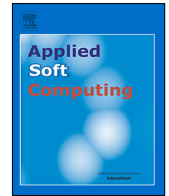ELSEVIER

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Re-evaluation of the healthcare service quality criteria for the Covid-19 pandemic: Z-number fuzzy cognitive map

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ABSTRACT

Hospitals as healthcare centers have faced many challenges with the Covid-19 spread, which results in a decline in the quality of health care. Because the number of patients referred to hospitals increases dramatically during the pandemic, providing high-quality services and satisfying them is more important than ever to maintain community health and create loyal customers in the future. However, health care quality standards are generally designed for normal circumstances. The SERVPERF standard, which measures customer perceptions of service quality, has also been adjusted for hospital service quality measurement. In this study, the SERVPERF standard criteria for health services are evaluated in the Covid-19 pandemic. For this purpose, by considering the causal relationships between the criteria and using Z-Number theory and Fuzzy Cognitive Maps (FCMs), the importance of these criteria in the prevalence of infectious diseases was analyzed. According to the results, hospital reliability, hospital hygiene, and completeness of the hospital with ratios 0.9559, 0.9305, and 0.9268 are respectively the most influential criteria in improving the quality of health services in the spread of infectious diseases circumstances such as the Covid-19 pandemic. A review of the literature shows that in previous studies, comprehensive research has not been done on prioritizing the criteria for measuring the quality of health services in the context of the spread of infectious diseases.

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1. Introduction

In December 2019, a new strain of the Covid-19 virus appeared in Wuhan, China. The number of people with this disease has increased rapidly worldwide, and official reports indicate that as of January 18, 2021, 95.2 million people were infected, and 2.03 million had died. The virus is widespread and affects general public [1,2], economy [3,4], culture [5,6], ecology [7], environment [8], health systems [9] and other fields [10–12]. Hospitals are often the central point of health care, and have played a vital role in responding to this crisis [13]. Accordingly, one of the most important public health measures to reduce the virus's spread rate is the rapid diagnosis and isolation of infected people [14]. Covid-19 is a unique disease due to the high prevalence, possibility of an epidemic, lack of primary scientific data, and media coverage. Therefore, these features face hospitals with many new challenges [15].

These challenges start before the suspected patients of Covid-19 infection enter the hospitals because predicting a potential increase in cases is critical to hospitals' readiness. Also, the patient increase can lead to bed shortages and the need for more

medical staff [13,15]. After the arrival of patients suspected of Covid-19 in the hospital, the correct diagnosis is one other crucial step. After this step, patient management and isolation in emergency and intensive care units, triage, and scarce resource management are other possible challenges [13]. Logistics and transfer of patients for radiological and surgical examinations and separation of Covid-19 patients from others are also problematic. Infectious and hazardous waste management is conspicuous during infected patient care. Throughout this period, from the beginning of the pandemic until now, protecting healthcare personnel on the front lines and preventing nosocomial infections has been a significant challenge [16–18]. Like other infectious diseases, infection prevention and control is especially important in hospital and healthcare environment. What challenged this fact is the lack of personal protective equipment and freshman staff, the physical and psychological stress of dealing with a pandemic, intensity of work and lack of rest, need for training, etc. One other crucial issue is increasing awareness of health care providers to prevent and control infectious respiratory disease in the hospitals [17,18]. Facing any of these challenges means a decline in the quality of hospital health services. To evaluate, address and tackle these challenges, criteria for measuring the quality of health services in different areas have been defined. However, most healthcare quality standards and scales are designed for

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typical situations and may not necessarily be appropriate in crisis times, such as the Covid-19 pandemic [19].

During the infectious disease spread such as Covid-19 pandemic, the number of patients referred to health centers, including hospitals, are more than before. This increase means that more people are receiving health services from a specific organization than before. Since the low quality of health services has a severe direct and indirect impact on the loss of an organization's customers, [20] if the organization's services are not of good quality, it will have a tremendous negative impact on customer loss. The importance of paying attention to the quality of health services is due to its relationship with human health and lives, so it is essential to provide services that satisfy the customer [21]. On the other hand, improving system-based quality can reduce shift work time and costs, enhancing return on investment, increase consumer satisfaction and provide better services. Health centers offer different service quality levels despite providing similar services [22]; this quality is a strategic differentiation tool to maintain a competitive advantage [23]. Performance is one of the most critical competitive advantages in service quality. Performance differentiates between services and leads to more loyal customers [22]. Sum of all these facts makes it essential to address the quality of health services during any infectious disease prevalence like the Covid-19 pandemic.

Based on numerous pieces of evidence, it can provide a conclusion that the perceived quality of health care services has a significant impact on consumer's behavior, including patient satisfaction, selection, referral, and reuse services of that specific health center. One of the most significant human concerns is health issues. An improper understanding of health services' quality can significantly discourage patients from using available resources or using them as a last choice [24]. In terms of perceived quality of services, customer satisfaction [25–28] can be a notable factor because it significantly impacts the customer's intention to repurchase [29]. Patient satisfaction is also a vital concern that is intertwined with strategic decisions [26] and should be considered in quality assessment as well as in the designing and management of healthcare systems [30].

Different measurement methods and models are proposed by considering different available definitions for service quality [31, 32]. Grönroos [33] developed the first service quality measurement model and measured perceived service quality based on qualitative methods. In this model, service quality dimensions are performance quality, functional quality, and organizational image. Performance quality is more important than technical quality for service differentiation and customer perception because technical quality addresses delivered services. In other words, the customer evaluates received services, while performance quality refers to how the service is provided and how the customer uses that service. Company image also has a positive effect on customer perception. Most of the service quality measurement research was completed using SERVPERF and SERVQUAL scales [32, 34]. The SERVQUAL model measures service quality based on the difference between customer's expectation and their perception of service performance [35]. Cronin and Taylor [36] developed the SERVPERF model with SERVQUAL modification. This model uses only the customer's perception of performance to measure service quality [29,36]. A wide range of service industries, including aviation, banking, and healthcare, have used these two models to evaluate service quality [20].

Researchers have used different scales to evaluate the service quality in the healthcare industry. Donabedian [37–39] is the first person who studied the quality of healthcare services. SERVQUAL and SERVPERF are also the most widely used models in measuring health services' quality [20]. In general, these scales or their modifications have been broadly selected to assess the quality of health services [26,40–57]. Also, Lee [58] developed the HEALTHQUAL model based on the SERVQUAL scale. Another model is the PubHosQual (Public Hospital Service Quality) model, developed from a patient perspective [59,60]. Similarly, the HospitalQual model was derived from the development of SERVPERF. [61]. Researchers have also used multi-criteria decision analysis (MCDA) methods to assess the quality of health services. To identify the most effective criteria for the quality of health services, Büyüközkan et al. [21] used the SERVQUAL scale criteria and evaluated the quality of health services using fuzzy AHP. Also, to find the criteria for hospitals' success in meeting customer expectations for the quality of health services, Shieh et al. [62] used SERVQUAL scale criteria and DEMATEL method to find more effective criteria [62].

However, most of the measuring service quality models have shortcomings [20]. Brown et al. [63] discussed the problems of measuring the difference between customer expectations and their perception of service performance on the SERVQUAL scale. Also, many shortcomings in the main SERVQUAL scale addressed by Babakus and Boller [64], including methodological problems and the need to use appropriate criteria for each type of service, and major problems in measuring the difference between expectation and perception of service performance. On the other hand, the data collected for the SERVQUAL scale may be memory-based or intentional, as most of the data is collected after the service is provided [65]. Specialized in hospitals, Reidenbach and Sandifer-Smallwood [55] showed the existence of measurement problems on the SERVQUAL scale. Moreover, service quality expectations may not play a role in the relationship between service quality and other critical measures mentioned in [43]. Similarly, Cronin and Taylor [36] stated that the service quality could be adequately assessed only with the customer's understanding of performance and introduced the SERVPERF model. One of the limitations of SERVQUAL-derived models such as the PubHosQual model is that these models are designed specifically for the Indian health-care system and do not include healthcare services' technical aspects [59,60]. Also, the HospitalQual model's limitation is that it is designed for the in-patient department of Indian hospitals only. Distinctive characteristics of health services such as intangibility, heterogeneity, simultaneity, complex nature, different interests of service providers, and the need to address ethical considerations are barriers to comprehensive quality management methods in health care centers [66]. Zineldin [67] expressed that models for measuring the quality of health services are designed for the Western world and are not necessarily suitable for developing countries; therefore these countries should design appropriate models for their health care systems. It is essential to mention that almost none of the methods and models of evaluating the quality of health services did consider correlation and each criterion's effect on other criteria of the service quality evaluation models, except some MADM methods, including the ANP and DMATEL methods [68]. Also, these models and methods do not consider the reliability and ambiguity in the information received from individuals to evaluate the quality of services. In the real world, uncertainty is an inevitable phenomenon, and most of the information on which the decision-making process is implemented suffers from uncertainty [69]. We also know that since all services contain abstraction, health centers' quality of services is inevitably vague (fuzzy) [70]. Therefore, there is a need for a new approach to assessing the quality of health services which preserve the benefits of previous methods and covers the relevance and effectiveness of criteria and also the reliability and ambiguity of information.

In this study, the Z-number theory, which Zadeh [71] first introduced, is used to cover data reliability. The information that underlies decisions can only be practical when they are

reliable. This theory was presented as a general version of the uncertainty for calculating unreliable numbers. This theory, unlike fuzzy theory, considers reliability of numbers [72]. The Z-number concept has been used in many fields, especially in economics, decision analysis, and risk assessment for anticipation and rule-based characterization of imprecise functions and relations [71]. In healthcare, researchers have also benefited from multi-criteria decision analysis methods with Z-numbers, including the work of Chen et al. [73] which adopted a new multi-criteria group decision method in the Z-number environment to select a sustainable method for managing healthcare waste. They used Z-number in expert comments and evaluation of their reliability. In one of the recent articles to improve the quality of health services, key indicators that affect the hospital's performance have been identified. In this study, Jiang et al. [74] achieved this goal through an extensive group evaluation method using linguistic Z-number and DEMATEL approach. They used the Z-number theory to comprehensively and flexibly collect decision information and prevent distortion and crucial information loss. Also, Hsu et al. A [75] used a combination of Z-number and DEMATEL to assess the healthcare industry's development. They used Z-numbers to optimize ordinary fuzzy numbers and increase expert opinions' reliability.

Another approach to investigate the relationship and ambiguity of factors affecting health services' quality is the fuzzy cognitive mapping (FCM) method. In this study, fuzzy cognitive maps (FCMs) have also been used to cover the ambiguity of service quality and consider each criterion's relationship and causal effect on other service quality evaluation criteria. Kosko [76] first introduced the FCM method by which complex structures can be modeled. FCM results from directional and weighted relationships between a system's fundamental and practical components and is structured like a neural network [77]. FCMs show how changes can influence the entire system and make scenario analysis possible for the future [70]. FCMs have been adopted in many research fields; in some applications, the dynamic features and FCM learning methods have been used to model, analyze, and forecast to improve system performance. These applications include engineering, business, medicine, environment, etc. [78]. For instance, researchers have applied evolutionary fuzzy cognitive maps to improve predictive performance, including the prediction of lung infections [79], the prognosis of prostate cancer, and leukemia in [80] and [81], respectively. FCMs are also applicable to develop dynamic decision support systems for medical informatics decision-making [82]. Amirkhani et al. [83] discussed in detail the applications of FCMs in medicine, health, and treatment.

In this research, a new method is adopted to evaluate health services' quality with a Covid-19 pandemic case study. This method combines the SERVPERF scale and the Z-number Fuzzy Cognitive Map approach. The SERVPERF scale was selected because of the relationships between patient's perception and their satisfaction with services and the effect of patient's satisfaction on their future behaviors [24]. It is noteworthy that SERVPERF requires half of SERVQUAL data [32], and this reduces the burden of requiring large amounts of data during the Covid-19 pandemic due to the less access to experts. This method's main advantage is determining each criterion's effect on the other (using FCM) and covering the data's reliability (using the concept of Z-numbers) [69]. The purpose of this study is to update standards in terms of ranking the criteria for measuring the quality of health services through a Covid-19 pandemic case study. The results of this study can be mentioned to improve the quality of health services, which is vital in two ways: 1) socially: it leads to patient health. Better care for patients means better system performance, and better learning of the treatment staff means professional advancement which supports the patient's

safety [84], 2) economic: leads to patient satisfaction and has a positive effect on the patient's willingness to reuse the services of that hospital [29] and also expands the "word of mouth" marketing [22]. Therefore, the main contributions of this research are as the following:

1- Modifying the healthcare service quality criteria for the pandemic of infectious diseases,
2- Prioritizing the healthcare service quality criteria in the context of the spread of infectious diseases,
3- Proposing an approach based on Z-number theory and FCMs to evaluate the service quality scales by considering the interactions among service quality criteria and uncertainty of experts.

The remainder of this paper is organized as follows. In Section 2, the theories and models used in this paper are described. Section 3 discussed the proposed approach. The case study and the results are explained in Sections 4 and 5, respectively. Finally, concluding remarks are given in Section 6.

2. Methodology (theories and models)

The purpose of this study is to evaluate the criteria for measuring the quality of health services by considering the epidemic conditions of infectious diseases, such as the conditions caused by the prevalence of Covid-19. Therefore, the emphasis of service quality criteria provided in the SERVPERF standard is examined by using a combined approach based on Z-number theory and fuzzy cognitive map. First, the SERVPERF scale is discussed, focusing on health services; then, the Z-number theory and the fuzzy cognitive map method will be explained.

2.1. The SERVPERF scale

The SERVQUAL model measures service quality based on the difference between customer expectation and their perception of service performance [35]. However, in previous studies, several problems were raised to measure the difference between customers' expectations and their perception of service performance [63–65]. Cronin and Taylor [36] proposed the SERVPERF model to solve the problems of the SERVQUAL model. They believed that customers' expectations of service performance did not reflect "their understanding of service quality"; therefore, they developed the SERVPERF scale based solely on customer perceptions of service performance. The SERVPERF model offers more reliable estimation, better convergence, and discriminant validity, as well as more significant explained variance, and consequently less bias than SERVQUAL [29,85]. Finally, they concluded that SERVQUAL is not a suitable scale for evaluating service quality and proposed the SERVPERF model. SERVPERF criteria are the same as SERVQUAL criteria, including 22 criteria (measures), divided into five categories: 1) Tangibles, 2) Reliability, 3) Responsiveness, 4) Assurance, and 5) Empathy. Tangibles refer to the equipment, facilities and appearance of the personnel. Reliability is the ability to do the services reliably and correctly. Responsiveness implies the readiness to provide on-time services and help clients. Assurance denotes the knowledge and ability of employees to build trust in customers. Finally, empathy points toward the care and attention to customers.

Based on the SERVQUAL scale, these 22 criteria can be answered in two ways, once about expectation and once about perceived performance quality; that means 44 data must be taken from each person. However, for the SERVPERF scale, 22 data per person are required, only in terms of perceived performance. This SERVPERF feature facilitates the data collection process [32].
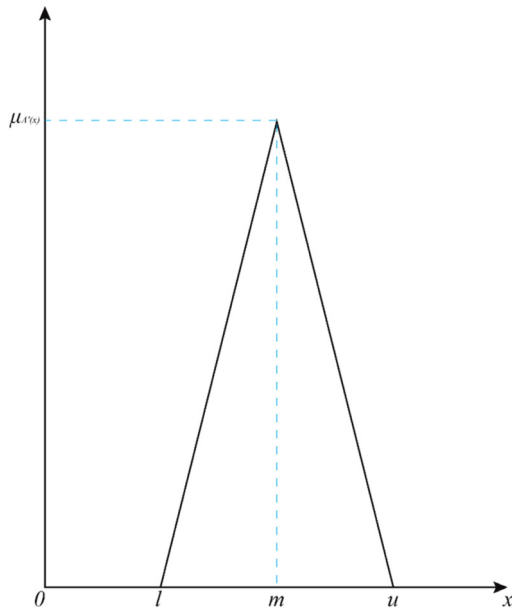
Fig. 1. Triangular fuzzy number.

However, the literature review indicates that the proposed framework and SERVPERF measurement criteria are not always efficient [24]. Accordingly, it may be necessary to remove, modify or add some criteria [23]. In this regard, health services such as services provided in hospitals have been adjusted [26]. Due to differences in health care conditions during infectious epidemics, a new interpretation of some SERVPERF scale criteria may be required. For this purpose, the SERVPERF scale criteria in health services have been revised, taking into account the epidemic conditions using experts' opinions. A description of these criteria is available in Table A.1 (Appendix).

2.2. Fuzzy set theory

Fuzzy logic is a flexible and convenient method to translate and represent the knowledge of experts and verbal expressions in a mathematical manner. Also, fuzzy logic is a valuable method by which ambiguity and uncertainty of data can be dealt with [86]. Fuzzy logic which is based on fuzzy set theory, first proposed by Zadeh [87]. In fuzzy set theory, each component is characterized by a membership function between [0,1]. Therefore, membership function determines the extent that an element belongs to a set [88]. In the following, some definitions of fuzzy sets are explained.

Definition 1. Eq. (1) represents the fuzzy set A' which is defined in the reference set U.

$$A' = \{(x, \mu_{A'}(x)) \,|x \in U\} \tag{1}$$

where, $\mu_{A'}(X) : U \to [0, 1]$ is membership function of set A'. The membership function $\mu_{A'}(X)$ indicates the extent to which $x \in U$ belongs to A'. Among the fuzzy numbers, triangular fuzzy number (TFN) is used in this study, which is defined as follows:

Definition 2. The TFN is stated as a triple (l, m, u), whose membership function is represented by Eq. (2) and Fig. 1. define

$$\mu_{A'}(x) = \begin{cases} 0 & x \in (-\infty, l) \\ \dfrac{x-l}{m-l} & x \in [l, m] \\ \dfrac{u-x}{u-m} & x \in [m, u] \\ 0 & x \in (u, \infty) \end{cases} \tag{2}$$

where, $l < m < u$ and the parameters l and u show the lower and upper limits of the triangular fuzzy number, respectively [87].

Definition 3. linguistic variables are defined as variables that take words and sentences in human or machine languages. Linguistic terms are utilized to express the values of a linguistic variable. For example, when "quality" is considered as a linguistic variable, the terms "low medium", "low", "medium high", and "high" can be used as a set of terms [89]. Linguistic variables can be defined as fuzzy numbers.

Definition 4. Converting fuzzy numbers to crisp numbers is called defuzzification. A defuzzification method combines specific properties of a fuzzy set into a crisp number. There are several defuzzification methods. In this research, the center of gravity (COG) / center of area (COA) method is employed. This method provides a crisp value based on the center of gravity of the fuzzy set [90]. A sample defuzzified fuzzy set is represented in Fig. 2.

2.3. Z-number theory

In the real world, uncertainty is an inevitable phenomenon. Humans have considerable ability to decide rationally based on inexact, inaccurate, or inadequate information. Formulating this ability is a challenge that is almost impossible to overcome. In this regard, Zadeh [71] has introduced a concept called Z-number which is an orderly pair of fuzzy numbers displayed as $Z = (A, B)$. Where, A is a fuzzy subset of the X domain and B a fuzzy subset indicating component A's reliability. A and B are usually described in linguistic terms. For example, A and B for "temperature" can be described as "high" and "completely confident", respectively.

2.3.1. Conversion of Z-numbers to TFNs

Suppose that $A = \{(x, \mu_A(x)) \,|x \in U\}$ and $B = \{(x, \mu_B(x)) \,|x \in U\}$ are TFN membership functions and $Z = (A, B)$. Eqs. (3) and (4) are used to convert the fuzzy set B to a crisp number [72].

$$\alpha = \frac{\int x\mu_B(x)\,dx}{\int \mu_B(x)\,dx} \tag{3}$$

$$Z^\alpha = \{(x, \mu_{A^\alpha}) \,|\mu_{A^\alpha}(x) = \alpha\mu_A(x)\, , x \in [0, 1]\} \tag{4}$$

For instance, assume that a fuzzy number corresponding to "Very High" equals (0.65, 0.8, 0.9) and a fuzzy number corresponding to "Medium" equals (0.3, 0.5, 0.7). Also, let $Z = (A, B)$ be a Z-number with each of its components equal to $A =$ (Very High) and $B =$ (Medium). Therefore, we have $Z = [(0.65, 0.8, 0.9), (0.3, 0.5, 0.7)]$. Eq. (3) is used to convert the second component of Z to a crisp number which results in $\alpha = 0.5$. So, the number Z is converted to a TFN using Eq. (4) as,

$$Z' = \left(0.65 \times \sqrt{0.5}, 0.8 \times \sqrt{0.5}, 0.9 \times \sqrt{0.5}\right)$$
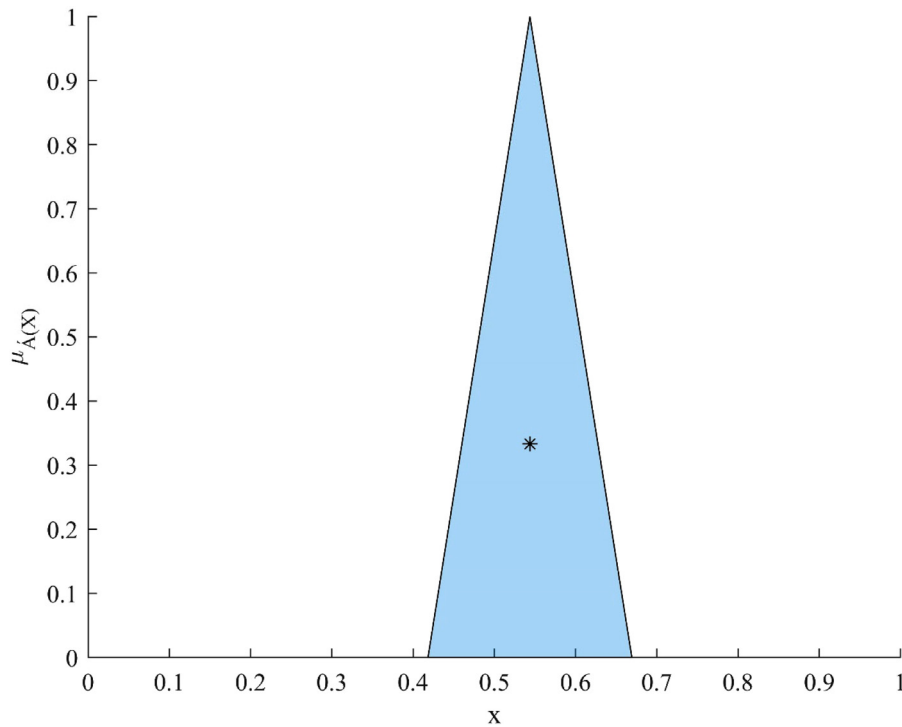
$$= (0.46, 0.56, 0.64)$$

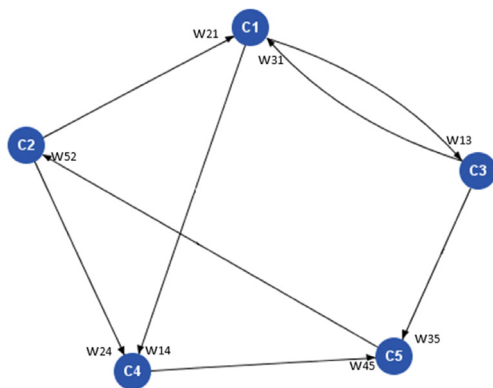**Fig. 2.** Crisp value (indicated by *) of a sample fuzzy set.

Fig. 3. Schematic of a simple FCM.

2.4. Fuzzy cognitive maps (FCMs)

FCMs are a soft computing tool created by combining fuzzy logic, cognitive maps, and neural networks to take advantage of their core benefits [91]. FCM was first introduced by Kosko [76], which is a way to demonstrate knowledge of systems formed by uncertainties, causal relationships, and complex processes [82, 92]. Each FCM consists of concepts and causal relations between them. In general, concepts represent the system's components or the factors that affect it [77]. In a graphic diagram, each concept is plotted by a node, and a directional arc plots each causal relationship according to Fig. 3.

In Fig. 3, each concept for $i = 1, \ldots, 5$ is denoted by C_i. The C_i concept's causal relationship on the C_j concept, w_{ij}, is displayed with an arrow starting at C_i and reaching the end of the arrow at C_j. FCMs have several advantages, some of which include:

- Application of the model to analyze the scenarios, simulate and measure the impact of resizing each concept on the whole system, and predict the behavior of the system in case of improvement or weakening of other parameters [91],
- A helpful tool for designing knowledge base and modeling complex systems [91],
- Easier construction and parameterization than other knowledge development projects [82],
- No need for experts to quantify causal relationships [93],
- Get more information on the relationships between concepts than traditional maps [94],
- Expressing hidden relationships [94],
- Capable of handling the full range of system feedback structures, including density-dependent effects [82],
- It is dynamic and able to combine and adjust [94],
- Extremely versatile and advantageous based on the involvement degree of the participants [95].

Each FCM is implemented in three steps, which are:

1. Constructing a network: identifying concepts and causal relationships by experts,
2. Determining each concept's overall effectiveness: experts determine each concept's overall effectiveness with verbal terms, which have corresponding fuzzy numbers. This attribute is displayed with A^0. The overall impact rate expresses how each concept affects the entire system,
3. Determining the type and impact rate of one concept on another: Experts also determine the type (in terms of positive or negative) and the extent of the impact of each concept on another one in linguistic terms, which have corresponding fuzzy numbers. This feature is named as weight matrix and is denoted by W. This attribute is a fuzzy number for any concept and after converting to a crisp number, it is a real number that belongs to the range between -1 and 1.

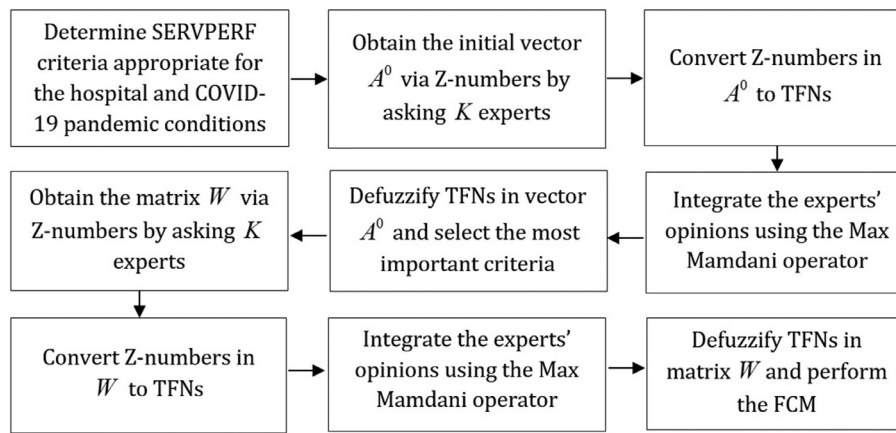In general, three types of causal relationships are as follows: [96]

Fig. 4. Roadmap of the study.

1. If $w_{ij} > 0$, then criterion C_i has a positive impact on criterion C_j. In words, by increasing C_i, the value of C_j increases by $|w_{ij}|$,
2. If $w_{ij} < 0$, then criterion C_i has a negative impact on criterion C_j. In words, by increasing C_i, the value of C_j decreases by $|w_{ij}|$,
3. If $w_{ij} = 0$, then the criterion C_i does not impact the criterion C_j.

The fuzzy nature of FCM is only when experts use linguistic terms to determine the vector A^0 and the weight matrix W. In other words, fuzzy operations are not used in implementing the steps of FCM [92]. In this regard, the values in vector $A^0 = [A_1^0, A_2^0, \ldots, A_N^0]$ are repeatedly updated by Eq. (5).

$$A_i^t = f \left(A_i^{t-1} + \sum_{j \neq i, j=1}^{N} A_j^{t-1} \cdot w_{ji} \right) \tag{5}$$

where, A_i^t is the overall effectiveness of concept C_i in the iteration t, w_{ji} is the weight of the connection from concept C_j to the concept C_i in the iteration $t-1$, and N is the number of concepts. The function $f(x)$ is a threshold function for converting the results to a number in the range [0,1] or [−1, 1]. Bueno and Salmeron [97] showed that the sigmoid function, as represented by Eq. (6), has the best performance among other threshold functions.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{6}$$

In Eq. (6), λ is a real positive number that models the slope of the function. Vector A_i^t is iteratively updated by Eqs. (5) and (6) until a stopping condition is met [98]. The resulting vector A contains the overall importance of different concepts. In general, there are two methods for determining the stopping condition of the FCM algorithm: 1) difference between two consecutive vectors is less than a predetermined value, and 2) a predefined number of iterations is performed.

3. The proposed approach

In this section, an approach is presented to update the criteria of healthcare quality standards. In this approach, an attempt has been made to cover some of the shortcomings of healthcare quality assessment models. In this regard, SERVPERF, Z-number, and FCM benefits, which were explained in detail in the first section, have been used. The proposed approach is presented in eleven steps as follows:

Step 1. Select the SERVPERF scale criteria which are suitable for the healthcare services. At this stage, criteria from the original scale may be removed, modified, or added.

Step 2. Obtain initial vector A^0. In this regard, K experts are asked to determine the overall relative importance of each criterion via a Z-number, $Z = (A, B)$. In words, experts give to linguistic terms for each question, one for answer of the question, A, and the other for the reliability of the answer, B.

Step 3. Convert Z-numbers in A^0 to TFNs by using Eqs. (3) and (4).

Step 4. Integrate the expert opinions. In this paper, the Max Mamdani operator [90] is utilized for integrating the TFNs derived from the opinions of experts. Therefore, vector A^0 of K experts are integrated to give a single vector A^0.

Step 5. Defuzzify TFNs in vector A^0. At the end of this step, the most important criteria based on A^0 are chosen for obtaining the matrix W and performing the FCM.

Step 6. Obtain the matrix W. In this regard, K experts are asked to determine the impact of the selected criteria in step 5 on each other via Z-numbers.

Step 7. Convert Z-numbers in W to TFNs by using Eqs. (3) and (4).

Step 8. Integrate the expert opinions by the Max Mamdani operator. Therefore, the matrix W of K experts are integrated to give a single matrix W.

Step 9. Defuzzify TFNs in matrix W.

Step 10. Use the defuzzified A^0 and W to perform the FCM. The FCM repeatedly updates the values in vector A^0 to find the overall importance of healthcare service quality criteria.

These steps are schematically presented in Fig. 4.

4. Case study

In this study, the SERVPERF scale criteria are adjusted to investigate hospitals' special conditions during the Covid-19 pandemic crisis. In this regard, the 22 criteria which had been adapted for the hospital by Gilbert et al. [26] and finally reached 15 criteria, were reviewed. To this end, two experts were interviewed: the supervisors of patients with Covid-19, each with 25 years of work experience in different hospitals. The classification of research criteria of Shieh et al. [62] and Büyüközkan et al. [21], who evaluated health services using MCDA methods, were also used for the defined conditions.
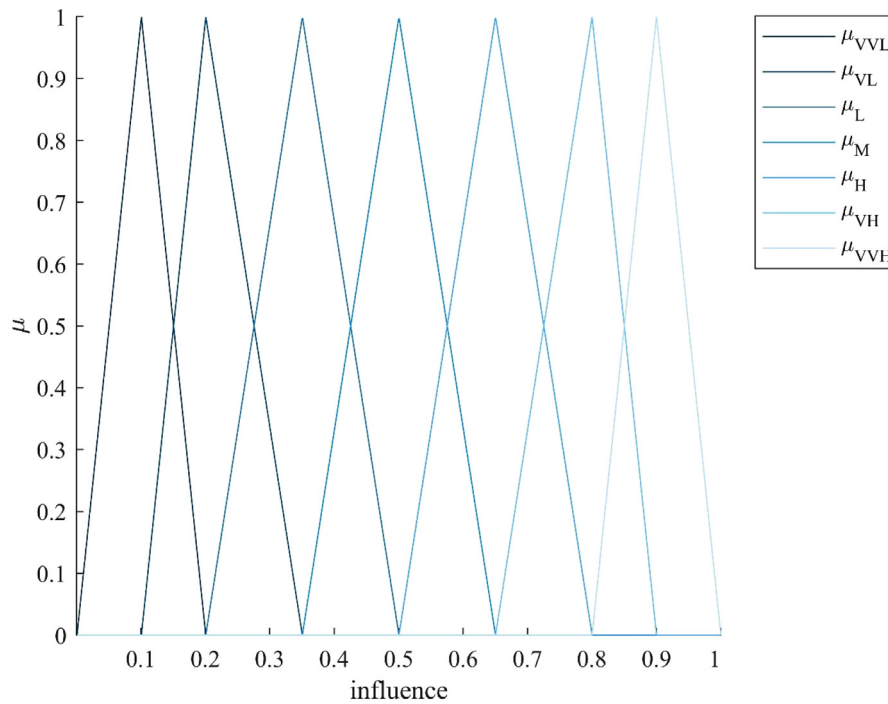
Fig. 5. The membership functions of the linguistic terms used to determine the overall effectiveness of each criterion (question 1).

Table 1
The linguistic terms used to determine the overall effectiveness of each criterion (question 1).

Linguistic variable	Membership function
Very Very Low (VVL)	(0, 0.1, 0.2)
Very Low (VL)	(0.1, 0.2, 0.35)
Low (L)	(0.2, 0.35, 0.5)
Medium (M)	(0.35, 0.5, 0.65)
High (H)	(0.5, 0.65, 0.8)
Very High (VH)	(0.65, 0.8, 0.9)
Very Very High (VVH)	(0.8, 0.9, 1)

Table 2
The linguistic terms used to determine the degree of confidence (questions 1 and 2).

Linguistic variable	Membership function
Very Low (VL)	(0,0,0.1)
Low(L)	(0,0.1,0.3)
Medium Low (ML)	(0.1,0.3,0.5)
Medium(M)	(0.3,0.5,0.7)
Medium High (MH)	(0.5,0.7,0.9)
High(H)	(0.7,0.9,1)
Very High (VH)	(0.9,1,1)

Table 3
Completed questionnaire of one of the experts for question 1.

Criterion	A — Overall impact degree	B — Confidence degree in the overall impact
C_1	VVH	VH
C_2	M	H
C_3	L	MH
C_4	VVH	VH
C_5	H	H
C_6	VH	H
C_7	M	MH
C_8	M	MH
C_9	VH	H
C_{10}	H	MH
C_{11}	VH	H
C_{12}	H	MH
C_{13}	VH	H
C_{14}	VH	H
C_{15}	VVH	VH
C_{16}	VH	VH
C_{17}	L	MH
C_{18}	VH	H
C_{19}	M	MH
C_{20}	VH	VH
C_{21}	VH	VH
C_{22}	H	MH
C_{23}	M	MH
C_{24}	VH	M
C_{25}	M	M

Finally, using the results of our expert interviews, considering [21] and [62] researches, some performance [26] and technical [99] criteria were added to the modified SERVPERF scale criteria. We also revised some of the criteria to adapt the healthcare conditions. The revised criteria are accessible through Table A.1 (Appendix). After determining the criteria, experts answered questions during a questionnaire. The experts included three experienced physicians working with the care of patients with Covid-19 patients. In this questionnaire, two sets of questions were asked of the experts by applying a particular assumption.

Assumption: All criteria are in their ideal state during the Covid-19 pandemic and not in experts' workplaces.

Question 1: What is the impact of each criterion on the whole network of criteria (vector A^0)?

Experts answered this question in the form of Z-number linguistic terms as a regular pair of $Z = (A, B)$, in which the first component A is their opinion about each criterion impact on the whole network of criteria and component B is the degree of confidence to the answer of A. The Z-number linguistic terms are set to answer Part A of the first question as described in Table 1 and Fig. 5 [82], and to answer Part B as described in Table 2 [72].

For instance, one of the expert questionnaires is collected for the first question according to Table 3.

Table 4
Z-number conversion of A^0 vector to TFNs.

No	A	B	Z to TFN	No	A	B	Z to TFN
1	VVL	VL	[0.0,0.01826,0.03651]	26	H	M	[0.3536 0.4596 0.5657]
2	VL	VL	[0.01826,0.03651,0.0639]	27	VH	M	[0.4596 0.5657 0.6364]
3	L	VL	[0.0365 0.0639 0.0913]	28	VVH	M	[0.5657 0.6364 0.7071]
4	M	VL	[0.0639 0.0913 0.1187]	29	VVL	MH	[0 0.0837 0.1673]
5	H	VL	[0.0913 0.1187 0.1461]	30	VL	MH	[0.0837 0.1673 0.2928]
6	VH	VL	[0.1187 0.1461 0.1643]	31	L	MH	[0.1673 0.2928 0.4183]
7	VVH	VL	[0.1461 0.1643 0.1826]	32	M	MH	[0.2928 0.4183 0.5438]
8	VVL	L	[0 0.0408 0.0817]	33	H	MH	[0.4183 0.5438 0.6693]
9	VL	L	[0.0408 0.0817 0.1429]	34	VH	MH	[0.5438 0.6693 0.7530]
10	L	L	[0.0817 0.1429 0.2041]	35	VVH	MH	[0.6693 0.7530 0.8367]
11	M	L	[0.1429 0.2041 0.2654]	36	VVL	H	[0 0.0913 0.1826]
12	H	L	[0.2041 0.2654 0.3266]	37	VL	H	[0.0913 0.1826 0.3195]
13	VH	L	[0.2654 0.3266 0.3674]	38	L	H	[0.1826 0.3195 0.4564]
14	VVH	L	[0.3266 0.3674 0.4082]	39	M	H	[0.3195 0.4564 0.5934]
15	VVL	ML	[0 0.0548 0.1095]	40	H	H	[0.4564 0.5934 0.7303]
16	VL	ML	[0.0548 0.1095 0.1917]	41	VH	H	[0.5934 0.7303 0.8216]
17	L	ML	[0.1095 0.1917 0.2739]	42	VVH	H	[0.7303 0.8216 0.9129]
18	M	ML	[0.1917 0.2739 0.3560]	43	VVL	VH	[0 0.0966 0.1932]
19	H	ML	[0.2739 0.3560 0.4382]	44	VL	VH	[0.0966 0.1932 0.3381]
20	VH	ML	[0.3560 0.4382 0.4930]	45	L	VH	[0.1932 0.3381 0.4830]
21	VVH	ML	[0.4382 0.4930 0.5477]	46	M	VH	[0.3381 0.4830 0.6280]
22	VVL	M	[0 0.0707 0.1414]	47	H	VH	[0.4830 0.6280 0.7729]
23	VL	M	[0.0707 0.1414 0.2475]	48	VH	VH	[0.6280 0.7729 0.8695]
24	L	M	[0.1414 0.2475 0.3536]	49	VVH	VH	[0.7729 0.8695 0.9661]
25	M	M	[0.2475 0.3536 0.4596]				
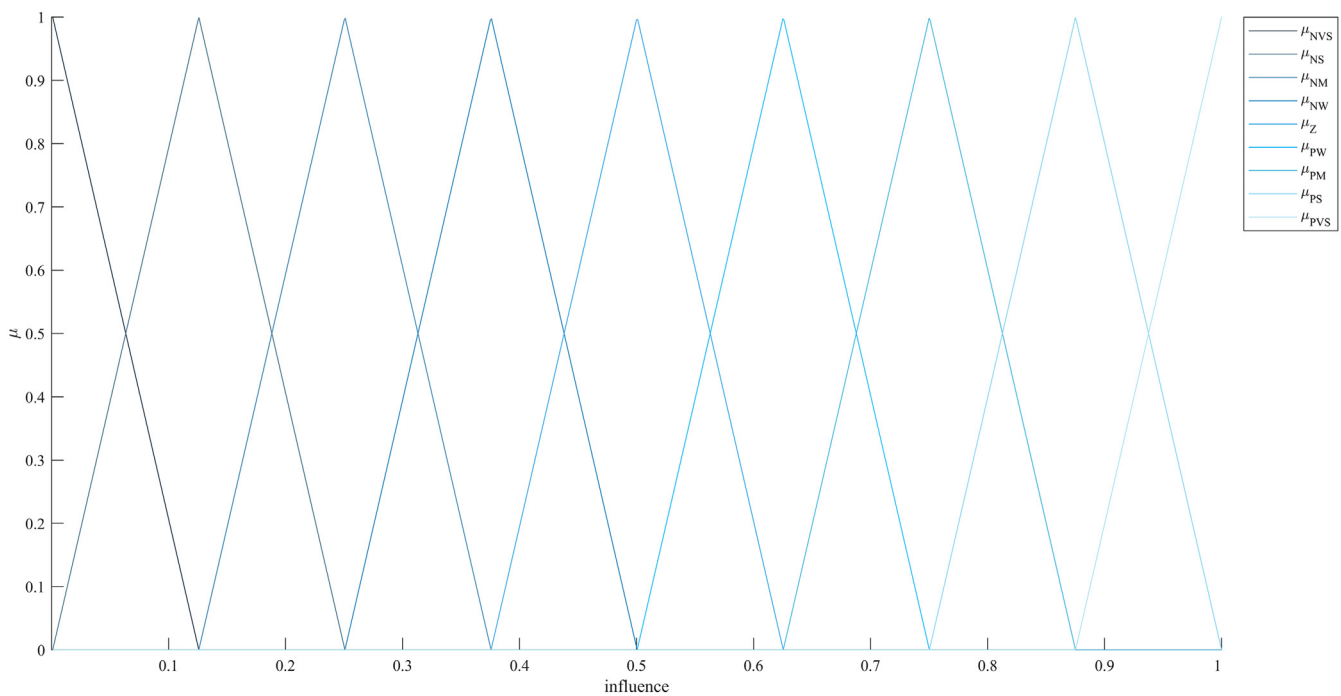
Fig. 6. The membership functions of the linguistic terms used to determine the degree of confidence to answers (question 2).

After collecting data through a questionnaire, Z-numbers were converted to TFNs using Eqs. (3) and (4). All conversions are given in Eq. (5) according to the values in Tables 1 and 2. Expert opinions were then merged using the Max Mamdani operator. After this step, a vector of A^0 was obtained from the opinions of all three experts. In the next step, TFNs were converted to crisp numbers using the COG/COA non-fuzzy method. At the end of this step, by comparing the scores obtained for each of the criteria in the vector A^0, the criteria that have a higher priority are identified. With the identification of the most priority criteria, the second question is entitled

Question 2: How much does each criterion affect the other (matrix W)?

Experts are asked through a questionnaire. Like the first question, the experts answered this question in the form of Z-number linguistic terms as an orderly pair $Z = (A, B)$. The first component A is their opinion about the extent to which each criterion affects the other. The second component B, is the degree of confidence in answer to the first component. The Z-number verbal terms are set to answer component A of the second question as described in Table 5 and Fig. 6 [93], and to answer component B as described in Table 2 [72](see Table 4).

Experts are asked through a questionnaire. After collecting data through a questionnaire, Z-numbers were converted to TFNs using Eqs. (3) and (4). All conversions are given in Table 6 according to the values in Tables 2 and 5. Expert opinions were

Table 5
Linguistic terms used to determine the degree of confidence of the answers (question 2).

Linguistic variable	Membership function
Negative Very Strong (NVS)	(−1, −1, −0.75)
Negative Strong (NS)	(−1, −0.75, −0.5)
Negative Medium (NM)	(−0.75, −0.5, −0.25)
Negative Weak (NW)	(−0.5, −0.25, 0)
Zero (Z)	(−0.25, 0, 0.25)
Positive Weak (PW)	(0, 0.25, 0.5)
Positive Medium (PM)	(0.25, 0.5, 0.75)
Positive Strong (PS)	(0.5, 0.75, 1)
Positive Very Strong (PVS)	(0.75, 1, 1)

Table 7
Initial prioritization of criteria (Initial state vector A^0).

No.	Criteria	Ratio	Priority	No.	Criteria	Ratio	Priority
1	C_1	0.8695	1	13	C_{13}	0.638	7
2	C_{15}	0.8695	1	14	C_8	0.6213	8
3	C_4	0.8051	2	15	C_{24}	0.6138	9
4	C_{20}	0.8051	2	16	C_7	0.6109	10
5	C_{21}	0.8051	2	17	C_{10}	0.5798	11
6	C_9	0.7855	3	18	C_{19}	0.5737	12
7	C_{11}	0.7855	3	19	C_{22}	0.5237	12
8	C_{18}	0.7855	3	20	C_{17}	0.5203	13
9	C6	0.7616	4	21	C_3	0.4446	14
10	C_{14}	0.7388	5	22	C_2	0.4405	15
11	C_{16}	0.7388	5	23	C_{12}	0.436	16
12	C_5	0.7076	6	24	C_{23}	0.4158	17

then merged using the Max Mamdani operator. After this step, a matrix of W was obtained from the opinions of all three experts. In the next step, TFNs were converted to crisp numbers using the COG/COA non-fuzzy method. At the end of this step, FCM is utilized to determine the most important criteria for the quality of healthcare services. In this research, FCMExpert [92] software is used for the implementation of FCM.

5. Analysis of the results

The experts' general opinion regarding the importance of the criteria in the context of the outbreak of the Covid-19 virus led to the initial prioritization of the criteria (primary vector A^0), as shown in Table 7. Based on the results, it seems that the prioritization of the criteria is quite reasonable.

5.1. Investigating the relationship between criteria priority and challenges in the Covid-19 pandemic situation

This section examines the relationship between the challenges encountered in the Covid-19 pandemic situation and the criteria that have the highest priority, according to Table 7. The difficulties of triage management and scarce resource management [13],

protecting front-line healthcare staff and preventing nosocomial infections [16–18], as well as the challenge of scarcity of personal protective equipment is associated with the priority of the C_1 criterion (up-to-date equipment and facilities). Also, the challenge of predicting the increase in hospital readiness and increasing the need for treatment staff and the challenge of shortage of refreshed treatment staff [13,15] mentions the priority of the C_{15} criterion (sufficient number of staff in proportion to the number of patients). The challenge of preventing nosocomial infections, the logistical challenge and the transfer of infected people to separate them from other clients, as well as the logistics and transfer of other patients for radiology and surgical examinations [16–18] and the challenge of infectious and hazardous waste management is relevant to prioritizing C_4 (Hospital hygiene). It also seemed that the challenges of protecting healthcare personnel at the forefront and preventing nosocomial infections and the lack of personal protective equipment mentioned earlier, lack of freshman treatment staff, the physical and psychological stress of dealing with a pandemic, intensity of workload and lack of repose, and ultimately need for training and awareness of healthcare

Table 6
Z-number conversion of matrix W to TFNs.

No.	A	B	Z to TFN	No.	A	B	Z to TFN
1	NVS	VL	[−0.1826 −0.1826 −0.1369]	33	PW	M	[0 0.1768 0.3536]
2	NS	VL	[−0.1826 −0.1369 −0.0913]	34	PM	M	[0.1768 0.3536 0.5303]
3	NM	VL	[−0.1369 −0.0913 −0.0456]	35	PS	M	[0.3536 0.5303 0.7071]
4	NW	VL	[−0.0913 −0.0456 0]	36	PVS	M	[0.5303 0.7071 0.7071]
5	Z	VL	[−0.0456 0 0.0456]	37	NVS	MH	[−0.8367 −0.8367 −0.6275]
6	PW	VL	[0 0.0456 0.0913]	38	NS	MH	[−0.8367 −0.6275 −0.4183]
7	PM	VL	[0.0456 0.0913 0.1369]	39	NM	MH	[−0.6275 −0.4183 −0.2092]
8	PS	VL	[0.0913 0.1369 0.1826]	40	NW	MH	[−0.4183 −0.2092 0]
9	PVS	VL	[0.1369 0.1826 0.1826]	41	Z	MH	[−0.2092 0 0.2092]
10	NVS	L	[−0.4082 −0.4082 −0.3062]	42	PW	MH	[0 0.2092 0.4183]
11	NS	L	[−0.4082 −0.3062 −0.2041]	43	PM	MH	[0.2092 0.4183 0.6275]
12	NM	L	[−0.3062 −0.2041 −0.1021]	44	PS	MH	[0.4183 0.6275 0.8367]
13	NW	L	[−0.2041 −0.1021 0]	45	PVS	MH	[0.6275 0.8367 0.8367]
14	Z	L	[−0.1021 0 0.1021]	46	NVS	H	[−0.9129 −0.9129 −0.6847]
15	PW	L	[0 0.1021 0.2041]	47	NS	H	[−0.9129 −0.6847 −0.4564]
16	PM	L	[0.1021 0.2041 0.3062]	48	NM	H	[−0.6847 −0.4564 −0.2282]
17	PS	L	[0.2041 0.3062 0.4082]	49	NW	H	[−0.4564 −0.2282 0]
18	PVS	L	[0.3062 0.4082 0.4082]	50	Z	H	[−0.2282 0 0.2282]
19	NVS	ML	[−0.5477 −0.5477 −0.4108]	51	PW	H	[0 0.2282 0.4564]
20	NS	ML	[−0.5477 −0.4108 −0.2739]	52	PM	H	[0.2282 0.4564 0.6847]
21	NM	ML	[−0.4108 −0.2739 −0.1369]	53	PS	H	[0.4564 0.6847 0.9129]
22	NW	ML	[−0.2739 −0.1369 0]	54	PVS	H	[0.6847 0.9129 0.9129]
23	Z	ML	[−0.1369 0 0.1369]	55	NVS	VH	[−0.9661 −0.9661 −0.7246]
24	PW	ML	[0 0.1369 0.2739]	56	NS	VH	[−0.9661 −0.7246 −0.4830]
25	PM	ML	[0.1369 0.2739 0.4108]	57	NM	VH	[−0.7246 −0.4830 −0.2415]
26	PS	ML	[0.2739 0.4108 0.5477]	58	NW	VH	[−0.4830 −0.2415 0]
27	PVS	ML	[0.4108 0.5477 0.5477]	59	Z	VH	[−0.2415 0 0.2415]
28	NVS	M	[−0.7071 −0.7071 −0.5303]	60	PW	VH	[0 0.2415 0.4830]
29	NS	M	[−0.7071 −0.5303 −0.3536]	61	PM	VH	[0.2415 0.4830 0.7246]
30	NM	M	[−0.5303 −0.3536 −0.1768]	62	PS	VH	[0.4830 0.7246 0.9661]
31	NW	M	[−0.3536 −0.1768 0]	63	PVS	VH	[0.7246 0.9661 0.9661]
32	Z	M	[−0.1768 0 0.1768]				

Table 8

The W matrix represents the values of the causal relationships between the 12 high priority criteria and the dependent criterion of overall satisfaction.

	C_1	C_4	C_5	C_6	C_9	C_{11}	C_{14}	C_{15}	C_{16}	C_{18}	C_{20}	C_{21}	C_{25}
C_1	0	0.6056	0.4462	0.6056	0.7537	0.358	0.2646	0.5962	0.7462	0.3535	0.2652	0.2572	0.7227
C_4	0.3064	0	0.2091	0.07113	0.4759	0	0.116	0	0.1152	0.1539	0.3885	0.1308	0.6056
C_5	0.336	0.3095	0	0.361	0.3963	0.07742	0.07113	0.07113	0.5232	0	0	0	0.4983
C_6	0.7227	0.6541	0.4192	0	0.6495	0.336	0.2638	0.2034	0.5707	0	0.1681	0.1207	0.6086
C_9	0.5693	0.3496	0.2562	0.4126	0	0.5569	0.3337	0.4872	0.6139	0.2694	0.373	0.4552	0.6139
C_{11}	0.3424	0.2267	0	0.2267	0.6541	0	0.1768	0.4527	0.5431	0.357	0.3345	0.3535	0.4213
C_{14}	0.3858	0.5803	0.2428	0.133	0.5325	0.2652	0	0.3424	0.3239	0.2627	0.3666	0.5409	0.7705
C_{15}	0.2398	0.3497	0.03986	0.4527	0.4527	0.3424	0.5327	0	0.1628	0.263	0.2652	0.4026	0.7705
C_{16}	0.5704	0.45	0.6847	0.5705	0.4712	0.5704	0.463	0.2338	0	0.2572	0.2812	0.262	0.7482
C_{18}	0.1768	0.3858	0.1695	0	0.442	0.6056	0.3535	0	0.361	0	0.2428	0.2606	0.7227
C_{20}	0.5325	0.4213	0.1768	0.3997	0.3777	0.5325	0.6863	0.7462	0.4093	0.5953	0	0.7214	0.7462
C_{21}	0.1618	0.5006	0.0884	0.4215	0.6847	0.5569	0.5029	0.4998	0.3345	0.4126	0.477	0	0.7482
C_{25}	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 9

Concept values per iteration of the FCM algorithm until the convergence is reached.

| Concepts	Iteration No.					
	1	2	3	4	5	6
C_1	0.8695	0.8901	0.9101	0.9143	0.9152	0.9154
C_4	0.8051	0.9073	0.9256	0.9294	0.9303	0.9305
C_5	0.7076	0.8023	0.8295	0.8351	0.8363	0.8366
C_6	0.7616	0.8598	0.8810	0.8858	0.8869	0.8871
C_9	0.7855	0.9370	0.9522	0.9552	0.9558	0.9559
C_{11}	0.7855	0.8841	0.9040	0.9082	0.9092	0.9094
C_{14}	0.7388	0.8644	0.8850	0.8895	0.8906	0.8908
C_{15}	0.8695	0.8647	0.8804	0.8849	0.8859	0.8861
C_{16}	0.7388	0.9006	0.9217	0.9257	0.9266	0.9268
C_{18}	0.7855	0.8237	0.8411	0.8459	0.8470	0.8473
C_{20}	0.8051	0.8366	0.8564	0.8612	0.8623	0.8625
C_{21}	0.8051	0.8545	0.8735	0.8781	0.8792	0.8794
C_{25}	0.3536	0.9646	0.9806	0.9821	0.9825	0.9825

Table 10

New prioritization of high priority criteria after causal relationships are applied.

No.	Criteria	Ratio	Priority
–	C_{25}	0.9825	–
1	C_9	0.9559	1
2	C_4	0.9305	2
3	C_{16}	0.9268	3
4	C_1	0.9154	4
5	C_{11}	0.9094	5
6	C_{14}	0.8908	6
7	C_6	0.8871	7
8	C_{15}	0.8861	8
9	C_{21}	0.8794	9
10	C_{20}	0.8625	10
11	C_{18}	0.8473	11
12	C_5	0.8366	12

professionals to prevent and control respiratory infections, all influence prioritizing of the C_{20} index (adequate hospital support from employees, so that employees can do their job well).

Regarding the priority of the C_{21} criterion (unique attention from hospital staff), experts said in an interview that hospital staff's complete attention has a significant impact on improving the patient's condition and even saving their life. Correctly diagnosing Covid-19 and the need for training and awareness of
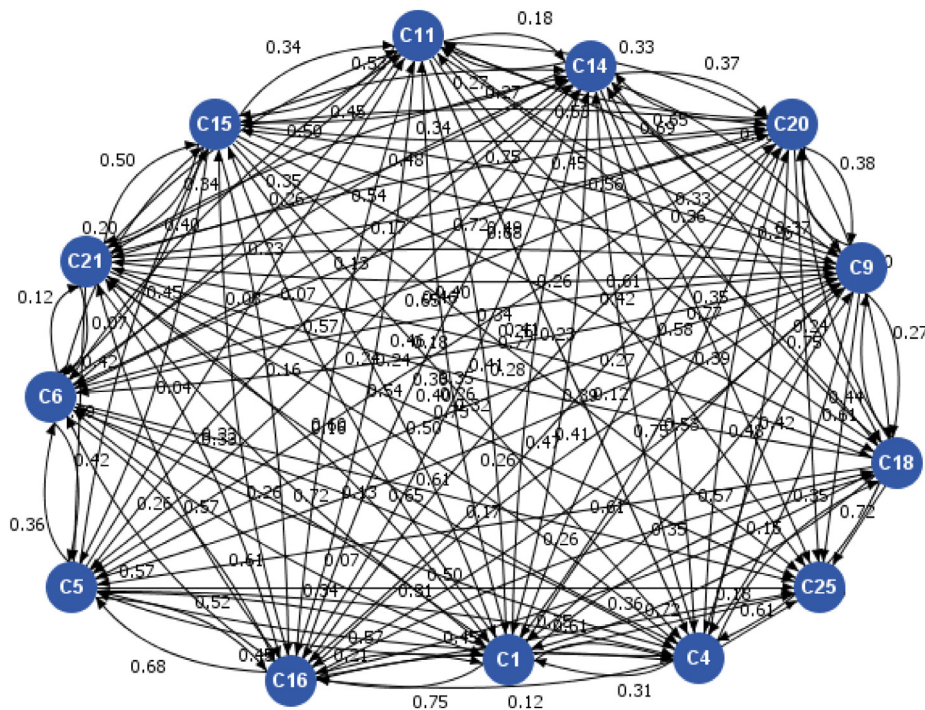
Fig. 7. Causal relationships between the 12 criteria with high priority.
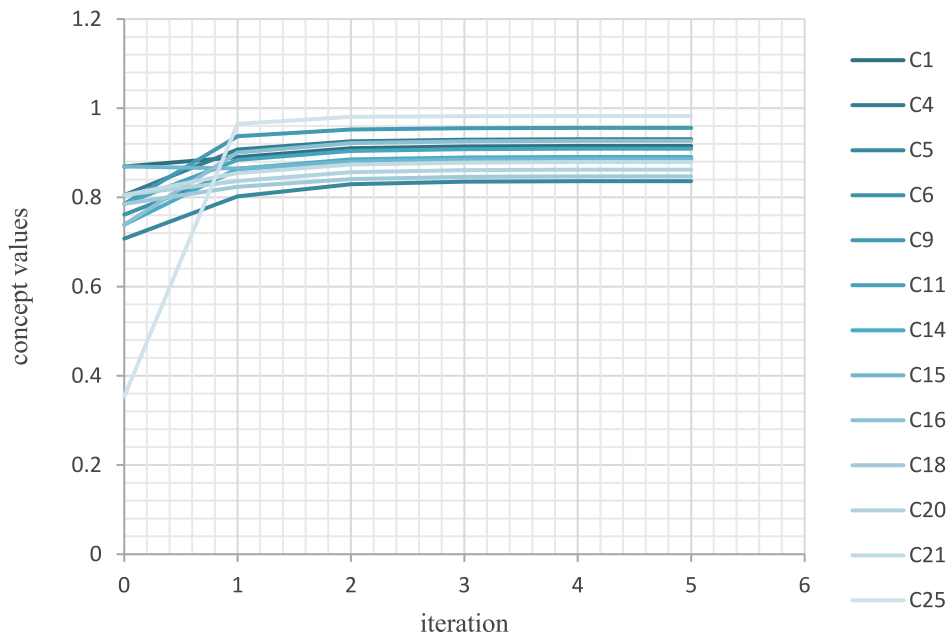
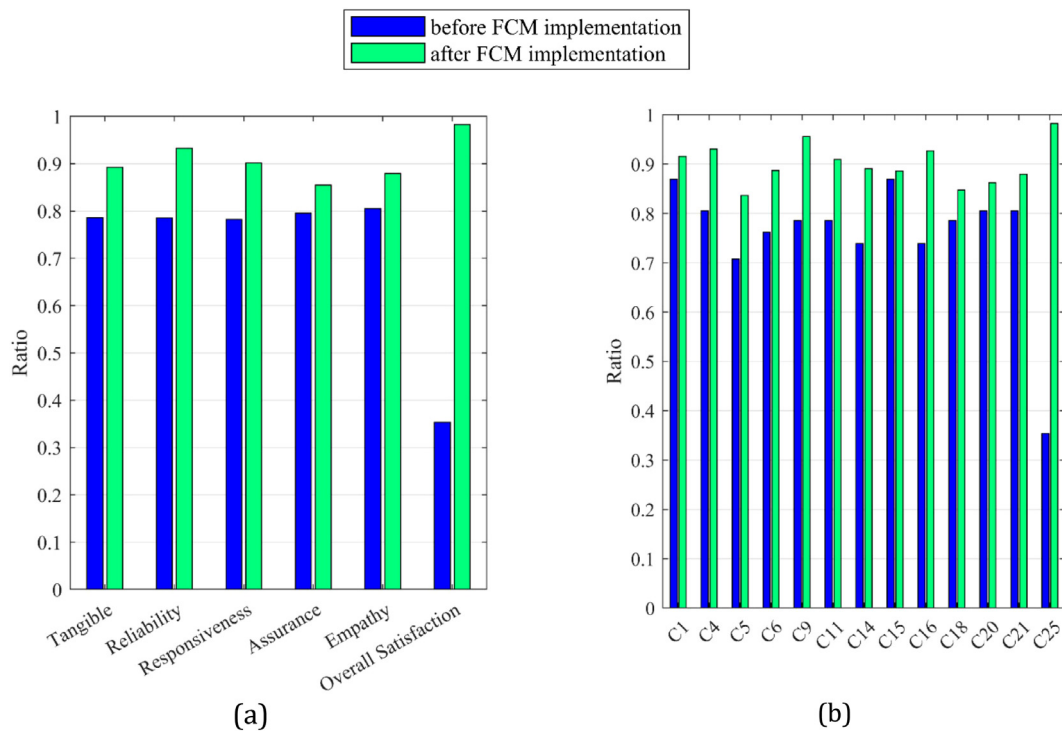Fig. 8. Convergence process of state vector *A* in five iterations.

Fig. 9. Bar chart of (a) average ratios for categories, and (b) ratios for criteria, before and after the implementation of FCM.

health professionals (other than infectious disease physicians) on ways to prevent and control respiratory infections [17,18] has led to the importance of C_9 criteria (the reliability of the hospital) and C_{11} (accuracy) and C_{18}(reliability of the hospital staff in terms of their knowledge). Regarding prioritizing the C_{14} criterion (the constant desire of hospital staff to help the patient), experts also said in an interview that the hospital staff's constant willingness to help the patient has a significant effect on accelerating the patient's recovery. Finally, the challenge of logistics and transfer of infected for separation from other clients and the logistics and transfer of other patients for radiology and surgical examinations

led to the importance of C_{16} (completeness) and C_5 (building layout).

As illustrated, 12 of the independent criteria for measuring the quality of health services challenged in the Covid-19 pandemic are among the first to sixth priorities in the initial prioritization. In these critical situations, the provision of services that satisfies the customer becomes more critical, which means that the dependent C_{25} criterion of overall customer satisfaction has also been challenged. However, the initial prioritization for the high priority criteria in Table 7 is without considering the causal relationships between these 12 criteria. The causal relationships
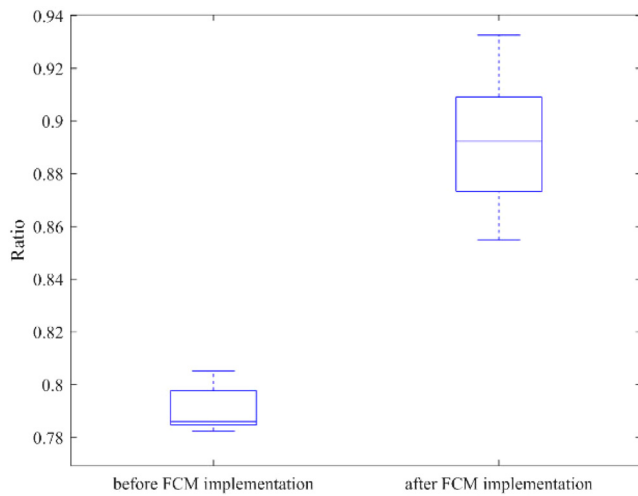
Fig. 10. Box plot of average ratios for categories, before and after the implementation of FCM.

Table 11
Comparison of prioritization of high priority criteria before and after causal relationships (FCM implementation).

Before applying causal relationships		After applying causal relationships	
Criteria	Priority	Criteria	Priority
C_1	1	C_9	1
C_{15}	1	C_4	2
C_4	2	C_{16}	3
C_{20}	2	C_1	4
C_{21}	2	C_{11}	5
C_9	3	C_{14}	6
C_{11}	3	C_6	7
C_{18}	3	C_{15}	8
C_6	4	C_{21}	9
C_{14}	5	C_{20}	10
C_{16}	5	C_{18}	11
C_5	6	C_5	12

between these 12 criteria are illustrated in Fig. 7. The W matrix, which represents the causal relationships' values between these criteria, is given in Table 8.

Also, Fig. 7 shows the cognitive map related to these 12 criteria plus the concept of patient satisfaction. In this cognitive map, each concept is proportional to its corresponding value in the initial prioritization of criteria (initial state vector A^0) and the magnitude of the causal relationship between C_i on C_j and w_{ij} on the arc that starts from the concept i and ends with the tip of the arrow to concept j, which is displayed with a number between 1 and -1. Accordingly, the density of causal relationships in Fig. 7 is very high, so there is a need for a new prioritization that addresses these causal relationships. In this research, the FCM algorithm has been implemented to achieve this new prioritization. With this algorithm's implementation, the initial prioritization of the criteria (initial state vector A^0) has reached convergence after five iterations. The process of convergence to an equilibrium is illustrated in Fig. 8. The values of the concepts in each iteration are also shown in Table 9. In this Table, zero is the same as the original state vector A^0. The stop criterion for running the FCM algorithm was to reach a specific convergence point with an accuracy of 0.001. The slope of the threshold function was considered 0.5 to specify 12 criteria in exactly 12 prioritizations.

5.2. Investigating prioritization by applying causal relationships between 12 criteria with high priority

As illustrated in Table 10, the criteria's prioritization has changed significantly after the causal relationship between them has been applied. This change is due to the causal relationships between the criteria.

Considering the dependent criterion C_{25} (overall patient satisfaction) scored the highest, this illustrates that the high-ranked criteria strongly influence patient satisfaction. Therefore, to increase the patient's understanding of hospital health services and satisfaction, the prioritization results of Table 10 should be invested in, respectively.

5.3. Comparison of prioritization of high priority criteria before and after the application of causal relationships (FCM implementation)

Investing in healthcare quality metrics based on new prioritization has a more significant impact on increasing patient perceptions of healthcare quality. This new prioritization comprises the causal relationships between these 12 challenging criteria. A comparison of the two prioritizations before and after causal relationships is given in Table 11.

As it figured in Table 11, before applying the causal relationship, the C_1 criterion, which indicated that the hospital was equipped with up-to-date equipment, was a top priority. But after using causal relationships, C_9, which shows the reliability of the hospital, is the first one. This means that improving C_9 will be more effective than enhancing C_1 to increase patients' perception of health service quality and satisfaction. Similarly, the priority of other criteria is determined by considering the causal relationships between them. Also, the application of the proposed method has led to a better distinction of ranking criteria.

5.4. Examining the most effective criteria in five categories of criteria for measuring the quality of health care services

This section will introduce the essential criteria of each category for measuring the quality of health services based on prioritization after applying causal relationships. According to Table 12, improving C_4 (hospital hygiene) will be the most effective investment to increase patients' perception of health services in the tangible area. Improving C_9 (hospital reliability) will be the most effective investment to increase patient's perception of health services in reliability. Improving C_{16} (completeness) will also be the most effective investment in increasing patient responsiveness to health services. Improving C_{20} (adequate hospital support for staff to do their job well) will be the most effective investment to increase the patient's understanding of health care. Finally, improving C_{21}(unique attention from hospital staff) will be the most effective investment to increase patient empathy in healthcare.

As shown in Table 12, by calculating the average ratios of each category, the categories can also be ranked. Fig. 9.a shows the ranking of categories based on average ratios before and after applying causal relations. After applying causal relationships, the Reliability category with the highest average ratio is ranked first, Responsiveness is ranked second, Tangible is ranked third, and Empathy and Assurance are ranked fourth and fifth, respectively. In this way, when constraints force the hospital to invest in one or two categories, it is possible to select the most effective categories.

The details of category ranking, namely the ratio of each criterion before and after the causal relationships, are given in Fig. 9.b. The ratios of C_9 and C_{11} criteria (Reliability category criteria) are higher than the criteria ratios of other categories. Similarly, C_{14},

Table 12

Initial prioritization and prioritization evaluation after causal relationships (FCM implementation) in five categories of healthcare quality assessment criteria.

Category	High ranked Criteria	Prioritization before FCM implementation				Prioritization after FCM implementation			
		Rank	Ratio	ratio ratio	Category rank	Rank	Ratio	Average ratio	Category rank
Tangible	C_1	1	0.8695			4	0.9154		
	C_4	2	0.8051			2	0.9305		
	C_5	6	0.7076	0.7860	3	12	0.8366	0.8924	3
	C_6	4	0.7616			7	0.8871		
Reliability	C_9	3	0.7855			1	0.9559		
	C_{11}	3	0.7855	0.7855	4	5	0.9094	0.9326	1
Responsiveness	C_{14}	5	0.7388			6	0.8908		
	C_{15}	1	0.8695	0.7824	5	8	0.8861	0.9012	2
	C_{16}	5	0.7388			3	0.9268		
Assurance	C_{18}	3	0.7855			11	0.8473		
	C_{20}	2	0.8051	0.7953	2	10	0.8625	0.8549	5
Empathy	C_{21}	2	0.8051	0.8051	1	9	0.8794	0.8794	4
Overall satisfaction	C_{25}	–	0.3536	–	–	–	0.9825		–

C_{15}, and C_{16} criteria (Responsiveness category criteria) are higher than the ratios of the other three categories.

Also, in Figs. 9.a and 9.b, it is clear that the dependent criterion of overall satisfaction (C_{25}) has the lowest and highest ratios before and after the implementation of FCM, respectively. This indicates the significant effect of criteria from all categories on the overall satisfaction of the patient.

Based on Fig. 9.a, the average ratios of the categories before considering the causal relationships are very concentrated (close to each other), but after considering the causal relationships, the average ratios of the categories increase and the variation between the average ratios increases. The box plot can schematically demonstrate the concentration and variation of criteria simultaneously. For this purpose, Fig. 10 illustrates the average ratios of the categories before and after the implementation of FCM. The average ratios of the categories increase significantly after the implementation of FCM, which indicates the effect of different criteria on each other. On the other hand, the variation of average category ratios has increased after the implementation of FCM, which confirms a significant difference between the average ratios. In other words, the criteria of some categories are more important than others.

Details of the criteria ratios can be seen before and after the causal relationships in Fig. 11. In other words, the opinions

of individual experts and the integrated opinion of experts are presented in Fig. 11. Expert opinions are given in the first three columns for each criterion. In the fourth and fifth columns, their final merged views are shown before and after the FCM, respectively. As can be seen, in most cases, the opinions of experts are similar. Also, the green column, is higher in all criteria than all other columns, which indicates the effect of causal relationships on increasing ratios and changing the prioritization of criteria.

5.5. Selecting the most effective criteria to increase the patient's understanding of health services

In the Covid-19 pandemic, hospitals should pay attention to the needs and expectations of patients under the existing conditions and challenges and improve the quality of their services to satisfy the patient. Using the updated SERVPERF relatively following the current conditions and challenges and benefiting from the FCM algorithm can be one of the practices to identify the criteria that need improvement. According to the results of this study, to increase the patient's understanding of the quality of health services and to satisfy its needs, hospitals should meet the criteria and invest in the criteria of C_9 (hospital reliability), C_4 (hospital hygiene), C_{16} (completeness), C_1 (up-to-date equipment
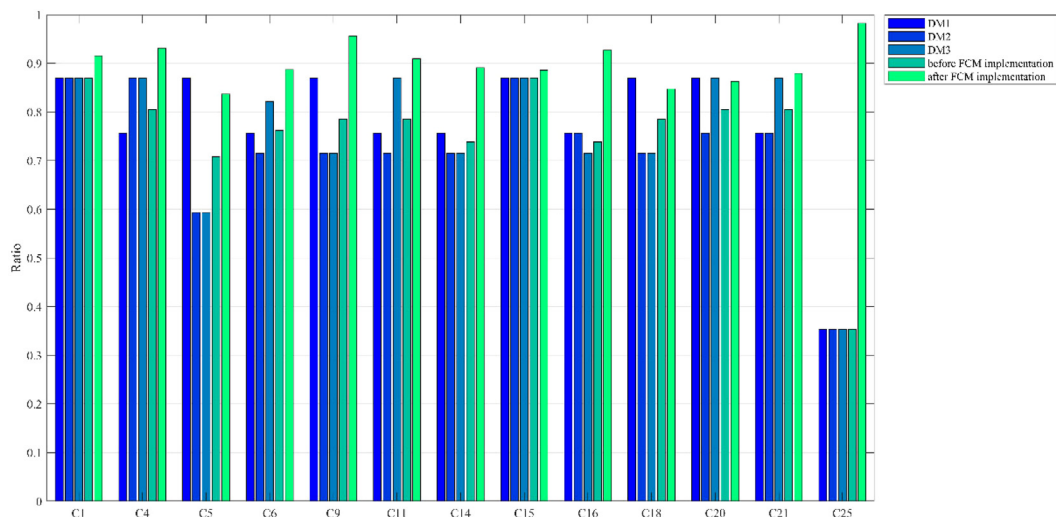

Fig. 11. The ratios resulted from the opinions of experts.

Table A.1

SERVPERF scale criteria in the original condition , adjusted for hospital and modified for specific conditions of COVID-19 pandemic.

Category	No.	criteria of original SERVPERF scale (O)	criteria of SERVPERF for hospital (H)	Criteria used in this study for Covid-19 pandemic conditions (C)	Criterion description for Covid-19 pandemic
Tangible	1	O_1. Up-to-date facilities and equipment.	H_1. The hospital has up-do-date equipment and facilities.	C_1. Up-to-date equipment and facilities have provided	Ventilator or mechanical ventilation, infusion pump, cardiac monitor, central oxygen, central suction, NIV mask quarantine unit, N95 mask, gun, goggles, face shield, hat, shoe cover, latex gloves
	2	O_2. Physical facilities are visually appealing.	H_2. The hospital's physical facilities are visually appealing.	C_2. Visually pleasing physical facilities	Facilities available in inpatient rooms like patient bed, refrigerator, furniture, interior decoration, and exterior building
	3	O_3. Employees are well dressed and appear neat	H_3. The hospital's employees appear neat.	C_3. Appropriate and recognizable coverage and appearance of different department's employees	- Employees of different departments wear clothes with different colors. For example; green for surgeons and blue for crew, - Writing the name and position of employees on their clothes.
	4	O_4. The appearance of the physical facilities is in keeping with the type of service provided.	None	None	–
	5	None	None	C_4. Hospital hygiene	Hygiene in two parts: 1) Personal hygiene, such as: hygiene of clothes and other protective coverings and hand hygiene, 2) Hospital hygiene, such as: hygiene of facilities and equipment used for patients and hospital environment hygiene
	6	None	None	C_5. Building layout	Items such as: - Separate emergency room for people with suspected for Covid-19 infection , isolation room, - Clear markings to guide relevant departments such as laboratory and radiology and CT scan Hospital comfort
	7	None	None	C_6. Adequate physical facilities	Adequate space, facilities and equipment to care for patients with Covid-19 infection, such as adequate beds in the hospital inpatient department for Covid-19 patients
Reliability	8	O_5. When XYZ__ promises to do something by a certain time, it does so.	H_4. The hospital provides its services at the time it promises to do so.	C_7. Doing on-time what has been promised within a specific time	–
	9	O_6. When you have problems, XYZ__is sympathetic and reassuring.	H_5. When patients have problems the hospital employees are sympathetic and reassuring.	C_8. Compassionate and reassuring hospital staff when a problem arises.	–
	10	O_7. XYZ__is dependable	None	C_9. Hospital reliability	In terms of facilities, equipment and drugs used.
	11	O_8. XYZ__ provides its services at the time it promises to do so.	None	None	–
	12	O_9. XYZ__ keeps its records accurately	H_6. The hospital is accurate in its billing.	C_{10}. Accurate preservation of records	–
	13	None	None	C_{11}. Accuracy	Accuracy and consistency of information provided (e.g., accuracy in diagnosing disease, calculating cost, etc.)
Responsiveness	14	O_{10}. XYZ__ tells its customers when services will be performed.	H_7. The hospital employees tell patients exactly when services will be performed.	C_{12}. Expressing the patient exactly how long the service will last.	Like when is the patient's turn? When will the test result be prepared?
	15	O_{11}. You receive prompt service from XYZ__ employees	H_8. Patients receive prompt service from the hospital's employees.	C_{13}. Receive prompt and appropriate services	- Medical services: such as delivering medicine to a patient, - Ancillary services: such as receiving food and the possibility of using the health service
	16	O_{12}. Employees of XYZ__ are always willing to help customers.	H_9. The hospital's employees are always willing to help patients.	C_{14}. The constant desire of hospital staff to help the patient	–

(*continued on next page*)

Table A.1 (continued).

Category	No.	criteria of original SERVPERF scale (O)	criteria of SERVPERF for hospital (H)	Criteria used in this study for Covid-19 pandemic conditions (C)	Criterion description for Covid-19 pandemic
	17	O_{13}. Employees of XYZ__ respond to customer requests promptly.	None	C_{15}. Adequate number of staff in proportion to the number of patients	–
	18	None	None	C_{16}. Completeness	Availability of relevant services such as radiology services and tests required (no referral of patients to hospitals or other centers to do this)
Assurance	19	O_{14}. You can trust employees of XYZ__.	H_{10}. Patients feel safe in their interactions with the hospital's employees.	C_{17}. Reliability of employees in terms of security in interaction	Such as employees' confidentiality of the patient's personal information
	20	O_{15}. You can feel safe in your transactions with XYZ __'s employees.	H_{11}. The hospital's employees are knowledgeable.	C_{18}. Reliability of hospital staff in terms of their knowledge	–
	21	O_{16}. Employees of XYZ__ are polite.	H_{12}. The hospital's employees are polite.	C_{19}. Politeness of employees	–
	22	O_{17}. Employees get adequate support from XYZ __to do their jobs well.	H_{13}. Employees get adequate support from the hospital to do their jobs well.	C_{20}. Adequate hospital support for staff so that staff can do their job well	- For example, if the number of doctors and nurses and their salaries are adequate and sufficient, they can take leave and will not have to work overtime, so they will perform better during their normal working hours; Because they had enough time to rest and recover. - Psychological and psychological support of employees. - Support for quality of Coronavirus protective equipment for staff.
	23	O_{18}. XYZ__ gives you individual attention.	None	None	–
	24	O_{19}. Employees of XYZ__ give you personal attention.	H_{14}. The hospital's employees give patients personal attention.	C_{21}. Unique attention from hospital staff	In such a way that each patient is important to the hospital staff, it is as if the patient is a relative of the staff.
	25	O_{20}. Employees of XYZ__ know what your needs are.	None	C_{22}. Recognition of patient needs by treatment staff	Such as emotional and psychological needs
Empathy	26	O_{21}. XYZ__ has your best interests at heart.	H_{15}. The hospital has patients' best interests at heart	C_{23}. Putting patient's needs in the spotlight of the hospital	–
	27	O_{22}. XYZ__ has operating hours convenient to all their customers.	None	C_{24}. Providing suitable working hours in the hospital for all clients	For example, at any time of the day or night, an appropriate number of employees from the level of specialist doctor to nurse should be present in the hospital.
Overall	28	None	None	C_{25}. Overall patient satisfaction	Overall patient satisfaction with hospital health services
Total No.		22	15	25	

and facilities), C_{11} (accuracy) and then on other criteria in the order of Table 10, to make the most effective choice despite the limited resources.

6. Conclusion

As hospitals faced several challenges during the COVID-19 pandemic, the quality of hospital healthcare declined sharply. Addressing the quality of healthcare in a pandemic is essential in two ways. First, human health and lives are at stake, and it is necessary to provide more reliable services at this time [21]. Second, in a pandemic situation where the number of patients referred to hospitals is much higher than before, the patient's inferior perception of health services leads to severe patient dissatisfaction with the services provided [20]. However, all health care quality standards have been designed and applied to normal conditions. In previous studies that have mainly dealt with the SERVQUAL and SERVPERF measures, the interaction of the criteria of these standards has not been considered in the analysis. Therefore, in this study, the importance of effective criteria in the quality of health services in hospitals in the spread of infectious diseases

was evaluated by considering the interactions they can have on each other. This study aimed to identify the most important criteria for measuring the quality of health services in pandemic conditions of diseases such as Covid-19.

Limited resources and critical circumstances require that the criteria, which are chosen to improve healthcare quality, be selected more intelligently. Therefore, in this study, using the Z-Numbers and FCM algorithm, we evaluated the causal relationships between the criteria of health services by adopting the SERVPERF standard to identify the most critical criteria in the outbreak of infectious diseases. For this purpose, the opinions of experts were collected and evaluated. 'The results of this study indicate that the criteria by which healthcare service quality can be evaluated, have casual relationships. The outputs clearly represent that the weights of criteria increase after the implementation of FCM. Also, the ratio of overall satisfaction from the healthcare services significantly increase after implementing the FCM. To this end, the importance of these criteria should be evaluated considering their interactions. In this regard, to improve the quality of health services more effectively during the pandemic, the following criteria should respectively receive more attention

from the healthcare system: 1) hospital reliability, 2) hospital hygiene, and completeness, 3) equipping the hospital with up-to-date equipment, 4) accuracy, and constant desire of hospital staff to help the patient, 5) adequate physical facilities, 6) sufficient and appropriate proportion of medical staff to the number of patients, 7) unique attention from hospital staff, 8) adequate hospital support for staff to do their job well, 9) reliability of hospital staff in terms of knowledge, and finally 10) the facility layout of the building. On the other hand, reliability of healthcare system is the most important category of service quality criteria. Similarly, responsiveness, tangible, empathy, and assurance are respectively the other categories that should gain attention. The results of this study can be helpful to adopt better health care strategies and policies that lead to an increase in the quality of services in hospitals in pandemic conditions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Table A.1.

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