity is selected as the best model. Spearman correlation test is used to measure this sensitivity. The model that has the highest correlation is the most consistent and is selected as the most appropriate model. The results of this section are given in Table 6. According to the results reported in this table, the BBC

Table 6
Spearman’s correlation coefficients between the ranks obtained before and after noise exposure.

DEA model	CCR input-oriented	CCR output-oriented	BCC input-oriented	BCC output-oriented
Correlation	0.9561	0.9173	0.9577	0.9179

input-oriented model is the best. DMUs are subsequently ranked based on performance scores obtained by the optimal DEA. Eventually, using Spearman’s correlation test, a correlation coefficient of 0.9038 is established between the ranks obtained from the BCC input-oriented model and the ranks previously calculated by the optimal ANN model. This value guarantees a high validity coefficient of the results obtained by the proposed approach.

5. Improvement actions

The SWOT tool compares and contrasts the opportunities and threats outside the organization with the strengths and weaknesses inside the organization. Therefore, it seems to be a suitable tool for evaluating the compatibility between the COCU and internal and external factors. As mentioned earlier, statistical tests were used to identify strengths and weaknesses in the sensitivity analysis. The results revealed that the center in question is not functioning properly and needs improvement in relation to preparedness, teamwork, redundancy, and work stress indicators. Logically, improving these factors will enhance the organization’s performance in terms of RE and WMF. Improvement suggestions include providing substitute staff, raising staff preparedness for crises, and increasing employees’ participation. Also, the indicators of learning, reporting culture, awareness, flexibility, fault tolerance, self-organization, management commitment, job satisfaction, job security, and overall workload are well applied in the center and are among its strengths.

In this study, the SWOT analysis was used to present a comprehensive and practical perspective to improve the performance of the studied COCU. Having identified the strengths and weaknesses, we drew on expert opinions to detect opportunities and threats in the unit. As a result, the study’s first step consisted of identifying the unit’s ultimate goals such as increasing productivity, resilience, and staff motivation. Appropriate and efficient strategies were proposed based on expert opinions and SWOT analysis. These strategies that can help improve performance at the operational level are presented in Table 7.

6. Conclusion

For the first time, this study examined the performance of a COCU with respect to resilience and motivation indicators. In the first stage, the required data were collected by distributing a valid and standard questionnaire among 122 employees of the unit. Afterward, we used ANN and statistical methods to estimate the efficiency of DMUs. For this purpose, resilience indicators were considered the network input and motivation indicators as output. Next, the values of motivational factors were predicted by MLP and RBF networks, and statistical methods and plots were used to select the best configuration. The DMU efficiency score was calculated subsequently, and sensitivity analysis was performed according to the considered indicators. The mean efficiency score was calculated for sensitivity analysis when all indicators were present. Then, each indicator was removed, and the effect of the removed indicator was evaluated to assess its significance in the performance of the COVID-19 unit. Accordingly, the indicators of management commitment, learning, reporting culture, awareness, flexibility, fault tolerance, self-organization, job satisfaction, job security, and overall workload were found as strengths. In contrast, the center’s performance was not satisfactory concerning the indicators of preparedness, teamwork, redundancy, and work stress. Nevertheless,

Table 7
SWOT matrix.

SWOT	Strengths	Weaknesses
	<ul style="list-style-type: none"> • Management commitment • Learning • Reporting culture • Awareness • Flexibility • Fault tolerance • Self-organization • Job satisfaction • Job security • Overall workload 	<ul style="list-style-type: none"> • Preparedness • Teamwork • Redundancy • Work stress
Opportunities	SO strategies	WO strategies
<ul style="list-style-type: none"> • Increased advancement in technology • People's trust in physicians and healthcare staff • Upgraded medical equipment in the country • Scientific and professional promotion of medical knowledge in the medium and long terms • Vaccination of people in most regions of the country • Advances in telemedicine • Further job opportunities in health services 	<ul style="list-style-type: none"> • Using modern diagnostic-therapeutic equipment • Improving staff skills • Improving organizational culture • Recruiting and hiring proper staff, retaining, and providing the necessary training to develop capabilities for higher motivation • Increasing deployment of educated officials in management positions in departments and care units • Applying leadership methods and influence on staff by hospital managers and officials for organizational purposes and trust-building • Optimal use of limited resources and investment for the future • Improving the physical health of employees in proportion to their contact with COVID-19 patients 	<ul style="list-style-type: none"> • Having welfare programs for staff • Clarifying the goals and policies of the hospital to all staff • Providing a sufficient and specialized workforce to establish a balance with the volume of activity • Designing and developing monitoring mechanisms • Providing facilities and amenities to employees • Managing risks in units and departments • Supporting employees by the managers and attempting to reduce job stress
Threats	ST strategies	WT strategies
<ul style="list-style-type: none"> • Decline in the income of hospitals and educational and healthcare centers • Reduced quality of clinical education due to the rise of online medical courses • Lack of a regular framework for the management and implementation of distance education programs due to COVID-19 disease • Instability and daily disorders at the forefront of the health system, including an increase in the number of patients, the unpredictability of human resource planning, etc. 	<ul style="list-style-type: none"> • To implement correct policies and necessary programs, hospital managers need to behave in a way that welcomes the reasonable suggestions of the staff and strengthens the spirit of consultation, trust, and cooperation in the organization, thereby increasing motivation and facilitating the achievement of organizational goals • Using strategic planning that is equipped with a correct decision-making system and 	<ul style="list-style-type: none"> • In terms of customer-orientedness, patients are known as potential hospital customers. Hence, providing appropriate, timely, and comprehensive services can be the basis for earning a good income • Increasing the number of beds for COVID-19 patients • Designing and implementing an employee satisfaction measurement system • Establishing a performance-based payment system • It is better to have gradual changes in

Table 7 (continued)

<ul style="list-style-type: none"> • Lack of complete preparedness of hospitals, health centers, and other departments in the face of COVID-19 disease • Prolonged period of tackling the COVID-19 crisis, fatigue, and mental and physical exhaustion of healthcare personnel • Unpredictability, high prevalence, the emergence of new variants of this disease, and the high mutation of the virus • Insurers' delays in payment of claims • Insignificant insurance deductions • High prices of equipment due to inflation 	<ul style="list-style-type: none"> hospital officials' adherence to it • Improving the method of monitoring the units' performance • Acquiring the satisfaction of staff on the manner of paying benefits • Providing the staff with more effective training on different situations of contact with COVID-19 patients • Designing and implementing a fair payment system 	<ul style="list-style-type: none"> laws, regulations, and structures when the conditions are paved; moreover, to prevent imbalances and crises, employees should be informed of the intention to make the change and ensure that this change could be beneficial.
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self-organization and teamwork indicators had the highest and lowest performance scores, respectively.

The DEA method was used to validate the proposed framework in this research. Eventually, the SWOT matrix was analyzed to propose measures that could improve the performance of this care unit. The findings of the current study are based on the perspective of the COCU staff. For further research, this topic can be evaluated from the perspective of COCU managers or patients. It is also necessary to cover other practical indicators such as lean management, ergonomics, and HSE (Health, Safety, and Environment) in assessing this and similar care units. Other suggestions for future research include examining the independence of the indicators studied in this research, examining various double and triple combinations of indicators, analyzing their sensitivity in terms of their impact on the performance of COCU or other centers/organizations, and implementing other well-known algorithms. Examples include combining meta-heuristic methods with neural networks, employing an adaptive network-based fuzzy inference system (ANFIS) approach and fuzzy DEA, and considering uncertainty.

Ethical approval

The authors certify that this paper does not contain any studies or involvement with human participants or animals performed by any authors in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this paper.

Declaration of competing interest

The authors declared no potential conflicts of interest for the research, authorship, and/or publication of this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compbimed.2022.106025>.

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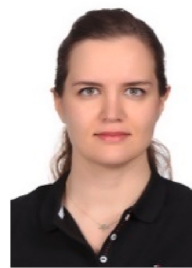
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