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SYSTEMS-LEVEL QUALITY IMPROVEMENT

Based on Real Time Remote Health Monitoring Systems: A New Approach for Prioritization "Large Scales Data" Patients with Chronic Heart Diseases Using Body Sensors and Communication Technology

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Abstract

This paper presents a new approach to prioritize "Large-scale Data" of patients with chronic heart diseases by using body sensors and communication technology during disasters and peak seasons. An evaluation matrix is used for emergency evaluation and large-scale data scoring of patients with chronic heart diseases in telemedicine environment. However, one major problem in the emergency evaluation of these patients is establishing a reasonable threshold for patients with the most and least critical conditions. This threshold can be used to detect the highest and lowest priority levels when all the scores of patients are identical during disasters and peak seasons. A practical study was performed on 500 patients with chronic heart diseases and different symptoms, and their emergency levels were evaluated based on four main measurements: electrocardiogram, oxygen saturation sensor, blood pressure monitoring, and non-sensory measurement tool, namely, text frame. Data alignment was conducted for the raw data and decision-making matrix by converting each extracted feature into an integer. This integer represents their state in the triage level based on medical guidelines to determine the features from different sources in a platform. The patients were then scored based on a decision matrix by using multi-criteria decision-making techniques, namely, integrated multi-layer for analytic hierarchy process (MLAHP) and technique for order performance by similarity to ideal solution (TOPSIS). For subjective validation, cardiologists were consulted to confirm the ranking results. For objective validation, mean ± standard deviation was computed to check the accuracy of the systematic ranking. This study provides scenarios and checklist benchmarking to evaluate the proposed and existing prioritization methods. Experimental results revealed the following. (1) The integration of TOPSIS and MLAHP effectively and systematically solved the patient settings on triage and prioritization problems. (2) In subjective validation, the first five patients assigned to the doctors were the most urgent cases that required the highest priority, whereas the last five patients were the least urgent cases and were given the lowest priority. In objective validation, scores significantly differed between the groups, indicating that the ranking results were identical. (3) For the first, second, and third scenarios, the proposed method exhibited an advantage over the benchmark method with percentages of 40%, 60%, and 100%, respectively. In conclusion, patients with the most and least urgent cases received the highest and lowest priority levels, respectively.

Keywords Real-time remote monitoring · Telemedicine · Patient prioritisation · Large-scale data · Multi-criterion decision making

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Introduction

Real-time remote health monitoring is important given that patients who live far from hospitals and use telemedicine may suffer from different chronic diseases, such as chronic heart disease, chronic blood pressure (BP), fall detection and diabetes. Chronic diseases are an increasingly important concern for e-healthcare systems worldwide. For example, clinical expenses for chronic diseases in the United States are projected to reach 80% of the total medical costs and more than 150 million people who are prone to chronic diseases will be included in "Large Scales of Data' by 2020 [1]. The Large Scales of Data in healthcare refer to the large and complex electronic health data sets that are difficult (or impossible) to manage either with traditional software and/or hardware or traditional or common data management tools and methods [2–5]. In healthcare, large scales of data are overwhelming not only because of their volume but also because of the diversity of data types and the speed at which they must be managed. The totality of data related to patient healthcare and well-being are the main components of large scales of data in the healthcare industry [2, 6, 7]. Thus, the applications in healthcare take advantage of data explosion to gain insights into making informed decisions [8]. However, such massive amounts of data, which are continuously created by sensing technologies, add to the big data problem [9]. Although the large scales of data concept and techniques [10] are used in various fields, such as Smart Cities, they are not widely used in biomedicine and telemedicine or patient monitoring for the use and integration of data from biosensors [11–20]. Despite some modern solutions, current data mining techniques, which involve patient monitoring in the medical domain, are generally at an alarmingly early state [11]. Continuous and daily monitoring of physiological data, such as heart rate or electrocardiogram (ECG) signals, is important in managing chronic diseases. Thus, healthcare researchers and developers have focused on health monitoring in out-of-hospital conditions, specifically in home environment, where telemedicine is used. Automatic diagnosis of heart diseases is an important and actual medical concern because they affect the health and working performance of patients specifically during disasters and peak times and in the elderly. The World Health Organisation estimated that 12 million deaths occur annually worldwide because of heart diseases [1].

Chronic heart diseases include several types of diseases and symptoms that manifest in patients. For example, cardiac arrhythmia is a life-threatening medical emergency that can result in cardiac arrest and sudden death. According to a medical report by the American Heart Association in 2010, approximately 55% of patients with heart diseases die because of arrhythmia [21]. Serious arrhythmia cases, such as ventricular tachycardia or fibrillation, are induced by vortex-like re-entrant electric waves in cardiac tissues. In addition, vital signs, such as ECG and oxygen saturation sensor (SpO_2), are important in triage setting because they objectively complement the triage decision and optimise inter-rater consistency [22]. Certain medical guidelines are followed in triage setting and prioritisation based on vital signs and chronic disease-related features of patients.

Patients who are physically present in the emergency department (ED) of a hospital are prioritised by triage nurses. Triage setting traditionally relies on the ability of nurses to prioritise cases. Triage setting and prioritisation become complicated when patients live far from the hospital and use telemedicine during disasters and peak times; in such cases, triage nurses and doctors are not physically available to help the patient; triage setting and prioritisation are more complex in telemedicine than that in actual ED situations [23]. Triage setting and prioritisation of patients who require the most urgent attention in telemedicine has gained considerable attention. In telemedicine, patients are triaged and prioritised for treatment and transportation to hospitals by assessing their vital signs [23, 24]. Patient condition must be primarily assessed to determine the priority category according to medical guidelines [23–25].

Technically, triage setting and prioritisation processes during disasters and peak times are complex decision-making procedures [26]. Thus, several triage scales have been designed to correspond to decision support systems and provide a guide for making correct decisions [26–30]. Triage setting and prioritisation processes during disasters and peak times involve simultaneous consideration of multiple attributes, including vital signs and features, and assignment of the proper weight for each feature to score a patient based on the most urgent case [24]. Patients under the most emergency cases must receive the highest priority level, whereas patients with less emergency cases must be given the lowest priority levels compared with other patients over the telemedicine environment. However, setting this prioritisation is a very difficult and challenging task because each patient with chronic heart disease requires a multi-attribute sensor for evaluation of their vital signs. For example, ECG and SpO_2 have been proven to be important in triage setting because they provide an objective complement to the triage decision-making process and optimise inter-rater consistency. Consequently, certain medical guidelines must be followed in the triage setting and prioritisation based on the vital signs and chronic heart disease-related features of patients. Furthermore, each decision maker (DM) provides different weights to these attributes (vital signs). On one hand, a server who aims to score a patient might give more weight to the vital feature rather than the other less interesting ones. On the other hand, developers who aim to use software to solve this problem will probably target different attributes as the most important ones. Thus, the triage setting and prioritisation processes of patients with chronic heart diseases are a multi-complex attribute problem during disasters and peak times, in which each patient is considered an available alternative for the DM.

This study presents a new real-time approach to aid the decision-making process for patients with chronic heart diseases in the telemedicine environment during disasters and peak times. An integrated model is proposed to evaluate and score patients based on Multi-layer for Analytic Hierarchy Process (MLAHP) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). The remaining sections of this paper are organised as follows. Section "Literature review" presents the literature review. Section "Methodology" describes the decision-making methodology for evaluation and scoring of patients with chronic heart diseases. Section "Results and discussion" reports the results and discussion. Section "Validation and evaluation" discusses the results of validating and evaluating the proposed method. Section "Summary points" highlights the contributions of the research as summary points. Section "Conclusion" concludes the report.

Literature review

Current literature on patient prioritisation methods is largely limited and scattered. Some attempts have been made to create strategies for these methods. Several studies investigated patient prioritisation to overcome the potential shortcomings of priority assignment in the traditional triage process [31].

A previous study [32] presented the use of utility theory in healthcare, specifically in improving triage decision-making, productivity and reducing cognitive load on triage nurses in EDs. The inherent uncertainty in this problem is the reason behind selecting utility theory to solve the problem of sorting patients in EDs. In this study, patients were ranked based on an emergency severity index and three descriptive variables, namely, age, gender and pain level. However, the small sample size of 21 patients and a determinant, such as pain level, may affect the accuracy of the results; moreover, this study did not consider the conflict in between the data and its resolution. The same author [33] also proposed dynamic grouping and prioritisation (DGP) algorithm to identify appropriate patient groups and prioritise them based on patient and system benefits. Based on discrete event simulation, the results provide statistical evidence that the DGP system outperforms alternative prioritisation methods in terms of all performance measures. However, the algorithm does not improve patient throughput over large scales of data based on multi-performance measures.

An approach referred to as the 'floating patient' method was proposed for optimising the schedule of patients for ED examination [31]. However, this study was applied inside the ED settings without considering multiple evaluations, which can affect the optimisation of the scheduling of patients based on their states.

Another study aimed to provide insights into the problem of patient prioritisation during complete evacuations in healthcare facilities [34]. The authors of this study proposed a dynamic programming model for emergency patient evacuation and concluded that continuous discussions among healthcare workers concerning the ethical dilemmas associated with making evacuation decisions are necessary. An algorithm with a column generation approach was also proposed [35]. However, this study was applied in a disaster situation and restricted to the allocation of emergency medical resources. A dynamic programming scheduling algorithm that included halting and a proposed simulation method were applied to crowded patients inside the ED [36]. However, both studies did not consider the problem of patient prioritisation based on emergency cases by using multi-measurement attributes.

Ref. [37] conducted an exploratory work using a hypothetical example of a methodology and multi-attribute utility analysis of healthcare. The hypothetical sample problem presented involves patient prioritisation in an ED. This study [38] also investigated the potential for integrating technology and multi-attribute utility theory in developing a dynamic decision support system for patient prioritisation in ED settings. The attributes studied in this research complied with preferential and utility independence with one another. However, this condition may not hold true when considering other attributes, such as complaints. Furthermore, both studies did not consider multiple attributes, which are related to the emergency state of patients.

Ref. [39] proposed a system using the electronic triage tag (e-Triage), which enables emergency medical technicians to identify the locations and conditions of patients. However, this work focused on the transportation scheduling problem after secondary triage of patients. Another study [40] attempted to maximise the number of expected saved patients under limited medical resources. The proposed heuristic algorithm was based on depth-limited search. The results showed that the average number of saved patients is 10% higher than that when using greedy methods. However, the algorithm cannot calculate patient priority based on multiple attributes. The priority level is only assumed in the simulation, and the patients are assumed to be already triaged.

The above-mentioned methods show disadvantages, and no particular study for any type of chronic disease is available and did not consider the large scales of data during disasters and peak times. Ref. [23] proposed a multi-source healthcare architecture (MSHA) to improve healthcare services by enhancing remote triaging and remote prioritisation processes for telemedicine of patients with chronic heart disease. The general scheme of telemedicine system consists of three tiers, namely, sensors/sources (e.g. ECG, SpO_2), base station and server. However, the simulation of MSHA is implemented only at the base station (Tier 2), indicating that patients who are physically present in the hospital (server side, Tier 3) are not addressed. The exclusion of in-hospital patients raises an ethical healthcare issue, including the consideration for all patients (i.e., in-hospital and telemedicine patients) in the prioritisation process and providing them with compatible healthcare services based on their emergency level. As an approach for prioritising patients with the most urgent status, the inclusion of in-hospital patients with telemedicine patients requires a robust method that can accommodate an increasing number of patients and handle an increasing data size as 'large scales of data' during disasters and peak times because triage setting and prioritisation processes involve simultaneous consideration of multiple attributes (vital signs) and assigning proper weight for each feature to score the patients based on the most urgent cases. Therefore, this process can be considered a multi-criterion decision problem. Multi-sensor sources are available. For each sensor source, the subset of features displays a range of different, conflicting data used in various triage levels for the difficult task of increasing data size during disasters and peak times.

Different methods have been applied to prioritise patients. However, healthcare decisions are generally complex and involve confronting trade-offs between multiple and often conflicting attributes. Specifically, the prioritisation of patients based on their medical condition and chance of survival is a complex decision-making problem [37, 41, 42] because the decision is made based on a set of attributes [43]. Additionally, patient prioritisation involves simultaneous consideration of multiple attributes (vital signs) and requires assigning proper weights for each feature to score the patients based on the most urgent cases. Therefore, using structured and explicit approaches in decisions involving multiple attributes can improve the quality of decision making, and a set of techniques, which are classified under the collective heading multiple criterion decision analysis (MCDA), can be used for this purpose. MCDA is a sub-discipline of operational research and explicitly considers multiple criteria in decision-making conditions, which occur in various actual situations of medical diagnosis [44]. Several useful techniques can be used to deal with multi-attribute decision-making or multi-criterion decision-making (MADM/MCDM) problems in real world. These methods help DMs organise the problems to be solved and perform analysis, ranking and scoring of alternatives [44, 45]. Accordingly, the scoring of a suitable alternative(s) must be performed. MADM/MCDM methods can solve the scoring problem of big data for patients with chronic diseases based on the most urgent cases in a telemedicine environment. In any MADM/MCDM ranking, fundamental terms must be defined, and these terms include decision or evaluation matrix (EM), alternatives and criteria [25]. EM consists of m alternatives and n criteria, which must be created. Considering the intersection of each alternative and criteria as x_{ij}, we obtain the following matrix$(x_{ij})_{m*n}$:

$$DM/EM = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array}$$

where $A_1, A_2, \dots, A_m$ are the possible alternatives scored by DMs (i.e. patients); and $C_1, C_2, \dots, C_n$ are criteria against which each alternative performance is measured (i.e. measurements). Finally, x_{ij} is the rating of an alternative A_i with respect to criterion C_j, and W_j is the weight of the criterion C_j. Certain processes, such as normalisation, maximisation of indicators and addition of weights must be completed to rank the alternatives.

Several MCDM theories or methods have been investigated. The most popular methods of MADM that use different concepts include multiplicative exponential weighting (MEW), weighted product method (WPM), weighted sum model (WSM), simple additive weighting (SAW), hierarchical adaptive weighting (HAW), analytic hierarchy process (AHP), analytic network process (ANP) and TOPSIS [45]. To our knowledge, none of these methods have been used in scoring large scales of data of patients with chronic diseases during disasters and peak times.

According to [46–58], the drawbacks, benefits and recommendations for the popular MCDM techniques can be summarised as follows: HAW and WSM techniques are easy to use and understand, but the weights of the attributes are arbitrarily assigned; moreover, both techniques become difficult to use as the number of criteria increases [59–63]. Another problem with these methods stems from the use of common numerical scales to obtain the final score. SAW considers all of the criteria, perform decisions intuitively and offers simple calculation. All values of the criteria must be maximum and positive. Moreover, SAW does not always reflect the real situation. The strengths of MEW and WPM include the ability to remove any unit of measure and the use of relative values rather than actual ones. However, no solution with an equal weight of decision matrices is offered. Meanwhile, the ANP model provides full understanding of the level of importance that a criterion can have by agreeing to its interrelationship with the other elements of the model. A benefit of the ANP model is that it allows assessment of the consistency of judgments, and such assessment is impossible to evaluate using a method that assigns weights by compromise. Another positive aspect of the ANP model is that it facilitates assigning weights because it splits up the problem into small parts, in which a group of academics can have a manageable discussion and only two criteria can be compared to assign the judgments. However, ANP suffers from two disadvantages. Firstly, providing a correct network structure for the criteria is difficult even for experts, and different structures lead to varying results. Secondly, to form a super matrix, all criteria must be pair-wisely compared with regard to all other criteria, and the comparison is difficult and unnatural [64, 65]. AHP enables DMs to arrange a decision-making problem into a hierarchy to understand and simplify the problem. This technique is time consuming because of the mathematical calculations and number of pairwise comparisons, which increase as the number of alternatives and criteria increases or changes. Ranking of alternatives in AHP depends on the alternatives considered for evaluation. Adding or deleting alternatives can change the final ranking (rank reversal problem).

The MCDM techniques discussed in this section are used to score big data of patients with chronic heart diseases and prioritise the most urgent cases. However, these techniques lack indicators of how well the healthcare service can satisfy the needs of patients. Another problem with these techniques is the non-adoption of a requirement-driven approach, which makes them inadequate for priority scoring based on decision making [44]. TOPSIS is functionally associated with problems of discrete alternatives and is one of the most practical methods for solving real-world problems. The relative advantage of TOPSIS is its ability to rapidly identify the optimal alternative. Therefore, TOPSIS is suitable for cases with numerous alternatives and attributes [66]. However, the major weakness of TOPSIS is the lack of provision for weight elicitation and consistency of checking for judgments. In this regard, TOPSIS requires an efficient technique to obtain the relative importance of different criteria with respect to the objective; AHP provides such a procedure. Given that AHP is used to set weights for objectives based on stakeholder preferences [66] and has been significantly restrained by the human capacity for information processing, the value of 7 ± 2 would be the ceiling for comparison [67]. From this viewpoint, TOPSIS alleviates the requirement of paired comparisons, and the capacity limitation may not significantly influence this process [68].

The newest trend with respect to MCDM is to combine two or more methods to compensate for the shortcomings of a single method [69–71]. TOPSIS and AHP have become widely accepted integrated MCDM methods for the following reasons: ability to provide complete ranking results, use of weights and objective data to calculate relative distances, suitability to be combined with stochastic analysis, smoothing of trade-offs by dealing with nonlinear relationships and easy conversion of the method into a programmable procedure [66, 70]. Hence, combining AHP and TOPSIS has been recommended for ranking patients with chronic diseases by using remote large scales of data and for prioritising the most urgent cases during disasters and peak times.

Methodology

This study provides a detailed overview of the alternative large scales of data of patients with chronic heart diseases based on a set of measures through the relatively infrequent route of actual measurement of patient data and reporting of hands-on evaluation results based on the ECG and SpO_2 sensors and other variables as raw data. Data alignment of raw data and decision-making matrix was performed by converting each extracted feature into an integer, which represents their state in the triage level based on medical guidelines. The input to this part (sources and inclusion criteria of subject articles) is discussed in subsequent subsections. Ranking of patients with chronic heart diseases by using big data is based on inputs received from medical guidelines, medical sensor evaluation and text frame sources. The output ranks the patients based on a constructed decision-making matrix by using integrated MLAHP and TOPSIS. All of the elements of our study are shown in the overall conceptual framework in Fig. 1.

Evaluation of medical sensors and sources

Several medical devices are used to measure the vital signs of patients. The number and type of sensors depend on the type of disease that must be monitored on the patient. Given that the focus of this research is chronic heart diseases, this section evaluates four relevant medical sources that demonstrate heart performance and reflect the medical symptoms of the patients. The three sensors used as signal sources and one text source [23] are shown in Table 1. For each source, certain medical features are considered (e.g. the ECG signal includes rhythm and ST elevation). The medical assessment of each feature with the related source is shown in Table 1.

Each sensor signal is represented by an array. In the dataset used as sensory data, each element in the signal represents two values, namely, time and voltage. The array of each signal contains two columns (each column represents a value). The number of rows is defined by the number of elements in the signal, starting from 0 to n. Meanwhile, the array of the text feature is 1×4 because four variables represent four non-sensory features. The mathematical representations for the multi-function feature extraction algorithm for each source are displayed in Fig. 2.

In Fig. 2, the early stage input data are processed and analysed using logically defined medical guidelines. The medical guidelines consider the rules that are defined and validated not only by research but also by practical experiences of medical doctors and experts to support the decision of an emergency level user [5]. Medical guidelines demonstrate the relation between user input vital sign as input data and medical diagnosis as output. In this study, 11 features from four heterogeneous sources are modelled (Table 1) and used as criteria in the proposed decision-making algorithm. The procedure for computing the features and details about the medical guidelines for each source are described in the following sections.

1. ECG Sensor

A real-time data processing multi-function algorithm was designed to extract ECG features. The ECG signal is represented by an array of two columns, which correspond to time (ms) and voltage (mv), and their values were used to extract the features. The ECG signal exhibits many cycles, as shown in Fig. 3. One ECG cycle demonstrates many ECG features,

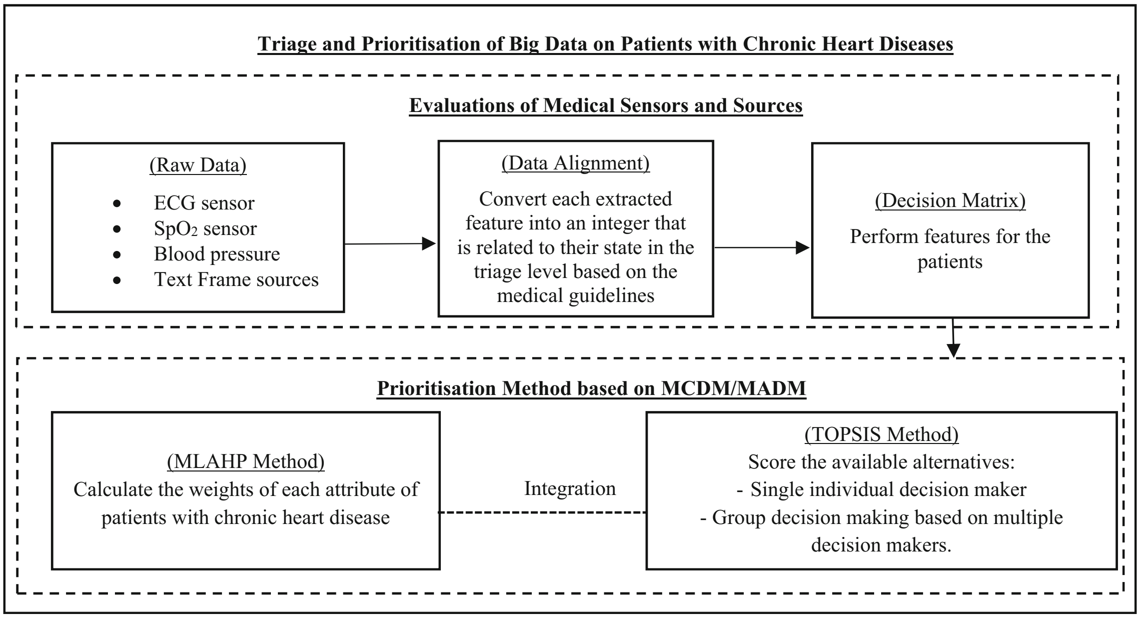

Fig. 1 Conceptual framework for triage and prioritisation patients with chronic heart diseases by using large scales of data

such as rhythm, QRS, ST and R–R regularity, which are represented in Fig. 3a. For each cycle, the signal values in time varied around the zero line, and those values were used to split the ECG cycle into up and down halves (Fig. 3b). Subsequently, the upper half was sorted based on voltage values to determine the maximum point, *R* (Fig. 3c). The upper half of the ECG cycle was split into right and left halves (Fig. 8c). The location of Q and S points was located (Fig. 3d) using certain functions presented in Fig. 1 to sort the values of the ECG cycle for each half (Up_Lift and Up_right) based on (t) and (v) values.

According to medical guidelines [23], the normal value of ECG rhythm is within 60–100 beats per minute. The normal range of QRS width is 0.06–0.12 ms. ST elevation is considered normal when the ST segment is straight and is abnormal when the ST segment is evaluated to be up or down. Finally,

Table 1 Description of four relevant medical sources used in monitoring patients

Source	Feature	Feature medical assessment	Description
ECG	Rhythm	Sinus bradycardia and sick sinus syndrome [72]; sinus tachycardia, atrial tachycardia and atrial flutter [23, 72]	Measure the electrical representation of contractile activity of the heart over time Electrical representation of contractile activity is used for short-term assessment of cardiovascular diseases, especially for people with chronic heart problems.
	QRS width	Reflects rapid left and right ventricular depolarisation [73] and bundle branch block [23, 72]	
	ST elevation	Acute myocardial infarction, Prinzmetal's angina and left ventricular aneurysm [72, 74]	
	R-R Regularity	Many diseases [23, 72]	
SpO_2	Percentage level	Ratio of oxyhaemoglobin to the total concentration of haemoglobin present in the blood [23]	The pulse oximeter is used to measure blood oxygen saturation level of a patient.
Blood pressure	High-level value	Tinnitus, dizziness, light-headedness, recurrent or worsening distended headache, nose bleeding, trembling, weakness, fatigue, disturbed sleep and sore back [23]	Measure the physiological data of systolic and diastolic blood pressure of a patient
	Low-level value	Dizziness, light-headedness, fatigue, depression and thirst [23]	
Text	Shortness of breath Chest pain Palpitation Rest or exercise	Related to chronic heart diseases [23, 72, 75]	Non-sensory measurements are used by triage nurses in hospital (ED) to prioritise patients according to several categories, such as chest pain and breathing.

Fig. 2 Feature extraction algorithm

$$\text{ECG} = \begin{pmatrix} e_i^0 & e_v^0 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ e_i^n & e_v^n \end{pmatrix} \quad \text{B} = \begin{pmatrix} b_i^0 & b_v^0 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ b_i^n & b_v^n \end{pmatrix} \quad \text{S} = \begin{pmatrix} s_i^0 & s_v^0 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ s_i^n & s_v^n \end{pmatrix} \quad \text{T} = \begin{pmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \end{pmatrix}$$

Inputs:

- Array of ECG element signal (ECG) for 1 min.
- Array of blood pressure element signal (B) for 1 min.
- Array of Spo2 element signal (S) for 1 min.
- Text variables (T).

Outputs:

- Rhythm, QRS width, ST-elevation and regularity for ECG.
- High- and low-blood-pressure value for B.P.
- Spo2 level.
- Text feature.

Buffered Reader ECG sensor
for all e_i^0 and e_v^0 ϵ ECG **DO**
    get Peaks ();
    getAvgCycleInterval ();
    getQRS ();
    isSTSegmentUP();
end for

Buffered Reader B.p. sensor
for all b_i^0 and b_v^0 ϵ B **DO**
    get highValue();
    get LowValue();
end for

Buffered Reader Spo2 sensor
for all s_i^0 and s_v^0 ϵ S **DO**
    get s value();
end for

for all t_i ϵ T DO
    chest Pain();
    Shortness of breath ();
    Palpitation ();
    rest Or Exercise ();
end for

regular and irregular patterns of peak-to-peak interval were regarded as normal and abnormal, respectively.

Technically, in Fig. 3, e_i^0 to e_v^0 represent all elements that belong to the ECG signal for 1 min. The (get Peaks ();) function is used to calculate the number of *R* in the ECG signal within 1 min. Therefore, the number of *R* represents the rhythm. The function (getAvgCycleInterval ()) is used to determine the average width cycle and the QRS width in the (getQRS ();) function. The ST elevation can be determined using the (isSTSegmentUP();) function, which is based on the differences in Δt and Δv values by using subtraction functions (Fig. 3e).

2. BP Sensor

BP measurements are commonly classified into normal and abnormal cases on the basis of the measurement of high and low BP levels for a patient [45]. According to medical guidelines [23], for patients with regularly high BP, values between 110 and 140 mmHg, 140 and 180 mmHg >180 mmHg are considered normal, abnormal and at risk, respectively. For patients with regularly low BP, values between 60 and 90 mmHg, 90 to 110 mmHg and >110 are regarded as normal, abnormal and at risk, respectively. Technically, the value of high and low BP is calculated using the (get HighValue ();)and (get LowValue ();) functions, respectively. These two functions are implemented for all elements of BP signals in 1 min, starting from b_i^0 and finishing at b_v^0 (Fig. 2).

3. SpO_2 Sensor

One feature value is extracted from SpO_2 sensors. The accelerometer (SpO_2) value can be changed for the same user in different activities. According to medical guidelines [59],

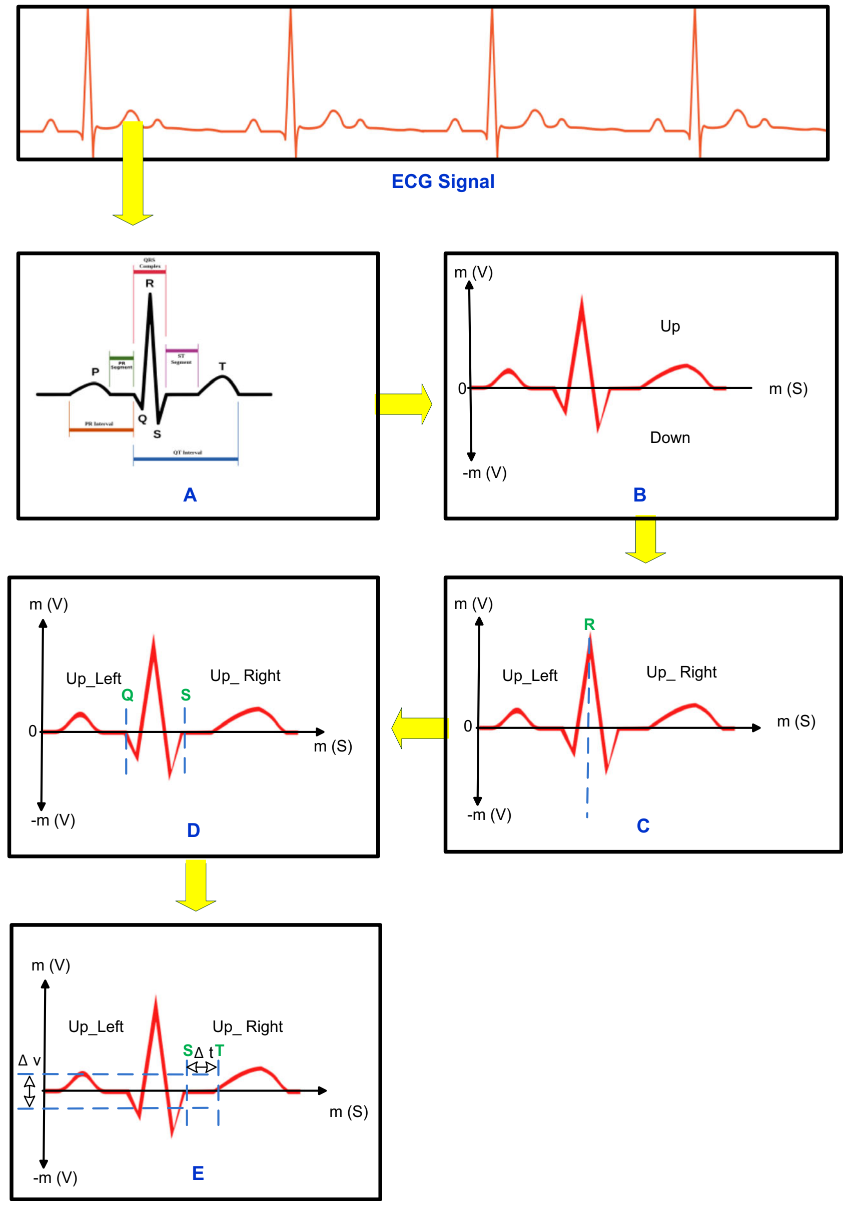

Fig. 3 ECG feature extraction processes

the levels of SpO_2 vary according to different types of chronic heart diseases. The normal, abnormal and at risk values of SpO_2 are 96%–100%, 90%–96% and <90%. Technically, the value of SpO_2 in 1 min can be extracted using the (get s value ();) function for all elements of SpO_2 signal starting from s_i^0 to s_v^0 (Fig. 2).

4. Text Source

Text features are important for chronic heart diseases because these features present the activity of muscles surrounding the heart [me]. In addition, text features are non-sensory data that add context to the user or patient. Patients generally present their complaints to physicians by manually completing forms to describe their pathological conditions. A series of discussions with doctors revealed that text features are important to chronic heart diseases [23]. Given that these features present the activity of muscles surrounding the heart, abnormal text features are common in all heart diseases, regardless of whether ECG features are normal or abnormal [23]. The presence of abnormal features in the ECG indicates that they are also present in the texts. In this instance, a patient is considered an urgent case. By contrast, when the ECG is normal and the text features are abnormal, a certain type of heart disease that is not classified under urgent cases and not previously classified is reflected. Technically, text inputs related to chronic heart diseases are chest pain, shortness of breath, palpitation and current activity of the patient (resting or exercising). A system that includes a graphical user interface equal to the diagnostic procedure is proposed to enable a user to answer four questions corresponding to four text features. Additional questions increase processing time and system complexity. Users answer either 'Yes' or 'No' to the questions, and the value of each feature is determined using functions (chest pain, shortness of breath, palpitation and rest or exercise; Fig. 1).

Using a single platform to consolidate all results from the evaluated features from various sources is challenging. This approach can improve the delivery of healthcare services, especially when the features exert a common medical influence on the diagnostics of a certain disease. Thus, the developed and proposed framework facilitates the integration of ECG, SpO_2 and BP sensors and text in a single approach dedicated to the diagnostics of chronic heart diseases. Table 2 demonstrates the features of the proposed framework for a sample of 40 patients over 500. However, the score evaluation of each feature requires validation based on medical guidelines.

Employing decision-making theory to the raw data presented in Table 2 is not mathematically applicable because of the following: (1) the raw data show inconsistent format (strings and numbers); and (2) the numbers are different in medical diagnostics. For example, the value of 80 in low BP represents 'risk triage level', whereas 80 in SpO_2 is regarded as 'normal triage level'. Thus, data alignment process must be designed and applied between raw data processing and decision-making matrix. Data alignment designates an integer to each extracted feature. The integers represent the state of the feature in the triage level based on medical guidelines. The measurements of SpO_2 and BP sources represented by five triage levels, namely, normal, cold state, sick, urgent and at risk, are replaced by the numbers 0, 1, 2, 3 and 4, respectively. The other two sources, namely, ECG and text sources, which correspond to normal and abnormal triage levels, are substituted by 0 and 1, respectively. According to the data alignment process, the raw data shown in Table 2 in the decision matrix are presented in Table 3.

As shown in Table 3, different sources exhibit varying features that show various triage levels. In a medical perspective, the vital features can simultaneously indicate more than one triage level for the same patient. For example, patients are in the normal triage level when they demonstrate shortness of breath and peak-to-peak feature (ECG features). However, the same patients are also considered to show abnormal triage levels according to the SpO_2 data and low BP features. Consequently, triage nurses cannot determine the triage levels of these patients. Therefore, the final decision that represents the triage levels of patients is difficult to make through paper-based triage system or basic automated triage system, which is generally used in hospitals. A decision-making algorithm and computer-based approach are necessary for mitigating the complexity of patient triage setting and prioritisation and addressing incongruent patient data.

Prioritising patients with chronic heart diseases

Patients with chronic heart diseases were evaluated through several criteria, such as ECG, SpO_2, BP sensors, diastolic BP and non-sensory measurement (text frame). Problems emerge when each patient with chronic heart disease exhibit several attributes, and each DM correspond to different weights for these attributes. In typical situations, weights can be assigned by experts, such as doctors. This situation is attributed to the varied opinions of doctors on critical criteria that influence focus on patients. This situation is incompatible with the objectives of different layers of criteria. Therefore, prioritisation of patients with the most urgent condition is difficult. In addition, a server might prefer ECG, SpO_2, BP sensors, diastolic BP and non-sensory measurement (text frame) over other features. By contrast, developers of this software may target different attributes. The ranking of patients with chronic heart diseases, particularly in software development, is a multi-attribute measurement problem.

Weights can be assigned to solve this problem in several ways through three scenarios. Firstly, weights are set according to the objectives of doctors. This scenario is recommended for researchers and academics who plan their evaluation and prioritisation. Secondly, multiple weights are assigned to evaluate and prioritise patients under different circumstances. In this instance, doctors are required to set different weights that represent different cases. Finally, three to six evaluators are used to set the preference weight. This scenario is recommended for servers that rank patients according to the number of emergency cases; that is, those with the most number of emergency cases represent high priority levels, whereas those with the minimum number of emergency cases acquire low priority levels. Notably, different evaluators exhibit different preferences, which create different ranking schemes. The final stage in this process is to consolidate these ranking orders into a final ranking scheme. Several recommended techniques, such as AHP, can be used to measure the weights of the criteria. This technique is highly recommended by researchers. The AHP algorithm generates pairwise comparisons among the criteria. In addition, AHP is a popular MCDM method [67]. A multilayer process of the AHP, that is, MLAHP, is adapted to calculate the weight of each attribute. Subsequently, TOPSIS is used to rank available patients. On the basis of the integration of TOPSIS and MLAHP, the proposed methodology can be used to solve complex multi-attribute measurements and selection problems in various medical diseases. The ranking scheme is shown in Fig. 4 and described as follows:

Weight calculation based on MLAHP Weights are assigned to each basic attribute in the hierarchy of criteria through MLAHP. Each basic criterion is rated in the hierarchy for each patient considered for evaluation. MLAHP is used to derive

Table 2 Evaluation matrix

Patient no.	Spo_2 sensor	Blood pressure sensor	Text features				ECG sensor			
	Spo_2 level %	Systolic /diastolic	Chest pain	Shortness of breath	Palpitation	Patient at rest?	Rhythm per min	QRS width	Peak-to-peak interval	ST elevation
1	97	230/120	false	false	false	false	67	0.06	0.06576267	true
2	97	230/120	false	false	false	true	67	0.06	0.06576267	true
3	97	230/120	false	true	false	false	67	0.06	0.06576267	true
4	97	230/120	false	true	false	true	67	0.06	0.06576267	true
5	97	230/120	false	false	true	false	67	0.06	0.06576267	true
6	80	230/120	true	true	false	true	77	0.047	0.266642311	true
7	80	230/120	true	false	true	false	77	0.047	0.266642311	true
8	80	230/120	true	false	true	true	77	0.047	0.266642311	true
9	80	230/120	true	true	true	false	77	0.047	0.266642311	true
10	80	230/120	true	true	true	true	77	0.047	0.266642311	true
11	92	230/120	true	true	false	false	64	0.169	0.336317901	false
12	92	230/120	true	true	false	true	64	0.169	0.336317901	false
13	92	230/120	true	false	true	false	64	0.169	0.336317901	false
14	92	230/120	true	false	true	true	64	0.169	0.336317901	false
15	92	230/120	true	true	true	false	64	0.169	0.336317901	false
16	92	230/120	true	true	true	true	64	0.169	0.336317901	false
17	92	230/120	false	false	false	false	67	0.06	0.06576267	true
18	92	230/120	false	false	false	true	67	0.06	0.06576267	true
19	92	230/120	false	true	false	false	67	0.06	0.06576267	true
20	92	230/120	false	true	false	true	67	0.06	0.06576267	true
21	92	230/120	false	true	false	false	67	0.06	0.065763	true
22	92	230/120	false	true	false	true	67	0.06	0.065763	true
23	92	230/120	false	true	true	false	67	0.06	0.065763	true
24	92	230/120	false	true	true	true	67	0.06	0.065763	true
25	92	230/120	true	false	false	false	67	0.06	0.065763	true
26	92	230/120	true	false	false	true	67	0.06	0.065763	true
27	92	230/120	true	false	true	false	67	0.06	0.065763	true
28	92	230/120	true	false	true	true	67	0.06	0.065763	true
29	92	230/120	true	true	false	false	67	0.06	0.065763	true
30	92	230/120	true	true	false	true	67	0.06	0.065763	true
31	92	230/120	true	true	true	false	67	0.06	0.065763	true
32	92	230/120	true	true	true	true	67	0.06	0.065763	true
33	97	150/100	false	false	false	false	67	0.06	0.065763	true
34	97	150/100	false	false	false	true	67	0.06	0.065763	true
35	97	150/100	false	false	true	false	67	0.06	0.065763	true
36	97	150/100	false	false	true	true	67	0.06	0.065763	true
37	97	150/100	false	true	false	false	67	0.06	0.065763	true
38	97	150/100	false	true	false	true	67	0.06	0.065763	true
39	97	150/100	false	true	true	false	67	0.06	0.065763	true
40	97	150/100	false	true	true	true	67	0.06	0.065763	true

ratio scales from pairwise comparisons, allowing small inconsistencies in judgment because humans are typically consistent. The ratio scales are derived from principal eigenvectors, and consistency index is derived from the principal eigenvalue. The number of required pairwise comparisons is equal to $n \times (n-1)/2$, where n is the number of criteria used during the evaluation. Evaluators are instructed to complete the comparisons among the criteria. The answers must follow the form designed according to the number of criteria. The MLAHP measurement matrices are processed to obtain weights

Table 3 Evaluation matrix of Table 2 in decision-making matrix

Patient no.	Spo_2 sensor	Blood pressure sensor	Text features				ECG sensor			
	Spo_2 level %	Systolic /diastolic	Chest pain	Shortness of breath	Palpitation	Patient at rest?	Rhythm per min	QRS width	Peak-to-peak interval	ST elevation
1	0	4	0	0	0	0	0	0	0	0
2	0	4	0	0	0	1	0	0	0	0
3	0	4	0	0	1	0	0	0	0	0
4	0	4	0	0	1	1	0	0	0	0
5	0	4	0	1	0	0	0	0	0	0
6	0	4	0	1	0	1	0	0	0	0
7	0	4	0	1	1	0	0	0	0	0
8	0	4	0	1	1	1	0	0	0	0
9	0	4	1	0	0	0	0	0	0	0
10	0	4	1	0	0	1	0	0	0	0
11	0	4	1	0	1	0	0	0	0	0
12	0	4	1	0	1	1	0	0	0	0
13	0	4	1	1	0	0	0	0	0	0
14	0	4	1	1	0	1	0	0	0	0
15	0	4	1	1	1	0	0	0	0	0
16	0	4	1	1	1	1	0	0	0	0
17	1	4	0	0	0	0	0	0	0	0
18	1	4	0	0	0	1	0	0	0	0
19	1	4	0	0	1	0	0	0	0	0
20	1	4	0	0	1	1	0	0	0	0
21	1	4	0	1	0	0	0	0	0	0
22	1	4	0	1	0	1	0	0	0	0
23	1	4	0	1	1	0	0	0	0	0
24	1	4	0	1	1	1	0	0	0	0
25	1	4	1	0	0	0	0	0	0	0
26	1	4	1	0	0	1	0	0	0	0
27	1	4	1	0	1	0	0	0	0	0
28	1	4	1	0	1	1	0	0	0	0
29	1	4	1	1	0	0	0	0	0	0
30	1	4	1	1	0	1	0	0	0	0
31	1	4	1	1	1	0	0	0	0	0
32	1	4	1	1	1	1	0	0	0	0
33	0	3	0	0	0	0	0	0	0	0
34	0	3	0	0	0	1	0	0	0	0
35	0	3	0	0	1	0	0	0	0	0
36	0	3	0	0	1	1	0	0	0	0
37	0	3	0	1	0	0	0	0	0	0
38	0	3	0	1	0	1	0	0	0	0
39	0	3	0	1	1	0	0	0	0	0
40	0	3	0	1	1	1	0	0	0	0

according to the preference of evaluators. The level of emergency cases with different objectives can be obtained through the assignment of these weights. The MLAHP measurement steps for the weight preferences assumed for each evaluator are shown in Fig. 5.

In Fig. 5, E = ECG, S = Spo_2 level, B = blood pressure, T = text, R = rhythm, RP = R-R regularity, ST = ST elevation, H = high blood level, L = low blood level, CP = chest pain, SOB = shortness of breath, PAL = palpitation, PIR = patient in rest and Q = QRS. Six doctors who specialise in cardiologist and

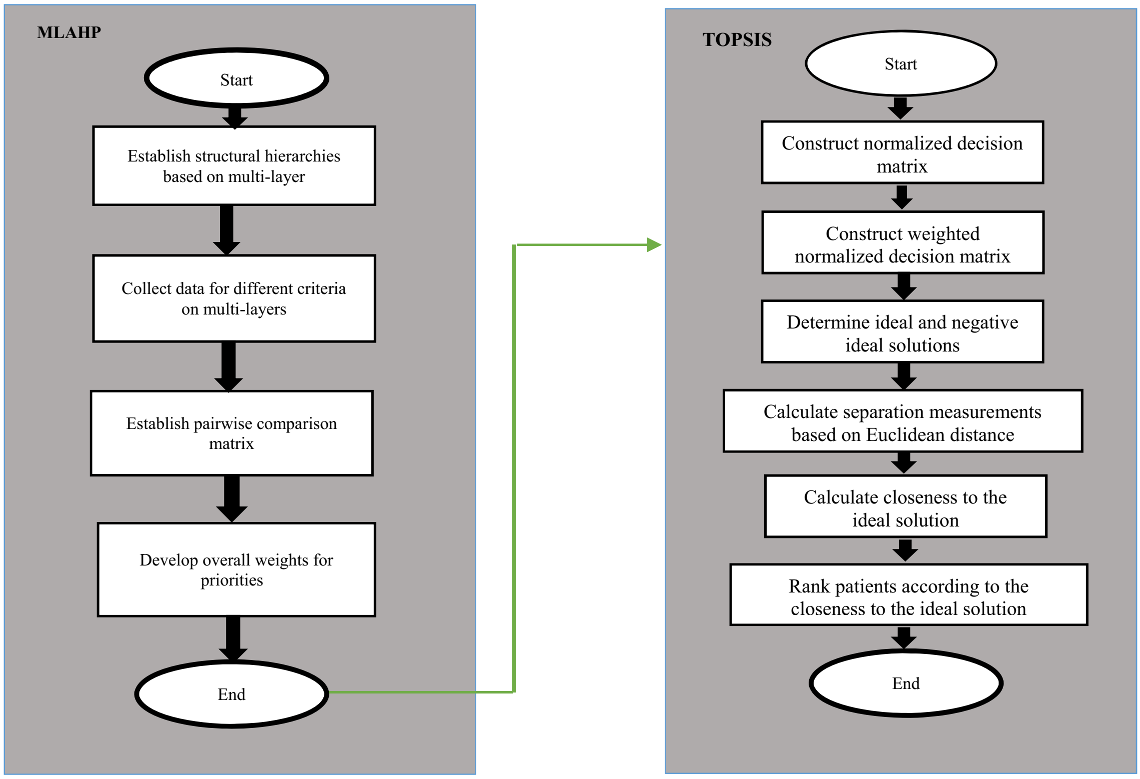

Fig. 4 Integrated TOPSIS and MLAHP model for patient prioritisation

with >3 years of experience are selected to complete MLAHP. A total of six copies, which includes 19 pairwise comparisons, among all criteria on layer 1 and sub-criteria on layer 2 are presented to the doctors, and their responses to these criteria are obtained. The relative scale (1 to 9) is created to quantify the preferred criteria of the doctors. Each doctor critically analyses these criteria according to their experience and knowledge. After attaining the responses on the pairwise comparisons, four reciprocal matrices are created from the pairwise comparisons; the results obtained from the MLAHP sequence process are listed in Table 4. Eleven features for each doctor are calculated, and the results provide the corresponding relative weight of the criteria.

Ranking patients using TOPSIS The available patient scores are ranked in descending order, and the most urgent patients are prioritised according to TOPSIS (Fig. 5). The aggregate scores roughly classify the patients. Individuals are expected to score the most urgent cases, similar to other ranking options. TOPSIS allocates scores to each alternative (per patient) according to their geometric distance from the positive and negative ideal solutions [44, 45]. The patients are ranked in this method, and those with the most number of emergency cases exhibit the shortest geometric distance to the positive ideal solution and the longest geometric distance to the negative ideal solution, as described in the following steps.

- 1: Construction of normalised decision matrix

This process attempts to transform the dimensions of various attributes (vital features) into non-dimensional attributes. It also allows comparisons across the attributes. The matrix $(x_{ij})_{m*n}$ is normalised from $(x_{ij})_{m*n}$ to the matrix $R = (r_{ij})_{m*n}$ by the following method:

$$r_{ij} = \boldsymbol{x_{ij}} / \sqrt{\sum_{i=1}^{m} \boldsymbol{x_{ij}^2}} \tag{1}$$

This process will generate a new matrix **R,** which is shown below

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix}$$

- 2: Construction of MLAH-based weighted and normalised decision matrix

In this process, the weights for each attribute are calculated according to the MLAHP model. A set of weights $w = w_1, w_2, w_3, \cdots, w_j, \cdots, w_n$ from the DM are integrated into the normalised decision matrix. The resulting matrix can be calculated by multiplying each column of the normalised decision

Layer 1 Process for (Main-Criteria)

	Criteria	Original Matrix: ECG	Original Matrix: Blood Pressure	Original Matrix: SpO_2	Original Matrix: Text	Normalised Matrix: ECG	Normalised Matrix: Blood Pressure	Normalised Matrix: SpO_2	Normalised Matrix: Text	Aggregation	Global Weight
Each Evaluator	ECG	E(1)	E/B	E/S	E/T	E(1)/Sum1	(E/B)/Sum2	(E/S)/Sum3	(E/T)/Sum4	Sum-E	W1=Sum_ E/n
	Blood Pressure	B/E	B(1)	B/S	B/T	(B/E)/Sum1	B1/Sum2	(B/S)/Sum3	(B/T)/Sum4	Sum_B	W2=Sum_ B/n
	SpO2	S/E	S/B	S(1)	S/T	(S/E)/Sum1	(S/B)/Sum2	S1/Sum3	(S/T)/Sum4	Sum_S	W3=Sum_ S/n
	Text	T/E	T/B	T/S	T(1)	(T/E)/Sum1	(T/B)/Sum2	(T/S)/Sum3	T1/Sum4	Sum_T	W4=Sum_ T/n
	Sum	Sum1	Sum2	Sum3	Sum4						1

Layer 2 Process for (Sub-Criteria)

	Criteria	Original matrix: ST segment	Original matrix: Rhythm	Original matrix: QRS	Original matrix: R-to-R distance	Normalised Matrix: ST segment	Normalised Matrix: Rhythm	Normalised Matrix: QRS	Normalised Matrix: R-to-R distance	Aggregation	Global Weight
Each Evaluator	ST segment	ST(1)	ST/R	ST/Q	ST/RR	ST ST(1) /Sum1	(ST/B) /Sum2	(ST/Q)/Sum3	(ST/RR) /Sum4	Sum_ ST	W1=Sum_ ST /n
	Rhythm	R/ST	R (1)	R/Q	R RR	(R/ST) /Sum1	R 1/Sum2	(R/Q)/Sum3	(R/RR) /Sum4	Sum_ R	W2=Sum_ R/n
	QRS	Q/ST	Q/R	Q (1)	Q/RR	(Q/ST) /Sum1	(Q/R) /Sum2	Q1/Sum3	(Q/RR) /Sum4	Sum_Q	W3=Sum_Q/n
	R-to-R distance	RR/ ST	RR/ R	RR/ Q	RR (1)	(RR/ST) /Sum1	(RR/R) /Sum2	(RR/Q) /Sum3	RR1/Sum4	Sum_ RR	W4=Sum_RR/n
	Sum	Sum1	Sum2	Sum3	Sum 4						1

	Criteria	Original Matrix: HBP	Original Matrix: LBP	Normalised Matrix: HBP	Normalised Matrix: LBP	Aggregation	Global Weight
Each Evaluator	HBP	H(1)	H/L	H (1)/Sum1	(H / L) /Sum2	Sum_ H	W1=Sum_ H/n
	LBP	/H	L (1)	(L/H)/Sum1	L1/Sum2	Sum_ L	W2=Sum_ L/n
	Sum	Sum1	Sum2				1

	Criteria	Original matrix: chest pain	Original matrix: shortness of breath	Original matrix: patient in rest	Original matrix: patient in rest	Normalised matrix: chest pain	Normalised matrix: Shortness of breath	Normalised matrix: patient in rest	Normalised matrix: patient in rest	Aggregation	Global Weight
Each Evaluator	chest pain	C(1)	C/SB	C/P	C/PR	C (1) /Sum1	(C/SB) /Sum2	(C/P) /Sum3	(C/PR) /Sum4	Sum_ C	W1=Sum_ C /n
	shortness of breath	SB/ C	SB (1)	SB/P	SB/PR	(SB/C) /Sum1	SB1 /Sum2	(SB/P) /Sum3	(SB/PR) /Sum4	Sum_ SB	W2=Sum_ SB /n
	palpitation	P/C	P/SB	P (1)	P/PR	(P/C) /Sum1	(P/SB) /Sum2	P1/Sum3	(P/PR) /Sum4	Sum_ P	W3=Sum_ P /n
	patient in rest	PR/C	PR/SB	PR/P	PR (1)	(PR/C) /Sum1	(PR/SB) /Sum2	(PR/P) /Sum3	PR 1/Sum4	Sum_ PR	W4=Sum_ PR /n
	Sum	Sum1	Sum2	Sum3	Sum 4						1

Each local weight X main global Weight in order to compute the Global Weights for (ECG sub-criteria)

Each local weight X main global weight to compute the global weights for (Blood Pressure sub-criteria)

Multiply each local weight by main global **weight** to compute the global weights for (Text sub-criteria)

Fig. 5 MLAHP measurement steps

matrix R with its associated weight w_j. Moreover, the set of weights is equal to 1.

$$\sum_{j=1}^{m} w_j = 1 \tag{2}$$

This process will produce a new matrix V, such that

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}$$

- 3: Determining ideal and negative ideal solutions

In this process, two artificial patients, namely, A^* (Most critical case for each criterion) and A^- (Least critical case for each criterion), are defined as follows:

$$A^* = \left\{ \left(\left(\max_i \; v_{ij} | j \in J \right) | i = 1, 2, \dots, m \right) \right\} = \left\{ v_1^*, v_2^*, \dots, v_j^*, \cdots v_n^* \right\} \tag{3}$$

$$A^- = \left\{ \left(\left(\min_i \; v_{ij} | j \in J \right) | i = 1, 2, \dots, m \right) \right\} = \left\{ v_1^-, v_2^-, \dots, v_j^-, \cdots v_n^- \right\} \tag{4}$$

Table 4 Results of weight calculated for six evaluators

Main criteria	Sub-criteria	Doctors who specialise on chronic heart diseases					
		Doctor 1	Doctor 2	Doctor 3	Doctor 4	Doctor 5	Doctor 6
ECG	ST segment	0.296	0.065	0.345	0.274	0.275	0.142
	Rhythm	0.030	0.024	0.026	0.136	0.078	0.146
	QRS Width (s)	0.030	0.136	0.067	0.100	0.074	0.059
	P-to-P Distance	0.129	0.130	0.087	0.037	0.028	0.041
Text	Chest Pain	0.039	0.006	0.008	0.028	0.008	0.011
	Shortness of Breath	0.014	0.008	0.039	0.010	0.009	0.053
	Palpitation	0.028	0.016	0.012	0.020	0.023	0.017
	Patient at Rest	0.004	0.037	0.003	0.003	0.028	0.004
Blood Pressure	High Blood Pressure	0.048	0.078	0.151	0.214	0.166	0.082
	Low Blood Pressure	0.241	0.234	0.076	0.054	0.140	0.246
Spo_2	Peak Value	0.140	0.266	0.187	0.125	0.170	0.200

- 4: Calculation of separation measurement according to Euclidean distance

In this process, separation measurement is performed by calculating the distance between each patient in $V$and the ideal vector A^* through Euclidean distance, which is provided by the following:

$$S_{i^*} = \sqrt{\sum_{j=1}^{n}\left(v_{ij}-v_j^*\right)^2},\ \ i=(1,2,\cdots m) \tag{5}$$

Similarly, separation measurement for each patient in V from the negative ideal A^- is provided by the following:

$$S_{i^-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij}-v_j^-\right)^2},\ \ i=(1,2,\cdots m) \tag{6}$$

At the end of step 4, S_i^* and S_i^- for each patient are counted. These two values represent the distance between a patient and both the ideal and negative ideal.

- 5: Calculation of closeness to the ideal solution

In this step, the closeness of A_i to the ideal solution A^* is defined as

$$C_{i^*} = S_{i^-}/(S_{i^-}+S_{i^*}),\ \ 0 < C_{i^*} < 1,\ \ i=(1,2,\cdots m) \tag{7}$$

Evidently, $C_i^* = 1$, if and only if $A_i = A^*$. Similarly, $C_i^* = 0$, if and only if $A_i = A^-$

- 6: Ranking patients according to their closeness to the ideal solution

The set of patient A_i can now be ranked according to the descending order of C_i^*. High values indicate optimal performance. A patient who is near the high record and far from the worst record is an emergency case and must be given the highest priority level.

Decision-making contexts Two main decision-making contexts are emphasised: decision making based on a single individual DM and group decision making based on multiple DMs. Multi-criterion group decision-making (GDM) is a situation in which individuals collectively select from the alternatives before them. The decision is no longer attributable to any single individual who is a member of the group because all individuals contribute to the outcome. GDM techniques systematically collect and combine knowledge and judgment of experts from different fields. In a group context, each expert provides his/her judgment to the criteria that require subjective judgment. In addition, the weight of each criterion is also assigned by the same expert. TOPSIS can be extended to a group-decision environment through two methods, namely, internal and external aggregation [76]. Internal aggregations aim to apply the aggregation process at the separation stage. In this case, the separation is a group separation by aggregating different decision values of distances to positive and negative ideals and proceeding to the next process. The mathematical operator in this case is a geometric mean. In external aggregation, the same operators are used to aggregate the total score achieved from each evaluator.

Results and discussion

The proposed system was simulated in JAVA, which possess many desirable features, such as real-time implementation, parallel execution, portability, cross-platform usability and compatibility with different operating systems (e.g. Android, Windows, and Linux).

Figure 6 demonstrates that XAMMP can be used on the server side (Tier 3). XAMPP is a small and light Apache distribution tool that contains the most used web development technologies in a single package. XAMPP is an open-source software program. Each letter in XAMPP represents the following: (X) cross-platform for Web server, (A) HTTP Apache Server, (M) MySQL database, (P) PHP script writing language and (P) Perl programming language. Researchers prefer XAMPP when they develop and test applications because of its content, size and portability [77]. In the simulation, JAVA was used as the programming language.

The data sent from Tier 2 to Tier 3 include the vital signs of a user, and such data are used by doctors in Tier 3 to personalise the healthcare services for that user. The improvement in remote triage, prioritising and healthcare services using such data was previously demonstrated. However, the objective of this section is to demonstrate how adding this data affects the total message size and how these data are considered big data in the server (Tier 3). The size of the message sent by the user can satisfy the big data requirement through several stages (number of users, number of requests for a single user per day, telemedicine users and users from certain departments of hospitals, such as ED). Figure 8 shows that data size increased in the healthcare server (Tier 3) for many users per day when the size of the sending message reached 314.647460 KB; the data included three sensory signals, namely, ECG, SpO_2 and BP, for 1 min and the text features. When a user updated his or her profile in the hospital server every 5 min, the total size of data in the server for one day nearly reached 91 MB. In addition, nearly 1000 individuals used telemedicine, and 1000 users were physically present in the hospital. As a result, the total size of the data reached almost 2.2 TB for one day. Figure 7 demonstrates the increase in data size of telemedicine users inside and outside of the hospital during disasters and peak times.

Current technologies introduce new Internet and mobile cellular communication protocols that can easily and successfully accommodate the increase in message size between Tier 2 and Tier 3. However, computing the large scales of data in Tier 3 to extract knowledge on the emergency level of a user remains difficult.

The input dataset used to evaluate the proposed model varied in several aspects, such as gender, age, patient location and available medical history of the patient in the server of the hospital. For all datasets used, males and females constituted 60% and 40% of the dataset, respectively. Moreover, 50% of the patients aged between 40 and 65 years old, 40% were older than 65 years old and 10% were below 40 years old. Approximately 4.5% of the patients used telemedicine, and the remaining patients (95.5%) were distributed in different departments of the hospital. In addition, 50% of the patients had medical records.

In the evaluation, the values for the evaluation metric are presented as follows: ECG sensor, SpO_2 sensor, BP sensor, diastolic BP and non-sensory measurement (text frame). These values show the data in three aspects, namely, normal, abnormal and at risk, which are presented according to the data on the abovementioned alignment. An experiment based on the evaluation metric was performed by integrating MLAHP to calculate the weight; TOPSIS was also used to score the patients with chronic heart diseases with respect to urgency. The dataset presented different symptoms defined by doctors. These symptoms were related to chronic heart diseases. The standard ECG, SpO_2 and BP datasets from different data packages were used to validate the reliability of the standard dataset [77]. Each package includes the symptoms of chronic heart disease of each user.

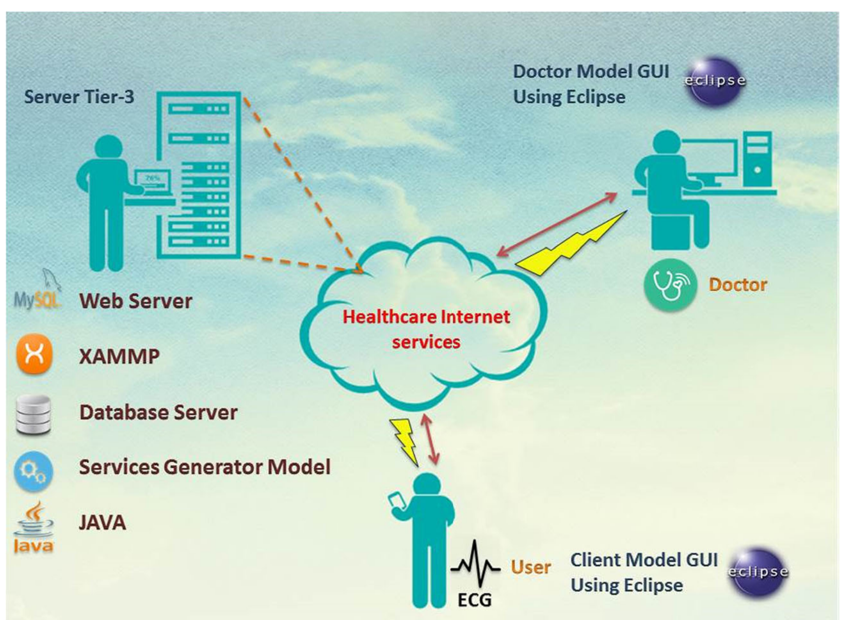

Fig. 6 Block diagram scheme of the simulation architecture of the proposed system

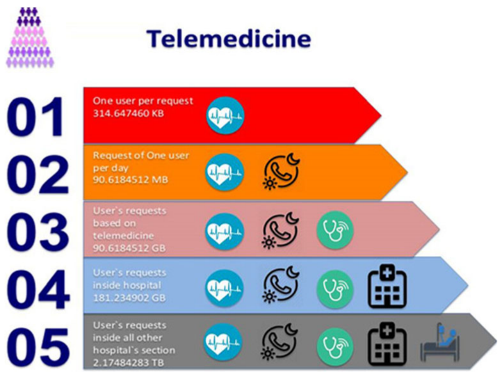

Fig. 7 Calculation of data size during disasters and peak times

Results of TOPSIS decision-making contexts

Two main decision-making contexts are stressed, namely, individual and group decision-making contexts. In this section, the results of the individual and group TOPSIS decision-making contexts are presented in the following subsections.

TOPSIS results of individual context for different weights of experts

Available alternative scores are ranked in descending order based on TOPSIS. TOPSIS allocates the scores to each alternative (per patient) based on its geometric distance from the positive and negative ideal solutions. The patients were ranked based on emergency cases (from the highest to the lowest). According to this technique, the patient with the highest emergency case will exhibit the shortest geometric distance to the positive ideal solution and the longest geometric distance to the negative ideal solution.

According to Table 4, the preference weights revealed the features of scoring the patients from the perspective of experts. Table 4 shows the results of six experts, who stated the importance of the evaluation criteria from the viewpoint of each expert. TOPSIS was used to prioritise 500 patients based on the urgency of their cases through the perspectives of six experts. TOPSIS identify the highest and lowest emergency cases of patients and compare each patient with the positive ideal (highest emergency case) and negative ideal (lowest emergency case). S− and S* represents the closeness of a patient to the lowest and highest emergency cases, respectively.

The weights of the main sources provided by the six experts according to the MLAHP results are shown below:

- First expert: 48.5% for ECG, 28.9% for BP, 14% for SpO2 and 8.6% for text. The values of the four sub-features of ECG, namely, ST, Rhy, QRS and P to P are 29.6%, 3%, 3% and 12.9%, respectively. Finally, the values for text, which represents the four sub features chest pain, shortness of breath, palpitation and patient at rest, are 3.9%, 1.4%, 2.8% and 0.4%, respectively. Each patient was evaluated according to these weights. Accordingly, TOPSIS ranking results provided by the first expert attained an average of 0.4932 ± 0.1868. The highest and lowest rank values are 0.8230 and 0.0078, respectively.
- According to the AHP results, the weights of the main sources generated by the second expert were 35.5% for ECG, 31.2% for BP, 26.6% for SpO_2 and 6.7% for text. ST, Rhy, QRS and P to P are 6.5%, 2.4%, 13.6% and 13%, respectively. Finally, the values for chest pain, shortness of breath, palpitation and patient at rest are 0.6%, 0.8%, 1.6% and 3.7%, respectively. Each patient was evaluated according to these weights. Accordingly, TOPSIS ranking results provided by the first expert attained an average of 0.4912 ± 0.1517. The highest and lowest rank values are 0.7698 and 0.0117, respectively.
- According to the AHP results, the weights of the main sources generated by the third expert are 52.4% for ECG, 22.7% for BP, 18.7% for SpO_2 and 6.2% for text. The values of ST, Rhy, QRS and P to P are 34.5%, 2.6%, 7.7% and 8.7%, respectively. Finally, the values for chest pain, shortness of breath, palpitation and patient at rest are 0.8%, 3.9%, 1.2% and 0.3%, respectively. Each patient was evaluated according to these weights. Accordingly, TOPSIS ranking results provided by the first expert attained an average of 0.4748 ± 0.2069. The highest and lowest rank values are 0.8402and 0.0057, respectively.
- According to the AHP results, the weights of the main sources generated by the fourth expert are 54.6% for ECG, 26.8% for BP, 12.5% for SpO_2 and 6.1% for text. The values for ST, Rhy, QRS and P to P are 27.4%, 13.6%, 10% and 3.7%, respectively. Finally, the values for chest pain, shortness of breath, palpitation and patient at rest are 2.8%, 1%, 2% and 0.3%, respectively. Each patient was evaluated according to these weights. Accordingly, TOPSIS ranking results provided by the first expert attained an average of 0.4691 ± 0.2239. The highest and lowest rank values are 0.9219 and 0.0056, respectively.
- According to the AHP results, the weights of the main sources generated by the fifth expert are 45.5% for ECG, 30.6% for BP, 17% for SpO_2 and 6.8% for text. The values of ST, Rhy, QRS and P to P are 27.5%, 7.8%, 7.4% and 2.8%, respectively. Finally, the values for chest pain, shortness of breath, palpitation and patient at rest are 0.8%, 0.9%, 2.3% and 2.8%, respectively. Each patient was evaluated according to these weights. Accordingly, TOPSIS ranking results provided by the first expert attained an average of 0.4920 ± 0.2079. The highest and lowest rank values are 0.9416 and 0.0169, respectively.
- According to the AHP results, the weights of the main sources generated by the sixth expert are 38.8% for ECG, 32.8% for BP, 20% for SpO_2 and 8.4% for text. The values of ST, Rhy, QRS and P to P are 14.2%, 14.6%, 5.9% and 4.1%, respectively. Finally, the values

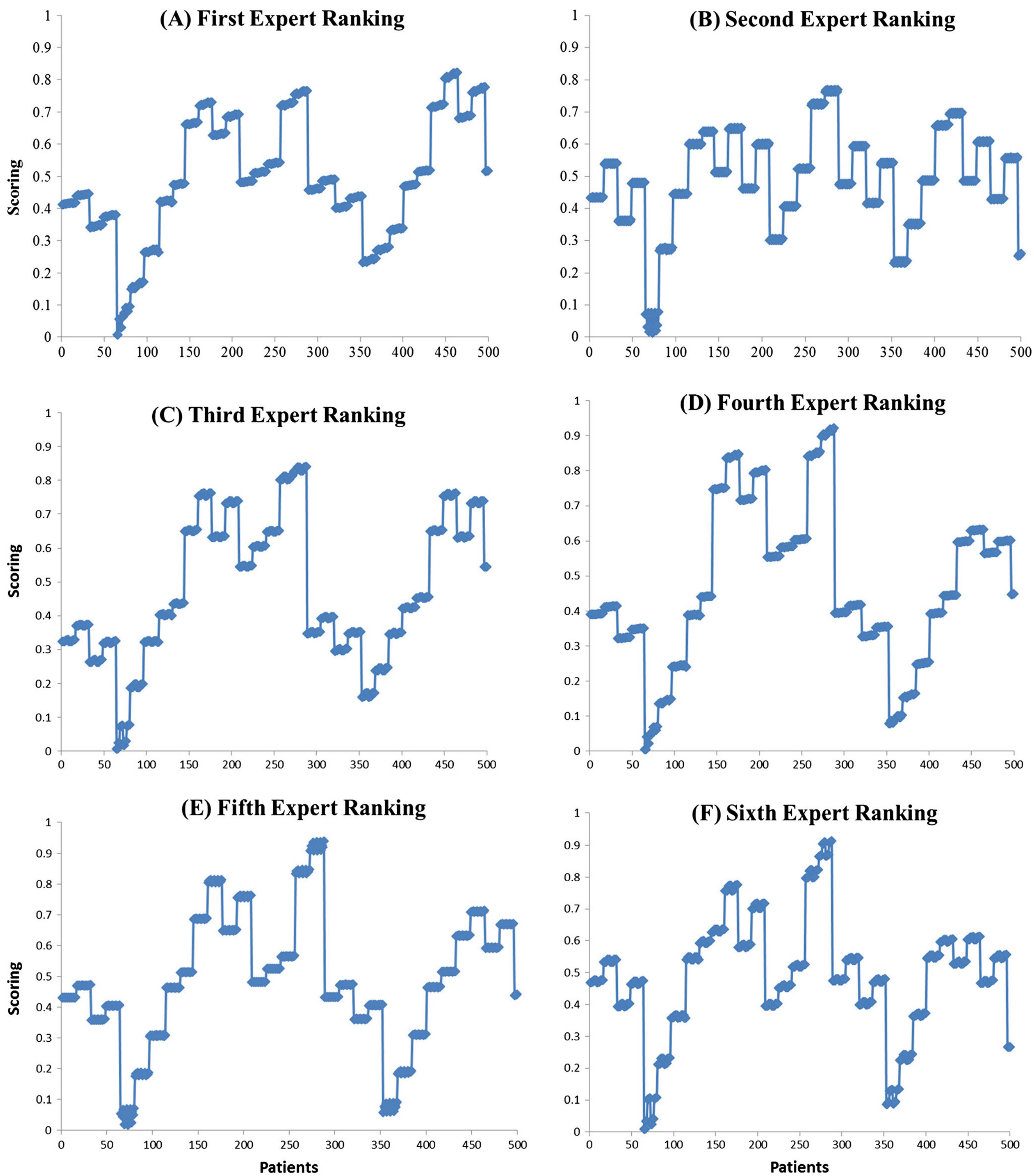

Fig. 8 Overall TOPSIS final ranking for six experts: (**a**) first group ranking, (**b**) second group ranking, (**c**) third group ranking, (**d**) fourth group ranking, (**e**) fifth group ranking, and (**f**) sixth group ranking

for chest pain, shortness of breath, palpitation and patient at rest are 1.1%, 5.3%, 1.7% and 0.4%, respectively. Each patient was evaluated according to these weights. Accordingly, TOPSIS ranking results provided by the first expert attained an average of 0.4929 ± 0.1795. The highest and lowest rank values are 0.9135 and 0.0082, respectively.

TOPSIS sample results of the first and last forty patients after applying the weights provided by the six experts are shown in Tables 11, 12, 13, 14, 15 and 16 in Appendix. After presenting the results of the TOPSIS ranking as an individual context for each expert, describing and discussing the ranking results generated by the six experts and recognising the closeness and variance among them are necessary. The TOPSIS final ranking results of the six experts are presented in Fig. 8.

As illustrated in Fig. 8 and Tables 11, 12, 13, 14, 15 and 16 in Appendix, the ranking results of the TOPSIS individual context from the six experts are presented. Discussion of the ranking results in the individual contexts is needed to illustrate differences in patient ranking among the six experts. The first five patients with the most emergency cases and the last five patients with the least emergency cases were chosen from the ranking results of each expert for comparison. In other words, the five patients with the most emergency cases of each expert were compared to demonstrate the matches and variances among the ranking provided by the experts. The five patients with the least emergency cases of each expert were compared to show the matches and variances among the ranking made by the experts. Regarding the five patients with the most emergency cases, the ranking results from five of the experts show that patient number 288 as the first patient with the most emergency case. However, the ranking from the other expert allocate patient number 464 as the first patient. The second patient position corresponds to patient numbers 287, 280 and 463, as recommended by three, two and one experts, respectively. The third patient position is allotted to patient numbers 284, 280 and 460, as recommended by three, two and one experts, respectively. The fourth patient position is given to patient numbers 297, 283 and 459, as recommended by two, one and one experts, respectively. The fifth patient position matches patient numbers 286 and 462, as recommended by five and one experts, respectively. Regarding the five patients with the less emergency cases, the first patient position is allocated to patient numbers 66 and 75, as recommended by four and two experts, respectively. The second patient position corresponds to patient numbers 65 and 69, according to four and two experts, respectively. The third patient position is determined for patient numbers 69, 77 and 73, as recommended by two experts for each patient. The fourth patient position matches patient numbers 70 and 74, according to two and two experts as a fourth patient. The fifth patient position is assigned to patient numbers 67 and 75 according to four and two experts, respectively. In summary, the ranking results of TOPSIS in the individual context for six experts are presented, and the first and last five patients with most and least emergency cases are described and discussed. Clearly, the results of the individual context show variances among the ranking from six experts'. Thus, applying a group TOPSIS decision-making context is required to provide patient ranking considering the overall DMs. The following section presents the results of the group TOPSIS decision-making context.

Group TOPSIS with internal and external aggregation

TOPSIS was extended to a group-decision environment through two strategies, namely, internal and external aggregation. Internal aggregations aim to apply aggregation process at the separation stage. For this case, the separation involves group separation by aggregating different decision values for distance positive and negative ideals, and the next process was then performed. Internal aggregation is calculated by the summation values of the negative separation divided by the negative separation values plus the positive separation values for each evaluator, whereas the external aggregation is computed by finding the average summation of the ranking values for each expert, as mentioned in "Ranking patients using TOPSIS" section. The results of the first and last forty patients of group TOPSIS with internal and external aggregation are presented in Table 5 below.

Furthermore, the external and internal aggregation results are illustrated in Figs. 9 and 10.

In external aggregation, the result of patient ranking attained a mean ± SD average of 0.4855 ± 0.1824, and the internal aggregation of patient ranking achieved a mean of 0.4851 ± 0.1810. The results of mean ± SD for the internal and external aggregation ranking demonstrated the similarity in the ranks estimated by the mentioned methods. For this reason, the external aggregation method will then be considered for validation and evaluation in the next section.

Validation and evaluation

This section describes in detail the validation and evaluation of the proposed work. The validation process is presented in Section "Validation process", the ranking results are validated objectively and subjectively based on different characteristics in this section. Section "Evaluation process" demonstrates the evaluation process by providing scenarios and checklist benchmarking.

Validation process

Validation is an important measure for many empirical studies to prove the validity and accuracy of results. Two validation processes, namely, objective and subjective validation, were used in this research, as presented in Figure 11, and explained in the following subsections.

Objective validation

At this stage, the final ranking results of the prioritised patients are divided into four equal groups, as in Qader et al. [78]. Each group comprised 125 patients. Mean ± SD is calculated for each group to ensure that the prioritised patients undergo systematic ranking. The results of the first and second groups are

Table 5 Group decision making of TOPSIS with internal and external aggregation (for the first and last 40 patients)

S-	S+	Internal agg.	External agg.
First forty patients			
0.104659	0.150731	0.409800	0.409637
0.104893	0.150553	0.410627	0.410443
0.104933	0.150537	0.410744	0.410585
0.105166	0.150358	0.411570	0.411390
0.105219	0.150331	0.411737	0.411615
0.105453	0.150152	0.412562	0.412421
0.105492	0.150136	0.412678	0.412561
0.105726	0.149958	0.413502	0.413365
0.104964	0.150521	0.410842	0.410691
0.105198	0.150343	0.411668	0.411496
0.105236	0.150326	0.411783	0.411636
0.105470	0.150148	0.412608	0.412440
0.105524	0.150120	0.412776	0.412668
0.105758	0.149942	0.413601	0.413473
0.105795	0.149925	0.413714	0.413610
0.106029	0.149747	0.414538	0.414414
0.112274	0.132363	0.458941	0.460047
0.112488	0.132138	0.459837	0.460962
0.112533	0.132145	0.459923	0.461033
0.112746	0.131918	0.460819	0.461949
0.112792	0.131894	0.460966	0.462138
0.113005	0.131668	0.461862	0.463054
0.113050	0.131675	0.461947	0.463124
0.113263	0.131448	0.462843	0.464040
0.112566	0.132137	0.460011	0.461115
0.112780	0.131911	0.460907	0.462031
0.112823	0.131918	0.460991	0.462099
0.113037	0.131691	0.461886	0.463015
0.113083	0.131667	0.462035	0.463206
0.113297	0.131441	0.462931	0.464121
0.113340	0.131447	0.463014	0.464189
0.113553	0.131221	0.463910	0.465105
0.078494	0.153058	0.338991	0.339242
0.078806	0.152883	0.340136	0.340357
0.078859	0.152867	0.340310	0.340566
0.079169	0.152692	0.341450	0.341677
0.079238	0.152665	0.341684	0.341975
0.079549	0.152490	0.342825	0.343089
0.079600	0.152474	0.342994	0.343290
0.079910	0.152299	0.344130	0.344400
Last forty patients			
0.157627	0.071860	0.686868	0.689390
0.157804	0.071528	0.688102	0.690603
0.157808	0.071356	0.688624	0.691325
0.157985	0.071023	0.689866	0.692545
0.133676	0.104914	0.560275	0.560519
0.133904	0.104693	0.561214	0.561474
0.133889	0.104602	0.561401	0.561713
0.134116	0.104380	0.562341	0.562669
0.134145	0.104372	0.562413	0.562713
0.134372	0.104150	0.563352	0.563668
0.134357	0.104059	0.563541	0.563909
0.134584	0.103837	0.564482	0.564865
0.133893	0.104535	0.561567	0.561929
0.134121	0.104313	0.562507	0.562885
0.134106	0.104220	0.562701	0.563135
0.134333	0.103998	0.563642	0.564092
0.134362	0.103991	0.563709	0.564126
0.134589	0.103770	0.564649	0.565082
0.134574	0.103675	0.564846	0.565335
0.134801	0.103453	0.565787	0.566291
0.140254	0.078084	0.642371	0.642834
0.140459	0.077774	0.643621	0.644091
0.140457	0.077653	0.643973	0.644546
0.140663	0.077342	0.645229	0.645808
0.140695	0.077330	0.645315	0.645862
0.140900	0.077019	0.646570	0.647120
0.140898	0.076896	0.646931	0.647588
0.141103	0.076584	0.648191	0.648851
0.140466	0.077556	0.644273	0.644941
0.140671	0.077246	0.645527	0.646200
0.140669	0.077115	0.645909	0.646705
0.140874	0.076803	0.647169	0.647969
0.140907	0.076799	0.647234	0.647985
0.141112	0.076488	0.648493	0.649245
0.141109	0.076355	0.648885	0.649763
0.141314	0.076042	0.650149	0.651028
0.104723	0.146465	0.416910	0.411087
0.105081	0.146303	0.418009	0.412342
0.105009	0.146259	0.417917	0.412145
0.105366	0.146097	0.419011	0.413394

presented in Table 6, and the results of the third and fourth are presented in Table 7. The numbers in the tables represent the scores generated by the TOPSIS process, and scores of 25 patients are shown in a single column.

The data on prioritised patients presented in Tables 6 and 7 above are visualised in graphical formats to further discuss their comparisons. In Fig. 12, Figures A, B, C and D illustrate patient groups 1, 2, 3 and 4, respectively. The ranking results of the four patient groups are combined in Figure E. Initial observation of the ranking results of the four patient groups show that the patient groups are systematically distributed as the ranking results of the second group start from the end of the ranking results of the first group. Furthermore, the ranking

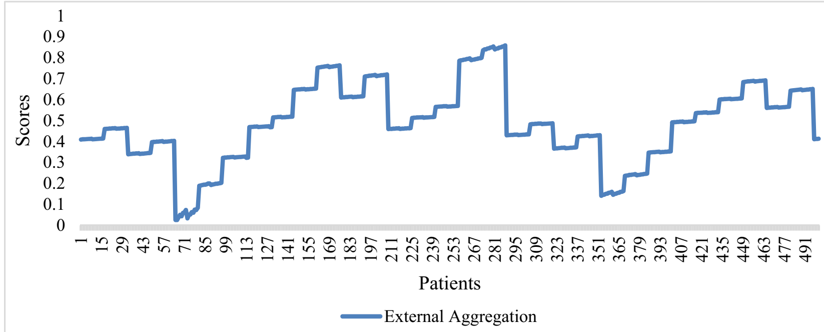

Fig. 9 Results of external aggregation

results of the third and fourth groups start from the end of the ranking results of second and third groups, respectively.

Statistical analysis was performed among the groups after dividing the prioritised patients into four groups. The results are presented in Table 8 and Fig. 13.

The results of statistical analysis for the four groups are presented in Table 8. In the first group, the value is M = 0.716 ± 0.075 with a minimum value of 0.612 and a maximum value of 0.859. The first group was the highest scoring among the four groups because the mean and SD exhibited the highest values. The second group obtained a value of M = 0.539 ± 0.039 with minimum and maximum values of 0.484 and 0.611, respectively. The second group obtained lower scores than the first group but higher scores than the third and fourth groups. The third and fourth groups showed a value of M = 0.436 ± 0.029 and M = 0.250 ± 0.105 with a minimum value of 0.370 and 0.025 and a maximum value of 0.483 and 0.370, respectively. The fourth group demonstrated the lowest scores among the four groups. For each group, the patient with the highest ranking result (with maximum value) acquired a lower value than the patient with the lowest ranking result (with minimum value) in the next patient group. To ensure that significant differences are present amongst the four groups of the prioritised patients, *p* value is calculated, as shown in Table 9.

As shown in Table 9, the *P* value results showed significant differences among the four groups with a $P < 0.05$. The first group was significantly different from the second, third and fourth groups by 1.99E-12, 6.85E-23 and 1.77E-04, respectively. The second group was significantly different from the third and fourth groups by 1.33E-03 and 6.52E-25, respectively. Finally, the third group was significantly different from the fourth group by 1.33E-03. These results indicated that all the groups are statistically different among one another with a $P < 0.05$. Thus, the statistical results indicate that the ranking results underwent systematic ranking.

Subjective validation

At this stage, the patient prioritisation results have been validated by a medical committee. To prove the effectiveness of prioritising the patients, we decided to validate the patient ranking through evaluation of vital signs of patients by the medical committee. Asking the expert to intervene with the ranking of 500 patients was difficult in this case. Thus, after discussing with the experts, the medical committee was presented with the first and last five patients from the patient prioritisation list. In other words, rather than judging all patients, the medical committee only evaluate the first five patients with the most emergency cases who require fast response and the last five patients with the less emergency cases who can wait. The experts used their clinical experience and their knowledge to confirm patient ranking and to ensure whether the first five patients on the list are the most emergency cases and medically deserving to be in the highest priority level upon evaluating their clinical symptoms. This method ensures that the last five patients are given the lowest priority level as they demonstrate the less emergency cases. Furthermore, this strategy allows determining if a patient needs to be moved up in the queue when one or more of the vital signs approach critical values. The scenario process that is followed by the three experts to check the patient position within the ranking based on the group decision-making method is as follows.

The first five patients are considered as the patients with the highest priority level, so they require rapid response from the

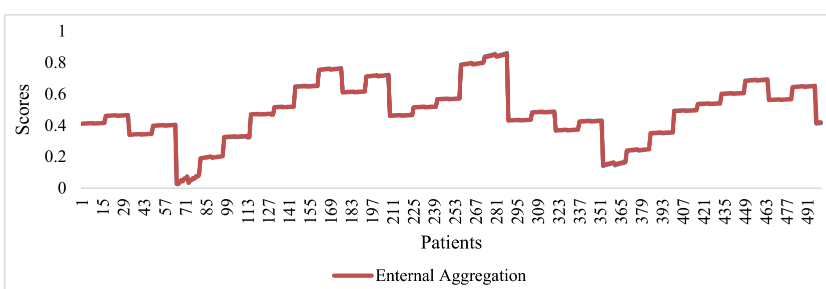

Fig. 10 Results of internal aggregation

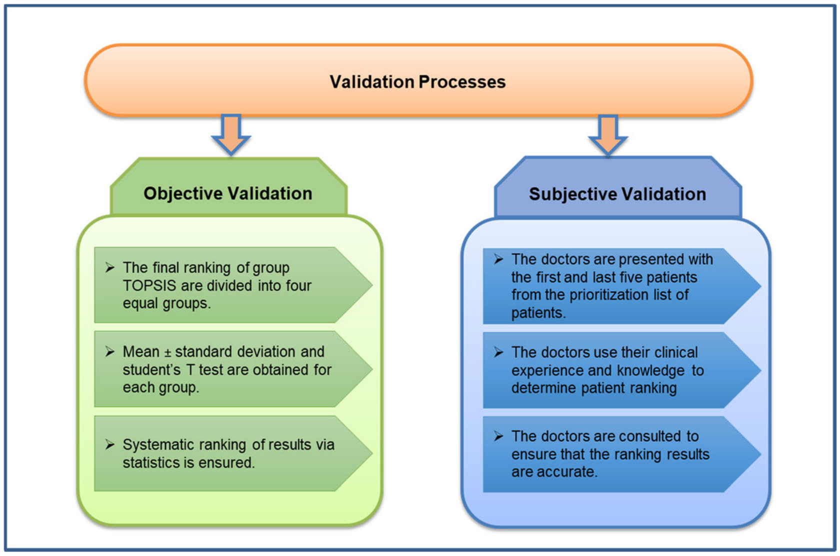

Fig. 11 Structure of validation processes

server to receive healthcare services. According to the evaluation of the expert for the overall 10 features used in the proposed method, the first five patients exhibited six common abnormal features (Spo2, BP, shortness of breath, Rhythm, QRS width and ECG ST Elevation) and one common normal feature (peak-to-peak interval). However, the other three features (chest pain, palpitation and patient at rest) demonstrated different medical classifications. Patient 1 showed three abnormal features (chest pain, palpitation and patient at rest), so this patient is ranked first and triaged to the most emergent case.

Table 6 Results of the first and second groups (TOPSIS scores)

1st group					2nd group				
0.858996	0.791322	0.718426	0.687003	0.647783	0.611437	0.568227	0.560519	0.517122	0.495637
0.854488	0.790780	0.718245	0.686394	0.647588	0.611167	0.568213	0.540492	0.516755	0.494674
0.854263	0.790769	0.716813	0.685859	0.647120	0.610171	0.567446	0.539558	0.516744	0.494641
0.853351	0.788477	0.716618	0.685242	0.646870	0.605991	0.567432	0.539518	0.516680	0.494577
0.849864	0.788412	0.716461	0.684033	0.646705	0.605156	0.567315	0.539458	0.516249	0.494561
0.849441	0.787943	0.716185	0.652764	0.646200	0.604823	0.567221	0.538593	0.516238	0.493616
0.849020	0.785649	0.714835	0.651847	0.645862	0.604565	0.566534	0.538584	0.516217	0.493598
0.848873	0.763856	0.714575	0.651491	0.645808	0.604009	0.566439	0.538527	0.516150	0.493537
0.845178	0.762089	0.714392	0.651261	0.644941	0.603991	0.566310	0.538485	0.515776	0.493503
0.844520	0.761455	0.714202	0.651028	0.644546	0.603731	0.566291	0.537661	0.515713	0.492542
0.844424	0.761246	0.712783	0.650576	0.644091	0.603415	0.565529	0.537620	0.515703	0.492477
0.843743	0.759719	0.712579	0.650534	0.642834	0.603175	0.565335	0.537560	0.515667	0.492461
0.840169	0.759486	0.712171	0.650344	0.616232	0.602846	0.565082	0.537554	0.515334	0.491403
0.839934	0.759386	0.710565	0.650002	0.615233	0.602589	0.564865	0.536688	0.515266	0.487320
0.839647	0.758911	0.692545	0.649763	0.614948	0.602582	0.564126	0.536631	0.514735	0.486351
0.835899	0.757628	0.691325	0.649617	0.614745	0.602013	0.564092	0.536588	0.514700	0.486342
0.799933	0.757179	0.690603	0.649266	0.613951	0.601755	0.563909	0.535659	0.514689	0.486279
0.797548	0.757032	0.690068	0.649245	0.613917	0.601442	0.563668	0.519013	0.514626	0.485374
0.796951	0.756810	0.689525	0.649088	0.613746	0.600610	0.563135	0.518128	0.513721	0.485311
0.796922	0.755303	0.689390	0.649036	0.613472	0.570133	0.562885	0.518106	0.513658	0.485300
0.794603	0.755057	0.688849	0.648851	0.612919	0.569351	0.562713	0.518040	0.513649	0.485265
0.794577	0.754518	0.688306	0.648353	0.612638	0.569219	0.562669	0.517722	0.512680	0.484333
0.794026	0.752794	0.688214	0.648120	0.612476	0.569125	0.561929	0.517223	0.496774	0.484297
0.793689	0.720525	0.687605	0.647985	0.612435	0.568437	0.561713	0.517155	0.495716	0.484287
0.791717	0.718894	0.687076	0.647969	0.611642	0.568343	0.561474	0.517133	0.495698	0.484224

Table 7 Results of the third and fourth groups (TOPSIS scores)

3rd group					4th group				
0.483320	0.463412	0.460047	0.427797	0.410691	0.370021	0.348153	0.325429	0.237911	0.154822
0.483256	0.463369	0.459508	0.426668	0.410585	0.369835	0.347236	0.325370	0.236144	0.151127
0.483245	0.463312	0.434471	0.426668	0.410443	0.369824	0.345857	0.324883	0.203270	0.150980
0.482278	0.463206	0.433690	0.426589	0.409637	0.368819	0.344748	0.324516	0.201184	0.150559
0.473247	0.463124	0.433561	0.426497	0.403405	0.368810	0.344557	0.324487	0.200189	0.150136
0.472288	0.463054	0.433466	0.425459	0.402284	0.368626	0.344400	0.323941	0.199382	0.146649
0.472186	0.463015	0.432779	0.425367	0.402138	0.368513	0.343444	0.323577	0.199382	0.145737
0.472067	0.462446	0.432685	0.425284	0.401999	0.367609	0.343290	0.323065	0.198064	0.145512
0.471228	0.462440	0.432568	0.424154	0.401015	0.367499	0.343140	0.323065	0.198003	0.141004
0.471129	0.462380	0.432554	0.414414	0.400877	0.367308	0.343089	0.322122	0.196095	0.083840
0.471109	0.462339	0.431787	0.413610	0.400786	0.366291	0.342029	0.322122	0.195907	0.075011
0.471003	0.462138	0.431773	0.413473	0.400724	0.353130	0.341975	0.247206	0.194846	0.073256
0.470171	0.462099	0.431657	0.413394	0.399664	0.352217	0.341831	0.245482	0.194042	0.073137
0.470069	0.462031	0.431563	0.413365	0.399600	0.351880	0.341677	0.244943	0.193962	0.063015
0.470045	0.461949	0.430875	0.412668	0.399515	0.351647	0.340717	0.244697	0.192712	0.062176
0.469949	0.461515	0.430781	0.412561	0.399376	0.350964	0.340566	0.243190	0.191937	0.060423
0.469111	0.461473	0.430649	0.412440	0.398391	0.350912	0.340357	0.242968	0.190671	0.059413
0.468991	0.461416	0.430306	0.412421	0.398254	0.350734	0.339242	0.242821	0.188527	0.051610
0.468885	0.461407	0.429867	0.412342	0.398097	0.350383	0.328654	0.242372	0.164101	0.050254
0.467927	0.461115	0.429177	0.412145	0.396972	0.349998	0.327717	0.241089	0.160353	0.050247
0.465105	0.461033	0.429101	0.411636	0.372341	0.349656	0.327237	0.240614	0.160066	0.043486
0.464341	0.460962	0.429008	0.411615	0.371328	0.349466	0.326872	0.240514	0.159831	0.038353
0.464189	0.460542	0.427971	0.411496	0.371149	0.349424	0.326308	0.240281	0.156257	0.033271
0.464121	0.460482	0.427879	0.411390	0.371034	0.348739	0.326296	0.238754	0.155576	0.025325
0.464040	0.460442	0.427798	0.411087	0.370133	0.348509	0.325933	0.238545	0.155480	0.025325

Patient 2 presented with one normal feature (patient at rest) and two abnormal features (chest pain and palpitation). Patient 3 also displayed one normal feature (chest pain) and two abnormal features. Patient 4 also exhibited one normal feature (palpitation). Although patients 2, 3 and 4 demonstrated the same number of abnormal features, they differed in the type of features and obtained different medical assessment and weight for each feature. In other words, patient 2 ranked higher than patient 3 because the weight of the chest pain feature is higher than that of being at rest, and patient 3 was ranked higher than patient 4 because the weight of the palpitation is higher than the weight of chest pain. Finally, two features were abnormal for patient 5 (chest pain and patient at rest). Thus, patient 5 was ranked fifth. The last five patients exhibited six common normal features (SpO2 level, blood pressure, ECG rhythm, QRS width, peak-to-peak interval and ST elevation). However, the other four features (chest pain, shortness of breath, palpitation and patient in rest) demonstrated different medical classifications. Patients 499, 498, 497 and 496 showed only one abnormal feature, which are patient at rest, chest pain, palpitation and shortness of breath, respectively. Although the four patients presented with the same number of abnormal features, patient 498 ranked before patient 499 because the patient at rest feature is of lower importance in terms of medical assessment than the chest pain feature. Patient 497 ranked before 498 because the chest pain feature is lower in importance in terms of medical assessment than palpitation feature. Furthermore, patient 496 ranked before patient 497 because palpitation feature is of lower importance in terms of medical assessment than shortness-of-breath feature.

In summary, based on the actions of experts, the proposed method has suggested and confirmed that the first five patients deserve to be in the high priority levels with the most emergency case. On the other hand, the last five patients deserve to be in the lowest priority levels because they exhibit less emergency cases. Thus, we subjectively indicate that the ranking results are systematically accurate.

Evaluation process

In this section, a number of scenarios are presented to demonstrate situations and cases requiring patient prioritisation methods.

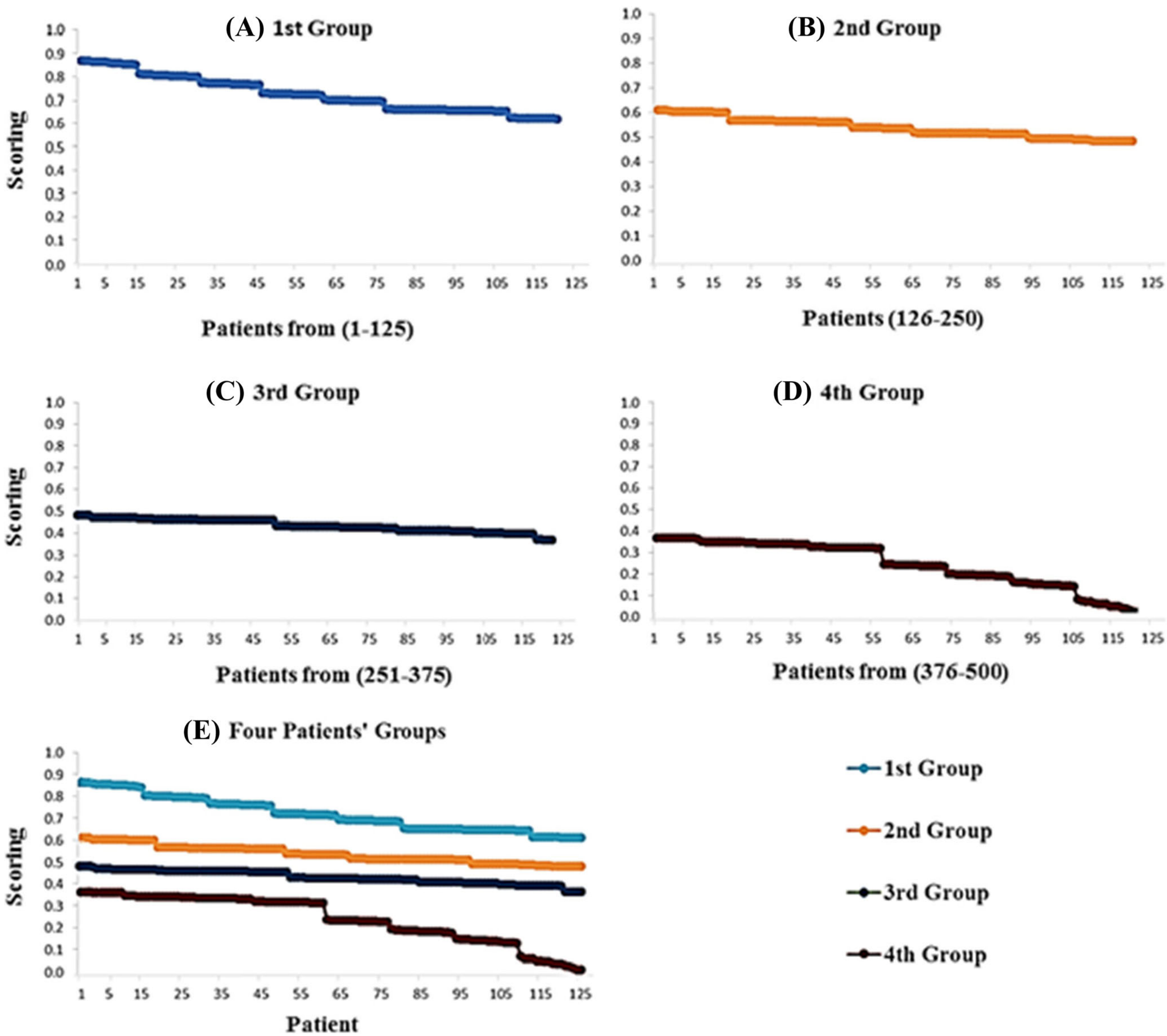

Fig. 12 Results of four groups of patients. **a** 1st group. **b** 2nd group. **c** 3rd group. **d** 4th group. **e** Four patient groups

Scenario 1 considers a large scale of patients expected to occur in several aspects, such as population aging, disasters and MCIs reported in a specific area. From one perspective, this area exhibits a large population of elderly patients remotely monitored by their providers. From another perspective, remote patients are critically affected by MCIs and disasters [79]. The server of a hospital or healthcare agency monitoring these patients must assess the situations of patients and prioritise their services and treatments with regard to the urgency of their medical condition. However, for remotely monitored patients, the overwhelming heterogeneous data can cause difficulty in deciding among numerous patients to whom the care must first be given and who follows [80]. Therefore, the prioritisation method must support a multi-criteria ranking that considers the scalability issue and can handle large data. Furthermore, identifying the targeted tier and the environment where the prioritisation process is executed is necessary to provide services and treatments for each prioritised patients, from the most to the least emergency ones.

Scenario 2 demonstrates two or more home patients with a slight difference in their healthcare emergency conditions and who must be prioritised. In this case, the healthcare providers

Table 8 Results of patients according to groups

	1st group	2nd group	3rd group	4th group
Mean	0.716	0.539	0.436	0.250
Std	0.075	0.039	0.029	0.105
Min	0.612	0.484	0.370	0.025
Max	0.859	0.611	0.483	0.370
Count	125	125	125	125

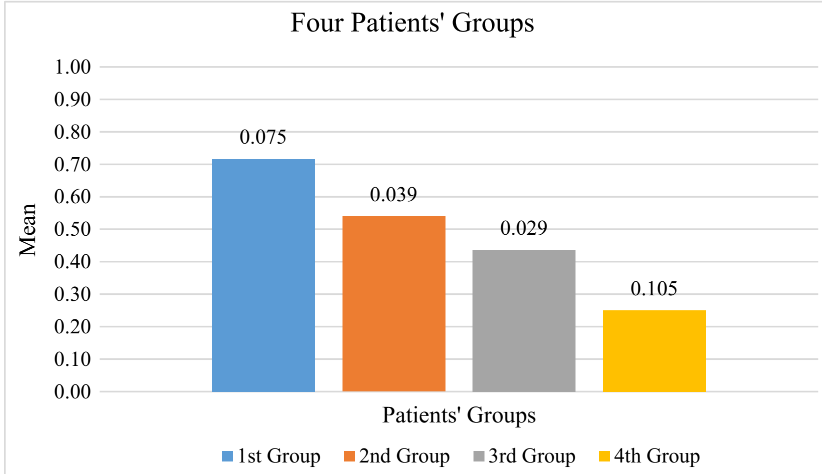

Fig. 13 Bar chart for mean and standard deviation results of the four groups

encounter a problem in recognising slight differences from the many vital signs of patients regardless of the time needed for the process to prioritise them at the end. Meanwhile, traditional triage and prioritisation methods allocate patients in a similar scale or category [38]. Therefore, the prioritisation method must consider the smallest difference between two patient records and improve patient prioritisation accuracy. Providing patient order through supporting feature weighing method and multi-criteria ranking is therefore necessary.

Scenario 3 presents two patients with different emergency conditions and who sent requests to the server but at different times. However, the patient who first sends the request suffers from a less urgent situation. In this case, the most urgent case must be prioritised before the previous one, as they deserve to be serviced and treated. Thus, applying FCFS in these cases may jeopardise the life of patients, and the FCFS cannot be used in reality [37, 81]. Therefore, the prioritisation methods must consider the medical condition of patients and support feature weighting method. In summary, three main scenarios showing situations and cases covering patient prioritisation are identified and explained. After describing the scenarios, some issues were recognised and highlighted for each scenario and further required consideration in the patient prioritisation method. These issues are extracted, and the connections between each scenario and the related points are described in Fig. 14.

Table 9 *P* Value of four groups

Groups	*P* value	Difference
1st and 2nd	1.99E-12	Significant
1st and 3rd	6.85E-23	Significant
1st and 4th	1.77E-04	Significant
2nd and 3rd	1.33E-03	Significant
2nd and 4th	6.52E-25	Significant
3rd and 4th	1.33E-03	Significant

$p < 0.05$.

After describing the scenarios and their related issues, these issues are defined to consider as comparison points in the checklist benchmarking. Three general points must be considered in patient prioritisation methods, namely, targeted disease, whether to support vital signs and chief complaints. Each method must be validated and evaluated. The descriptions of terms on the checklist comparison points are presented as follows:

- **Targeted disease:** The disease is adopted as the case study for applying and testing the prioritisation process. Targeting a specific disease helps to directly and accurately identify vital signs and complaints indicating disease severity [23], in contrast with setting the prioritisation process for general illness and diseases.
- **Support vital signs:** This point indicates that the vital signs were considered and used in the prioritisation process, considering that vital signs are important in evaluating patient condition [23, 29].
- **Support chief complaints:** This point indicates that the chief complaints were taken into consideration and used in the patient prioritisation process because non-sensory data are necessary in remote healthcare monitoring [23].
- **Targeted tier:** Identifying the tier involved in the prioritisation process is important because the remote healthcare monitoring and telemedicine architecture embodies three tiers, namely Tiers 1, 2 and 3, which represent sensors, base station and remote server [23, 82].
- **Support scalability:** This point shows whether scalability was accommodated and handled. In this study, scalability is defined as the increase in the number of patients. It a challenge in both remote healthcare monitoring and the prioritisation process [23].
- **Remote environment:** This point shows whether the patient prioritisation process was executed in the remote environment. The prioritisation process is important to support continuous care of remote patients in a pervasive environment [80]. In a remote environment, the

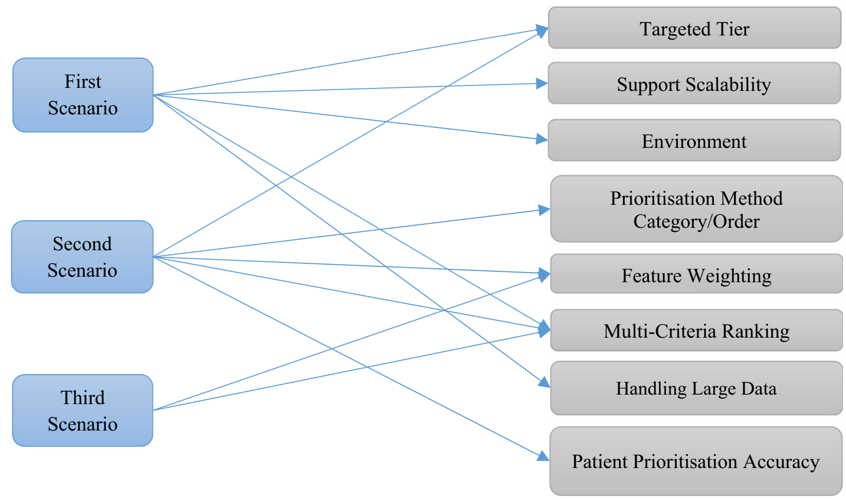

Fig. 14 Relations between comparison issues and scenarios

overwhelming heterogeneous data from patients hinder the prioritisation process.

- **Prioritisation method category/order:** This shows whether the prioritisation process supports categories or order methods. Categorisation method classifies patients and prioritises them according to prioritisation levels, whereas order method provides a rank for patients according to their emergency situations. Although most triage systems categorise patients into a priority group, the patient order is typically determined using an FCFS principle [38].
- **Feature weighting:** This point shows the technique used for feature weighting. A server aiming to provide a score for a patient may assign more weight to the vital features rather than to other features that gain less interest than these attributes. Additionally, the judgments and preferences of experts are important in extracting the weights of the vital signs [33, 37, 83, 84].
- **Multi-criteria ranking:** This point indicates whether the study addresses the multi-criteria in the prioritisation process. Patient prioritisation is a complex decision-making problem [26, 37, 41, 42], and the decision is made based on a set of attributes [43].
- **Handling large data:** This point concerns the handling of overwhelming data from multiple sources for a large number of patients. Supporting large data is important because overwhelming data can cause difficulty in deciding over numerous patients requiring prioritisation and those that follow [80].
- **Patient prioritisation accuracy:** This point indicates the accuracy of patient prioritisation process in representing the ranking of patients according to their urgent situation in consideration of their medical condition. Likewise, accuracy is reflected in the recognition of slight differences in the urgent situation between patients.
- **Validation:** This point shows whether a validation was provided, including the methods used for validation.
- **Evaluation:** This point shows whether an evaluation was provided, including the methods used for evaluation.

After recognising and defining the checklist comparison issues, the proposed patient prioritisation method is compared with the most relevant study in this research area regarding these specific issues. Based on literature review analysis, the study of Salman et al. [23] is the most relevant remote patient prioritisation study. After describing the comparison issues of the checklist, the checklist comparison between the proposed and the benchmark studies are presented in Table 10.

As presented in Table 10, the checklist benchmarking points are discussed between the proposed and benchmark method. The first three general checklist points, namely, targeted disease, support vital signs and chief complaints, are addressed by both methods. Investigating whether the scenarios covered by these methods address the comparison points of each scenario is necessary to compare the proposed and benchmark methods. Regarding the first scenario, only three issues, namely, targeted tier, support scalability and environment representing 60% of the scenario, are addressed by both methods. The proposed method alone handles multi-criteria ranking and large data. Thus, two out of five main issues related to the first scenario are disregarded by the benchmark method, which indicates that the first scenario is covered by the benchmark method with a percentage of 60%. The proposed method addresses all issues covering the first scenario with a percentage of 100%. Regarding the second scenario, only two issues, namely, targeted tier and prioritisation method category/order representing 40% of the scenario, are addressed by both methods, whereas the proposed method alone addresses feature weighting, multi-criteria ranking and patient prioritisation accuracy. Thus, three out of five main issues related to the second scenario are disregarded by the benchmark method, which means the second scenario is covered by the benchmark method with a percentage of 40%. The proposed method addresses all

Table 10 Checklist benchmarking

Checklist issues	Benchmark	Proposed
Targeted disease	Chronic heart Diseases	Chronic heart Diseases
Support vital signs	Supported	Supported
Support chief complaints	Supported	Supported
Targeted tier	The priority process performed in Tier 2 (base station) provides a PC value without comparing the value on other patients in the server.	The priority process is performed in Tier 3 (server) and compares each patient with the other patients in the server.
Support scalability	Supported	Supported
Remote environment	Supported	Supported
Prioritisation method Category/order	Ranking	Ranking
Feature weighting	Set and test technique are applied for five diseases according to the dataset of patients without specifying whether the overall or part of the data set is used in the set and test method. The dataset may not reflect all cases that show the exact weights for each feature.	MLAHP technique is used to extract the importance of each source and feature against the others using pairwise comparisons based on judgments of experts to specify a fixed weight for each feature. The judgments of six experts are involved for setting the weights.
Multi-criteria ranking	Data fusion is applied to estimate the current medical condition of patients from multi-sources. However, data fusion is particularly difficult when the input data are heterogeneous (non-commensurate) [85–87].	MCDM is applied to deal with multiple heterogeneous sources from patients. The patient evaluation process must consider the different effects of these features on patient evaluation.
Handling large data:	No consideration	Decision matrix is used to accommodate large data by listing the alternatives representing patients (in column) and the multi-criteria representing features used to evaluate patients.
Patient prioritisation accuracy	The patients are prioritised using a PC ranging from 0 to 100. However, only patients within this range can be prioritised, whereas patients with the same PC value in the server are sorted in descending order using the FCFS principle. However, FCFS cannot be used in reality, given that some patients may feature more urgent cases than the others who previously came [37, 81].	The patients are prioritised with simultaneous consideration of multiple attributes, such as vital signs and complaints, with respect to the proper weight assigned for each attribute to score patients based on the most urgent cases without considering the FCFS technique. Specifically, the MCDM ranks and provides patient prioritisation based on the urgency of cases for each patient regardless of the request time.
Validation	No validation provided	Objective and subjective validation
Evaluation	With benchmark guidelines	Checklist benchmarking

issues covering the second scenario with a percentage of 100%. Regarding the third scenario, two main issues must be considered, namely, feature weighting and multi-criteria ranking, each of which represents 50% of the scenario. For the benchmark method, the two main issues related to the third scenario are disregarded, indicating that the third scenario is not covered (0%). Meanwhile, the proposed method addresses all issues covering the third scenario (100%). The differences in method coverage for the scenarios are presented in Fig. 15. As shown in Table 10, validation and evaluation are considered in the proposed method, whereas no validation or evaluation is provided in the benchmark method.

As shown in Fig. 15, the proposed method covers all scenarios and their related issues, yielding 100% for all scenarios, whereas the benchmark method does not cover the scenarios, considering that not all issues related to each scenario are addressed, obtaining 60%, 40% and 0% for the first, second and third scenarios, respectively. The advantages and strengths of the issues considered by the proposed method and ignored by the benchmark are the following. Firstly, multi-criteria ranking is crucial for patient prioritisation as the complex decision-making problem and decision making are based on a set of attributes. Secondly, handling large data is important because it facilitates the prioritisation decisions with overwhelming data and helps in deciding who among the numerous patients must first be attended. Third, the feature weighting technique extracts the importance of each source and feature against the others involving judgments from experts to specify a fixed weight for each feature. Lastly, the accuracy of patient prioritisation is important in simultaneous consideration of multiple attributes, namely, vital signs and complaints, with respect to the proper weight assigned for each attribute to score patients based on the most urgent cases and the disregarding FCFS technique. Thus, the proposed method addressing these issues is essential for patient prioritisation. In conclusion, regarding the first, second and third scenarios, the proposed

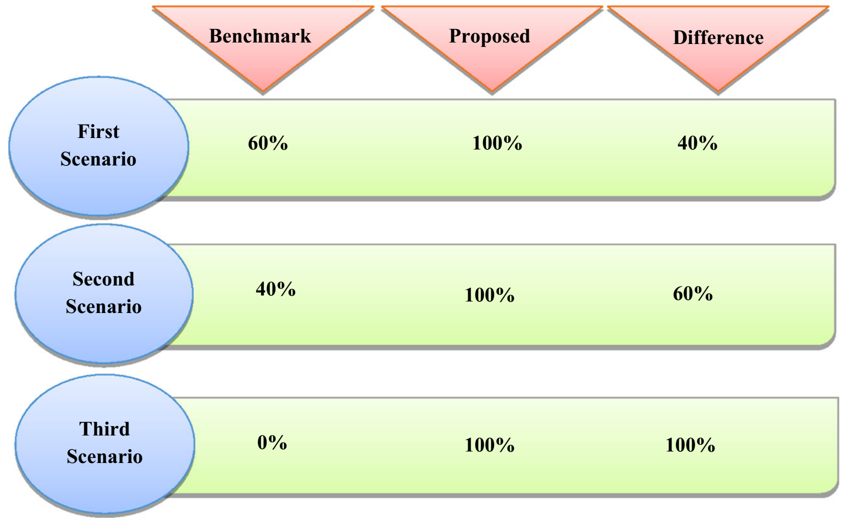

Fig. 15 Differences in method coverage for the scenarios

method offers an advantage over the benchmark method with percentages of 40%, 60% and 100%, respectively.

Summary points

What is already known?

- No particular study was conducted on multi-attribute analysis on triage setting and prioritization for large-scale data of patients with any type of chronic disease in telemedicine during disasters and peak seasons.
- A multi-attribute sensor for evaluating vital signs and the multi-attribute patients are considered complex problems for the existing approaches. Each decision matrix (DM) is assigned with different weights for these attributes. Other issues include a server, which scores a single type of patient and provides more weight to a certain criterion than other features. Ranking of patients is a multi-attribute problem.
- Improper triage and prioritization of patients may result to wrong strategical decisions, especially when the patients with emergency case are assigned to a lower than required triage priority, thereby endangering their health.

What does this study contribute?

- A new real-time approach is developed to prioritize "Large-scale Data" of patients with chronic heart diseases by using body sensor information and communication technology. These patients require urgent attention as indicated by the multi-measurement criterion records in telemedicine during disasters and peak seasons.
- Integrated multi-layer for analytic hierarchy process (MLAHP) is used to calculate the weight of each attribute for each patient with chronic heart disease. Technique for order performance by similarity to ideal solution (TOPSIS) is subsequently used to score the available alternatives that can be considered. The proposed algorithms are used to solve the complex multi-attribute selection problems in patients with chronic heart diseases.
- The results of the proposed work are validated and evaluated. During validation, the ranking results are validated objectively and subjectively based on different characteristics. Evaluation is conducted by providing scenarios and checklist benchmarking to assess the proposed and existing prioritization methods. The patients who exhibited the most and least emergency cases obtained the highest and lowest priority levels, respectively, when their scores are identical.

Conclusion

This study presented a new real-time approach in allocating and prioritising large-scale data on patients with chronic heart diseases in a telemedicine environment during disasters and peak times. An integrated model was formulated to evaluate and score the patients according to MLAHP and TOPSIS. A hands-on study was performed, and 500 patients exhibiting different symptoms and emergency levels of heart diseases were separately evaluated according to the following main measurements: ECG, SpO_2 and BP sensors and non-sensory measurement, that is, text frame. The patients were then scored based on the measurement outcomes from the integrated methods. The results demonstrated that the subjective and statistical evaluations exhibited similar results such that patients with the most and least emergency cases obtained the highest and lowest priority levels, respectively. An adaptive and integrated decision-making platform for different chronic diseases, such as heart disease, diabetes and abnormal BP, requires further investigation in the future. The platform can be used to designate priority levels to patients, considering the diversity of diseases and emergency levels of each patient. Moreover, increasing the sources, such as, video, audio, image, medical sensors and GPS, for triage for the prioritisation and designation of appropriate emergency levels to patients remains an issue. Finally, the challenge in formulating a single model that can integrate servers and databases from several hospitals for triage and prioritisation requires further studies, analyses and justifications.

Potential future research

The findings of this study can be used in providing healthcare services. In normal scenario of providing healthcare services in telemedicine architecture, the medical center server (Tier 3) is connected with distributed hospitals to control the healthcare services and send the services as a response to client side (Tier 2). Telemedicine architecture has many drawbacks associated with providing healthcare services. These shortcomings can be solved by this study as a future direction of the new designs of telemedicine architecture as provided below:

New design of telemedicine architecture for providing healthcare services within medical center server (Tier 3)

The medical center server monitors and makes decisions for a selected appropriate hospital to provide healthcare services to patients at home (considering that the movement of patient is static within a specific area). Providing healthcare services to patients with chronic heart diseases based on triage level and number of available services in hospitals is a challenging task. On the one hand, the numbers of services vary from one hospital to another, thus requiring the medical center to balance and provide healthcare services after selecting the appropriate hospital. On the other hand, the medical center server can receive vital signs of 500 patients exhibiting different symptoms and emergency levels of heart diseases from the following main measurements: ECG, SpO2, and BP sensors and non-sensory measurement, namely, text frame. Their triage level is calculated by Dempster–Shafer theory as a three emergency levels (risk, urgent, or sick). Hospitals can provide healthcare services to patients with chronic heart disease based on their triage levels. The three healthcare services packages are package 1 (Alarm1), package 2 (Alarm), and package 3 (Direction). Therefore, accurate triage system and integrated platform between triage levels and healthcare packages can solve the major issues by using Dempster–Shafer theory. Hospital selection should be based on triage level and the available services in distributed hospitals. A new design in telemedicine architecture can be adopted by developing a new integrated model to evaluate and score the hospitals according to analytic hierarchy process (AHP) and TOPSIS methods. Such new design can provide healthcare services from appropriate hospital for only one patient. This condition is considered as a limitation in providing healthcare services because the medical center should provide real-time

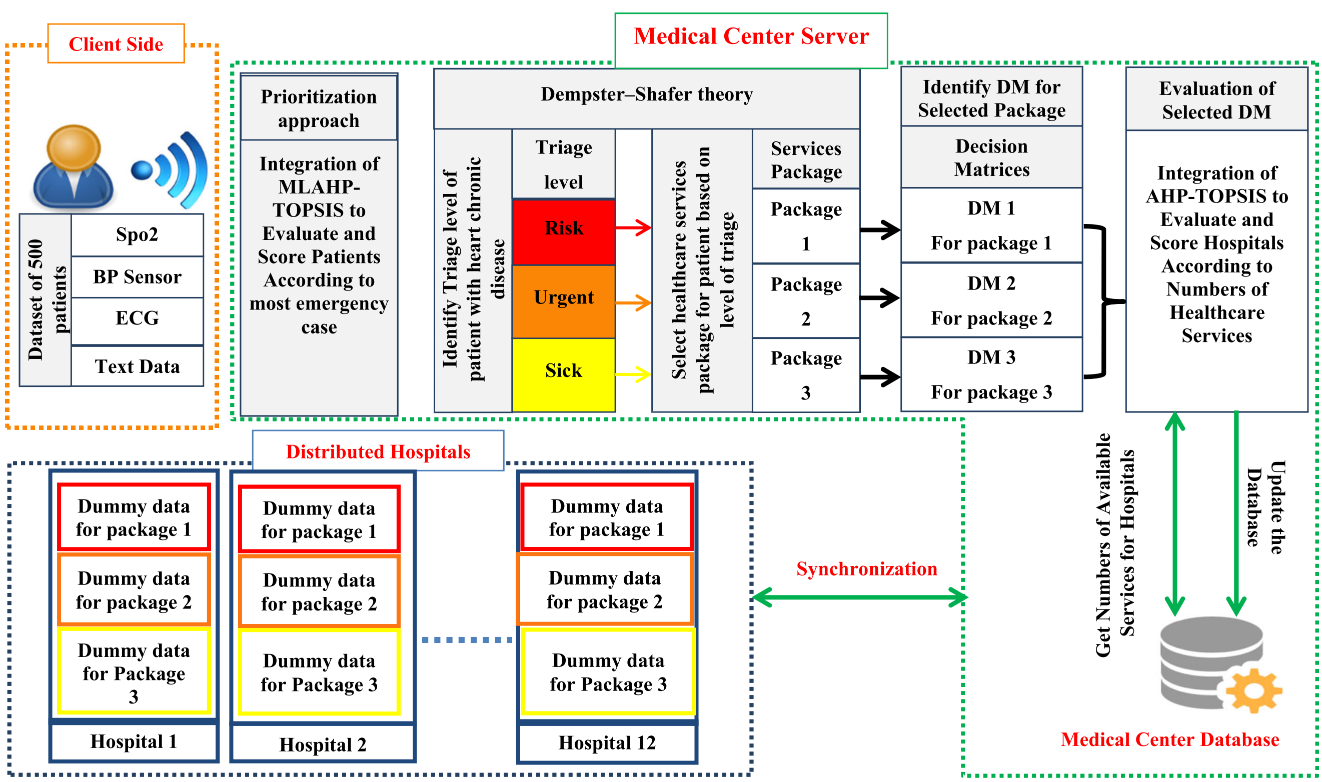

Fig. 16 New design of telemedicine architecture for providing healthcare services within medical center server (Tier 3)

healthcare services to many patients. Another problem is the prioritization of patients. The patients with the most emergency case (for instance, risk level) should be prioritized and provided healthcare services before attending to other patients (urgent and sick levels). Therefore, this study can be used in the new design to solve these major problems. The new design of telemedicine architecture that uses the new prioritization approach is explained in the Fig. 16 below.

First, this study can integrate a new design to a medical center to prioritize the patients. After being prioritized, the patients can be provided with healthcare services through three decision matrices based on triage level from an accurate triage system. The dummy data can represent the number of healthcare services in distributed hospitals (12 hospitals as a proof of concept) to complete the full scenario of the decision-making process. Such new design constructs a decision-making matrix within the medical center server based on a crossover of multi-services and hospitals lists. In the decision-making matrix, the hospitals represent the alternatives, whereas the services represent the multi-criteria that are used to evaluate the hospitals according to their numbers of healthcare services. In conclusion, hospitals with many available healthcare services obtain the highest ranking, whereas hospitals with few services obtain low ranking.

New design of telemedicine architecture for providing healthcare services within mHealth (Tier 2) in case of medical center server (Tier3) failure

Selecting a hospital within mHealth to provide healthcare services to patient with chronic heart diseases based on triage level is a challenging task due to many issues. In a normal scenario of telemedicine as explained in section "New design of telemedicine architecture for providing healthcare services within medical center server (Tier 3)", the medical center server monitors and decides the selection of appropriate hospital and fully controls the telemedicine architecture. Typical healthcare services in telemedicine are based on client–server architecture, where the availability of such structure is a complex issue due to many possible configurations and scalability challenges. Therefore, any disruption to the telemedicine network and medical center server can lead to link outage and

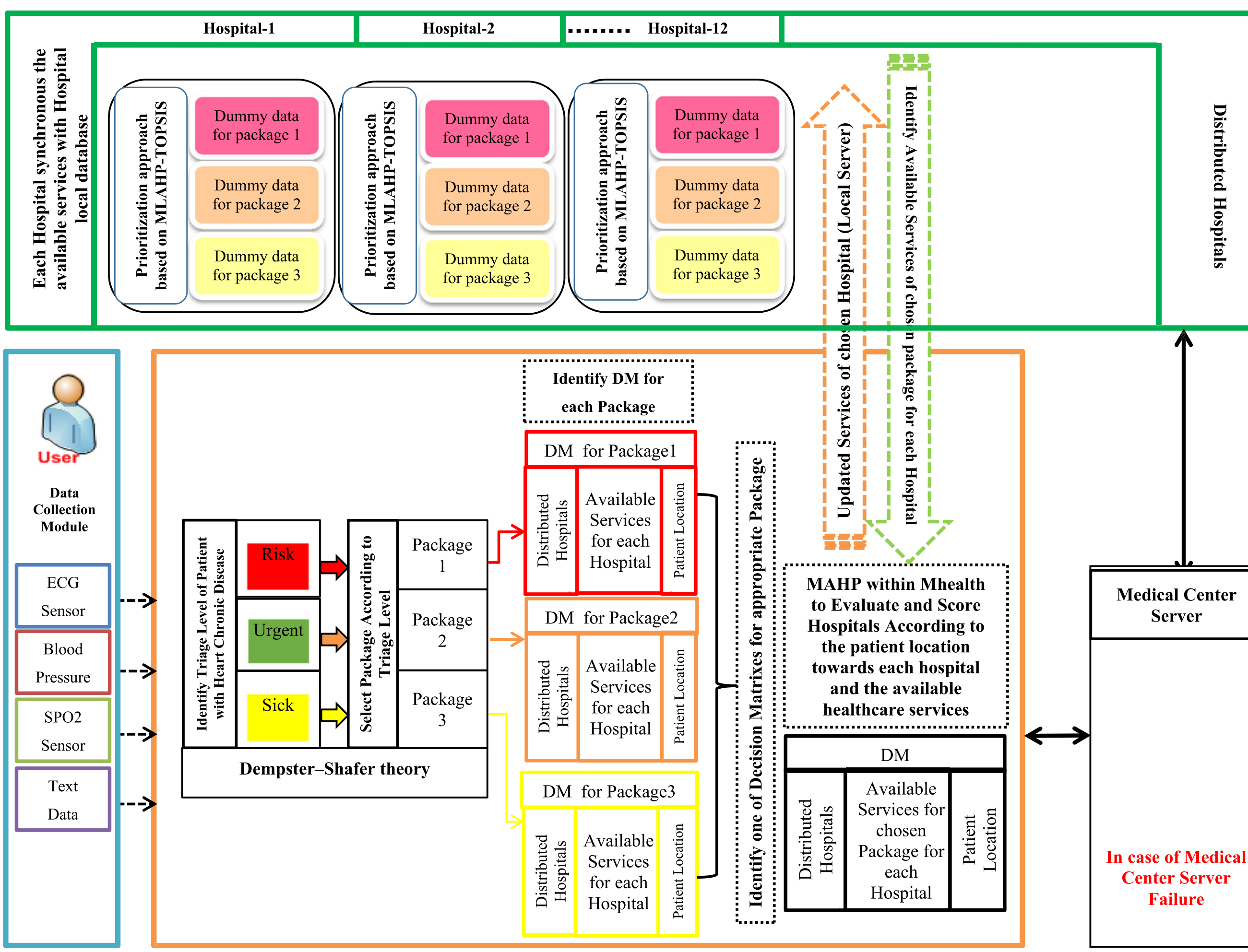

Fig. 17 New design of telemedicine architecture for providing healthcare services within mHealth (Tier 2) in case of medical center server (Tier3) failure

potentially to severe consequences. The availability of healthcare services varies from one hospital to another. Therefore, mHealth can connect directly with distributed hospital servers as a backup of first design (section "New design of telemedicine architecture for providing healthcare services within medical center server (Tier 3)") to identify the available healthcare services of each hospital and ensure the continuity of providing healthcare services in case of any failure in the medical center server. mHealth can calculate the triage level of patients and decide the package services after receiving the vital signs of the patients with heart diseases. Vital signs are measured using ECG, SpO2, and BP sensors and non-sensory measurement, namely, text frame. Their triage level is calculated by Dempster–Shafer theory as a three emergency levels (risk, urgent, or sick). Furthermore, patient location with reference to each hospital is an important factor in hospital selection and in patient life. In this design, the situation of patient location is a frequent movement (dynamic). The new design aims to aid decision-makers in hospital selection based on multi-criteria decision making within mHealth doctor (Tier 2) in a telemedicine environment. This design can construct a DM based on a crossover of patient location/multi-services and hospital lists. In this decision-making matrix, the hospitals represent the alternatives, whereas the services and patient location represent the multi-criteria that are used to evaluate and score the hospitals and their available healthcare. Both patient location and availability of healthcare services in distributed hospitals can be represented by using dummy data to complete the full scenario of decision making. The hospitals can be subsequently prioritized and ranked by using multi-criteria decision-making techniques, namely, multi-analytic hierarchy process (MAHP).

Problem arises when several patients use mHealth and are admitted at the same time in the same hospital. The selected hospital then needs to provide priority healthcare services for the patient with a high emergency level rather than those with other levels. Therefore, this study can solve this problem by using a prioritization approach for the patients in each hospital. The Fig. 17 below illustrates the new design of telemedicine architecture for providing healthcare services within mHealth (Tier 2) in case of medical center server (Tier3) failure, which adopts the new prioritization approach.

In the Fig. 17, mHealth (patient) can deal with the distributed hospitals and send a request to receive the data representing their healthcare services. mHealth will identify these services and obtain a copy record of the local database for only available services from each hospital. Hence, the decision-making matrix will rank the hospitals according to the last update of package services (available services) for each local server in the distributed hospitals. mHealth will then select the appropriate hospital and update the services in the database of the selected hospital (local server).

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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

Informed consent Informed consent was obtained from all individual participants included in the study.

Appendix

Table 11 TOPSIS sample results of the first and last forty patients for the first expert

No.	S-	S*	Final rank
1	0.017487	0.024905	0.412506
2	0.017489	0.024904	0.412540
3	0.017579	0.024840	0.414406
4	0.017580	0.024839	0.414440
5	0.017512	0.024888	0.413016
6	0.017513	0.024887	0.413049
7	0.017603	0.024823	0.414913
8	0.017605	0.024822	0.414947
9	0.017661	0.024782	0.416119
10	0.017663	0.024781	0.416152
11	0.017752	0.024717	0.418005
12	0.017754	0.024716	0.418038
13	0.017686	0.024764	0.416624
14	0.017687	0.024763	0.416658
15	0.017776	0.024699	0.418509
16	0.017778	0.024698	0.418542
17	0.018222	0.023272	0.439146
18	0.018223	0.023270	0.439180
19	0.018310	0.023202	0.441068
20	0.018311	0.023201	0.441102
21	0.018245	0.023253	0.439661
22	0.018247	0.023252	0.439695
23	0.018333	0.023184	0.441582
24	0.018335	0.023183	0.441616
25	0.018389	0.023140	0.442803
26	0.018391	0.023138	0.442837
27	0.018476	0.023070	0.444716
28	0.018478	0.023069	0.444749
29	0.018412	0.023121	0.443316
30	0.018414	0.023120	0.443350
31	0.018500	0.023051	0.445227
32	0.018501	0.023050	0.445261

Table 11 (continued)

No.	S-	S*	Final rank
33	0.013115	0.025286	0.341533
34	0.013117	0.025285	0.341580
35	0.013237	0.025222	0.344189
36	0.013240	0.025221	0.344236
37	0.013148	0.025269	0.342247
38	0.013150	0.025268	0.342294
39	0.013270	0.025205	0.344896
40	0.013272	0.025204	0.344942
461	0.028839	0.006474	0.816665
462	0.028840	0.006470	0.816772
463	0.028895	0.006221	0.822850
464	0.028896	0.006216	0.822962
465	0.025781	0.012112	0.680359
466	0.025782	0.012110	0.680411
467	0.025844	0.011979	0.683288
468	0.025845	0.011976	0.683340
469	0.025798	0.012077	0.681140
470	0.025799	0.012074	0.681192
471	0.025860	0.011943	0.684079
472	0.025861	0.011940	0.684131
473	0.025900	0.011857	0.685971
474	0.025901	0.011854	0.686024
475	0.025962	0.011720	0.688972
476	0.025963	0.011718	0.689026
477	0.025917	0.011820	0.686771
478	0.025918	0.011818	0.686824
479	0.025979	0.011683	0.689782
480	0.025980	0.011681	0.689836
481	0.026285	0.008247	0.761173
482	0.026286	0.008244	0.761257
483	0.026346	0.008050	0.765967
484	0.026347	0.008046	0.766053
485	0.026302	0.008195	0.762443
486	0.026303	0.008191	0.762527
487	0.026363	0.007996	0.767275
488	0.026364	0.007993	0.767362
489	0.026401	0.007867	0.770433
490	0.026403	0.007863	0.770521
491	0.026462	0.007660	0.775521
492	0.026463	0.007656	0.775613
493	0.026418	0.007812	0.771779
494	0.026419	0.007808	0.771868
495	0.026479	0.007603	0.776912
496	0.026480	0.007599	0.777005
497	0.022196	0.020818	0.516018
498	0.022197	0.020817	0.516049
499	0.022268	0.020741	0.517761
500	0.022270	0.020739	0.517792

Table 12 TOPSIS sample results of the first and last forty patients for the second expert

No.	S-	S*	Final rank
1	0.018877	0.024829	0.431902
2	0.019020	0.024719	0.434852
3	0.018904	0.024808	0.432459
4	0.019047	0.024698	0.435406
5	0.018884	0.024824	0.432046
6	0.019027	0.024714	0.434995
7	0.018911	0.024803	0.432603
8	0.019054	0.024693	0.435550
9	0.018880	0.024826	0.431976
10	0.019024	0.024716	0.434925
11	0.018907	0.024806	0.432533
12	0.019051	0.024696	0.435480
13	0.018887	0.024821	0.432120
14	0.019031	0.024711	0.435069
15	0.018914	0.024800	0.432677
16	0.019058	0.024690	0.435624
17	0.021230	0.018256	0.537661
18	0.021358	0.018106	0.541197
19	0.021254	0.018228	0.538327
20	0.021382	0.018078	0.541865
21	0.021236	0.018249	0.537833
22	0.021364	0.018099	0.541370
23	0.021261	0.018221	0.538499
24	0.021388	0.018071	0.542038
25	0.021233	0.018252	0.537749
26	0.021361	0.018103	0.541286
27	0.021258	0.018224	0.538415
28	0.021385	0.018074	0.541954
29	0.021240	0.018245	0.537922
30	0.021367	0.018095	0.541459
31	0.021264	0.018217	0.538588
32	0.021391	0.018067	0.542127
33	0.014157	0.025274	0.359043
34	0.014348	0.025166	0.363120
35	0.014194	0.025253	0.359816
36	0.014384	0.025145	0.363883
37	0.014167	0.025268	0.359243
38	0.014358	0.025160	0.363318
39	0.014203	0.025248	0.360016
40	0.014393	0.025140	0.364080
461	0.023467	0.015275	0.605732
462	0.023583	0.015095	0.609717
463	0.023489	0.015241	0.606480
464	0.023604	0.015061	0.610473
465	0.017321	0.023220	0.427237
466	0.017477	0.023103	0.430682
467	0.017350	0.023198	0.427888
468	0.017506	0.023081	0.431329
469	0.017328	0.023215	0.427406
470	0.017485	0.023097	0.430850
471	0.017358	0.023192	0.428057
472	0.017514	0.023075	0.431497
473	0.017325	0.023217	0.427324
474	0.017481	0.023100	0.430768
475	0.017354	0.023195	0.427975
476	0.017510	0.023078	0.431415
477	0.017332	0.023212	0.427493
478	0.017488	0.023094	0.430936
479	0.017362	0.023190	0.428144
480	0.017518	0.023072	0.431583
481	0.019860	0.015999	0.553823
482	0.019996	0.015828	0.558167
483	0.019885	0.015967	0.554640
484	0.020022	0.015796	0.558989

Table 12 (continued)

No.	S-	S*	Final rank
485	0.019866	0.015991	0.554035
486	0.020003	0.015820	0.558380
487	0.019892	0.015959	0.554852
488	0.020028	0.015788	0.559202
489	0.019863	0.015995	0.553932
490	0.020000	0.015824	0.558276
491	0.019889	0.015963	0.554749
492	0.020025	0.015792	0.559098
493	0.019870	0.015987	0.554143
494	0.020006	0.015816	0.558489
495	0.019895	0.015955	0.554961
496	0.020032	0.015783	0.559312
497	0.009979	0.029551	0.252435
498	0.010248	0.029458	0.258087
499	0.010030	0.029533	0.253515
500	0.010298	0.029441	0.259133

Table 13 TOPSIS sample results of the first and last forty patients for the third expert

No.	S-	S*	Final rank
1	0.013735	0.028712	0.323579
2	0.013736	0.028711	0.323603
3	0.013757	0.028701	0.324008
4	0.013758	0.028701	0.324032
5	0.013957	0.028604	0.327929
6	0.013958	0.028604	0.327952
7	0.013979	0.028594	0.328350
8	0.013980	0.028593	0.328373
9	0.013745	0.028707	0.323782
10	0.013746	0.028706	0.323806
11	0.013767	0.028696	0.324210
12	0.013768	0.028696	0.324234
13	0.013967	0.028599	0.328128
14	0.013969	0.028599	0.328151
15	0.013989	0.028589	0.328548
16	0.013990	0.028588	0.328572
17	0.015331	0.026177	0.369347
18	0.015332	0.026176	0.369369
19	0.015350	0.026165	0.369747
20	0.015351	0.026165	0.369769
21	0.015530	0.026059	0.373418
22	0.015531	0.026058	0.373440
23	0.015549	0.026047	0.373813
24	0.015551	0.026047	0.373835
25	0.015340	0.026171	0.369536
26	0.015341	0.026171	0.369558
27	0.015359	0.026160	0.369936
28	0.015361	0.026159	0.369958
29	0.015539	0.026053	0.373605
30	0.015540	0.026053	0.373627
31	0.015559	0.026042	0.374000
32	0.015560	0.026041	0.374022
33	0.010301	0.028916	0.262667
34	0.010303	0.028916	0.262701
35	0.010330	0.028906	0.263284
36	0.010332	0.028905	0.263319
37	0.010596	0.028810	0.268890
38	0.010597	0.028809	0.268923
39	0.010624	0.028799	0.269487

Table 13 (continued)

No.	S-	S*	Final rank
40	0.010626	0.028799	0.269520
461	0.028938	0.009101	0.760738
462	0.028939	0.009100	0.760778
463	0.028949	0.009068	0.761466
464	0.028949	0.009066	0.761506
465	0.026496	0.015499	0.630940
466	0.026497	0.015498	0.630962
467	0.026508	0.015479	0.631332
468	0.026508	0.015478	0.631353
469	0.026612	0.015299	0.634970
470	0.026613	0.015298	0.634992
471	0.026624	0.015279	0.635366
472	0.026624	0.015278	0.635389
473	0.026502	0.015490	0.631125
474	0.026502	0.015488	0.631147
475	0.026513	0.015470	0.631517
476	0.026514	0.015469	0.631539
477	0.026618	0.015290	0.635157
478	0.026618	0.015288	0.635179
479	0.026629	0.015270	0.635554
480	0.026630	0.015269	0.635576
481	0.027358	0.010053	0.731276
482	0.027358	0.010052	0.731313
483	0.027369	0.010023	0.731941
484	0.027369	0.010022	0.731978
485	0.027470	0.009742	0.738198
486	0.027471	0.009740	0.738237
487	0.027481	0.009711	0.738889
488	0.027482	0.009710	0.738928
489	0.027363	0.010039	0.731590
490	0.027363	0.010037	0.731627
491	0.027374	0.010009	0.732256
492	0.027374	0.010007	0.732293
493	0.027475	0.009728	0.738524
494	0.027476	0.009726	0.738563
495	0.027486	0.009697	0.739216
496	0.027487	0.009695	0.739255
497	0.024412	0.020422	0.544495
498	0.024413	0.020421	0.544512
499	0.024424	0.020407	0.544799
500	0.024425	0.020407	0.544816

Table 14 TOPSIS sample results of the first and last forty patients for the fourth expert

No.	S-	S*	Final rank
1	0.016211	0.025400	0.389592
2	0.016212	0.025399	0.389611
3	0.016262	0.025368	0.390635
4	0.016263	0.025367	0.390653
5	0.016225	0.025391	0.389871
6	0.016226	0.025391	0.389890
7	0.016275	0.025359	0.390913
8	0.016276	0.025358	0.390932
9	0.016307	0.025338	0.391576
10	0.016308	0.025338	0.391594
11	0.016358	0.025306	0.392613
12	0.016359	0.025305	0.392631
13	0.016321	0.025330	0.391854
14	0.016322	0.025329	0.391872
15	0.016371	0.025297	0.392890

Table 14 (continued)

No.	S-	S*	Final rank
16	0.016372	0.025297	0.392909
17	0.016836	0.024150	0.410770
18	0.016837	0.024150	0.410789
19	0.016885	0.024116	0.411809
20	0.016885	0.024116	0.411828
21	0.016849	0.024141	0.411049
22	0.016850	0.024141	0.411067
23	0.016898	0.024107	0.412087
24	0.016898	0.024107	0.412106
25	0.016928	0.024086	0.412748
26	0.016929	0.024085	0.412766
27	0.016977	0.024052	0.413783
28	0.016978	0.024051	0.413801
29	0.016941	0.024076	0.413025
30	0.016942	0.024076	0.413043
31	0.016990	0.024042	0.414059
32	0.016991	0.024042	0.414078
33	0.012159	0.025721	0.320978
34	0.012160	0.025721	0.321004
35	0.012226	0.025689	0.322452
36	0.012227	0.025689	0.322478
37	0.012177	0.025713	0.321374
38	0.012178	0.025712	0.321400
39	0.012244	0.025681	0.322846
40	0.012245	0.025680	0.322872
461	0.025439	0.014817	0.631937
462	0.025440	0.014816	0.631958
463	0.025471	0.014761	0.633102
464	0.025472	0.014760	0.633123
465	0.022538	0.017362	0.564865
466	0.022539	0.017361	0.564884
467	0.022575	0.017315	0.565931
468	0.022575	0.017314	0.565950
469	0.022548	0.017349	0.565151
470	0.022549	0.017348	0.565169
471	0.022584	0.017302	0.566217
472	0.022585	0.017301	0.566236
473	0.022607	0.017272	0.566898
474	0.022608	0.017271	0.566916
475	0.022644	0.017224	0.567967
476	0.022644	0.017223	0.567986
477	0.022617	0.017259	0.567184
478	0.022618	0.017258	0.567203
479	0.022653	0.017212	0.568254
480	0.022654	0.017211	0.568273
481	0.022992	0.015477	0.597679
482	0.022992	0.015476	0.597700
483	0.023027	0.015423	0.598876
484	0.023028	0.015423	0.598898
485	0.023001	0.015462	0.597999
486	0.023002	0.015461	0.598020
487	0.023037	0.015409	0.599198
488	0.023037	0.015408	0.599219
489	0.023059	0.015375	0.599963
490	0.023060	0.015374	0.599984
491	0.023095	0.015322	0.601167
492	0.023096	0.015321	0.601188
493	0.023069	0.015361	0.600285
494	0.023070	0.015360	0.600306
495	0.023104	0.015308	0.601490
496	0.023105	0.015307	0.601511
497	0.018977	0.023406	0.447759
498	0.018978	0.023405	0.447776
499	0.019021	0.023371	0.448692
500	0.019021	0.023370	0.448708

Table 15 TOPSIS sample results of the first and last forty patients for the fifth expert

No.	S-	S*	Final rank
1	0.018527	0.024513	0.430466
2	0.018612	0.024448	0.432240
3	0.018582	0.024471	0.431602
4	0.018667	0.024407	0.433372
5	0.018537	0.024505	0.430672
6	0.018622	0.024441	0.432445
7	0.018592	0.024464	0.431806
8	0.018677	0.024399	0.433576
9	0.018535	0.024507	0.430623
10	0.018620	0.024442	0.432396
11	0.018589	0.024466	0.431758
12	0.018674	0.024401	0.433528
13	0.018545	0.024499	0.430828
14	0.018630	0.024435	0.432601
15	0.018599	0.024458	0.431962
16	0.018684	0.024393	0.433732
17	0.019539	0.022031	0.470019
18	0.019619	0.021959	0.471863
19	0.019590	0.021985	0.471199
20	0.019671	0.021913	0.473042
21	0.019548	0.022023	0.470232
22	0.019629	0.021951	0.472076
23	0.019600	0.021977	0.471412
24	0.019680	0.021905	0.473254
25	0.019546	0.022025	0.470182
26	0.019627	0.021953	0.472026
27	0.019597	0.021979	0.471361
28	0.019678	0.021907	0.473204
29	0.019555	0.022017	0.470395
30	0.019636	0.021945	0.472239
31	0.019607	0.021971	0.471574
32	0.019687	0.021898	0.473417
33	0.013895	0.024946	0.357743
34	0.014009	0.024883	0.360202
35	0.013968	0.024906	0.359318
36	0.014081	0.024842	0.361763
37	0.013909	0.024939	0.358029
38	0.014022	0.024876	0.360484
39	0.013981	0.024898	0.359602
40	0.014094	0.024835	0.362045
461	0.027249	0.011162	0.709406
462	0.027308	0.011020	0.712487
463	0.027287	0.011071	0.711371
464	0.027345	0.010927	0.714483
465	0.023521	0.016192	0.592265
466	0.023588	0.016094	0.594419
467	0.023564	0.016130	0.593642
468	0.023631	0.016031	0.595802
469	0.023528	0.016181	0.592514
470	0.023595	0.016083	0.594669
471	0.023571	0.016118	0.593891
472	0.023638	0.016020	0.596053
473	0.023526	0.016184	0.592454
474	0.023594	0.016086	0.594609
475	0.023569	0.016121	0.593832
476	0.023637	0.016023	0.595993
477	0.023534	0.016172	0.592703
478	0.023601	0.016074	0.594859
479	0.023577	0.016110	0.594081
480	0.023644	0.016011	0.596244
481	0.024325	0.012112	0.667597
482	0.024390	0.011980	0.670604
483	0.024367	0.012028	0.669516
484	0.024432	0.011895	0.672545
485	0.024333	0.012097	0.667943
486	0.024398	0.011965	0.670953
487	0.024374	0.012013	0.669864
488	0.024439	0.011880	0.672898

Table 15 (continued)

No.	S-	S*	Final rank
489	0.024331	0.012100	0.667861
490	0.024396	0.011969	0.670870
491	0.024372	0.012016	0.669781
492	0.024437	0.011884	0.672814
493	0.024338	0.012085	0.668207
494	0.024403	0.011953	0.671220
495	0.024380	0.012001	0.670130
496	0.024445	0.011868	0.673167
497	0.018977	0.024166	0.439865
498	0.019060	0.024100	0.441614
499	0.019030	0.024124	0.440984
500	0.019113	0.024058	0.442730

Table 16 TOPSIS sample results of the first and last forty patients for the sixth expert

No.	S-	S*	Final rank
1	0.019822	0.022372	0.469776
2	0.019823	0.022371	0.469810
3	0.019850	0.022348	0.470401
4	0.019851	0.022346	0.470435
5	0.020105	0.022118	0.476157
6	0.020106	0.022117	0.476192
7	0.020132	0.022093	0.476780
8	0.020134	0.022092	0.476814
9	0.019835	0.022361	0.470071
10	0.019836	0.022359	0.470105
11	0.019863	0.022336	0.470695
12	0.019864	0.022335	0.470730
13	0.020118	0.022107	0.476451
14	0.020119	0.022105	0.476486
15	0.020145	0.022082	0.477073
16	0.020147	0.022080	0.477108
17	0.021117	0.018477	0.533337
18	0.021119	0.018476	0.533377
19	0.021143	0.018447	0.534048
20	0.021145	0.018446	0.534088
21	0.021383	0.018169	0.540634
22	0.021385	0.018167	0.540674
23	0.021409	0.018138	0.541350
24	0.021410	0.018137	0.541390
25	0.021130	0.018463	0.533673
26	0.021131	0.018462	0.533712
27	0.021156	0.018433	0.534384
28	0.021157	0.018432	0.534424
29	0.021395	0.018155	0.540972
30	0.021397	0.018153	0.541012
31	0.021421	0.018124	0.541688
32	0.021423	0.018122	0.541728
33	0.014866	0.022915	0.393488
34	0.014868	0.022913	0.393535
35	0.014903	0.022890	0.394334
36	0.014905	0.022889	0.394381
37	0.015242	0.022667	0.402068
38	0.015244	0.022665	0.402114
39	0.015278	0.022642	0.402897
40	0.015280	0.022641	0.402943
461	0.023695	0.015031	0.611863
462	0.023696	0.015029	0.611909
463	0.023718	0.014994	0.612678
464	0.023719	0.014992	0.612724
465	0.018019	0.020528	0.467447
466	0.018020	0.020527	0.467489
467	0.018049	0.020501	0.468197
468	0.018051	0.020500	0.468238
469	0.018330	0.020251	0.475098
470	0.018331	0.020250	0.475139
471	0.018360	0.020224	0.475844
472	0.018361	0.020222	0.475885
473	0.018033	0.020516	0.467801
474	0.018035	0.020514	0.467843
475	0.018064	0.020489	0.468550
476	0.018065	0.020487	0.468592
477	0.018344	0.020238	0.475450
478	0.018346	0.020237	0.475491
479	0.018374	0.020211	0.476195
480	0.018376	0.020209	0.476237
481	0.019435	0.016196	0.545453
482	0.019436	0.016194	0.545502
483	0.019463	0.016162	0.546338
484	0.019465	0.016160	0.546387
485	0.019723	0.015843	0.554553
486	0.019725	0.015841	0.554602
487	0.019751	0.015808	0.555448
488	0.019753	0.015806	0.555497
489	0.019448	0.016180	0.545871
490	0.019450	0.016178	0.545920
491	0.019477	0.016145	0.546756
492	0.019478	0.016144	0.546806
493	0.019737	0.015826	0.554975
494	0.019738	0.015825	0.555025
495	0.019765	0.015792	0.555870
496	0.019766	0.015790	0.555920
497	0.010182	0.028103	0.265949
498	0.010185	0.028102	0.266014
499	0.010236	0.028083	0.267121
500	0.010239	0.028082	0.267186

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