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ORIGINAL RESEARCH

Dempster–Shafer theory for classification and hybridised models of multi-criteria decision analysis for prioritisation: a telemedicine framework for patients with heart diseases

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Abstract
Hybridised classification and prioritisation of patients with chronic heart diseases (CHDs) can save lives by categorising them on the basis of disease severity and determining priority patients. Such hybridisation is challenging and thus has not been reported in the literature on telemedicine. This paper presents an intelligent classification and prioritisation framework for patients with CHDs who engage in telemedicine. The emergency status of 500 patients with CHDs was evaluated on the basis of multiple heterogeneous clinical parameters, such as electrocardiogram, oxygen saturation, blood pressure and non-sensory measurements (i.e. text frame), by using wearable sensors. In the first stage, the patients were classified according to Dempster–Shafer theory and separated into five categories, namely, at high risk, requires urgent care, sick, in a cold state and normal. In the second stage, hybridised multi-criteria decision-making models, namely, multi-layer analytic hierarchy process (MLAHP) and technique for order performance by similarity to ideal solution (TOPSIS), were used to prioritise patients according to their emergency status. Then, the priority patients were queued in each emergency category according to the results of the first stage. Results demonstrated that Dempster–Shafer theory and the hybridised MLAHP and TOPSIS model are suitable for classifying and prioritising patients with CHDs. Moreover, the groups' scores in each category showed remarkable differences, indicating that the framework results were identical. The proposed framework has an advantage over other benchmark classification frameworks by 33.33% and 50%, and an advantage over earlier benchmark prioritisation by 50%. This framework should be considered in future studies on telemedicine architecture to improve healthcare management.

Keywords Telemedicine · Classification · Prioritisation · Chronic heart disease · Dempster–Shafer theory · Multi-criteria decision-making

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1 Introduction

This section introduces the research background and significance of telemedicine, automated classification and prioritisation of remote patients. Moreover, the academic literature of related works is presented and criticised before describing the research contribution of the study. Five sequential questions are presented as follows.

First question: *'What is telemedicine and why it's important?'*.

Telemedicine, which is currently a global trend, aims to bring health services closer to patients. This technology can be applied to several situations; it allows the provision of health services at home or during emergency cases (Ahmed et al. 2020). Telemedicine attends to different patient needs to provide healthcare services by offering inexpensive medical services in underserved and remote areas (Mohammed et al. 2021a, b). Remote health monitoring is an important issue in telemedicine. Hence, various network technologies and wireless communications have been developed to provide healthcare services anywhere at any time (Kalid et al. 2018a, b; Qiao and Koutsakis 2008). ‘Remote patients’ are those patients who are far from a hospital and utilise telemedicine applications (Baig and Gholamhosseini 2013; Okura et al. 2016). The severity of remote patients is often addressed by classifying them into different triage levels.

Second question: ‘*What is the importance of remote patient classification?’.*

Classification is a method of categorising patients during emergency situations and determining the order by which aid is provided on the basis of disease severity and urgency (Tomozawa et al. 2009). Automation of this method may effectively improve the provision of quality healthcare services and hospitalisation, thereby saving lives (Lee et al. 2018). The growth of an ageing population and an increase in the frequency of natural disasters can overwhelm the capacity of healthcare systems and the number of already insufficient specialists (Burke et al. 2012). Triage systems can guarantee that patients in need of urgent care are promptly attended to when emergency departments (EDs) are being overwhelmed (Eijk et al. 2015). Triage systems help physicians prioritise patients according to medical urgency (Murphy et al. 2013). Rapid dissemination of the vital signs of patients is crucial to ensure reliable ED data and immediate emergency care (Zvikhachevskaya et al. 2009). Prioritisation is essential to provide prompt healthcare services. Physicians measure the vital signs of patients to determine disease severity and current health condition, prioritise patients who need immediate treatment and then provide appropriate life-saving treatment. Subsequently, they will identify, label and follow up their patients (Rodriguez et al. 2014). In local and ED settings, patients are prioritised on the basis of the criticality of their condition (Xiong et al. 2012).

Third question: ‘*What is the importance of the prioritisation of remote patients?’.*

During an emergency, the highest priority is given to patients needing the most urgent care in a telemedicine environment (Kalid et al. 2018a, b). Differences in the severity and urgency of patients with chronic heart diseases (CHDs) contribute to the difficulty in deciding who should be treated first among remote patients (Sarkar and Sinha 2014). Triage determines the severity of health condition in emergency settings (Moreno et al. 2016). Prioritisation is important to deliver patient records quickly and reliably, especially in emergency situations (Algaet et al. 2014). In reality, first come, first served (FCFS) care is adopted in EDs (Claudio and Okudan 2009). However, FCFS cannot be used in actual situations; hence, a rapid, well-informed and timely decision in patient prioritisation is needed (Claudio and Okudan 2009; Tan 2013). Improper classification and patient prioritisation can lead to incorrect strategic decisions which can endanger patient lives (Kalid et al. 2018a, b). In a medical situation, if the classification process is individually performed, then patient prioritisation within each category cannot be determined. Such a case will cause a decline in prioritisation performance. If patients only receive treatment with classification but without prioritisation, then the most urgent cases will be at risk. Prioritisation performance is defined as the ability to prioritise patients into categories according to different issues, namely, scalability of support, targeted tier, environment, method of prioritisation (category/order), weighting of features, ranking of multiple patient triage criteria, accuracy of patient prioritisation and handling large amounts of data (Kalid et al. 2018a, b).

Fourth question: ‘*What is the criticism and gap analysis of the related academic literature?’.*

To the best of our knowledge, only three studies on telemedicine environment proposed a solution for classifying and prioritising patients with CHD. In (Salman et al. 2014), a multi-source data fusion (MSHA) framework is proposed. This framework considers multiple clinical parameters as measured by wireless body area network devices, such as electrocardiogram (ECG), oxygen saturation (SpO_2) and blood pressure (BP), and regards texts inputs as the health complaint. MSHA is utilised to enhance healthcare scalability challenges by improving distant classification in a telemedicine environment. In (Albahri et al. 2019a, b), patients with CHD are categorised into four emergency levels by using a new four-level remote triage and a localisation algoritm. Such algoritm is developed within a smart real-time hospital selection framework. This framework can be used to select the best healthcare provider for each patient with CHD by using integrated multi-criteria decision making (MCDM) techniques. In (Albahri et al. 2019a, b), a risk-level localisation triage within a fault-tolerant mHealth framework is developed for triaging and classifying high-risk patients with CHD and then selecting the best hospital for each patient. Only two relevant telemedicine studies proposed a prioritisation solution for patients with CHD. In (Kalid et al. 2018a, b), large data of patients with CHD were evaluated and scored according to the hybridisation of models of multi-layer analytic hierarchy process (MLAHP) and technique for order performance by similarity to ideal solution methods (TOPSIS) to improve prioritisation in a telemedicine environment. In (Salman et al. 2017), large data of patients with CHD requiring immediate medical attention were evaluated and prioritised. Prioritisation was also based on TOPSIS. However, the models of (Albahri et al. 2019a, b; Salman et al. 2014) only classify/triage emergency levels into different categories and do not prioritise the ranking within each category. Moreover, the method for evaluating the diagnostic value of patient classification presented in

Kalid et al. (2018a, b) and Salman et al. (2017) is considered an inaccurate approach. These earlier studies only focused on prioritisation and neglected classification. For example, their methods assign high priority to sick patients over high-risk patients. Thus, their approaches do not simultaneously optimise all emergency levels within all categories. An approach combining the classification and prioritisation of patients with CHD within an integrated framework has not been developed in telemedicine studies. Such a combination can address the limitations of earlier approaches.

Fifth question: *'What is the contribution of the present study?'*.

A medical practitioner must categorise patients at different levels according to the condition of patients and individually prioritise them within each category to increase prioritisation performance. This approach is the primary contribution of the present study. This process is called prioritisation of emergency for emergency and urgent for urgent. The present research focuses on classifying and prioritising remote patients who seek medical services in a telemedicine environment. A framework which integrates classification and prioritisation can classify and prioritise numerous patients with CHD to receive emergency and treatment-based services.

This paper is organised as follows. Section 2 describes the research methodology. Section 3 presents the results and discussion. Section 4 reports the validation and evaluation results of the proposed framework. Section 5 concludes the study and offers research avenues for future works.

2 Methodology

This section provides an overview and explanation of the proposed methodology. Figure 1 summarises the focus of the subsequent sections.

2.1 Identification of targeted tier in telemedicine architecture

The telemedicine architecture consists of three tiers (Zaidan et al. 2020). The client side is represented by Tiers 1 and 2, and the server side is represented by Tier 3 (Mohammed et al. 2020b). Tier 1 (data collection) data are collected from medical sensors and manual inputs (i.e. texts) related to CHDs (Albahri et al. 2018a, b, c). Three biomedical sensors are responsible for transferring the vital signs and reliable datasets (i.e. ECG, SpO_2 and BP) of patients for processing by the server side (Tier 3). Text inputs include chest pain, shortness of breath, palpitation and the physical condition (i.e. rest or exercise) of patients, which are answerable by 'yes' (if abnormal) or 'no' (if normal) (Mohammed et al. 2019). Tier 2 (i.e. laptop or smartphone) is responsible for transferring the medical sensor/source signals from Tier 1 to Tier 3 by using mobile cellular networks or other communication protocols (Albahri et al. 2018a, b, c). In the server, the data from the sensors are analysed by the proposed framework. In this context, Tier 3 is the targeted tier in this study. The process at the server side is an estimation of the medical situation of patients, thereby triaging and prioritising urgent cases as defined by specific features (Albahri and Zaidan et al. 2018). The client side processes (i.e. Tiers 1 and 2) are beyond the scope of this study. Tier 3 includes real-time remote health monitoring which enables doctors to analyse data and provide patients with compatible services. The server usually contains medical records, reports on user history and database (Touati and Tabish 2013). The server is where processes and decisions are made, and it can resolve several problems. Among these issues and as stated in this research, the following requirements in the server side should be fulfilled:

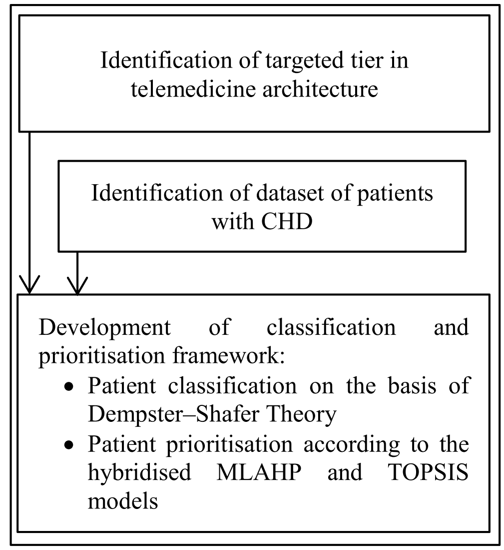

Fig. 1 Proposed methodology

- **Classification**: Classify patients according to emergency level and separate them into five categories, namely, at high risk, requires urgent care, sick, cold state and normal.
- **Prioritisation**: Prioritise patients in each category according to emergency status and then assign them in a queue.

2.2 Identification of patients with CHD and dataset

This section specifies the type and number of patients. The patients identified in this research (n = 500) were patients with CHD who seek medical services remotely via telemedicine. In January 2021, a data row was derived from the most reliable and relevant medical database (Goldberger et al. 2000) which currently has 9645 citations according to Google scholar index. This reliable medical database might be useful for other researchers because it contains many datasets validated and verified by medical experts. Several recent telemedicine studies have used these data in various ideas even though they were published in 2000. The first telemedicine study (Salman et al. 2014) used and processed these data for classifying patients with CHD into different emergency levels remotely. Moreover, this dataset was adopted in the prioritisation of single CHD patients (Kalid et al. 2018a, b; Salman et al. 2017) and multiple CHD patients (Mohammed et al. 2020a; Zaidan et al. 2020) in a telemedicine environment. Meanwhile, authors in (Albahri et al. 2019a, b; Albahri 2021) used the mentioned data in the classification of CHD patients followed by selecting an appropriate healthcare provider for each. The study by Salman et al. (2020) used these data for reducing the waiting time of remote patients with CHD, taking into account admitted patients in the ED. In the present study, the adopted dataset is presented in Table A.1 in Appendix. The dataset includes physical and medical information, such as gender, age, patient location and medical history in the hospital server. Males accounted for 60% of the dataset used, whereas females accounted for the remaining 40%. Furthermore, 50% of the patients were between the ages of 40 and 65 years, 40% were over the age of 65 years and 10% were under the age of 40 years.

2.3 Framework development

In this section, the classification and prioritisation framework was developed using three sequential models. The first classification model is based on Dempster–Shafer theory (Salman et al. 2014). The two other prioritisation models are based on hybridised MLAHP and TOPSIS models (Kalid et al. 2018a, b). The present study combines these classification and prioritisation models to develop a unified classification and prioritisation framework at Tier 3, as presented in Fig. 2.

As mentioned in Sect. 2.1, this study focused on and contributed to the medical central server (Tier 3) via two sequential and successful stages. In the first stage, the patients were classified according to case severity and separated into five categories. This process may serve as a guideline for describing emergency status and determining patients who are at high risk, require urgent situation, sick, in a cold state or normal. In the second stage, each emergency category from the first stage is prioritised according to the hybridised MCDM models, namely, MLAHP and TOPSIS. At this stage, MLAHP is used to obtain weights for each of the four sources and related features from six experts on CHD. TOPSIS is then used to prioritise and rank the available patients within each emergency level, and each patient is prioritised according to weights extracted from MLAHP. The following subsection further describes each model.

2.3.1 Classification model based on Dempster–Shafer theory

Dempster–Shafer theory is adopted at Tier 3 to classify 500 patients with CHD according to emergency status and separate them into five categories, namely, at high risk (represented in red), requires urgent care (represented in orange), sick (represented in yellow), in a cold state (represented in blue) and normal (represented in green). The classification process is based on ECG sensors, BP

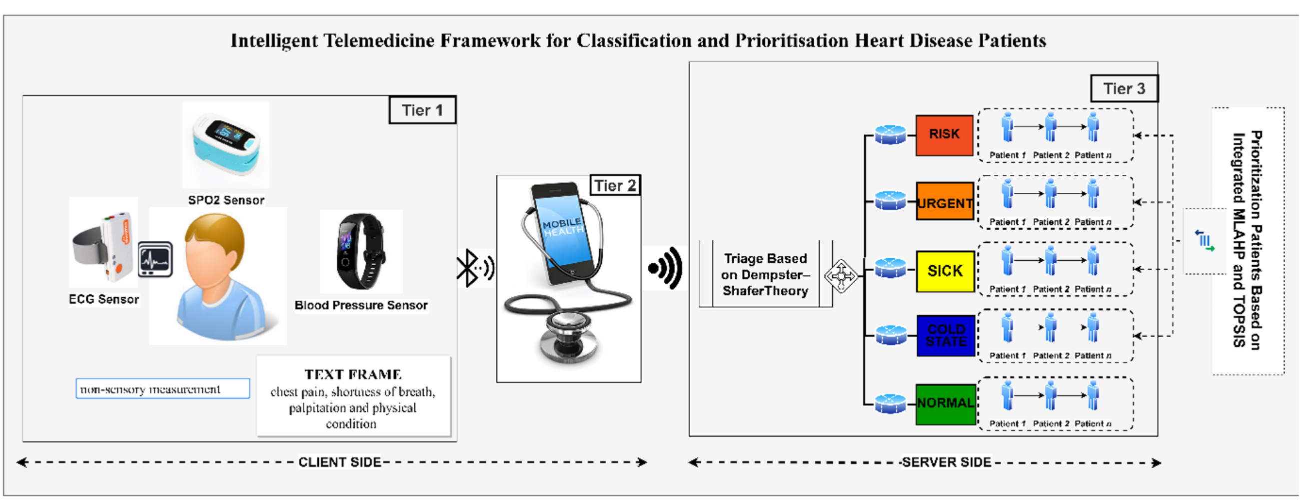

Fig. 2 Intelligent telemedicine classification and prioritisation framework

sensors, SpO_2 sensors and texts. The combination of multiple sources within the data fusion framework improves the estimation of the current vital status of remote users and generates a triage tag called 'Priority Code (PC)' (Salman et al. 2014). PC is utilised to classify patients and identify each emergency case. A number from 0 to 100 is then used to draw a conclusion. This number denotes the PC and can be considered as a guideline for describing the emergency status, as shown in Table 1 (Salman et al. 2014). For example, if the PC is equal to 75, then the patient is classified as a high-risk patient (red) and thus should be afforded with appropriate medical care. This process is considered a description guideline in addressing patients who are at high risk, require urgent care, sick, in a cold state and normal.

Table 1 Medical classification guideline

PC indicator	
Value	Emergency status
66–100	At high-risk
51–65	Requires urgent care
26–50	Sick
03–25	In a cold state
0–02	Normal

2.3.2 Prioritisation models based on MLAHP and TOPSIS

At this step, the patients' classification according to emergency status is presented in the classification model. The patients are categorised into five triage levels. Each triage level has a corresponding emergency level. MCDM is used to decide which patient is prioritised for each triage level. The integrated MLAHP and TOPSIS prioritises patients according to a set of measurements, as shown in Fig. 3 (Kalid et al. 2018a, b). In this context, prioritisation is achieved on the basis of the MLAHP and TOPSIS models.

The MLAHP model is utilised to distribute weights for each feature in the criterion hierarchy (Khatari et al. 2021; Malik et al. 2021; Mohammed et al. 2021a, b; Sharma et al. 2020). Each main feature is rated in the hierarchy for each patient with CHD involved in the evaluation. By comparison, the MLAHP model is used to obtain ratio scales for each criterion used in the evaluation process (Kalid et al. 2018a, b). At this stage, several steps are performed to assign adequate weights to multi-source criteria by using MLAHP (Prasad et al. 2020). A cardiologist designs and distributes a comparison questionnaire to six experts on heart diseases

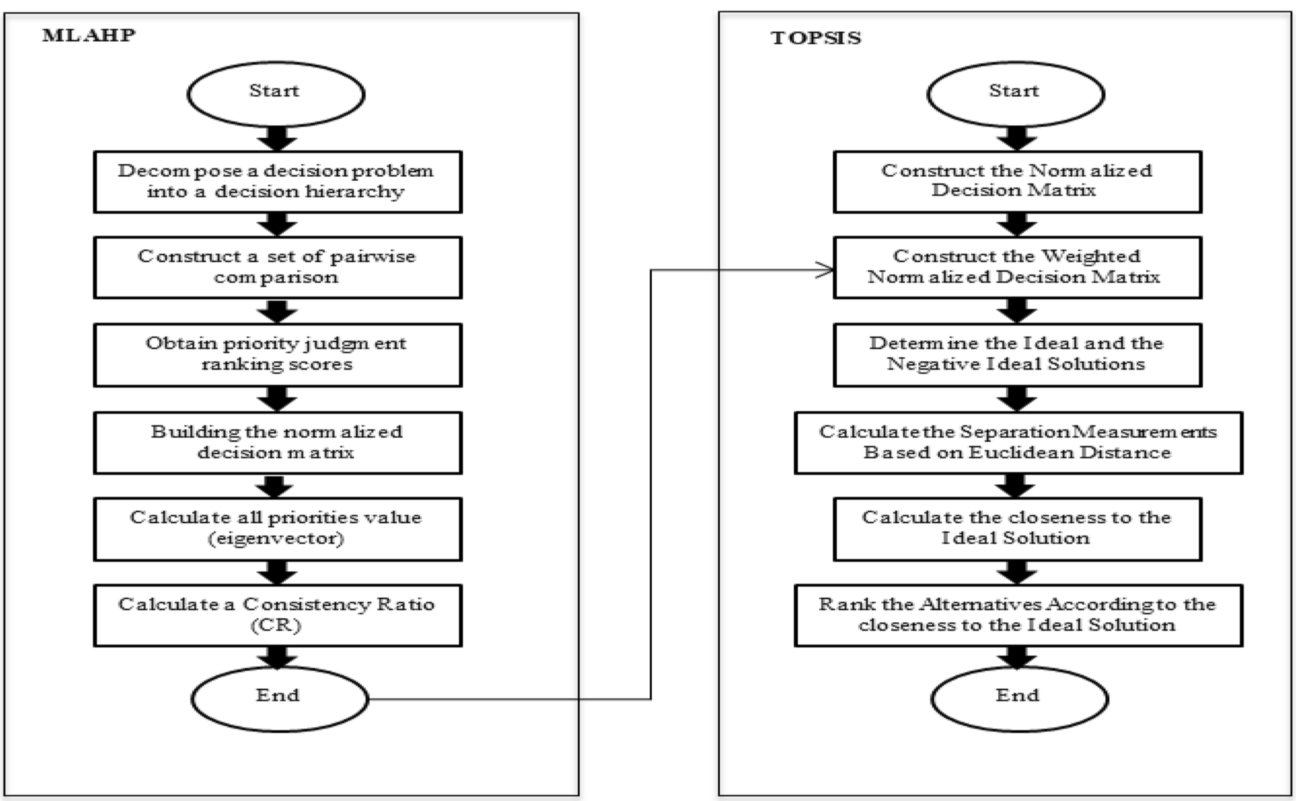

Fig. 3 Integrated MLAHP and TOPSIS model for patient prioritisation (Kalid et al. 2018a, b)

(Kalid et al. 2018a, b). The experts first render their judgement on the basis of four primary criteria and related characteristics, namely, SpO_2, ECG, BP and text (sources), to compare them and demonstrate the relative importance of each criterion (Kalid et al. 2018a, b).

The TOPSIS model is used during this stage (Kalid et al. 2018a, b) to prioritise patients with CHD. TOPSIS can prioritise and rank patients according to emergency status and show them in a queue at each classification level. The overall weights of MLAHP are drawn to address the main weaknesses of TOPSIS, which are its lack of provision for weight generation and inconsistent checks on judgements (Kalid et al. 2018a, b).

The available alternatives are scored in a descending order, and patients requiring the most urgent care are prioritised according to TOPSIS. The aggregate score provides an idea of which patients should be given more urgent attention (Ramasamy et al. 2020). As with other ranking options, relying on people to rank the most urgent case is always possible. On the basis of geometric distance from negative and positive ideal solutions, TOPSIS assigns the rank to each patient at each classification level. According to this technique, patients who require urgent care in emergency settings would have the shortest geometric distance to the ideal positive solution but the longest geometric distance to the ideal negative solution (i.e. have the highest value amongst all patients) (Kalid et al. 2018a, b). The steps of the TOPSIS method (Kalid et al. 2018a, b) are described as follows:

Step 1: Construct the normalised decision matrix

This process attempts to transform the dimensions of various attributes (vital features) into non-dimensional attributes. Step 1 also allows the attributes to be compared (Alaa et al. 2019; Zaidan et al. 2020). The matrix (x_{ij})_(m*n) is normalised from (x_{ij})_(m*n) to the matrix R = $(r_{ij}$)_(m*n) via the normalisation method shown in Eq. (1):

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

This process produces a new matrix R:

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

Step 2: Construct the weighted (scoring points) and normalised decision matrixes

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 decision-maker is accommodated to the normalised decision matrix; the resulting matrix can be calculated by multiplying each column of the normalised decision matrix R with its associated weight w_j (Kalid et al. 2018a, b). The set of the weights is equal to 1, as illustrated in Eq. (3):

$$\sum_{j=1}^{m} w_j = 1. \tag{3}$$

This process produces a new matrix V:

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}. \tag{4}$$

Step 3: Determine the ideal and negative ideal solutions

In this process, two artificial alternatives, namely, A* (ideal alternative) and A − (negative ideal alternative), are defined by Eqs. (5) and (6), respectively:

$$A^* = \left\{ \left(\left(\max_i v_{ij} | j \in J \right), \left(\min_i v_{ij} | j \in J^- \right) | i = 1,2,\dots,m \right) \right\} = \left\{ v_1^*, v_2^*, \dots, v_j^*, \cdots v_n^* \right\}, \tag{5}$$

$$A^- = \left\{ \left(\left(\min_i v_{ij} | j \in J \right), \left(\max_i v_{ij} | j \in J^- \right) | i = 1,2,\dots,m \right) \right\} = \left\{ v_1^-, v_2^-, \dots, v_j^-, \cdots v_n^- \right\}, \tag{6}$$

where J is a subset of{i = 1,2, … , m}, which presents the benefit attribute (i.e. offering an increasing utility with its higher values) and J^{-} is the complement set of$J$. The opposite could be added as well for the cost type attribute as denoted by J^{c}.

Step 4: Calculate the separation measurement by using the Euclidean distance

A separation measurement is performed by calculating the distance between each alternative in V and the ideal vector $A*$ with the Euclidean distance, which is given by Eq. (7) as follows:

$$S_{i^*} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^*\right)^2}, i = (1,2, \cdots m). \tag{7}$$

Similarly, the separation measurement for each alternative in V from the negative ideal A^{-} is given by Eq. (8) as follows:

$$S_{i^-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, \tag{8}$$

where $i = (1,2, \cdots m)$.

At the end of step 4, the values of S_(i*) and S_(i$^-$) for each alternative are counted. These two values represent the distance between each alternative and both the ideal and negative ideal solutions.

Step 5: Calculate the closeness to the ideal solution

The closeness of A_i to the ideal solution A^* is defined in Eq. (9):

$$C_{i^*} = S_{i^-}/\left(S_{i^-} + S_{i^*}\right), 0 < C_{i^*} < 1, i = (1,2, \cdots m), \tag{9}$$

where C_(i*) = 1, if and only if (A_i = A*). Similarly, C_(i*) = 0, if and only if (A_i = A$^-$).

Step 6: Prioritise patients according to their closeness to the ideal solution

The set of patients 〖A〗 _i can now be prioritised in the descending order of 〖C〗 _ (i*). The highest value indicates the optimal performance.

3 Results and discussion

This section presents the results of patient classification and prioritisation. As described in Sect. 2.3, three models were used to develop the classification and prioritisation framework. One of them is related to classification, whereas the two other models are related to prioritisation.

3.1 Results of patient classification

The proposed framework classified patients into different emergency levels as mentioned in Sect. 2.3.1. The output of Dempster–Shafer theory is PC. Table 2 presents the classification results of 500 patients with CHD.

Five rules were applied to classify patients: 66 were high-risk patients, 151 patients required urgent care, 260 patients were sick, 23 patients were in a cold state and no patient was normal. Emergency status was identified and classified. The structure of the classification results is shown in Fig. 4. All patients within each level are then prioritised.

3.2 Results of patient prioritisation

The hybridised MLAHP and TOPSIS decision-making model was used to score and prioritise patients in each level. At this stage, the classification results of 500 patients from Sect. 3.1 were prioritised. In the prioritisation model, the four main clinical data sources and their related features were used in prioritisation. The patients were prioritised on the basis of measurement outcomes from the integrated MLAHP and TOPSIS model.

3.2.1 Measurement results of the MLAHP model

To convert judgements, the MLAHP model performs mathematical calculations of the weights assigned by six experts to the four sources and their related features. The results of MLAHP measurements for the weight preferences of the six experts are listed in Table 3 (Kalid et al. 2018a, b). The overall consistency ratio (CR) was acceptable to all experts.

The weight preferences for each criterion and sub-criterion of the six experts were clearly different. Accordingly, the arithmetic mean for the final weights of the six experts was used to correctly eliminate variations among the weights they assigned to each criterion and sub-criterion. The arithmetic mean was then used in prioritising the patients by the TOPSIS model. The arithmetic means for the six experts are listed in Table 4.

Table 2 Patient classification results

Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level
1	32	Sick	126	64	Requires urgent care	251	56	Requires urgent care	376	50	Sick
2	34	Sick	127	74	Risk	252	58	Requires urgent care	377	48	Sick
3	44	Sick	128	76	Risk	253	50	Sick	378	50	Sick
4	46	Sick	129	44	Sick	254	52	Requires urgent care	379	60	Requires urgent care
5	38	Sick	130	46	Sick	255	62	Requires urgent care	380	62	Requires urgent care
6	40	Sick	131	56	Requires urgent care	256	64	Requires urgent care	381	54	Requires urgent care
7	50	Sick	132	58	Requires urgent care	257	32	Sick	382	56	Requires urgent care
8	52	Requires urgent care	133	50	Sick	258	34	Sick	383	66	Risk
9	50	Sick	134	52	Requires urgent care	259	44	Sick	384	68	Risk
10	52	Requires urgent care	135	62	Requires urgent care	260	46	Sick	385	36	Sick
11	62	Requires urgent care	136	64	Requires urgent care	261	38	Sick	386	38	Sick
12	64	Requires urgent care	137	62	Requires urgent care	262	40	Sick	387	48	Sick
13	56	Requires urgent care	138	64	Requires urgent care	263	50	Sick	388	50	Sick
14	58	Requires urgent care	139	74	Risk	264	52	Requires urgent care	389	42	Sick
15	68	Risk	140	76	Risk	265	50	Sick	390	44	Sick
16	70	Risk	141	68	Risk	266	52	Requires urgent care	391	54	Requires urgent care
17	38	Sick	142	70	Risk	267	62	Requires urgent care	392	56	Requires urgent care
18	40	Sick	143	80	Risk	268	64	Requires urgent care	393	54	Requires urgent care
19	50	Sick	144	82	Risk	269	56	Requires urgent care	394	56	Requires urgent care
20	52	Requires urgent care	145	26	Sick	270	58	Requires urgent care	395	66	Risk
21	44	Sick	146	28	Sick	271	68	Risk	396	68	Risk
22	46	Sick	147	38	Sick	272	70	Risk	397	60	Requires urgent care
23	56	Requires urgent care	148	40	Sick	273	38	Sick	398	62	Requires urgent care
24	58	Requires urgent care	149	32	Sick	274	40	Sick	399	72	Risk
25	56	Requires urgent care	150	34	Sick	275	50	Sick	400	74	Risk
26	58	Requires urgent care	151	44	Sick	276	52	Requires urgent care	401	42	Sick
27	68	Risk	152	46	Sick	277	44	Sick	402	44	Sick
28	70	Risk	153	44	Sick	278	46	Sick	403	54	Requires urgent care
29	62	Requires urgent care	154	46	Sick	279	56	Requires urgent care	404	56	Requires urgent care
30	64	Requires urgent care	155	56	Requires urgent care	280	58	Requires urgent care	405	48	Sick
31	74	Risk	156	58	Requires urgent care	281	56	Requires urgent care	406	50	Sick
32	76	Risk	157	50	Sick	282	58	Requires urgent care	407	60	Requires urgent care
33	26	Sick	158	52	Requires urgent care	283	68	Risk	408	62	Requires urgent care
34	28	Sick	159	62	Requires urgent care	284	70	Risk	409	60	Requires urgent care
35	38	Sick	160	64	Requires urgent care	285	62	Requires urgent care	410	62	Requires urgent care
36	40	Sick	161	32	Sick	286	64	Requires urgent care	411	72	Risk
37	32	Sick	162	34	Sick	287	74	Risk	412	74	Risk

Table 2 (continued)

Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level
38	34	Sick	163	44	Sick	288	76	Risk	413	66	Risk
39	44	Sick	164	46	Sick	289	36	Sick	414	68	Risk
40	46	Sick	165	38	Sick	290	38	Sick	415	78	Risk
41	44	Sick	166	40	Sick	291	48	Sick	416	80	Risk
42	46	Sick	167	50	Sick	292	50	Sick	417	48	Sick
43	56	Requires urgent care	168	52	Requires urgent care	293	42	Sick	418	50	Sick
44	58	Requires urgent care	169	50	Sick	294	44	Sick	419	60	Requires urgent care
45	50	Sick	170	52	Requires urgent care	295	54	Requires urgent care	420	62	Requires urgent care
46	52	Requires urgent care	171	62	Requires urgent care	296	56	Requires urgent care	421	54	Requires urgent care
47	62	Requires urgent care	172	64	Requires urgent care	297	54	Requires urgent care	422	56	Requires urgent care
48	64	Requires urgent care	173	56	Requires urgent care	298	56	Requires urgent care	423	66	Risk
49	32	Sick	174	58	Requires urgent care	299	66	Risk	424	68	Risk
50	34	Sick	175	68	Risk	300	68	Risk	425	66	Risk
51	44	Sick	176	70	Risk	301	60	Requires urgent care	426	68	Risk
52	46	Sick	177	20	In a cold state	302	62	Requires urgent care	427	78	Risk
53	38	Sick	178	22	In a cold state	303	72	Risk	428	80	Risk
54	40	Sick	179	32	Sick	304	74	Risk	429	72	Risk
55	50	Sick	180	34	Sick	305	42	Sick	430	74	Risk
56	52	Requires urgent care	181	26	Sick	306	44	Sick	431	84	Risk
57	50	Sick	182	28	Sick	307	54	Requires urgent care	432	86	Risk
58	52	Requires urgent care	183	38	Sick	308	56	Requires urgent care	433	20	In a cold state
59	62	Requires urgent care	184	40	Sick	309	48	Sick	434	22	In a cold state
60	64	Requires urgent care	185	38	Sick	310	50	Sick	435	32	Sick
61	56	Requires urgent care	186	40	Sick	311	60	Requires urgent care	436	34	Sick
62	58	Requires urgent care	187	50	Sick	312	62	Requires urgent care	437	26	Sick
63	68	Risk	188	52	Requires urgent care	313	60	Requires urgent care	438	28	Sick
64	70	Risk	189	44	Sick	314	62	Requires urgent care	439	38	Sick
65	20	In a cold state	190	46	Sick	315	72	Risk	440	40	Sick
66	22	In a cold state	191	56	Requires urgent care	316	74	Risk	441	38	Sick
67	32	Sick	192	58	Requires urgent care	317	66	Risk	442	40	Sick
68	34	Sick	193	26	Sick	318	68	Risk	443	50	Sick
69	26	Sick	194	28	Sick	319	78	Risk	444	52	Requires urgent care
70	28	Sick	195	38	Sick	320	80	Risk	445	44	Sick
71	38	Sick	196	40	Sick	321	30	Sick	446	46	Sick
72	40	Sick	197	32	Sick	322	32	Sick	447	56	Requires urgent care
73	38	Sick	198	34	Sick	323	42	Sick	448	58	Requires urgent care

Table 2 (continued)

Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level
74	40	Sick	199	44	Sick	324	44	Sick	449	26	Sick
75	50	Sick	200	46	Sick	325	36	Sick	450	28	Sick
76	52	Requires urgent care	201	44	Sick	326	38	Sick	451	38	Sick
77	44	Sick	202	46	Sick	327	48	Sick	452	40	Sick
78	46	Sick	203	56	Requires urgent care	328	50	Sick	453	32	Sick
79	56	Requires urgent care	204	58	Requires urgent care	329	48	Sick	454	34	Sick
80	58	Requires urgent care	205	50	Sick	330	50	Sick	455	44	Sick
81	26	Sick	206	52	Requires urgent care	331	60	Requires urgent care	456	46	Sick
82	28	Sick	207	62	Requires urgent care	332	62	Requires urgent care	457	44	Sick
83	38	Sick	208	64	Requires urgent care	333	54	Requires urgent care	458	46	Sick
84	40	Sick	209	14	In a cold state	334	56	Requires urgent care	459	56	Requires urgent care
85	32	Sick	210	16	In a cold state	335	66	Risk	460	58	Requires urgent care
86	34	Sick	211	26	Sick	336	68	Risk	461	50	Sick
87	44	Sick	212	28	Sick	337	36	Sick	462	52	Requires urgent care
88	46	Sick	213	20	In a cold state	338	38	Sick	463	62	Requires urgent care
89	44	Sick	214	22	In a cold state	339	48	Sick	464	64	Requires urgent care
90	46	Sick	215	32	Sick	340	50	Sick	465	14	In a cold state
91	56	Requires urgent care	216	34	Sick	341	42	Sick	466	16	In a cold state
92	58	Requires urgent care	217	32	Sick	342	44	Sick	467	26	Sick
93	50	Sick	218	34	Sick	343	54	Requires urgent care	468	28	Sick
94	52	Requires urgent care	219	44	Sick	344	56	Requires urgent care	469	20	In a cold state
95	62	Requires urgent care	220	46	Sick	345	54	Requires urgent care	470	22	In a cold state
96	64	Requires urgent care	221	38	Sick	346	56	Requires urgent care	471	32	Sick
97	32	Sick	222	40	Sick	347	66	Risk	472	34	Sick
98	34	Sick	223	50	Sick	348	68	Risk	473	32	Sick
99	44	Sick	224	52	Requires urgent care	349	60	Requires urgent care	474	34	Sick
100	46	Sick	225	20	In a cold state	350	62	Requires urgent care	475	44	Sick
101	38	Sick	226	22	In a cold state	351	72	Risk	476	46	Sick
102	40	Sick	227	32	Sick	352	74	Risk	477	38	Sick
103	50	Sick	228	34	Sick	353	24	In a cold state	478	40	Sick
104	52	Requires urgent care	229	26	Sick	354	26	Sick	479	50	Sick
105	50	Sick	230	28	Sick	355	36	Sick	480	52	Requires urgent care
106	52	Requires urgent care	231	38	Sick	356	38	Sick	481	20	In a cold state
107	62	Requires urgent care	232	40	Sick	357	30	Sick	482	22	In a cold state
108	64	Requires urgent care	233	38	Sick	358	32	Sick	483	32	Sick
109	56	Requires urgent care	234	40	Sick	359	42	Sick	484	34	Sick

Table 2 (continued)

Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level	Patient no.	PC	Triage level
110	58	Requires urgent care	235	50	Sick	360	44	Sick	485	26	Sick
111	68	Risk	236	52	Requires urgent care	361	42	Sick	486	28	Sick
112	70	Risk	237	44	Sick	362	44	Sick	487	38	Sick
113	38	Sick	238	46	Sick	363	54	Requires urgent care	488	40	Sick
114	40	Sick	239	56	Requires urgent care	364	56	Requires urgent care	489	38	Sick
115	50	Sick	240	58	Requires urgent care	365	48	Sick	490	40	Sick
116	52	Requires urgent care	241	26	Sick	366	50	Sick	491	50	Sick
117	44	Sick	242	28	Sick	367	60	Requires urgent care	492	52	Requires urgent care
118	46	Sick	243	38	Sick	368	62	Requires urgent care	493	44	Sick
119	56	Requires urgent care	244	40	Sick	369	30	Sick	494	46	Sick
120	58	Requires urgent care	245	32	Sick	370	32	Sick	495	56	Requires urgent care
121	56	Requires urgent care	246	34	Sick	371	42	Sick	496	58	Requires urgent care
122	58	Requires urgent care	247	44	Sick	372	44	Sick	497	8	In a cold state
123	68	Risk	248	46	Sick	373	36	Sick	498	10	In a cold state
124	70	Risk	249	44	Sick	374	38	Sick	499	20	In a cold state
125	62	Requires urgent care	250	46	Sick	375	48	Sick	500	22	In a cold state

3.2.2 Measurement results of the TOPSIS model

In the second stage of prioritisation, the TOPSIS model was used to prioritise the available patients at each level. The final weights of each criterion and sub-criterion are presented in Table 4. The final weights were used in prioritising the patients. Each patient was ranked according to these weights. The prioritisation results for all patients within each level are summarised in Tables 5, 6, 7 and 8 for patients who are at high risk (n = 66), require urgent care (n = 151), sick (n = 260) and in cold state (n = 23 patients), respectively.

Each table presents the sequence of each patient in the dataset, the classification level for each patient, the prioritisation score according to the TOPSIS model and their order from the highest to the lowest values. A high value indicates that the patient should be prioritised.

4 Validation and evaluation

The proposed framework was validated and evaluated in this section. The validation process is presented in Sect. 4.1. The optimisation results were objectively validated on the basis of different features. The process by which the proposed framework was evaluated based on scenarios and checklist benchmarking is illustrated in Sect. 4.2.

4.1 Validation

The results were objectively validated. Data are expressed as mean ± standard deviation to ensure systematic ranking of patient prioritisation, which are calculated using Eqs. (10) and (11):

$$\text{Mean} = \frac{1}{n}\sum_{i=1}^{n} x_i. \tag{10}$$

$$\text{Standard Deviation} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2} \tag{11}$$

The prioritised patients were divided into three groups for each classification level to validate the prioritisation results. The patient's number within each group varies from one group to another, and the number of groups or patients within each group does not affect the validation results (Albahri et al. 2020a, b; Almahdi et al. 2019; Alsalem et al. 2019; Mohammed et al. 2020a). Validation was conducted using a statistical platform based on the two methods (Salih et al. 2021). The mean ± standard deviation for each data row was measured for each group after normalisation and weighing, and the first group obtained the highest score. Assuming

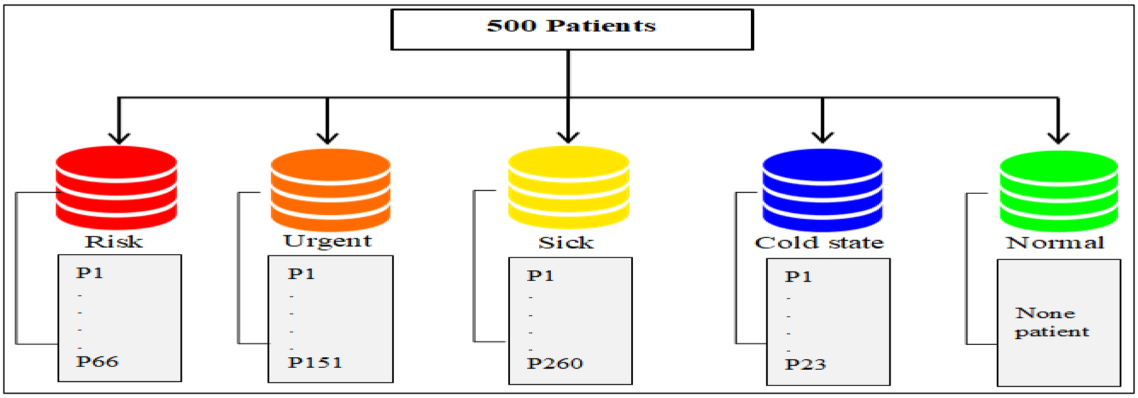

Fig. 4 Results of classification process

that the first group has the highest mean ± standard deviation, a comparison with the two other groups is considered to validate the result. The mean ± standard deviation of the second group must be lower than or equal to that of the first group. Lastly, the mean ± standard deviation of the third group must be lower than that of the first and second groups or equal to that of the second group. On the basis of the results of systematic ranking, the first group should be statistically proved to be the highest group among all groups. The results of the statistical analyses of the three groups of prioritised patients within each triage level are summarised in Table 9.

The three groups were compared, and results revealed that the first group was the best and highest group, followed by the second group. Thus, the proposed framework that prioritised patients within each triage level tho underwent systematic ranking was valid. In conclusion, the prioritisation of patients in need of urgent care underwent systematic ranking.

4.2 Evaluation

Patients outside ED have been classified and prioritised to target other types of patients. Providing scenarios which represent all the environments and circumstances which may arise during patient prioritisation is important. Each scenario reflects certain issues which must be identified and addressed in classification and prioritisation. These issues were considered as comparison points for the proposed framework with the most relevant existing classification and prioritisation frameworks in checklist benchmarking. Comparisons were made on the basis of whether or not the comparative methods addressed the issues for each scenario as in previous studies (Abdulkareem et al. 2020; Ibrahim et al. 2019). Evaluation is illustrated in this section to determine the performance of the proposed framework. The proposed framework was compared with the most relevant frameworks in this area according to specific issues. Two scenarios are presented to determine the comparison points and issues in checklist benchmarking.

In scenario 1 (classification scenario), numerous patients are assumed, which is expected during disasters and accidents. The patients are classified according to emergency or classification level. Patients who may be very sick (high-risk patients) are assumed to be immediately attended to, but they may probably die even with intensive care. As a result, the other less sick patients (i.e. in urgent need to medical attention, sick, in a cold state and normal) will not receive immediate care, which may exacerbate their condition and lead to their death. Triage results in the best outcome for the greatest number of people when classification is performed properly. After the patients are classified, they are prioritised as urgent in each classification level. The record of each patient must be sent immediately to the hospital server for remote service and treatment. Therefore, the scalability issue and the ability to handle large amounts of data must be supported.

The second scenario (i.e. prioritisation scenario) has three sub-scenarios. In the first sub-scenario, numerous patients are present because of several situations, namely, population ageing, disasters and MCIs, in a specific area. In one perspective, this area has a large population of elderly patients who are remotely monitored by their providers. In another perspective, these remote patients are critically affected by MCIs and disasters (Wyte-Lake et al. 2016). The server of a hospital or a healthcare agency which monitors these patients must assess the situation and prioritise them according to the urgency of their medical condition. Therefore, prioritisation should support multi-criteria ranking considering the scalability issue and the ability to handle large amounts of data. Furthermore, the targeted tier and the environment where prioritisation is executed must be identified to prioritise patients from the most to the least urgent case to provide appropriate services and treatments. In the

Table 3 Measurements of weights calculated for the six experts

Criteria	Weights	Sub-criteria	Weights	Criteria	Weights	Sub-criteria	Weights
1st Expert				***4th Expert***			
ECG	0.485	ST	0.296	ECG	0.546	ST	0.274
		Rhy	0.030			Rhy	0.136
		QRS	0.030			QRS	0.100
		PtoP	0.129			PtoP	0.037
Text	0.086	CP	0.039	Text	0.061	CP	0.028
		SOB	0.014			SOB	0.010
		PAL	0.028			PAL	0.020
		PIR	0.004			PIR	0.003
BP	0.289			BP	0.268		
SPO2	0.140			SPO2	0.125		
CR>0.1				CR>0.1			
2nd Expert				***5th Expert***			
ECG	0.355	ST	0.065	ECG	0.455	ST	0.275
		Rhy	0.024			Rhy	0.078
		QRS	0.136			QRS	0.074
		PtoP	0.130			PtoP	0.028
Text	0.067	CP	0.006	Text	0.069	CP	0.008
		SOB	0.008			SOB	0.009
		PAL	0.016			PAL	0.023
		PIR	0.037			PIR	0.028
BP	0.312			BP	0.306		
SPO2	0.266			SPO2	0.170		
CR>0.1				CR>0.1			
3rd Expert				***6th Expert***			
ECG	0.524	ST	0.345	ECG	0.388	ST	0.142
		Rhy	0.026			Rhy	0.146
		QRS	0.067			QRS	0.059
		PtoP	0.087			PtoP	0.041
Text	0.062	CP	0.008	Text	0.084	CP	0.011
		SOB	0.039			SOB	0.053
		PAL	0.012			PAL	0.017
		PIR	0.003			PIR	0.004
BP	0.227			BP	0.328		
SPO2	0.187			SPO2	0.200		
CR > 0.1				CR > 0.1			

Table 4 Final AHP weight for the arithmetic mean of six experts for each criterion

Criteria	Final weights
ST segment	0.232833
Rhythm	0.073333
QRS width	0.077667
P-to-P distance	0.075333
Chest pain	0.016667
Shortness of breath	0.022167
Palpitation	0.019333
Patient in rest	0.013167
Blood pressure	0.288333
SpO2	0.181333

second sub-scenario, two or more patients at home must be prioritised with a slight difference in their healthcare emergency conditions. In this case, healthcare providers face the problem of recognising slight differences between the patients in terms of certain vital signs, regardless of the time needed to prioritise their patients. Traditional classification and prioritisation methods allocate such patients within the same scale or category (Claudio et al. 2014). Therefore, in prioritisation, the smallest difference between two patient records should be considered, and the accuracy of prioritisation must be improved. Thus, the order by which patients are attended to must be provided via supporting feature-weighting methods and multi-criteria rankings. In the third sub-scenario, two patients have different emergency conditions and send their requests to the server side at different

Table 5 Results of prioritising high-risk patients

Data set	Classification level	Prioritisation score	Rank	Data set	Classification level	Prioritisation score	Rank
15	Risk-patient	0.505162394	56	316	Risk-patient	0.512507271	35
16	Risk-patient	0.504641505	58	317	Risk-patient	0.515494474	20
27	Risk-patient	0.51397321	27	318	Risk-patient	0.512340136	38
28	Risk-patient	0.510286618	44	319	Risk-patient	0.513696085	30
31	Risk-patient	0.511625401	40	320	Risk-patient	0.511362936	41
32	Risk-patient	0.50934094	48	335	Risk-patient	0.505624039	55
63	Risk-patient	0.507695501	52	336	Risk-patient	0.505062112	57
64	Risk-patient	0.506406403	54	347	Risk-patient	0.512519157	34
111	Risk-patient	0.499718506	65	348	Risk-patient	0.509858034	46
112	Risk-patient	0.500706713	63	351	Risk-patient	0.510925319	43
123	Risk-patient	0.514763403	25	352	Risk-patient	0.509115768	49
124	Risk-patient	0.511134913	42	383	Risk-patient	0.499391188	66
127	Risk-patient	0.512426877	37	384	Risk-patient	0.500386943	64
128	Risk-patient	0.510091476	45	395	Risk-patient	0.504252682	61
139	Risk-patient	0.518348026	12	396	Risk-patient	0.504006925	62
140	Risk-patient	0.513926515	28	399	Risk-patient	0.504555447	59
141	Risk-patient	0.517735243	14	400	Risk-patient	0.504282834	60
142	Risk-patient	0.513682304	31	411	Risk-patient	0.516308906	17
143	Risk-patient	0.515345825	21	412	Risk-patient	0.513033674	32
144	Risk-patient	0.512444056	36	413	Risk-patient	0.515910286	18
175	Risk-patient	0.531949284	3	414	Risk-patient	0.512857127	33
176	Risk-patient	0.529971241	7	415	Risk-patient	0.514174308	26
271	Risk-patient	0.531727597	4	416	Risk-patient	0.511870419	39
272	Risk-patient	0.529800068	8	423	Risk-patient	0.518200884	13
283	Risk-patient	0.533525123	1	424	Risk-patient	0.5148499	24
284	Risk-patient	0.531403092	5	425	Risk-patient	0.521982836	9
287	Risk-patient	0.532043621	2	426	Risk-patient	0.516832089	15
288	Risk-patient	0.530126411	6	427	Risk-patient	0.518867723	10
299	Risk-patient	0.509820416	47	428	Risk-patient	0.515175499	22
300	Risk-patient	0.508007065	51	429	Risk-patient	0.518378424	11
303	Risk-patient	0.508890826	50	430	Risk-patient	0.514931636	23
304	Risk-patient	0.50760469	53	431	Risk-patient	0.516384532	16
315	Risk-patient	0.515907824	19	432	Risk-patient	0.513748621	29

Table 6 Results of prioritising patients who require urgent care

Data set	Classification level	Prioritisation score	Rank	Data set	Classification level	Prioritisation score	Rank
8	Urgent-patient	0.411667029	103	174	Urgent-patient	0.764342188	15
10	Urgent-patient	0.410212149	108	188	Urgent-patient	0.627113764	40
11	Urgent-patient	0.41061802	107	191	Urgent-patient	0.628073691	39
12	Urgent-patient	0.410999462	105	192	Urgent-patient	0.628553985	38
13	Urgent-patient	0.410976513	106	203	Urgent-patient	0.72350412	24
14	Urgent-patient	0.411357665	104	204	Urgent-patient	0.724293465	23
20	Urgent-patient	0.451795847	88	206	Urgent-patient	0.725038286	22
23	Urgent-patient	0.452577207	84	207	Urgent-patient	0.725884386	21
24	Urgent-patient	0.452967048	81	208	Urgent-patient	0.726683684	20
25	Urgent-patient	0.451088281	90	224	Urgent-patient	0.484217756	64
26	Urgent-patient	0.451478789	89	236	Urgent-patient	0.528813343	52
29	Urgent-patient	0.452260434	86	239	Urgent-patient	0.529581404	51
30	Urgent-patient	0.452650415	83	240	Urgent-patient	0.52996502	50
43	Urgent-patient	0.340469322	126	251	Urgent-patient	0.570315305	49
44	Urgent-patient	0.341002561	123	252	Urgent-patient	0.57068343	48
46	Urgent-patient	0.341502743	121	254	Urgent-patient	0.571029608	47
47	Urgent-patient	0.342067451	120	255	Urgent-patient	0.571421463	46
48	Urgent-patient	0.342597539	119	256	Urgent-patient	0.571790279	45
56	Urgent-patient	0.389935163	109	264	Urgent-patient	0.793055866	8
58	Urgent-patient	0.388000415	114	266	Urgent-patient	0.788971951	13
59	Urgent-patient	0.388540547	113	267	Urgent-patient	0.790098316	12
60	Urgent-patient	0.389047891	111	268	Urgent-patient	0.791165904	10
61	Urgent-patient	0.389017375	112	269	Urgent-patient	0.791101424	11
62	Urgent-patient	0.389524085	110	270	Urgent-patient	0.792176566	9
76	Urgent-patient	0.051943529	151	276	Urgent-patient	0.834585767	5
79	Urgent-patient	0.062217894	150	279	Urgent-patient	0.837253363	3
80	Urgent-patient	0.066667194	149	280	Urgent-patient	0.838608552	1
91	Urgent-patient	0.186005937	144	281	Urgent-patient	0.832223512	7
92	Urgent-patient	0.187218736	143	282	Urgent-patient	0.833521142	6
94	Urgent-patient	0.188348298	142	285	Urgent-patient	0.836164208	4
95	Urgent-patient	0.189614422	141	286	Urgent-patient	0.837506594	2
96	Urgent-patient	0.190794278	140	295	Urgent-patient	0.43007582	93
104	Urgent-patient	0.316394702	130	296	Urgent-patient	0.430443479	91
106	Urgent-patient	0.314416281	135	297	Urgent-patient	0.428671041	96
107	Urgent-patient	0.31496929	134	298	Urgent-patient	0.429039567	95
108	Urgent-patient	0.315488246	132	301	Urgent-patient	0.429777026	94
109	Urgent-patient	0.315457045	133	302	Urgent-patient	0.430144867	92
110	Urgent-patient	0.315974913	131	307	Urgent-patient	0.470826326	75
116	Urgent-patient	0.452726533	82	308	Urgent-patient	0.471209729	73
119	Urgent-patient	0.453538667	79	311	Urgent-patient	0.47197737	72
120	Urgent-patient	0.453943856	77	312	Urgent-patient	0.472360473	70
121	Urgent-patient	0.451991089	87	313	Urgent-patient	0.470514834	76
122	Urgent-patient	0.452396985	85	314	Urgent-patient	0.47089832	74
125	Urgent-patient	0.453209419	80	331	Urgent-patient	0.36608267	118
126	Urgent-patient	0.453614757	78	332	Urgent-patient	0.366570975	116
131	Urgent-patient	0.499058717	62	333	Urgent-patient	0.366541607	117
132	Urgent-patient	0.499405597	60	334	Urgent-patient	0.367029209	115
134	Urgent-patient	0.499731598	59	343	Urgent-patient	0.414116269	99
135	Urgent-patient	0.500100383	58	344	Urgent-patient	0.414594219	97
136	Urgent-patient	0.50044726	57	345	Urgent-patient	0.412288464	102

Table 6 (continued)

Data set	Classification level	Prioritisation score	Rank	Data set	Classification level	Prioritisation score	Rank
137	Urgent-patient	0.498776964	63	346	Urgent-patient	0.412768216	101
138	Urgent-patient	0.499123846	61	349	Urgent-patient	0.413727712	100
155	Urgent-patient	0.659923348	37	350	Urgent-patient	0.414206042	98
156	Urgent-patient	0.660393273	36	363	Urgent-patient	0.164170186	148
158	Urgent-patient	0.660835674	35	364	Urgent-patient	0.165493452	147
159	Urgent-patient	0.661337026	34	367	Urgent-patient	0.168099854	146
160	Urgent-patient	0.661809464	32	368	Urgent-patient	0.169379947	145
168	Urgent-patient	0.765044249	14	379	Urgent-patient	0.236733056	139
170	Urgent-patient	0.761772896	19	380	Urgent-patient	0.237587487	137
171	Urgent-patient	0.762677839	18	381	Urgent-patient	0.23753619	138
172	Urgent-patient	0.763533682	16	382	Urgent-patient	0.238386395	136
173	Urgent-patient	0.763482043	17	391	Urgent-patient	0.340575351	125
392	Urgent-patient	0.341043579	122	422	Urgent-patient	0.517175318	53
393	Urgent-patient	0.338781382	129	444	Urgent-patient	0.619800519	43
394	Urgent-patient	0.339252767	128	447	Urgent-patient	0.620625646	42
397	Urgent-patient	0.340194432	127	448	Urgent-patient	0.621038324	41
398	Urgent-patient	0.340663326	124	459	Urgent-patient	0.697274147	29
403	Urgent-patient	0.472504762	69	460	Urgent-patient	0.697875369	28
404	Urgent-patient	0.472903239	67	462	Urgent-patient	0.698441931	27
407	Urgent-patient	0.473701067	66	463	Urgent-patient	0.699084643	26
408	Urgent-patient	0.474099238	65	464	Urgent-patient	0.699690931	25
409	Urgent-patient	0.472181025	71	480	Urgent-patient	0.586514649	44
410	Urgent-patient	0.472579586	68	492	Urgent-patient	0.661388028	33
419	Urgent-patient	0.516500147	56	495	Urgent-patient	0.662584369	31
420	Urgent-patient	0.516848183	54	496	Urgent-patient	0.663183696	30
421	Urgent-patient	0.516827235	55				

times. The patient who has a less urgent situation sends the request first. The urgent situation should be prioritised first over the other less urgent situations. In addition, FCFS cannot serve patients in such a situation and may jeopardise the lives of patients. Moreover, FCFS cannot be used in reality (Claudio and Okudan 2010; Tan 2013). Therefore, methods for prioritising patients should consider all the conditions of all patients via feature-weighting methods.

The scenarios and related issues identified herein are regarded as comparison points in checklist benchmarking. The descriptions of each checklist comparison point are as follows:

- **Support vital signs:** This point emphasises that vital signs are used in classification and prioritisation. Vital signs are important in evaluating a patient's condition (Sakanushi et al. 2013; Salman et al. 2014).
- **Support chief complaint:** This point considers the main complaints and uses them in patient classification and prioritisation because remote healthcare monitoring requires non-sensory data (Salman et al. 2014).
- **Targeted tier:** This point identifies the level of classification and prioritisation. Three levels of architecture are available for remote healthcare monitoring and telemedicine, namely, sensors (Tier 1), base station (Tier 2) and remote server (Tier 3) (Claudio et al. 2014; Salman et al. 2014).
- **Remote environment:** This point indicates whether or not classification and prioritisation are performed in a remote environment. Prioritisation is important for the continuous care of remote patients in a pervasive environment (Sarkar and Sinha 2014). The overwhelming heterogeneity of patient data in remote environments causes problems in classification and prioritisation.

Table 7 Results of prioritising sick patients

Data set	Classification level	Prioritisation score	Rank	Data set	Classification level	Prioritisation score	Rank
1	Sick-patient	0.442635567	168	78	Sick-patient	0.070214283	250
2	Sick-patient	0.443083349	166	81	Sick-patient	0.218634983	238
3	Sick-patient	0.443785656	164	82	Sick-patient	0.219880869	237
4	Sick-patient	0.444232742	159	83	Sick-patient	0.221815812	236
5	Sick-patient	0.443925843	161	84	Sick-patient	0.223035727	233
6	Sick-patient	0.444372846	157	85	Sick-patient	0.222199306	234
7	Sick-patient	0.445073944	155	86	Sick-patient	0.223416151	231
9	Sick-patient	0.443844404	162	87	Sick-patient	0.226499168	228
17	Sick-patient	0.507770105	130	88	Sick-patient	0.226499168	228
18	Sick-patient	0.508263632	129	89	Sick-patient	0.221976631	235
19	Sick-patient	0.509038387	128	90	Sick-patient	0.223195257	232
21	Sick-patient	0.50919314	127	93	Sick-patient	0.225463922	230
22	Sick-patient	0.509686813	126	97	Sick-patient	0.368251123	216
33	Sick-patient	0.368772819	215	98	Sick-patient	0.368779918	213
34	Sick-patient	0.369390238	212	99	Sick-patient	0.369608197	211
35	Sick-patient	0.370357004	206	100	Sick-patient	0.370134788	208
36	Sick-patient	0.370971434	203	101	Sick-patient	0.369773371	209
37	Sick-patient	0.370549748	204	102	Sick-patient	0.370299696	207
38	Sick-patient	0.371163817	200	103	Sick-patient	0.37112413	201
39	Sick-patient	0.372125381	199	105	Sick-patient	0.369677423	210
40	Sick-patient	0.372736533	197	113	Sick-patient	0.368251123	216
41	Sick-patient	0.370437786	205	114	Sick-patient	0.368779918	213
42	Sick-patient	0.371052065	202	115	Sick-patient	0.526917317	121
45	Sick-patient	0.372205731	198	117	Sick-patient	0.527076598	120
49	Sick-patient	0.442157957	169	118	Sick-patient	0.527584793	119
50	Sick-patient	0.44277324	167	129	Sick-patient	0.525612335	125
51	Sick-patient	0.443737969	165	130	Sick-patient	0.526120055	124
52	Sick-patient	0.444351935	158	133	Sick-patient	0.57294739	79
53	Sick-patient	0.443930498	160	145	Sick-patient	0.607907435	65
54	Sick-patient	0.444544306	156	146	Sick-patient	0.608402449	64
55	Sick-patient	0.445506758	154	147	Sick-patient	0.609180712	63
57	Sick-patient	0.443818653	163	148	Sick-patient	0.609677354	60
67	Sick-patient	0.044976873	260	149	Sick-patient	0.609336337	61
68	Sick-patient	0.052609946	257	150	Sick-patient	0.609833179	58
69	Sick-patient	0.047521026	258	151	Sick-patient	0.610614337	57
70	Sick-patient	0.054754694	255	152	Sick-patient	0.611112839	55
71	Sick-patient	0.064274332	253	153	Sick-patient	0.609245918	62
72	Sick-patient	0.069555579	251	154	Sick-patient	0.609742644	59
73	Sick-patient	0.046062416	259	157	Sick-patient	0.610679787	56
74	Sick-patient	0.053520792	256	161	Sick-patient	0.73160075	21
75	Sick-patient	0.063255624	254	162	Sick-patient	0.73252926	20
77	Sick-patient	0.064997401	252	163	Sick-patient	0.733996203	19
164	Sick-patient	0.734936947	16	261	Sick-patient	0.781675195	9
165	Sick-patient	0.734290599	17	262	Sick-patient	0.782961193	7
166	Sick-patient	0.735232867	15	263	Sick-patient	0.785002584	6
167	Sick-patient	0.736721809	14	265	Sick-patient	0.781442175	10
169	Sick-patient	0.73411951	18	273	Sick-patient	0.830149297	5
179	Sick-patient	0.56649952	90	274	Sick-patient	0.831734156	4
180	Sick-patient	0.567030775	87	275	Sick-patient	0.834265361	3
181	Sick-patient	0.566666016	88	277	Sick-patient	0.834777496	2

Table 7 (continued)

Data set	Classification level	Prioritisation score	Rank	Data set	Classification level	Prioritisation score	Rank
182	Sick-patient	0.567197413	85	278	Sick-patient	0.836426316	1
183	Sick-patient	0.568032428	83	289	Sick-patient	0.459260516	153
184	Sick-patient	0.568564997	81	290	Sick-patient	0.459699688	152
185	Sick-patient	0.566569284	89	291	Sick-patient	0.460388653	151
186	Sick-patient	0.567100598	86	292	Sick-patient	0.460827351	149
187	Sick-patient	0.567935482	84	293	Sick-patient	0.460526202	150
189	Sick-patient	0.568102364	82	294	Sick-patient	0.460964843	148
190	Sick-patient	0.568634994	80	305	Sick-patient	0.526334497	123
193	Sick-patient	0.684330253	43	306	Sick-patient	0.526831841	122
194	Sick-patient	0.685214997	42	309	Sick-patient	0.527768838	118
195	Sick-patient	0.68661059	41	310	Sick-patient	0.528266649	117
196	Sick-patient	0.687504149	38	321	Sick-patient	0.391198321	190
197	Sick-patient	0.686890341	39	322	Sick-patient	0.39177784	189
198	Sick-patient	0.687784994	36	323	Sick-patient	0.392685742	188
199	Sick-patient	0.689196394	34	324	Sick-patient	0.393263067	185
200	Sick-patient	0.690100187	31	325	Sick-patient	0.392866821	186
201	Sick-patient	0.686727776	40	326	Sick-patient	0.393443881	183
202	Sick-patient	0.687621794	37	327	Sick-patient	0.394347965	182
205	Sick-patient	0.689314917	33	328	Sick-patient	0.394922882	181
211	Sick-patient	0.407798759	180	329	Sick-patient	0.392761632	187
212	Sick-patient	0.408275114	178	330	Sick-patient	0.393338846	184
215	Sick-patient	0.409170813	175	337	Sick-patient	0.46492705	147
216	Sick-patient	0.409645752	172	338	Sick-patient	0.465527058	146
217	Sick-patient	0.407861365	179	339	Sick-patient	0.466468255	145
218	Sick-patient	0.408337654	177	340	Sick-patient	0.46706751	143
219	Sick-patient	0.409084261	176	341	Sick-patient	0.466656148	144
220	Sick-patient	0.40955929	173	342	Sick-patient	0.467255314	142
221	Sick-patient	0.409233232	174	354	Sick-patient	0.156252997	249
222	Sick-patient	0.409708108	171	355	Sick-patient	0.15899875	248
223	Sick-patient	0.410452517	170	356	Sick-patient	0.160713917	245
227	Sick-patient	0.470387913	141	357	Sick-patient	0.159539232	246
228	Sick-patient	0.470886185	138	358	Sick-patient	0.161246345	243
229	Sick-patient	0.470544137	139	359	Sick-patient	0.163875723	242
230	Sick-patient	0.471042354	136	360	Sick-patient	0.165520305	240
231	Sick-patient	0.471824028	134	361	Sick-patient	0.159225549	247
232	Sick-patient	0.472321808	132	362	Sick-patient	0.160937329	244
233	Sick-patient	0.47045338	140	365	Sick-patient	0.164093096	241
234	Sick-patient	0.470951629	137	366	Sick-patient	0.165734639	239
235	Sick-patient	0.471733351	135	369	Sick-patient	0.259717949	227
237	Sick-patient	0.471889429	133	370	Sick-patient	0.260686917	226
238	Sick-patient	0.472387188	131	371	Sick-patient	0.262197331	225
241	Sick-patient	0.536726159	116	372	Sick-patient	0.26315302	222
242	Sick-patient	0.537163876	115	373	Sick-patient	0.262497479	223
243	Sick-patient	0.537851279	114	374	Sick-patient	0.263451584	220
244	Sick-patient	0.538289439	111	375	Sick-patient	0.264939108	219
245	Sick-patient	0.53798862	112	376	Sick-patient	0.26588049	218
246	Sick-patient	0.538426836	109	377	Sick-patient	0.262323167	224
247	Sick-patient	0.539115032	108	378	Sick-patient	0.263278191	221
248	Sick-patient	0.539553706	105	385	Sick-patient	0.387537423	196
249	Sick-patient	0.537908829	113	386	Sick-patient	0.388037702	195

Table 7 (continued)

Data set	Classification level	Prioritisation score	Rank	Data set	Classification level	Prioritisation score	Rank
250	Sick-patient	0.538347012	110	387	Sick-patient	0.388821626	194
253	Sick-patient	0.539172649	107	388	Sick-patient	0.389320213	192
257	Sick-patient	0.778028338	13	389	Sick-patient	0.388978	193
258	Sick-patient	0.779283219	12	390	Sick-patient	0.389476383	191
259	Sick-patient	0.781274324	11	401	Sick-patient	0.544789619	94
260	Sick-patient	0.782556839	8	402	Sick-patient	0.545305679	93
405	Sick-patient	0.546278276	92	458	Sick-patient	0.691475391	26
406	Sick-patient	0.546795179	91	461	Sick-patient	0.692910837	23
417	Sick-patient	0.589073842	67	467	Sick-patient	0.539518507	106
418	Sick-patient	0.589547483	66	468	Sick-patient	0.540031812	103
435	Sick-patient	0.584248235	78	471	Sick-patient	0.540999121	100
436	Sick-patient	0.584717174	75	472	Sick-patient	0.541513164	97
437	Sick-patient	0.584395197	76	473	Sick-patient	0.539585925	104
438	Sick-patient	0.584864275	73	474	Sick-patient	0.540099263	102
439	Sick-patient	0.585601454	71	475	Sick-patient	0.540905528	101
440	Sick-patient	0.586071681	69	476	Sick-patient	0.541419524	98
441	Sick-patient	0.584309813	77	477	Sick-patient	0.541066635	99
442	Sick-patient	0.58477881	74	478	Sick-patient	0.541580712	96
443	Sick-patient	0.585515862	72	479	Sick-patient	0.542388159	95
445	Sick-patient	0.585663201	70	483	Sick-patient	0.644273216	54
446	Sick-patient	0.586133487	68	484	Sick-patient	0.64503116	51
449	Sick-patient	0.688680719	35	485	Sick-patient	0.644510617	52
450	Sick-patient	0.689432426	32	486	Sick-patient	0.645269174	49
451	Sick-patient	0.690617397	30	487	Sick-patient	0.646463811	47
452	Sick-patient	0.691375597	27	488	Sick-patient	0.647227468	45
453	Sick-patient	0.690854812	28	489	Sick-patient	0.644372674	53
454	Sick-patient	0.691613817	25	490	Sick-patient	0.645130875	50
455	Sick-patient	0.6928104	24	491	Sick-patient	0.646324945	48
456	Sick-patient	0.6935761	22	493	Sick-patient	0.646564016	46
457	Sick-patient	0.690716854	29	494	Sick-patient	0.647327937	44

- **Prioritisation in terms of category/order:** This type of prioritisation shows whether or not categories or order methods support prioritisation. The categorisation method classifies and prioritises patients according to prioritisation level. Simultaneously, the order method classifies patients according to their emergencies. Most triage systems classify patients as prioritises, and patient order is usually determined according to the FCFS principle (Claudio et al. 2014).
- **Feature weighting:** This point shows the weighing technique used. A server which scores a patient can provide more weight to the vital features over other features of less interest. In addition, the experts' judgements and preferences are important in extracting the weights of vital signs (Abbasgholizadeh Rahimi et al. 2015; Claudio and Okudan 2009).
- **Multi-criteria ranking:** This point shows whether or not a study deals with multiple criteria during prioritisation. Patient prioritisation is a complex problem in decision making (Ashour and Okudan 2010; Claudio and Okudan 2009; Göransson et al. 2008; Seising and Tabacchi 2013), and the decision is made based on a set of attributes (Faulin et al. 2012).
- **Handling large amounts of data:** This point involves the handling of large numbers of patients with overwhelming data from multiple sources. Supporting large amounts of data is important because an overwhelming amount of data can be used to decide which patient should receive care first difficult (Sarkar and Sinha 2014).
- **Patient prioritisation accuracy:** This point represents the accuracy of patient prioritisation. In the exact ranking of patients, prioritisation accuracy is reflected in the

Table 8 Results of prioritising patients in a cold state

Data set	Classification level	Prioritisation score	Rank
65	Cold-state-patient	0.023076003	22
66	Cold-state-patient	0.023076003	23
177	Cold-state-patient	0.518388248	6
178	Cold-state-patient	0.518731832	5
209	Cold-state-patient	0.303574286	16
210	Cold-state-patient	0.304013173	15
213	Cold-state-patient	0.307278397	14
214	Cold-state-patient	0.307709983	13
225	Cold-state-patient	0.488475776	12
226	Cold-state-patient	0.488755033	11
353	Cold-state-patient	0.115759468	21
433	Cold-state-patient	0.558357267	4
434	Cold-state-patient	0.558647752	3
465	Cold-state-patient	0.49492351	10
466	Cold-state-patient	0.495265776	9
469	Cold-state-patient	0.497833365	8
470	Cold-state-patient	0.498175548	7
481	Cold-state-patient	0.72959153	2
482	Cold-state-patient	0.730228325	1
497	Cold-state-patient	0.271053864	20
498	Cold-state-patient	0.271569388	19
499	Cold-state-patient	0.277616203	18
500	Cold-state-patient	0.278114256	17

urgency of the situation with regard to the medical condition of patients. Accuracy also reflects the recognition of slight differences among patients during an urgent situation.

After recognising and defining the comparative checklist issues, the classification and prioritisation framework proposed herein was compared with those from other relevant studies. Each scenario had a 50% value divided by issues identified from each scenario. In the first scenario, six issues were identified, and the score for each issue was 8.33. In the second scenario, 10 issues were identified, and the score for each issue was 5. The comparison of checklist issues between the proposed work and those of benchmark studies is presented in Table 10.

The scenarios covered were investigated by addressing the comparison points of each scenario to compare the proposed and benchmark frameworks. With regard to the first scenario, all issues had already been covered by the benchmark studies (Albahri et al. 2019a, b) and the proposed framework. The issues covered by Salman et al. (2014) include targeted tier, scalability, remote environment and patient classification. The issue of handling large amounts of data for classification was not covered by Salman et al. (2014). Moreover, all issues of this scenario were not covered by previous prioritisation benchmark studies (Kalid et al. 2018a, b; Salman et al. 2017). Thus, the score for the first scenario of the proposed framework and benchmark studies (Albahri et al. 2019a, b) is 50%. The score for the benchmark of Salman et al. (2014) is 41.67%. The scores of both benchmark studies of Kalid et al. (2018a, b) and Salman et al. (2017) are 0%.

With regard to the second scenario, all issues were covered by the proposed framework and earlier benchmark prioritisation frameworks (Kalid et al. 2018a, b; Salman et al. 2017). In these three approaches [i.e. the proposed work and that of (Kalid et al. 2018a, b; Salman et al. 2017)], the prioritisation process performed is in Tier 3 (server), and each patient is compared with the other patients in the server. The MLAHP technique is used to determine the importance of each source and feature relative to other sources and features. Afterwards, pairwise comparisons are performed on the experts' judgements to assign a fixed weight for each feature. The judgements of six experts were considered in setting the weights. A decision matrix is used to accommodate large amounts of data by listing alternatives which represent the patients

Table 9 Statistical analysis results

Risk level	1st Group	2nd Group	3rd Group	Urgent level	1st Group	2nd Group	3rd Group
Mean	0.013	0.007	0.005	Mean	0.009	0.005	0.003
SD	0.019	0.012	0.01	SD	0.011	0.009	0.006
Count	22	22	22	Count	50	50	51
Sick level	1st Group	2nd Group	3rd Group	Cold state level	1st Group	2nd Group	3rd Group
Mean	0.007	0.004	0.002	Mean	0.02	0.016	0.006
SD	0.009	0.007	0.005	SD	0.032	0.026	0.014
Count	86	86	88	Count	7	7	9

Table 10 Benchmarking checklist

Scenario	Checklist issues	Classification benchmark (Salman et al. 2014)	Classification benchmark (Albahri et al. 2019a, b)	Classification benchmark (Albahri et al. 2019a, b)	Prioritisation benchmark (Kalid et al. 2018a, b)	Prioritisation benchmark (Salman et al. 2017)	Proposed framework
Classification scenario	Support vital signs	✓	✓	✓	✗	✗	✓
	Support chief complaints	✓	✓	✓	✗	✗	✓
	Support Scalability	✓	✓	✓	✗	✗	✓
	Remote Environment	✓	✓	✓	✗	✗	✓
	Classification patients	✓	✓	✓	✗	✗	✓
	Handling large amount of data	✗	✓	✓	✗	✗	✓
	Score	*41.67*	*50*	*50*	*0*	*0*	*50*
	Differences	*8.33*	*0*	*0*	*50*	*50*	*/*
Prioritisation scenario	Support vital signs	✓	✗	✗	✓	✓	✓
	Support chief complaints	✓	✗	✗	✓	✓	✓
	Targeted tier	✗	✗	✗	✓	✓	✓
	Support Scalability	✓	✗	✗	✓	✓	✓
	Remote Environment	✓	✗	✗	✓	✓	✓
	Prioritisation in terms of category/order	✓	✗	✗	✓	✓	✓
	Feature Weighting	✗	✗	✗	✓	✓	✓
	Multi criteria ranking	✗	✗	✗	✓	✓	✓
	Handling large amount of data	✗	✗	✗	✓	✓	✓
	Patient Prioritisation Accuracy	✗	✗	✗	✓	✓	✓
	Score	*25*	*0*	*0*	*50*	*50*	*50*
	Difference	*25*	*50*	*50*	*0*	*0*	*/*

(in column) and multiple criteria which represent the features used to evaluate the patients. Both approaches also adopted the MCDM model to deal with multiple heterogeneous sources from patients. The patient evaluation process should recognise that these features have different effects on patient evaluation. Patients are prioritised via simultaneous consideration of multiple attributes (vital signs and complaints) with respect to the proper weight assigned for each attribute to score the patients according to the most urgent cases without considering the FCFS technique. Thus, the MCDM model ranks and provides the order by which patients would be attended to on the basis of the urgency of each case regardless of request time. However, the issues already covered by a previous classification benchmark (Salman et al. 2014) are support vital signs, support chief complaints, support scalability, remote environment and prioritisation in terms of category/order. The issues not yet covered are (a) targeted tier as the prioritisation process performed in Tier 2 (base station) and assigning a PC value without comparing it with that of other patients in the server; (b) feature weighting as the set and test technique is 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 (in addition, a dataset may not reflect all cases which show the exact weights for each feature); (c) multi-criteria ranking due to data fusion has been applied to estimate the current medical condition of patients from various sources (however, data fusion is particularly difficult if the input data are heterogeneous [non-commensurate]); (d) handling large amounts of data; and (e) accuracy of patient prioritisation because 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 in the server are sorted in descending order via the FCFS principle. However, this principle cannot be used in reality because the situation of some patients may be more urgent than those of other patients who arrived at the ED earlier. Moreover, the benchmark studies of (Albahri et al. 2019a, b) did not cover any of the aforementioned issues in prioritisation scenarios.

The score for the second scenario of the proposed framework and the benchmark prioritisation frameworks (Kalid et al. 2018a, b; Salman et al. 2017) is 50% because they already covered all issues in this scenario (i.e. prioritisation). The score of the classification benchmark of Salman et al. (2014) is 25%, and that of classification benchmark studies of Albahri et al. (2019a, b) is 0%.

On the basis of the results of both benchmarking scenarios (i.e. classification and prioritisation), the total score and performance of the proposed framework is 100%; by contrast, that of the benchmark classification study of Salman et al. (2014) is 66.67%, and that of the benchmark classification studies of Albahri et al. (2019a, b) is 50%. The difference between the performance of the proposed framework and the classification study of Salman et al. (2014) is 33.33%. The difference between the performance of the proposed framework and that of previous studies (Albahri et al. 2019a, b; Kalid et al. 2018a, b; Salman et al. 2017) is 50%.

5 Conclusion

This study developed an emergency classification and prioritisation framework for managing patients with CHD who engage in remote health monitoring systems. In the telemedicine architecture, the improvements were achieved by remotely classifying and prioritising patients with CHD within each category in the server side (Tier 3). The patients are categorised into different emergency levels, namely, high risk, in need of urgent care, sick, in a cold state and normal, by using Dempster–Shafer theory. The patients within each emergency level are prioritised using a hybridised model of MLAHP and TOPSIS. The MLAHP model is utilised to extract subjective weights from six medical experts for each medical source. The TOPSIS model is employed to prioritise the available patients within each emergency level according to weights extracted from the MLAHP model. The validation and evaluation of the proposed framework were then achieved properly. The proposed framework can be used to increase the performance of classification and prioritisation in telemedicine environments and improve healthcare management. Recommendations for future works are multi-faceted. CHD complications are determined by the type of diabetes the patient is suffering from. Future studies may consider one or both types of diabetes. Thus, different classification and prioritisation models for diabetes must be investigated.

Appendix

See Table A.1.

Table A.1 Dataset presentation

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
1	97	23	12	False	False	False	False	67	0.06	0.065763	True
2	97	23	12	False	False	False	True	67	0.06	0.065763	True
3	97	23	12	False	False	True	False	67	0.06	0.065763	True
4	97	23	12	False	False	True	True	67	0.06	0.065763	True
5	97	23	12	False	True	False	False	67	0.06	0.065763	True
6	97	23	12	False	True	False	True	67	0.06	0.065763	True
7	97	23	12	False	True	True	False	67	0.06	0.065763	True
8	97	23	12	False	True	True	True	67	0.06	0.065763	True
9	97	23	12	True	False	False	False	67	0.06	0.065763	True
10	97	23	12	True	False	False	True	67	0.06	0.065763	True
11	97	23	12	True	False	True	False	67	0.06	0.065763	True
12	97	23	12	True	False	True	True	67	0.06	0.065763	True
13	97	23	12	True	True	False	False	67	0.06	0.065763	True
14	97	23	12	True	True	False	True	67	0.06	0.065763	True
15	97	23	12	True	True	True	False	67	0.06	0.065763	True
16	97	23	12	True	True	True	True	67	0.06	0.065763	True
17	92	23	12	False	False	False	False	67	0.06	0.065763	True
18	92	23	12	False	False	False	True	67	0.06	0.065763	True
19	92	23	12	False	False	True	False	67	0.06	0.065763	True
20	92	23	12	False	False	True	True	67	0.06	0.065763	True
21	92	23	12	False	True	False	False	67	0.06	0.065763	True
22	92	23	12	False	True	False	True	67	0.06	0.065763	True
23	92	23	12	False	True	True	False	67	0.06	0.065763	True
24	92	23	12	False	True	True	True	67	0.06	0.065763	True
25	92	23	12	True	False	False	False	67	0.06	0.065763	True
26	92	23	12	True	False	False	True	67	0.06	0.065763	True
27	92	23	12	True	False	True	False	67	0.06	0.065763	True
28	92	23	12	True	False	True	True	67	0.06	0.065763	True
29	92	23	12	True	True	False	False	67	0.06	0.065763	True
30	92	23	12	True	True	False	True	67	0.06	0.065763	True
31	92	23	12	True	True	True	False	67	0.06	0.065763	True
32	92	23	12	True	True	True	True	67	0.06	0.065763	True
33	97	15	10	False	False	False	False	67	0.06	0.065763	True
34	97	15	10	False	False	False	True	67	0.06	0.065763	True
35	97	15	10	False	False	True	False	67	0.06	0.065763	True
36	97	15	10	False	False	True	True	67	0.06	0.065763	True
37	97	15	10	False	True	False	False	67	0.06	0.065763	True
38	97	15	10	False	True	False	True	67	0.06	0.065763	True
39	97	15	10	False	True	True	False	67	0.06	0.065763	True
40	97	15	10	False	True	True	True	67	0.06	0.065763	True
41	97	15	10	True	False	False	False	67	0.06	0.065763	True
42	97	15	10	True	False	False	True	67	0.06	0.065763	True
43	97	15	10	True	False	True	False	67	0.06	0.065763	True
44	97	15	10	True	False	True	True	67	0.06	0.065763	True
45	97	15	10	True	True	False	False	67	0.06	0.065763	True
46	97	15	10	True	True	False	True	67	0.06	0.065763	True
47	97	15	10	True	True	True	False	67	0.06	0.065763	True
48	97	15	10	True	True	True	True	67	0.06	0.065763	True
49	92	15	10	False	False	False	False	67	0.06	0.065763	True
50	92	15	10	False	False	False	True	67	0.06	0.065763	True

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
51	92	15	10	False	False	True	False	67	0.06	0.065763	True
52	92	15	10	False	False	True	True	67	0.06	0.065763	True
53	92	15	10	False	True	False	False	67	0.06	0.065763	True
54	92	15	10	False	True	False	True	67	0.06	0.065763	True
55	92	15	10	False	True	True	False	67	0.06	0.065763	True
56	92	15	10	False	True	True	True	67	0.06	0.065763	True
57	92	15	10	True	False	False	False	67	0.06	0.065763	True
58	92	15	10	True	False	False	True	67	0.06	0.065763	True
59	92	15	10	True	False	True	False	67	0.06	0.065763	True
60	92	15	10	True	False	True	True	67	0.06	0.065763	True
61	92	15	10	True	True	False	False	67	0.06	0.065763	True
62	92	15	10	True	True	False	True	67	0.06	0.065763	True
63	92	15	10	True	True	True	False	67	0.06	0.065763	True
64	92	15	10	True	True	True	True	67	0.06	0.065763	True
65	97	12	8	False	False	False	False	67	0.06	0.065763	True
66	97	12	8	False	False	False	True	67	0.06	0.065763	True
67	97	12	8	False	False	True	False	67	0.06	0.065763	True
68	97	12	8	False	False	True	True	67	0.06	0.065763	True
69	97	12	8	False	True	False	False	67	0.06	0.065763	True
70	97	12	8	False	True	False	True	67	0.06	0.065763	True
71	97	12	8	False	True	True	False	67	0.06	0.065763	True
72	97	12	8	False	True	True	True	67	0.06	0.065763	True
73	97	12	8	True	False	False	False	67	0.06	0.065763	True
74	97	12	8	True	False	False	True	67	0.06	0.065763	True
75	97	12	8	True	False	True	False	67	0.06	0.065763	True
76	97	12	8	True	False	True	True	67	0.06	0.065763	True
77	97	12	8	True	True	False	False	67	0.06	0.065763	True
78	97	12	8	True	True	False	True	67	0.06	0.065763	True
79	97	12	8	True	True	True	False	67	0.06	0.065763	True
80	97	12	8	True	True	True	True	67	0.06	0.065763	True
81	92	12	8	False	False	False	False	67	0.06	0.065763	True
82	92	12	8	False	False	False	True	67	0.06	0.065763	True
83	92	12	8	False	False	True	False	67	0.06	0.065763	True
84	92	12	8	False	False	True	True	67	0.06	0.065763	True
85	92	12	8	False	True	False	False	67	0.06	0.065763	True
86	92	12	8	False	True	False	True	67	0.06	0.065763	True
87	92	12	8	False	True	True	False	67	0.06	0.065763	True
88	92	12	8	False	True	True	True	67	0.06	0.065763	True
89	92	12	8	True	False	False	False	67	0.06	0.065763	True
90	92	12	8	True	False	False	True	67	0.06	0.065763	True
91	92	12	8	True	False	True	False	67	0.06	0.065763	True
92	92	12	8	True	False	True	True	67	0.06	0.065763	True
93	92	12	8	True	True	False	False	67	0.06	0.065763	True
94	92	12	8	True	True	False	True	67	0.06	0.065763	True
95	92	12	8	True	True	True	False	67	0.06	0.065763	True
96	92	12	8	True	True	True	True	67	0.06	0.065763	True
97	80	12	8	False	False	False	False	67	0.06	0.065763	True
98	80	12	8	False	False	False	True	67	0.06	0.065763	True
99	80	12	8	False	False	True	False	67	0.06	0.065763	True
100	80	12	8	False	False	True	True	67	0.06	0.065763	True

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
101	80	12	8	False	True	False	False	67	0.06	0.065763	True
102	80	12	8	False	True	False	True	67	0.06	0.065763	True
103	80	12	8	False	True	True	False	67	0.06	0.065763	True
104	80	12	8	False	True	True	True	67	0.06	0.065763	True
105	80	12	8	True	False	False	False	67	0.06	0.065763	True
106	80	12	8	True	False	False	True	67	0.06	0.065763	True
107	80	12	8	True	False	True	False	67	0.06	0.065763	True
108	80	12	8	True	False	True	True	67	0.06	0.065763	True
109	80	12	8	True	True	False	False	67	0.06	0.065763	True
110	80	12	8	True	True	False	True	67	0.06	0.065763	True
111	80	12	8	True	True	True	False	67	0.06	0.065763	True
112	80	12	8	True	True	True	True	67	0.06	0.065763	True
113	80	15	10	False	False	False	False	67	0.06	0.065763	True
114	80	15	10	False	False	False	True	67	0.06	0.065763	True
115	80	15	10	False	False	True	False	67	0.06	0.065763	True
116	80	15	10	False	False	True	True	67	0.06	0.065763	True
117	80	15	10	False	True	False	False	67	0.06	0.065763	True
118	80	15	10	False	True	False	True	67	0.06	0.065763	True
119	80	15	10	False	True	True	False	67	0.06	0.065763	True
120	80	15	10	False	True	True	True	67	0.06	0.065763	True
121	80	15	10	True	False	False	False	67	0.06	0.065763	True
122	80	15	10	True	False	False	True	67	0.06	0.065763	True
123	80	15	10	True	False	True	False	67	0.06	0.065763	True
124	80	15	10	True	False	True	True	67	0.06	0.065763	True
125	80	15	10	True	True	False	False	67	0.06	0.065763	True
126	80	15	10	True	True	False	True	67	0.06	0.065763	True
127	80	15	10	True	True	True	False	67	0.06	0.065763	True
128	80	15	10	True	True	True	True	67	0.06	0.065763	True
129	80	23	12	False	False	False	False	67	0.06	0.065763	True
130	80	23	12	False	False	False	True	67	0.06	0.065763	True
131	80	23	12	False	False	True	False	67	0.06	0.065763	True
132	80	23	12	False	False	True	True	67	0.06	0.065763	True
133	80	23	12	False	True	False	False	67	0.06	0.065763	True
134	80	23	12	False	True	False	True	67	0.06	0.065763	True
135	80	23	12	False	True	True	False	67	0.06	0.065763	True
136	80	23	12	False	True	True	True	67	0.06	0.065763	True
137	80	23	12	True	False	False	False	67	0.06	0.065763	True
138	80	23	12	True	False	False	True	67	0.06	0.065763	True
139	80	23	12	True	False	True	False	67	0.06	0.065763	True
140	80	23	12	True	False	True	True	67	0.06	0.065763	True
141	80	23	12	True	True	False	False	67	0.06	0.065763	True
142	80	23	12	True	True	False	True	67	0.06	0.065763	True
143	80	23	12	True	True	True	False	67	0.06	0.065763	True
144	80	23	12	True	True	True	True	67	0.06	0.065763	True
145	97	23	12	False	False	False	False	54	0.5	0.037372	False
146	97	23	12	False	False	False	True	54	0.5	0.037372	False
147	97	23	12	False	False	True	False	54	0.5	0.037372	False
148	97	23	12	False	False	True	True	54	0.5	0.037372	False
149	97	23	12	False	True	False	False	54	0.5	0.037372	False
150	97	23	12	False	True	False	True	54	0.5	0.037372	False

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
151	97	23	12	False	True	True	False	54	0.5	0.037372	False
152	97	23	12	False	True	True	True	54	0.5	0.037372	False
153	97	23	12	True	False	False	False	54	0.5	0.037372	False
154	97	23	12	True	False	False	True	54	0.5	0.037372	False
155	97	23	12	True	False	True	False	54	0.5	0.037372	False
156	97	23	12	True	False	True	True	54	0.5	0.037372	False
157	97	23	12	True	True	False	False	54	0.5	0.037372	False
158	97	23	12	True	True	False	True	54	0.5	0.037372	False
159	97	23	12	True	True	True	False	54	0.5	0.037372	False
160	97	23	12	True	True	True	True	54	0.5	0.037372	False
161	92	23	12	False	False	False	False	54	0.5	0.037372	False
162	92	23	12	False	False	False	True	54	0.5	0.037372	False
163	92	23	12	False	False	True	False	54	0.5	0.037372	False
164	92	23	12	False	False	True	True	54	0.5	0.037372	False
165	92	23	12	False	True	False	False	54	0.5	0.037372	False
166	92	23	12	False	True	False	True	54	0.5	0.037372	False
167	92	23	12	False	True	True	False	54	0.5	0.037372	False
168	92	23	12	False	True	True	True	54	0.5	0.037372	False
169	92	23	12	True	False	False	False	54	0.5	0.037372	False
170	92	23	12	True	False	False	True	54	0.5	0.037372	False
171	92	23	12	True	False	True	False	54	0.5	0.037372	False
172	92	23	12	True	False	True	True	54	0.5	0.037372	False
173	92	23	12	True	True	False	False	54	0.5	0.037372	False
174	92	23	12	True	True	False	True	54	0.5	0.037372	False
175	92	23	12	True	True	True	False	54	0.5	0.037372	False
176	92	23	12	True	True	True	True	54	0.5	0.037372	False
177	97	15	10	False	False	False	False	54	0.5	0.037372	False
178	97	15	10	False	False	False	True	54	0.5	0.037372	False
179	97	15	10	False	False	True	False	54	0.5	0.037372	False
180	97	15	10	False	False	True	True	54	0.5	0.037372	False
181	97	15	10	False	True	False	False	54	0.5	0.037372	False
182	97	15	10	False	True	False	True	54	0.5	0.037372	False
183	97	15	10	False	True	True	False	54	0.5	0.037372	False
184	97	15	10	False	True	True	True	54	0.5	0.037372	False
185	97	15	10	True	False	False	False	54	0.5	0.037372	False
186	97	15	10	True	False	False	True	54	0.5	0.037372	False
187	97	15	10	True	False	True	False	54	0.5	0.037372	False
188	97	15	10	True	False	True	True	54	0.5	0.037372	False
189	97	15	10	True	True	False	False	54	0.5	0.037372	False
190	97	15	10	True	True	False	True	54	0.5	0.037372	False
191	97	15	10	True	True	True	False	54	0.5	0.037372	False
192	97	15	10	True	True	True	True	54	0.5	0.037372	False
193	92	15	10	False	False	False	False	54	0.5	0.037372	False
194	92	15	10	False	False	False	True	54	0.5	0.037372	False
195	92	15	10	False	False	True	False	54	0.5	0.037372	False
196	92	15	10	False	False	True	True	54	0.5	0.037372	False
197	92	15	10	False	True	False	False	54	0.5	0.037372	False
198	92	15	10	False	True	False	True	54	0.5	0.037372	False
199	92	15	10	False	True	True	False	54	0.5	0.037372	False
200	92	15	10	False	True	True	True	54	0.5	0.037372	False

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
201	92	15	10	True	False	False	False	54	0.5	0.037372	False
202	92	15	10	True	False	False	True	54	0.5	0.037372	False
203	92	15	10	True	False	True	False	54	0.5	0.037372	False
204	92	15	10	True	False	True	True	54	0.5	0.037372	False
205	92	15	10	True	True	False	False	54	0.5	0.037372	False
206	92	15	10	True	True	False	True	54	0.5	0.037372	False
207	92	15	10	True	True	True	False	54	0.5	0.037372	False
208	92	15	10	True	True	True	True	54	0.5	0.037372	False
209	97	12	8	False	False	False	False	54	0.5	0.037372	False
210	97	12	8	False	False	False	True	54	0.5	0.037372	False
211	97	12	8	False	False	True	False	54	0.5	0.037372	False
212	97	12	8	False	False	True	True	54	0.5	0.037372	False
213	97	12	8	False	True	False	False	54	0.5	0.037372	False
214	97	12	8	False	True	False	True	54	0.5	0.037372	False
215	97	12	8	False	True	True	False	54	0.5	0.037372	False
216	97	12	8	False	True	True	True	54	0.5	0.037372	False
217	97	12	8	True	False	False	False	54	0.5	0.037372	False
218	97	12	8	True	False	False	True	54	0.5	0.037372	False
219	97	12	8	True	False	True	False	54	0.5	0.037372	False
220	97	12	8	True	False	True	True	54	0.5	0.037372	False
221	97	12	8	True	True	False	False	54	0.5	0.037372	False
222	97	12	8	True	True	False	True	54	0.5	0.037372	False
223	97	12	8	True	True	True	False	54	0.5	0.037372	False
224	97	12	8	True	True	True	True	54	0.5	0.037372	False
225	92	12	8	False	False	False	False	54	0.5	0.037372	False
226	92	12	8	False	False	False	True	54	0.5	0.037372	False
227	92	12	8	False	False	True	False	54	0.5	0.037372	False
228	92	12	8	False	False	True	True	54	0.5	0.037372	False
229	92	12	8	False	True	False	False	54	0.5	0.037372	False
230	92	12	8	False	True	False	True	54	0.5	0.037372	False
231	92	12	8	False	True	True	False	54	0.5	0.037372	False
232	92	12	8	False	True	True	True	54	0.5	0.037372	False
233	92	12	8	True	False	False	False	54	0.5	0.037372	False
234	92	12	8	True	False	False	True	54	0.5	0.037372	False
235	92	12	8	True	False	True	False	54	0.5	0.037372	False
236	92	12	8	True	False	True	True	54	0.5	0.037372	False
237	92	12	8	True	True	False	False	54	0.5	0.037372	False
238	92	12	8	True	True	False	True	54	0.5	0.037372	False
239	92	12	8	True	True	True	False	54	0.5	0.037372	False
240	92	12	8	True	True	True	True	54	0.5	0.037372	False
241	80	12	8	False	False	False	False	54	0.5	0.037372	False
242	80	12	8	False	False	False	True	54	0.5	0.037372	False
243	80	12	8	False	False	True	False	54	0.5	0.037372	False
244	80	12	8	False	False	True	True	54	0.5	0.037372	False
245	80	12	8	False	True	False	False	54	0.5	0.037372	False
246	80	12	8	False	True	False	True	54	0.5	0.037372	False
247	80	12	8	False	True	True	False	54	0.5	0.037372	False
248	80	12	8	False	True	True	True	54	0.5	0.037372	False
249	80	12	8	True	False	False	False	54	0.5	0.037372	False
250	80	12	8	True	False	False	True	54	0.5	0.037372	False

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
251	80	12	8	True	False	True	False	54	0.5	0.037372	False
252	80	12	8	True	False	True	True	54	0.5	0.037372	False
253	80	12	8	True	True	False	False	54	0.5	0.037372	False
254	80	12	8	True	True	False	True	54	0.5	0.037372	False
255	80	12	8	True	True	True	False	54	0.5	0.037372	False
256	80	12	8	True	True	True	True	54	0.5	0.037372	False
257	80	15	10	False	False	False	False	54	0.5	0.037372	False
258	80	15	10	False	False	False	True	54	0.5	0.037372	False
259	80	15	10	False	False	True	False	54	0.5	0.037372	False
260	80	15	10	False	False	True	True	54	0.5	0.037372	False
261	80	15	10	False	True	False	False	54	0.5	0.037372	False
262	80	15	10	False	True	False	True	54	0.5	0.037372	False
263	80	15	10	False	True	True	False	54	0.5	0.037372	False
264	80	15	10	False	True	True	True	54	0.5	0.037372	False
265	80	15	10	True	False	False	False	54	0.5	0.037372	False
266	80	15	10	True	False	False	True	54	0.5	0.037372	False
267	80	15	10	True	False	True	False	54	0.5	0.037372	False
268	80	15	10	True	False	True	True	54	0.5	0.037372	False
269	80	15	10	True	True	False	False	54	0.5	0.037372	False
270	80	15	10	True	True	False	True	54	0.5	0.037372	False
271	80	15	10	True	True	True	False	54	0.5	0.037372	False
272	80	15	10	True	True	True	True	54	0.5	0.037372	False
273	80	23	12	False	False	False	False	54	0.5	0.037372	False
274	80	23	12	False	False	False	True	54	0.5	0.037372	False
275	80	23	12	False	False	True	False	54	0.5	0.037372	False
276	80	23	12	False	False	True	True	54	0.5	0.037372	False
277	80	23	12	False	True	False	False	54	0.5	0.037372	False
278	80	23	12	False	True	False	True	54	0.5	0.037372	False
279	80	23	12	False	True	True	False	54	0.5	0.037372	False
280	80	23	12	False	True	True	True	54	0.5	0.037372	False
281	80	23	12	True	False	False	False	54	0.5	0.037372	False
282	80	23	12	True	False	False	True	54	0.5	0.037372	False
283	80	23	12	True	False	True	False	54	0.5	0.037372	False
284	80	23	12	True	False	True	True	54	0.5	0.037372	False
285	80	23	12	True	True	False	False	54	0.5	0.037372	False
286	80	23	12	True	True	False	True	54	0.5	0.037372	False
287	80	23	12	True	True	True	False	54	0.5	0.037372	False
288	80	23	12	True	True	True	True	54	0.5	0.037372	False
289	97	23	12	False	False	False	False	77	0.047	0.266642	True
290	97	23	12	False	False	False	True	77	0.047	0.266642	True
291	97	23	12	False	False	True	False	77	0.047	0.266642	True
292	97	23	12	False	False	True	True	77	0.047	0.266642	True
293	97	23	12	False	True	False	False	77	0.047	0.266642	True
294	97	23	12	False	True	False	True	77	0.047	0.266642	True
295	97	23	12	False	True	True	False	77	0.047	0.266642	True
296	97	23	12	False	True	True	True	77	0.047	0.266642	True
297	97	23	12	True	False	False	False	77	0.047	0.266642	True
298	97	23	12	True	False	False	True	77	0.047	0.266642	True
299	97	23	12	True	False	True	False	77	0.047	0.266642	True
300	97	23	12	True	False	True	True	77	0.047	0.266642	True

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
301	97	23	12	True	True	False	False	77	0.047	0.266642	True
302	97	23	12	True	True	False	True	77	0.047	0.266642	True
303	97	23	12	True	True	True	False	77	0.047	0.266642	True
304	97	23	12	True	True	True	True	77	0.047	0.266642	True
305	92	23	12	False	False	False	False	77	0.047	0.266642	True
306	92	23	12	False	False	False	True	77	0.047	0.266642	True
307	92	23	12	False	False	True	False	77	0.047	0.266642	True
308	92	23	12	False	False	True	True	77	0.047	0.266642	True
309	92	23	12	False	True	False	False	77	0.047	0.266642	True
310	92	23	12	False	True	False	True	77	0.047	0.266642	True
311	92	23	12	False	True	True	False	77	0.047	0.266642	True
312	92	23	12	False	True	True	True	77	0.047	0.266642	True
313	92	23	12	True	False	False	False	77	0.047	0.266642	True
314	92	23	12	True	False	False	True	77	0.047	0.266642	True
315	92	23	12	True	False	True	False	77	0.047	0.266642	True
316	92	23	12	True	False	True	True	77	0.047	0.266642	True
317	92	23	12	True	True	False	False	77	0.047	0.266642	True
318	92	23	12	True	True	False	True	77	0.047	0.266642	True
319	92	23	12	True	True	True	False	77	0.047	0.266642	True
320	92	23	12	True	True	True	True	77	0.047	0.266642	True
321	97	15	10	False	False	False	False	77	0.047	0.266642	True
322	97	15	10	False	False	False	True	77	0.047	0.266642	True
323	97	15	10	False	False	True	False	77	0.047	0.266642	True
324	97	15	10	False	False	True	True	77	0.047	0.266642	True
325	97	15	10	False	True	False	False	77	0.047	0.266642	True
326	97	15	10	False	True	False	True	77	0.047	0.266642	True
327	97	15	10	False	True	True	False	77	0.047	0.266642	True
328	97	15	10	False	True	True	True	77	0.047	0.266642	True
329	97	15	10	True	False	False	False	77	0.047	0.266642	True
330	97	15	10	True	False	False	True	77	0.047	0.266642	True
331	97	15	10	True	False	True	False	77	0.047	0.266642	True
332	97	15	10	True	False	True	True	77	0.047	0.266642	True
333	97	15	10	True	True	False	False	77	0.047	0.266642	True
334	97	15	10	True	True	False	True	77	0.047	0.266642	True
335	97	15	10	True	True	True	False	77	0.047	0.266642	True
336	97	15	10	True	True	True	True	77	0.047	0.266642	True
337	92	15	10	False	False	False	False	77	0.047	0.266642	True
338	92	15	10	False	False	False	True	77	0.047	0.266642	True
339	92	15	10	False	False	True	False	77	0.047	0.266642	True
340	92	15	10	False	False	True	True	77	0.047	0.266642	True
341	92	15	10	False	True	False	False	77	0.047	0.266642	True
342	92	15	10	False	True	False	True	77	0.047	0.266642	True
343	92	15	10	False	True	True	False	77	0.047	0.266642	True
344	92	15	10	False	True	True	True	77	0.047	0.266642	True
345	92	15	10	True	False	False	False	77	0.047	0.266642	True
346	92	15	10	True	False	False	True	77	0.047	0.266642	True
347	92	15	10	True	False	True	False	77	0.047	0.266642	True
348	92	15	10	True	False	True	True	77	0.047	0.266642	True
349	92	15	10	True	True	False	False	77	0.047	0.266642	True
350	92	15	10	True	True	False	True	77	0.047	0.266642	True

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
351	92	15	10	True	True	True	False	77	0.047	0.266642	True
352	92	15	10	True	True	True	True	77	0.047	0.266642	True
353	97	12	8	False	False	False	False	77	0.047	0.266642	True
354	97	12	8	False	False	False	True	77	0.047	0.266642	True
355	97	12	8	False	False	True	False	77	0.047	0.266642	True
356	97	12	8	False	False	True	True	77	0.047	0.266642	True
357	97	12	8	False	True	False	False	77	0.047	0.266642	True
358	97	12	8	False	True	False	True	77	0.047	0.266642	True
359	97	12	8	False	True	True	False	77	0.047	0.266642	True
360	97	12	8	False	True	True	True	77	0.047	0.266642	True
361	97	12	8	True	False	False	False	77	0.047	0.266642	True
362	97	12	8	True	False	False	True	77	0.047	0.266642	True
363	97	12	8	True	False	True	False	77	0.047	0.266642	True
364	97	12	8	True	False	True	True	77	0.047	0.266642	True
365	97	12	8	True	True	False	False	77	0.047	0.266642	True
366	97	12	8	True	True	False	True	77	0.047	0.266642	True
367	97	12	8	True	True	True	False	77	0.047	0.266642	True
368	97	12	8	True	True	True	True	77	0.047	0.266642	True
369	92	12	8	False	False	False	False	77	0.047	0.266642	True
370	92	12	8	False	False	False	True	77	0.047	0.266642	True
371	92	12	8	False	False	True	False	77	0.047	0.266642	True
372	92	12	8	False	False	True	True	77	0.047	0.266642	True
373	92	12	8	False	True	False	False	77	0.047	0.266642	True
374	92	12	8	False	True	False	True	77	0.047	0.266642	True
375	92	12	8	False	True	True	False	77	0.047	0.266642	True
376	92	12	8	False	True	True	True	77	0.047	0.266642	True
377	92	12	8	True	False	False	False	77	0.047	0.266642	True
378	92	12	8	True	False	False	True	77	0.047	0.266642	True
379	92	12	8	True	False	True	False	77	0.047	0.266642	True
380	92	12	8	True	False	True	True	77	0.047	0.266642	True
381	92	12	8	True	True	False	False	77	0.047	0.266642	True
382	92	12	8	True	True	False	True	77	0.047	0.266642	True
383	92	12	8	True	True	True	False	77	0.047	0.266642	True
384	92	12	8	True	True	True	True	77	0.047	0.266642	True
385	80	12	8	False	False	False	False	77	0.047	0.266642	True
386	80	12	8	False	False	False	True	77	0.047	0.266642	True
387	80	12	8	False	False	True	False	77	0.047	0.266642	True
388	80	12	8	False	False	True	True	77	0.047	0.266642	True
389	80	12	8	False	True	False	False	77	0.047	0.266642	True
390	80	12	8	False	True	False	True	77	0.047	0.266642	True
391	80	12	8	False	True	True	False	77	0.047	0.266642	True
392	80	12	8	False	True	True	True	77	0.047	0.266642	True
393	80	12	8	True	False	False	False	77	0.047	0.266642	True
394	80	12	8	True	False	False	True	77	0.047	0.266642	True
395	80	12	8	True	False	True	False	77	0.047	0.266642	True
396	80	12	8	True	False	True	True	77	0.047	0.266642	True
397	80	12	8	True	True	False	False	77	0.047	0.266642	True
398	80	12	8	True	True	False	True	77	0.047	0.266642	True
399	80	12	8	True	True	True	False	77	0.047	0.266642	True
400	80	12	8	True	True	True	True	77	0.047	0.266642	True

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
401	80	15	10	False	False	False	False	77	0.047	0.266642	True
402	80	15	10	False	False	False	True	77	0.047	0.266642	True
403	80	15	10	False	False	True	False	77	0.047	0.266642	True
404	80	15	10	False	False	True	True	77	0.047	0.266642	True
405	80	15	10	False	True	False	False	77	0.047	0.266642	True
406	80	15	10	False	True	False	True	77	0.047	0.266642	True
407	80	15	10	False	True	True	False	77	0.047	0.266642	True
408	80	15	10	False	True	True	True	77	0.047	0.266642	True
409	80	15	10	True	False	False	False	77	0.047	0.266642	True
410	80	15	10	True	False	False	True	77	0.047	0.266642	True
411	80	15	10	True	False	True	False	77	0.047	0.266642	True
412	80	15	10	True	False	True	True	77	0.047	0.266642	True
413	80	15	10	True	True	False	False	77	0.047	0.266642	True
414	80	15	10	True	True	False	True	77	0.047	0.266642	True
415	80	15	10	True	True	True	False	77	0.047	0.266642	True
416	80	15	10	True	True	True	True	77	0.047	0.266642	True
417	80	23	12	False	False	False	False	77	0.047	0.266642	True
418	80	23	12	False	False	False	True	77	0.047	0.266642	True
419	80	23	12	False	False	True	False	77	0.047	0.266642	True
420	80	23	12	False	False	True	True	77	0.047	0.266642	True
421	80	23	12	False	True	False	False	77	0.047	0.266642	True
422	80	23	12	False	True	False	True	77	0.047	0.266642	True
423	80	23	12	False	True	True	False	77	0.047	0.266642	True
424	80	23	12	False	True	True	True	77	0.047	0.266642	True
425	80	23	12	True	False	False	False	77	0.047	0.266642	True
426	80	23	12	True	False	False	True	77	0.047	0.266642	True
427	80	23	12	True	False	True	False	77	0.047	0.266642	True
428	80	23	12	True	False	True	True	77	0.047	0.266642	True
429	80	23	12	True	True	False	False	77	0.047	0.266642	True
430	80	23	12	True	True	False	True	77	0.047	0.266642	True
431	80	23	12	True	True	True	False	77	0.047	0.266642	True
432	80	23	12	True	True	True	True	77	0.047	0.266642	True
433	97	23	12	False	False	False	False	64	0.169	0.336318	False
434	97	23	12	False	False	False	True	64	0.169	0.336318	False
435	97	23	12	False	False	True	False	64	0.169	0.336318	False
436	97	23	12	False	False	True	True	64	0.169	0.336318	False
437	97	23	12	False	True	False	False	64	0.169	0.336318	False
438	97	23	12	False	True	False	True	64	0.169	0.336318	False
439	97	23	12	False	True	True	False	64	0.169	0.336318	False
440	97	23	12	False	True	True	True	64	0.169	0.336318	False
441	97	23	12	True	False	False	False	64	0.169	0.336318	False
442	97	23	12	True	False	False	True	64	0.169	0.336318	False
443	97	23	12	True	False	True	False	64	0.169	0.336318	False
444	97	23	12	True	False	True	True	64	0.169	0.336318	False
445	97	23	12	True	True	False	False	64	0.169	0.336318	False
446	97	23	12	True	True	False	True	64	0.169	0.336318	False
447	97	23	12	True	True	True	False	64	0.169	0.336318	False
448	97	23	12	True	True	True	True	64	0.169	0.336318	False
449	92	23	12	False	False	False	False	64	0.169	0.336318	False
450	92	23	12	False	False	False	True	64	0.169	0.336318	False

Table A.1 (continued)

P. no	Spo2	H. Blood	L. Blood	Chest pain	SH. Breath	Palip	Rest?	Peaks	QRS width	P-P	ST El
451	92	23	12	False	False	True	False	64	0.169	0.336318	False
452	92	23	12	False	False	True	True	64	0.169	0.336318	False
453	92	23	12	False	True	False	False	64	0.169	0.336318	False
454	92	23	12	False	True	False	True	64	0.169	0.336318	False
455	92	23	12	False	True	True	False	64	0.169	0.336318	False
456	92	23	12	False	True	True	True	64	0.169	0.336318	False
457	92	23	12	True	False	False	False	64	0.169	0.336318	False
458	92	23	12	True	False	False	True	64	0.169	0.336318	False
459	92	23	12	True	False	True	False	64	0.169	0.336318	False
460	92	23	12	True	False	True	True	64	0.169	0.336318	False
461	92	23	12	True	True	False	False	64	0.169	0.336318	False
462	92	23	12	True	True	False	True	64	0.169	0.336318	False
463	92	23	12	True	True	True	False	64	0.169	0.336318	False
464	92	23	12	True	True	True	True	64	0.169	0.336318	False
465	97	15	10	False	False	False	False	64	0.169	0.336318	False
466	97	15	10	False	False	False	True	64	0.169	0.336318	False
467	97	15	10	False	False	True	False	64	0.169	0.336318	False
468	97	15	10	False	False	True	True	64	0.169	0.336318	False
469	97	15	10	False	True	False	False	64	0.169	0.336318	False
470	97	15	10	False	True	False	True	64	0.169	0.336318	False
471	97	15	10	False	True	True	False	64	0.169	0.336318	False
472	97	15	10	False	True	True	True	64	0.169	0.336318	False
473	97	15	10	True	False	False	False	64	0.169	0.336318	False
474	97	15	10	True	False	False	True	64	0.169	0.336318	False
475	97	15	10	True	False	True	False	64	0.169	0.336318	False
476	97	15	10	True	False	True	True	64	0.169	0.336318	False
477	97	15	10	True	True	False	False	64	0.169	0.336318	False
478	97	15	10	True	True	False	True	64	0.169	0.336318	False
479	97	15	10	True	True	True	False	64	0.169	0.336318	False
480	97	15	10	True	True	True	True	64	0.169	0.336318	False
481	92	15	10	False	False	False	False	64	0.169	0.336318	False
482	92	15	10	False	False	False	True	64	0.169	0.336318	False
483	92	15	10	False	False	True	False	64	0.169	0.336318	False
484	92	15	10	False	False	True	True	64	0.169	0.336318	False
485	92	15	10	False	True	False	False	64	0.169	0.336318	False
486	92	15	10	False	True	False	True	64	0.169	0.336318	False
487	92	15	10	False	True	True	False	64	0.169	0.336318	False
488	92	15	10	False	True	True	True	64	0.169	0.336318	False
489	92	15	10	True	False	False	False	64	0.169	0.336318	False
490	92	15	10	True	False	False	True	64	0.169	0.336318	False
491	92	15	10	True	False	True	False	64	0.169	0.336318	False
492	92	15	10	True	False	True	True	64	0.169	0.336318	False
493	92	15	10	True	True	False	False	64	0.169	0.336318	False
494	92	15	10	True	True	False	True	64	0.169	0.336318	False
495	92	15	10	True	True	True	False	64	0.169	0.336318	False
496	92	15	10	True	True	True	True	64	0.169	0.336318	False
497	97	12	8	False	False	False	False	64	0.169	0.336318	False
498	97	12	8	False	False	False	True	64	0.169	0.336318	False
499	97	12	8	False	False	True	False	64	0.169	0.336318	False
500	97	12	8	False	False	True	True	64	0.169	0.336318	False

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional 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 participants of the study.

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