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An intelligent algorithm to evaluate and improve the performance of a home healthcare center considering trust indicators

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ABSTRACT

Home healthcare (HHC) is a beneficial choice for many people and especially an essential alternative to clinics and hospitals for infection prevention during the COVID-19 pandemic. Moreover, patient trust in HHC providers is critical to care success and highly affects patient satisfaction. In this paper, an intelligent algorithm is proposed to assess the performance of an HHC center considering trust indicators. For this purpose, the effect of these indicators on patient satisfaction was examined. First, the required data is collected from patients who received care from the HHC service under study through two validated questionnaires containing items related to trust and patient satisfaction. Efficiency scores for each decision-making unit were computed using an artificial neural network and statistical methods. Based on each trust indicator, sensitivity analysis and statistical tests were conducted to evaluate the (in) appropriateness of HHC center performance. In addition, a strengths-weaknesses-opportunities-threats analysis is conducted to suggest strategies for improving the HHC center performance. The algorithm was validated using the data envelopment analysis method. As far as we know, this is the first study to evaluate the performance of HHC centers based on trust indicators, and the model presented in this study can be implemented in other healthcare units to enhance patient satisfaction.

1. Introduction and literature review

Home healthcare (HHC) is an alternative to conventional clinical centers such as medical and paramedical centers for patients in their surroundings. The HHC services have burgeoned significantly over the past decade due to several reasons. For example, population aging, hospital congestion, and development of modern technologies, etc. HHC services could be affected appreciably during the Covid-19 pandemic in some ways. To prevent being infected with Covid-19, many patients prefer to receive their medical services at home rather than in hospitals [12]. Besides, many HHC centers provide Covid-19 related services, such as taking the polymerase chain reaction (PCR) tests and serum and drug injections during the pandemic. Therefore, the demand for HHC providers is increasing. The demand growth may lead to some adverse outcomes, including increased waiting time and low-quality services.

One of the critical concepts affecting the healthcare system's quality is trust. Trust means believing in something or someone's honesty, effectiveness, and reliability [15]. Trust is mostly a relational concept, which plays a significant role in relational systems like HHC systems. On the other hand, due to increasing competition between HHC providers appropriate healthcare service and patients' satisfaction are the system's main objectives [39]. Trust improves the quality of care and patients' satisfaction and brings about fewer complaints, which is very important, especially during the Covid-19 pandemic. Furthermore, it will help enhance business productivity, and HHC providers could survive in today's competitive environment.

Performance evaluation plays an important role for decision-makers to recognize the healthcare service quality. Therefore, many researchers measure the performance of different healthcare sections using various methods. For example, Yazdanparast et al. [42] analyzed patient satisfaction, job satisfaction, and integrated resilience engineering (IRE) using data envelopment analysis (DEA) and two artificial neural networks (ANN) in an emergency department. Hasni et al. [24] introduced a new DEA to find efficient decision-making units (DMU) in a hospital. The grey relational analysis (GRA) then scans the discovered DMUs and inputs to determine their preference order, therefore retrieving the benchmarked DMUs and most affecting factors to prioritize. Nour et al. [29] believed that determining the assessment criteria properly is the most efficient approach to utilize hospital resources. They employed machine learning (ML) to identify these criteria, which had previously

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been decided by consulting with experts.

Many researchers have investigated trust in healthcare systems and highlighted its significant effect on healthcare systems' function [16, 37]. Gilson [15] explained the notion of trust in the first part of her study. Then, by demonstrating the importance of trust in health systems, she concluded that a trust-based health system could build value in society. Croker et al. [11] explored factors affecting patients' confidence and trust in their doctor using questionnaires in England. Gopichandran and Chetlapalli [17] investigated the factors determining patients' trust in doctors. Then, based on the revealed categories, the respondents are segmented into groups. As each segment has common factors in defining trust, a unique strategy can be adapted to build trust for each patient segment. Meyer [28] provided a theoretical model to investigate trust in Australia's public and private healthcare systems. The results showed that many patients distrust and are concerned about the role of government in healthcare. Renbarger et al. [34] identified factors related to the building of trust between pregnant and postpartum women with substance use disorders (SUDs) and maternity nurses. Furthermore, Rasiah et al. [33] recently reviewed the literature on trust in healthcare. They surveyed the effective factors on trust and trust measurement tools in healthcare providers. Orrange et al. (2021) [31] assessed the relationship between patient satisfaction with telemedicine visits and patients' trust in the provider using descriptive statistics, Spearman correlation, and regression.

Some researchers have used state-of-art methods, such as artificial intelligence (AI), internet of things (IoT), machine learning (ML), and deep learning for healthcare systems [1,2]. These methods are also utilized for studying various aspects of HHC. Lin et al. [26] presented a service based on IoT to prioritize patients preferences to improve their satisfaction in HHC organizations. Meadow and Sangl [27] used data mining techniques to identify risk indicators related to the probability of readmission among a large sample of HHC patients [35]. employed a human-computer interaction design to develop an informatics tool to enhance communication between nurses and physicians in an HHC organization. Leff et al. [25] examined the communication between HHC clinicians and physicians using multi-level logistic regression models. Yang et al. [40] evaluated a chronic obstructive pulmonary patient condition by using the combination of the support vector machine, the decision tree, and the random forest. They provided a home care plan based on the results of their evaluation. Pham et al. [32] presented a cloud-based smart home environment to monitor health signals and understand behavioral changes. The related data are processed using data mining algorithms. Guo et al. [18] reviewed the application of AI in smart homes. According to their study, AI and ML are successfully implemented by researchers to detect changes in behavioral patterns.

Few papers evaluate healthcare performance according to trust measures. Yazdanparast et al. [42] provided an adaptive neuro-fuzzy approach for three large medical centers in Iran with considering trust. Their proposed algorithm investigates the optimal combination of patient demographic features of trust. The authors suggested that by comprehending the current situation of patients' trust, healthcare providers can benefit from different psychological techniques to improve trust. Tohidifard et al. [38] considered concepts of patient trust and resilience engineering simultaneously to evaluate the emergency department's performance concerning uncertainty. In their study, after validating the results, the Z-number DEA model is compared to the fuzzy DEA (FDEA) model. Boysen et al. [9] evaluated patient trust and safety based on a sample of low-priority ambulance patients referred to care at the community health center or the emergency department.

To the best of our knowledge, the performance evaluation of HHC has not been investigated. This paper proposes a comprehensive framework based on trust indicators to assess the HHC performance quantitatively in a real case study. This framework is based on two ANNs models including, multilayer perceptron (MLP) and radial basis function (RBF). Consequently, a standard questionnaire is used to collect data. Furthermore, DEA is utilized to verify the results, and finally, some managerial insights are provided by using strengths-weaknesses-opportunities-threats (SWOT) analysis.

2. Methodology

In this section, a comprehensive approach is presented for the performance evaluation of HHCs regarding trust indicators and patient satisfaction of the HHC staff. The steps of the approach are shown in Fig. 1 and summarized below:

Step 1: Data collection: Trust indicators were identified, and standard questionnaires were designed to collect required data.

Step 2: Reliability and validity of the questionnaire: The questionnaire's reliability and validity were checked by calculating Cronbach's alpha and conducting a suitable statistical test.

Step 3: Data preparation: The inputs and outputs of the model are determined and the gathered data are divided to train, validate, and test data.

Step 4: ANN execution with different architectures: Two different ANNs (MLP and RBF) are executed with different architectures.

Step 5: The optimum model selection: Different architectures for each network are compared based on the mean absolute percentage error (MAPE), and the one with the minimum MAPE on the test data set is selected as the best model architecture.

Step 6: Efficiency calculation: The efficiency scores are calculated for all of the DMUs based on the best ANN configuration.

Step 7: Sensitivity analysis: Examine how the elimination of each indicator affects output by using statistical tests.

Step 8: Proposing improvement actions: Appropriate improvement actions are suggested.

Step 9: Validation of the results: The efficiency scores are calculated for all of the DMUs using the DEA method, and the results are compared to those obtained by the ANN.

2.1. Data collection

Two questionnaires were designed and distributed among 472 patients of an HHC organization to collect the required data. One questionnaire contained trust factors-related questions, and the other was to evaluate patients' satisfaction. The Trust indicators were specified by studying the corresponding literature and also consulting with the experts. These indicators were divided into six main groups of questions:

- Patient focus of provider,
- Consequences of policies for patients,
- Health care provider's care,
- Quality of care,
- Information supply and communication,
- Quality of cooperation.

Patients could assign a number between 1 and 10 to answer each question based on how much they agreed with the question. Trust factors are inputs and patient satisfaction is the output of the proposed algorithm. The questionnaires are presented in Appendix I.

2.2. Validity and reliability of the questionnaire

After the data collection, the reliability and validity of the questionnaires were proved by Cronbach's alpha and statistical tests, respectively, using SPSS software. In this study, Cronbach's alpha was calculated for the satisfaction questionnaire and all indicators of the trust factor. The minimum acceptable value for Cronbach's alpha were considered 0.7 [5,7,30]. Moreover, the validation of the questionnaire was evaluated using the *t*-test or Wilcoxon signed-rank test.

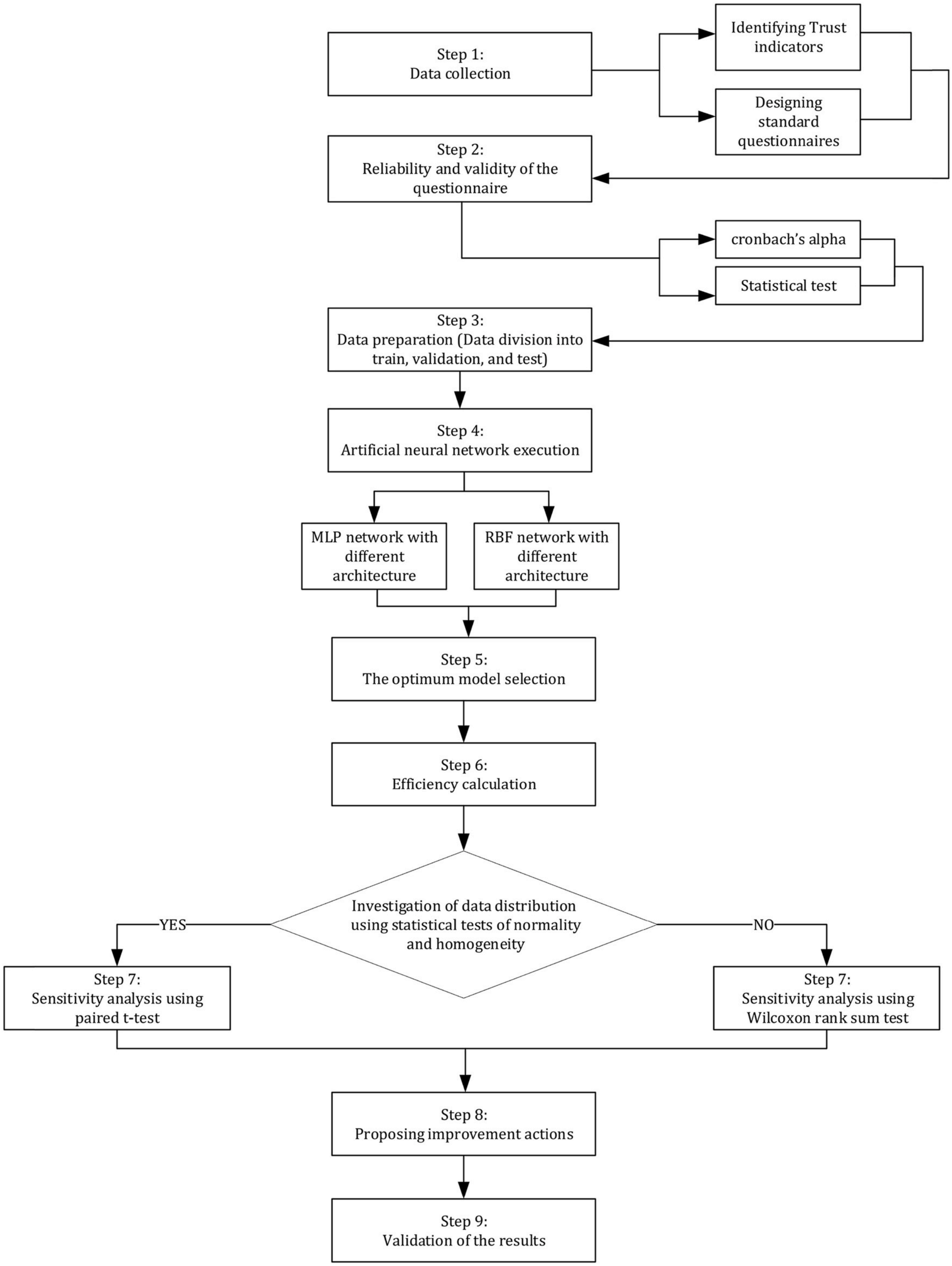

Fig. 1. Flowchart of the presented framework.

2.3. *Data preparation*

Before running ANN algorithms, collected data must be prepared. As mentioned before, trust factors were considered as inputs and patients' satisfaction as output for the corresponding model. The inputs should be the type of "the smaller, the better" and the output data "the bigger, the better" class, respectively. Consequently, Equations (1) and (2) were employed to normalize the inputs and output data. In the following Equations X_{ij} and Y_j present value of inputs and output variables. x_{ij} and y_j are the normalized value of inputs and output variables as well. The corresponding data were divided into three parts, 70% of which were considered as train data, 15% devoted to validation data, and the rest was for test data.

$$x_{ij} = \frac{\max(X_{ij}) - X_{ij}}{max(X_{ij}) - \min(X_{ij})} \quad ; \quad j = 1, ..., n \; ; \; i = 1, \ldots, m \tag{1}$$

$$y_j = \frac{Y_j - min(Y_j)}{max(Y_j) - min(Y_j)} \quad ; \quad j = 1, \ldots, n \tag{2}$$

2.4. Artificial neural network execution

An ANN is a data processing concept inspired by the human brain and patterned after how biological neurons interact with one another [19,41]. Among the many networks, the multi-layer perceptron (MLP) is the one that is most frequently utilized in engineering research. MLP networks are composed of an input layer and an output layer that are linked by one or more layers of hidden nodes [3,13,36]. Moreover, a radial basis function (RBF) is employed, in which the first layer represents the input of the ANN model, the second is the hidden layer consisting some non-linear activation units of RBF, and the third layer represents the outputs of the model [10]. Further explanations about these methods are presented in Section 1 of the "Supplementary Materials".

2.5. Selecting the best ANN architecture

We provided a procedure for selecting the most suitable architecture for MBF and RBF and determining the superior alternative between them using the following steps:

Step 1: Changing different parameters to achieve various architecture for both MLP and RBF models;

Step 2: Calculating the mean absolute percentage error (MAPE) for each of the achieved architectures by using Equation (3), where y_j represents the actual value of outputs and $\hat{y}_j$ corresponds to forecasted value of outputs. n is the number of DMUs, which is 472 in this study.

$$MAPE = \frac{100}{n} \sum_{k=1}^{n} \frac{|y_j - \hat{y}_j|}{y_j} \quad ; \quad j = 1, \ldots, n \tag{3}$$

Step 3: choosing the best architecture for MLP and RBF networks with the smallest MAPE value.

Step 4: choosing the best network between MLP and RBF based on statistical methods.

2.6. Calculating efficiency

We used the optimal ANN architecture to model the relation between inputs (trust indicators) and outputs (patient satisfaction). We have adopted the stated procedures by Azadeh et al. [4] to calculate efficiency scores:

Step 1: Compute the difference between the actual output value y_k and optimal forecasted output $\hat{y}_k$ value for each DMU using Equation (4):

$$E_j = y_j - \hat{y}_j \quad ; \quad j = 1, \ldots, n \tag{4}$$

Step 2: Compute frontier function shift (E_j') for calculating the impact of the largest positive error:

$$E_j' = \frac{E_j}{\hat{y}_j} \quad ; \quad j = 1, \ldots, n \tag{5}$$

Step 3: Determine the maximum value of E_j between patients (DMUs):

$$E_j' = \frac{E_j}{\hat{y}_j} \quad ; \quad j = 1, \ldots, n \tag{6}$$

$$E_{max}' = Max(E_j') \quad ; \quad j = 1, \ldots, n \tag{7}$$

Step 4: Computing the shift (Sh_j) for each patient; In Equation (7), $\hat{y}_m$ represents forecasted output value for the for DMU m which has the highest value of the E_j' :

$$Sh_j = \frac{E_{max}' * \hat{y}_j}{\hat{y}_m} \quad ; \quad j = 1, \ldots, n \tag{8}$$

Step 5: Computing the efficiency score (F_j) for each DMU:

$$F_j = \frac{y_j}{\hat{y}_j + Sh_j} \quad ; \quad j = 1, \ldots, n \tag{9}$$

2.7. Sensitivity analysis

A sensitivity analysis was performed for evaluating the effect of input (trust) and output (patient satisfaction) variables on HHC performance. Efficiency scores were recalculated after removing an indicator each time and running the selected ANN model for the rest indicators. Consequently, the results were compared to the primary model in which all indicators are considered. For this purpose, an appropriate statistical test should be selected based on the distribution of the data. Homogeneity and normality conditions should be checked to see whether a parametric or non-parametric test should be utilized. If both of the conditions are met, the paired t-test can be used. Otherwise, the Wilcoxon Rank Sum test is employed as a non-parametric test.

The null hypothesis (H_0) tests the equality of means ($\mu_1 = \mu_2$) before and after the removal of each indicator at the 95% confidence level. If the p-value is below 0.05, the null hypothesis is rejected, which means that the omitted indicator is influential on the efficiency score of HHC. Moreover, to assess whether the performance of the HHC is appropriate or inappropriate according to each indicator, the efficiency scores before and after each indicator's removal should be compared. If the mean efficiency score reduces after the elimination of an indicator, the performance of HHC is appropriate considering the related indicator. In contrast, the higher mean efficiency score after the removal of an indicator means a poor performance of HHC regarding the indicator.

2.8. Validation of results by data envelopment analysis

In this study, the DEA method were used to determine the efficiency scores of the DMUs, and the findings achieved by the ANN algorithm were compared to those obtained by DEA. The DEA model is a widely used non-parametric technique for calculating the relative efficiency of several decision-making units (DMUs) [8,20–22]. DEA offers several advantages that make it an attractive technique for academics. For instance, it is not required to establish a connection between inputs and outputs. Additionally, the units of the inputs and outputs might be somewhat dissimilar [14,23]. Above all, unlike many other techniques, there is no requirement for an explicit mathematical representation of the production function. In this paper, DMUs refer to the patients participating in the survey.

To ensure the algorithm's output is consistent with the output of DEA, the optimal DEA model should be chosen. To do so, four DEA models, including CCR input-oriented, CCR output-oriented, BCC input-oriented, and BCC output-oriented models are run. Noise is inserted into the data to choose a single model, and the model with the least vulnerability to the noise is selected as the best model. The results of each model before and after noise insertion are compared using Spearman's correlation test, and the best DEA model is the one with the highest coefficient. As a result, Spearman's correlation is also employed to compare the efficiency scores produced from the chosen DEA model to the scores previously calculated by the ANN model. The high coefficient value proves the validity of the algorithm's results.

The following mathematical programming models are given for the considered DEA models [5]. It should be noted that all of the models are customized for this study which has six indicators as inputs and one output.

- **CCR DEA model**

Model 1 examines the relative efficiency of 472 DMUs by reducing the input variables while keeping the output constant, which is an input-oriented model. There are 6 input variables and an output variable in each DMU. Increasing the output variables while keeping the input variables constant creates an output-oriented model. The output-oriented CCR model is shown in Model 2.

Model 1:
Min ω
s.t.

$$\begin{aligned} &\omega x_{i0} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \quad ; \quad i = 1, \dots, m \ ; \ j = 1, \dots, n \\ &y_0 \leq \sum_{j=1}^{n} \lambda_j y_j \quad ; \quad j = 1, \dots, n \\ &\lambda_j \geq 0 \quad ; \quad j = 1, \dots, n \end{aligned} \tag{10}$$

Model 2:
Max ω
s.t.

$$\begin{aligned} &x_{i0} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \quad ; \quad i = 1, \dots, m \\ &\omega y_0 \leq \sum_{j=1}^{n} \lambda_j y_j \quad ; \quad j = 1, \dots, n \\ &\lambda_j \geq 0 \quad ; \quad j = 1, \dots, n \end{aligned} \tag{11}$$

- **BCC DEA model**

Models 3 and 4 present the input-oriented and output-oriented CCR models, respectively.

Model 3:
Min ω
s.t.

$$\begin{aligned} &\omega x_{i0} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \quad ; \quad i = 1, \dots, m \\ &y_0 \leq \sum_{j=1}^{n} \lambda_j y_j \\ &\lambda_j \geq 0 \quad ; \quad j = 1, \dots, n \end{aligned} \tag{12}$$

Model 4:
Max ω
s.t.

$$\begin{aligned} &x_{i0} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \quad ; \quad i = 1, \dots, m \\ &\omega y_0 \leq \sum_{j=1}^{n} \lambda_j y_j \quad ; \quad j = 1, \dots, n \\ &\sum_{j=1}^{n} \lambda_j = 1 \\ &\lambda_j \geq 0 \quad ; \quad j = 1, \dots, n \end{aligned} \tag{13}$$

3. Computational results

In this section, we examined the performance of an HHC center in Tehran, Iran, according to trust indicators and patient satisfaction by executing the presented framework. Standard questionnaires were designed and distributed among 472 patients during three months. The results of executing the described steps are given below.

3.1. Results of reliability and validity of the questionnaire

Table 1 illustrates the Cronbach's alpha for each indicator calculated by SPSS software to assess the reliability of the data acquired from the questionnaires. These values are higher than 0.7 and within the acceptable level.

Table 1
Results of the reliability test.

Indicator	Cronbach's alpha
Patient focus of the provider	0.958
Consequences of policies for patients	0.938
Health care provider's care	0.934
Quality of care	0.891
Information supply and communication	0.916
Quality of cooperation	0.881
Overall	0.807
Patient satisfaction questionnaire	
Overall	0.851

Two random samples of 20 DMUs were taken from the patient satisfaction questionnaire and each of the six factors of the trust questionnaire to evaluate the questionnaires' adaptability and consistency. A suitable statistical test was employed to do this. The equality of sample averages ($\mu_1 = \mu_2$) is examined in the null hypothesis (H_0). If the estimated p-value is greater than 0.05, it is concluded that the DMUs are consistent and the validity of the questionnaire will be confirmed [6]. The Kolmogorov-Smirnov test were used to examine the normality of each factor and the overall patient satisfaction data for choosing an appropriate statistical test. According to Table 2, this test rejects the normality hypothesis for "Consequences of policies for patients" and "Information supply and communication" factors. Therefore, the Wilcoxon rank sum test were used for these two factors, and for the rest of the factors the independent two-tailed t-test were used to compare the means of the two independent samples.

The adaptability of the questionnaire is validated since the p-values for all of the factors in Table 3 are more than 0.05.

3.2. ANN execution with different architecture

MLP and RBF networks were employed in this article to assess the performance of HHC. Various architectures were investigated and compared using MAPE calculations for this aim. For MLP network, 32 distinctive architectures were designed. For this purpose, two hidden layers were considered with different number of neurons and two learning methods, Levenberg-Marquardt and BFGS Quasi-Newton. To convert the input signals to output signals, hyperbolic tangent sigmoid (tansig) and Log-sigmoid (logsig) transfer functions were used in the first and second layers, respectively. Furthermore, for MLP network, 20 distinctive architectures were designed using different number of neurons in the hidden layer.

A smaller MAPE score suggests the best architecture. Each architecture was run 100 times to eliminate model noise. The average value of MAPE is reported as shown in Tables 4 and 5 for different architectures of MLP and RBF networks, respectively. As a result, the model number 11 in Table 4 and the model number 8 in Table 5 are the best models for MLP and RBF networks, respectively.

In the next stage, we chose the best architecture by comparing the MAPE value of the selected architectures of both MLP and RBF networks.

Table 2
p-value of the normality test.

Indicator	p-value
Patient focus of the provider	0.075
Consequences of policies for patients	0.021
Health care provider's care	0.068
Quality of care	0.084
Information supply and communication	0.035
Quality of cooperation	0.065
Patient satisfaction questionnaire	
Overall	0.081

Table 3
Result of the mean equity test of random samples.

Indicator	*p*-value
Patient focus of the provider	0.275
Consequences of policies for patients	0.124*
Health care provider's care	0.514
Quality of care	0.148
Information supply and communication	0.449*
Quality of cooperation	0.254
Patient satisfaction questionnaire	0.216
Overall	0.326

"*" indicates that the Wilcoxon test is used to assess the hypothesis test.

Table 4
Comparison of different MLP structures.

Model number	Learning method	No. of neurons in the first hidden layer	No. of neurons in the second hidden layer	MAPE error
1	BFG	5	5	0.0827
2	BFG	5	10	0.0619
3	BFG	5	20	0.0568
4	BFG	5	30	0.0645
5	BFG	10	5	0.0722
6	BFG	10	10	0.0568
7	BFG	10	20	0.0589
8	BFG	10	30	0.0604
9	BFG	20	5	0.0710
10	BFG	20	10	0.0674
11	**BFG**	**20**	**20**	**0.0412**
12	BFG	20	30	0.0577
13	BFG	30	5	0.0835
14	BFG	30	10	0.0600
15	BFG	30	20	0.0698
16	BFG	30	30	0.0526
17	LM	5	5	0.0644
18	LM	5	10	0.0549
19	LM	5	20	0.0605
20	LM	5	30	0.0635
21	LM	10	5	0.0614
22	LM	10	10	0.0625
23	LM	10	20	0.0647
24	LM	10	30	0.0591
25	LM	20	5	0.0557
26	LM	20	10	0.0576
27	LM	20	20	0.0587
28	LM	20	30	0.0553
29	LM	30	5	0.0801
30	LM	30	10	0.0501
31	LM	30	20	0.0723
32	LM	30	30	0.0624

* First transfer function: tansig, Second transfer function: logsig.

Consequently, the MLP model number 11 with the lowest MAPE value of 0.0412 is selected as the best architecture.

3.3. Result of efficiency calculation

In this section, the efficiency score of each DMU was calculated using the algorithm introduced by Azadeh et al. [4]. Then, DMUs were ranked based on their efficiency scores. The related results are presented in Table s1 of the "Supplementary Material" section 2.

3.4. Results of sensitivity analysis

Statistical methods were used to evaluate the performance of the HHC center according to each trust indicator. As previously mentioned in the methodology section, the inputs (trust indicators) were removed one by one, and the selected architecture for the MLP model was rerun for the rest of the indicators. Then, the efficiency scores of the new model and the original model were compared using an appropriate statistical test. For this purpose, the normality of the data distribution and the homogeneity of variances were measured using the Kolmogorov-Smirnov test and the Levene test, respectively.

Table 5
Comparison of different RBF structures.

Model number	No. of neurons in the hidden layer	MAPE
1	5	0.18698
2	10	0.16654
3	15	0.09155
4	20	0.07635
5	25	0.07155
6	30	0.07027
7	35	0.06894
8	**40**	**0.06485**
9	45	0.07379
10	50	0.0802
11	55	0.08156
12	60	0.07512
13	65	0.08174
14	70	0.07531
15	75	0.07771
16	80	0.07511
17	85	0.0826
18	90	0.08314
19	95	0.08922
20	100	0.08723

According to Table 6, both criteria are not satisfied concurrently in all situations. As a result, all relevant comparisons were conducted using the Wilcoxon test, with the findings presented in Table 7. It is worth noting that all statistical tests were conducted using SPSS at the 0.05 level of significance.

As the *p*-value of the statistical tests is below 0.05 after the removal of each indicator, the performance of ORs could be assessed based on all of the indicators. In other words, the omission of the indicators has a statistically significant effect on the mean efficiency score of the HHC center. The mean efficiency scores before and after eliminating each of the shaking elements were compared to assess if the performance of HHC is appropriate or inappropriate.

According to Table 7, the mean efficiency score decreased after the elimination of the "Health care provider's care", "Quality of care", and "Quality of cooperation" indicators. Therefore, the performance of the HHC center has been appropriate according to these indicators. On the other hand, removing the "Consequences of policies for patients", "Patient focus of provider" and "Information supply and communication" increased the mean efficiency scores, indicating that the performance of the HHC center is inappropriate based on these indicators. In the other words, these indicators are the weaknesses of the HHC center, and remedial measures should be taken to enhance the performance based on these indicators as they seem to be negatively influenced by the COVID-19.

It should be noted that, based on Table 7, the HHC center has the most appropriate and most inappropriate performances based on "Quality of cooperation" and "Information supply and communication" indicators, respectively.

Table 6
Results of the normality and homogeneity test.

Omitted indicators	*p*-value (normality)	*p*-value (homogeneity)
None	0.075	
Patient focus of the provider	0.075	0.000
Consequences of policies for patients	0.124	0.000
Health care provider's care	0.014	0.255
Quality of care	0.021	0.063
Information supply and communication	0.040	0.005
Quality of cooperation	0.000	0.230

Table 7
Results of the sensitivity analysis.

Omitted indicators	$\mu_1 - \mu_2$	Hypothesis test	p-value (Wilcoxon signed-rank test)
Patient focus of the provider	−0.0120	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Consequences of policies for patients	−0.0126	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.034
Health care provider's care	0.1387	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Quality of care	0.0127	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.012
Information supply and communication	−0.0832	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000
Quality of cooperation	0.2233	$H_0 : \mu_1 = \mu_2$ $H_1 : \mu_1 \neq \mu_2$	0.000

3.5. Suggesting improvement strategies

According to the findings of the sensitivity analysis, the HHC center performs poorly in terms of patient focus of provider, consequences of policies for patients, and Information supply and communication indicators. As can be observed, the clinics' low performance is primarily due to weakness in the trust indicators. It should be noted that strengthening these indicators would increase both the trust indicators and patient satisfaction.

The SWOT analysis was used to offer a holistic perspective of acceptable strategies for enhancing HHC's performance in terms of trust indicators and patient satisfaction in this research. As discussed, statistical tests were used in the sensitivity analysis section to discover strengths and threats in the HHC center. Consequently, the HHC center's health care provider's care, quality of care, and quality of cooperation are all well-applied and regarded as strengths. In addition, the indicators of Patient focus of the provider, Consequences of policies for patients, and Information supply and communication indicators are not adequately implemented in the HHC center. The HHC's performance improved due to their removal, concluding that these indicators are weaknesses. Expert views were utilized to highlight opportunities and threats for the understudied HHC center after evaluating strengths and weaknesses.

As a result, the study HHC's ultimate objectives, which include increasing patient satisfaction and productivity, are determined in the first stage to propose suitable strategies for improvement. Consequently, the HHC center needs to develop specific strategies. Table 8 shows a SWOT analysis that may assist the HHC in improving its performance in terms of integrated trust indicators and patient satisfaction.

3.6. Verification and validation of the result

As previously stated, the suggested algorithm's validity was assessed using the DEA approach. The efficiency rankings were determined using the four models that were presented for the data. To find the optimal DEA model, we created 25% noise in 10% of the data and recalculated the efficiency ranking. Finally, the Spearman correlation test was used to determine the correlation between each model's pre-noise and post-noise findings. The CCR input-oriented model was chosen as the best model based on the data in Table 9. Following that, the DMUs are rated based on the efficiency ranking produced by the chosen DEA. Table s1 of the "Supplementary Material" section contains the pertinent findings. Finally, a correlation coefficient of 0.841 was found between the resulting scores and the scores previously estimated by the ANN model using the Spearman correlation test. The high validity of the algorithm's findings is shown by this coefficient value.

4. Conclusion and future study

In the Covid-19 pandemic, HHC clients experience similar or

Table 8
SWOT matrix.

SWOT	Strengths:	Weaknesses:
	• Health care provider's care • Quality of care • Quality of cooperation	• Patient focus of the provider • Consequences of policies for patients • Information supply and communication
Opportunities: • Employing qualified and experienced physicians in various fields in the center • The center has a good history and reputation in the province • The center has up-to-date medical equipment • In the presence of a pandemic, there are many opportunities to serve patients in their own homes, according to the advice of the country's health officials to reduce the number of visits to hospitals to prevent COVID-19. • The center has an up-to-date information system. • The center has enough vehicles. • The center has a large and well-equipped laboratory. • The center cooperates with many insurance companies	**SO strategies** • Using the expertise of the executive staff to train new employees • Using an effective feedback system to improve the process and quality of treatment • Provide personal online profiles for patients for easy access to treatment process information and prescription drugs • Provide a communication platform for medical staff to share experiences and scientific synergy to improve the quality of treatment • Attract investors with the help of reputation and communication of the center • Providing services related to COVID-19 treatment in patients' homes	**WO strategies** • Use a free online platform to guide and answer patients' questions • Enabling the possibility of online visits of patients to increase the system response rate • Using an optimal planning and scheduling system with the use of past data • Using information system data to track the status of previous patients of the center and provide possible future services • Utilizing a comprehensive notification system to increase the level of patient awareness about their disease and possible treatments • Collaborate with insurance companies to develop programs to provide better and cheaper services to patients • Accurate and transparent information of the center's services on different platforms to increase the level of public awareness and to be better known than competitors
Threats: • Risk of staff getting COVID-19 and absenteeism during quarantine. • Increasing the number of competing centers in the province • The number of medical and nursing staff of the center is much less than its demand. • Funds received from the government have been reduced. • Patients 'complaints about nurses' behavior • Long waiting time for patients to receive services • Medical team and nurses complain about overwork • The number of medical equipment	**ST strategies** • Optimal pricing for center services to increase competitiveness • Provide a staff performance evaluation system to improve the services of the center • Employing On call out-of-center nurses to compensate for the lack of staff in an emergency (like when some nurses are infected with COVID-19) • Holding various technical training courses for staff to improve the quality of services	**WT strategies** • Increase the number of nurses and medical staff to meet more demands • Provide more medical equipment to meet more demands • Improving nurses' communication skills with patients by involving them in relevant courses • Provide a feedback system from patients on the behavior and performance of nurses • Use of multifunctional medical equipment to reduce costs and increase the efficiency of the center

(continued on next page)

Table 8 (*continued*)

SWOT	Strengths:	Weaknesses:
available at the center is not enough to meet all the demands.		

Table 9
Correlation for each DEA model before and after noise for each DEA model.

DEA model	CCR input-oriented	CCR output-oriented	BCC input-oriented	BCC output-oriented
Correlation	**0.964**	0.945	0.952	0.937

superior health outcomes. When persons with chronic diseases receive home care, research has shown that clinical outcomes are equivalent or better, with fewer complications. As a result, healthcare providers place a high priority on increasing the performance of HHC centers. This study aimed to assess the performance of an HHC center based on trust indicators and patient satisfaction. The relevant data were obtained using a standard questionnaire whose validity and reliability were established via experts' opinions and Cronbach's alpha calculation, respectively. The efficiency of DMUs was then estimated using two ANN models and statistical approaches. As a result, trust indicators were used as inputs, while patient satisfaction was used as output. After that, MLP and RBF networks were employed to predict patient satisfaction, and statistical approaches were utilized to choose the best architecture. Each DMU's efficiency score was calculated and ranked based on the acquired results. The suggested algorithm was then re-executed after the trust indicators were eliminated one by one to evaluate HHC performance according to the indications. Statistical tests were used to investigate the impact of each indicator in this way.

Based on statistical tests, the performance of the study HHC center could be judged through all of the indicators. The performance of HHC based on the "Health care provider's care," "Quality of care," and "Quality of cooperation" indicators was statistically appropriate, as the mean efficiency scores dropped after they were eliminated. HHC, on the other hand, performed poorly based on the indicators "Policy Consequences for Patients," "Patient Focus of Provider," and "Information Supply and Communication," since the elimination of these indicators resulted in a rise in the mean efficiency ratings of DMUs. These indicators have been identified as affecting HHC's performance, and improvement actions have been offered based on expert advice. Finally, the suggested algorithm's validity was tested using the DEA approach. To do this, the most stable of the four distinct forms of DEA was chosen and used to determine the efficiency scores. DMUs were re-ranked to reflect this. The validity of the used algorithm was demonstrated by the correlation between the DEA-computed ranks and the algorithm-proposed ranks.

For future research, we could consider patient safety and quality factors in HHC. Furthermore, the job satisfaction of HHC personnel could be assessed through the proposed algorithm. Also, fuzzy ANN methods like ANFIS could be used to consider uncertain data.

Declaration of competing interest

The authors of this research entitled "An intelligent algorithm to evaluate and improve the performance of a home healthcare center considering trust indicators" certify that there is no any affiliation with or involvement in any organization or entity with financial interest (e.g., honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (e.g., personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compbiomed.2022.105656.

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