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# Novel Methodology for Triage and Prioritizing Using "Big Data" Patients with Chronic Heart Diseases Through Telemedicine Environmental

O. H. Salman*, A. A. Zaidan†,‡, B. B. Zaidan†, Naserkalid† and M. Hashim†

*Al-Iraqia University
Al Adhmia - HaibaKhaton, Baghdad, Iraq

†Department of Computing, Faculty of Arts
Computing and Creative Industry
Universiti Pendidikan Sultan Idris
Tanjong Malim, Perak, Malaysia
‡aws.alaa@gmail.com

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**Problem Statement:** Improper triage and prioritization of big-data patients may result in erroneous strategic decisions. An example of such wrong decision making includes the triage of patients with chronic heart disease to low-priority groups. Incorrect decisions may jeopardize the patients' health.
**Objective:** This study aims to evaluate and score the big data of patients with chronic heart disease and of those who require urgent attention. The assessment is based on multicriteria decision making in a telemedical environment to improve the triage and prioritization processes.
**Methods:** A hands-on study was performed. A total of 500 patients with chronic heart disease manifested in different symptoms and under various emergency levels were evaluated on the basis of the following four main measures. An electrocardiogram sensor was used to measure the electrical signals of the contractile activity of the heart over time. A $SpO_2$ sensor was employed to determine the blood oxygen saturation levels of the patients. A blood pressure sensor was used to obtain the physiological data of the systolic and diastolic blood pressures of the patients. Finally, a non-sensory measurement (text frame) was conducted to assess chest pain and breathing. The patients were prioritized on the basis of a set of measurements by utilizing integrated back-forward adjustment for weight computation and technique for order performance by similarity to ideal solution.
**Discussion Results:** Patients with the most urgent cases were given the highest priority level, whereas those with the least urgent cases were assigned with the lowest priority level among all patients' scores. The first three patients assigned to the medical committee of doctors were proven to be the most critical emergency cases with the highest priority level on the basis of their clinical symptoms. By contrast, the last three patients were proven to be the least critical emergency cases and given the lowest priority levels relative to other patients. The throughput measurement in terms of scalability based on our proposed algorithm was more efficient than that of the benchmark algorithm. Finally, the new method for determining the "big data" patients characteristics based on "4Vs" was suggested.

*Keywords*: Healthcare services; multicriteria analysis; big data; telemedicine.

‡Corresponding author.

### List of Abbreviations

- Back-Forward Adjustment for Weight Computing (BFAWC)
- Technique for Order Performance by Similarity to Ideal Solution methods (TOPSIS).
- Blood pressure (BP)
- Emergency department (ED)
- Global system for mobile communication (GSM)
- Healthcare Aware Optimized Congestion (HOCA)
- Media access control (MAC)
- Wireless body area network (WBAN)
- Multi-attribute or multi-criterion decision-making (MADM/MCDM)
- Decision maker(s) (DMs)
- Evaluation matrix (EM)
- Multiplicative Exponential Weighting (MEW)
- Weighted Product Method (WPM)
- Weighted Sum Model (WSM)
- Simple Additive Weighting (SAW)
- Hierarchical Adaptive Weighting (HAW)
- Analytic hierarchy process (AHP)
- Analytic network process (ANP)

## 1. Introduction

Chronic diseases have increasingly become a significant concern in electronic healthcare systems worldwide. For instance, by 2020, clinical expenses on chronic diseases in the United States are projected to reach 80% of total medical costs, and more than 150 million people are expected to suffer from chronic diseases.[1] Chronic heart disease is a critical condition that includes several types and presents different clinical manifestations. For example, cardiac arrhythmia is life threatening and may cause cardiac arrest and sudden death. In a medical report by the American Heart Association in 2010, approximately 55% of patients with heart diseases who died because of arrhythmia were considered "big data".[2–13] Serious arrhythmia cases, such as fibrillation or ventricular tachycardia, are induced by vortex-like re-entrant electric waves in the cardiac tissue. Vital signs, such as electrocardiogram (ECG) and $SpO_2$, are important in triage setting because these indicators provide an objective complement to triage decision making and optimize inter-rater consistency.[2] Certain medical guidelines are followed in triage setting and prioritization based on patients' vital signs and features related to chronic diseases.

Patients physically present at the emergency department (ED) of a hospital are prioritized by triage nurses. Triage has traditionally relied on the ability of the nurses to prioritize cases.[3–5] Moreover, triage and prioritization become complicated for patients who reside far from the hospital. In these cases, triage nurses and doctors are not physically available to help the patient. Evidently, triage and prioritization are more complex in telemedicine than in actual ED situations.[3,6] The triage and prioritization of patients who require the most urgent attention in telemedicine have gained considerable prominence. In telemedicine, patients are triaged and prioritized for treatment and transportation to hospitals through vital sign assessment.[5,7] Under the remote healthcare system, the patient's condition is the primary basis for assigning priority categories in accordance with medical guidelines on priority assessment.[5,7,8]

Healthcare systems have gained significant attention for their important role in people's lives.[9,77–83] The number of users of such systems has increased per unit area because of population aging and disaster. This development is considered as the main problem of healthcare service providers of remote healthcare systems.[7,10] The problem is heightened in the prioritization of the most critical emergency cases in remote setting.[7] The issue is also related to large-scale patient data, defined as "big data". Hence, triage and prioritization on the basis of the "big data" of patients are considered a complex decision-making process during peak times or when a large number patients are accommodated simultaneously.[11]

As a concept, big data is "the data that exceeds the processing capacity of conventional database systems".[12] The data are exceedingly massive, move exceedingly fast, or are not appropriate within the constraints of traditional database architectures.[13] Big-data characteristics can be described by the "4Vs", namely, volume, velocity, variety, and veracity.[14–21] (1) Volume refers to the data size, which could be in terabytes (TB: approximately 1012 bytes), petabytes (PB: approximately 1015 bytes), and zettabytes (ZB: approximately 1021 bytes). (2) Velocity is considered because of the increasing amount of data that must be provided instantly whenever the need for real-time processing arises.[22] (3) Variety corresponds to the data collected from various sources.[23] This attribute covers all data types, such as structured data from relational tables; semistructured data from key-value web clicks; and unstructured data from email messages, articles, and streamed video and audio. Meanwhile, (4) veracity comprises two aspects, namely, data reliability and consistency (or certainty).[24] Data can be doubtful because of uncertainty, deception, ambiguities, incompleteness, and data inconsistency.

In the healthcare domain, big data refers to "electronic health datasets so large and complex that it is difficult to manage with traditional or common data management methods and traditional software and/or hardware".[25] Some data related to healthcare are characterized by a need for timeliness. An example includes data from implantable or wearable biometric sensors; the heart rate or $SpO_2$ which is commonly gathered and analyzed in real time.[26] Sufficient large-scale analysis usually requires the gathering of data from multiple sources (heterogeneous data). For instance, obtaining the comprehensive health status of a patient (or a population) requires the integration and analysis of medical health records besides Internet-available environmental data and various meter readings (e.g., accelerometers, heart meters, and glucose meters).[27] Big data in the healthcare system and medical application offers many benefits.[24] One advantage is the application of innovative analytics to patient characteristics, profiles, and healthcare outcomes and costs; all of these factors might help in identifying the most cost-effective and clinically sound treatments. Furthermore, identifying individuals who may benefit from preventive care or lifestyle change is important. In this study, big data was collected/generated from a large number of telemonitoring healthcare system users who live far from hospitals. The big data was gathered from heterogeneous sources, such as medical sensors and text. Then, an advanced analysis method was applied to benefit from big data by prioritizing remote patients with the most critical emergency cases. Consequently, the "4Vs" of big data in our study are presented as follows:

- Volume is related to the amount of generated data growing rapidly each day.[22] In systems as in Refs. 7 and 28, the telemedicine architecture consists of the following three tiers: Tier 1 (user), Tier 2 (base station), and Tier 3 (server).[7] The transmitted data from Tier 2 to Tier 3 consider the users' vital signs utilized in Tier 3 by doctors to provide the user with personalized healthcare services. Improvements in remote triage, prioritization, and healthcare services using these data have been demonstrated previously. However, this section aims to show how adding these data affects the total message size and how these data are considered big data in the server (Tier 3). The size of the message sent by the user can reach the level of "big data" by considering many stages (number of users, number of requests for one user per day, telemedicine users, and in-hospital users for many departments inside the hospital, such as ED). Figure 1 illustrates the increasing data size of users/patients inside and outside the hospital who utilize the telemedicine system.

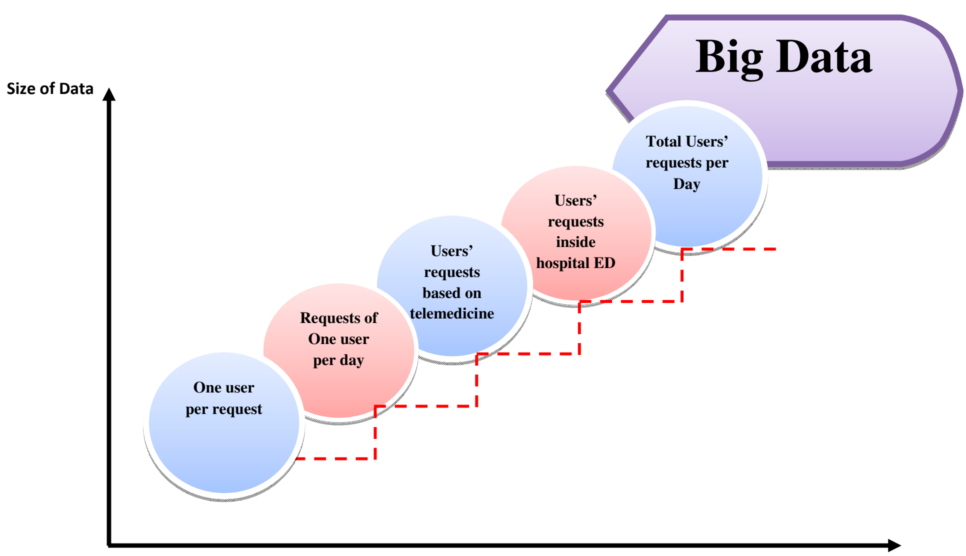



Fig. 1. Increasing measured data size in the healthcare server (Tier 3) for many users per day.

- Variety corresponds to the different data forms, such as wearable sensor data, clinical data, genomic data, user behavior data, and device data.[24] In the proposed framework, data formats vary as the signals of the wearable medical sensors and user context data are considered. The variation in format of the collected data for one user per time slot holds the following benefits. The format variation improves the outcomes of healthcare through precise and accurate diagnoses, individualized patient care (personalized medicine), and identification of patients at the risk of poor outcomes. The variable format also reduces costs through early disease detection. Finally, health risks are managed and predicted, and healthcare fraud is recognized efficiently and quickly.
- Velocity refers to the frequency of data (1) produced, (2) processed, and (3) analyzed.[29] In this study, the velocity of "big data" was marked as follows. (1) Data were produced from the wearable medical sensors in the form of signals. Signals were produced as continuous real-time signals in Tier 1 and sent to Tier 3 using a Tier 2 device. Then, (2) in Tier-3, the signals were processed as records. Each signal was converted to a record. Each record typically contained 10 of the vital signs samples (i.e., data) per second of the signal. Moreover, in Tier 3, (3) records were analyzed, and the "big data" was converted to information and then to knowledge on the basis of a decision-making matrix.
- Veracity involves data uncertainty. This factor can be defined as "data assurance". Veracity assumes the concurrent upgrade in performance and granularity of the architectures, platforms, algorithms, methodologies, and tools to cover big-data needs.[30] In this study, "big data" analytics were executed by a server (Tier 3) and utilized a paradigm of cloud-computing platform. Moreover, data were processed using data-mining algorithm and decision-making techniques integrated with medical guidelines.

Given the "big data" of patients, the challenge in the triage and prioritization processes lies in the simultaneous consideration of multiple attributes (vital signs and features) and assignment of proper weights for each feature. As such, the processes score the patients on the basis of the urgency of their conditions.[5] Patients with the most urgent cases receive the highest priority level, whereas those with the least urgent cases are given the lowest priority levels. This ranking is performed on the basis of other patients' scores in a telemedicine environment. Nevertheless, setting this prioritization is a difficult and challenging task because each patient with chronic heart disease uses multiple attribute sensors for vital sign evaluation. For example, ECG and $SpO_2$ are important in triage because they provide an objective complement to triage decision making and optimize inter-rater consistency. Hence, certain medical guidelines related to chronic heart disease should be followed in triage and prioritization on the basis of patient's vital signs and features. Furthermore, each decision maker gives different weights to these attributes (vital signs). A server who aims to provide a score for a patient may give further weight to vital features than other features of lower interest. By contrast, developers who aim to develop a software for solving this problem may target different characteristics as the most important attribute. Thus, the triage and prioritization processes for the "big data" of patients with chronic heart disease comprise a multicomplex attribute problem, where each patient is considered as an available alternative for the decision maker.

The present study provides a new methodology to assist in the decision making for the "big data" of patients with chronic heart disease in the telemedical environment. An integrated model is proposed to evaluate and score the patients on the basis of integrated back-forward adjustment for weight computation (BFAWC) and technique for order performance by similarity to ideal solution (TOPSIS). The other sections of this paper are structured as follows: Section 2 presents the literature review. Section 3 describes the decision-making methodology for scoring patients with chronic heart disease. Section 4 reports the discussion results. Section 5 discusses the research contributions as summary points. Section 6 concludes the report.

## 2. Literature Review

The current literature on triaging and prioritizing algorithms over the telemedical environment is largely limited and scattered. However, some scholars attempted to create a module for these algorithms.

Ashour and Okudan[31] presented the use of utility theory in healthcare, specifically in improving triage decision making and productivity, as well as in reducing the cognitive load on triage nurses in Emergency Departments (EDs). The inherent uncertainty in this problem is the reason behind the selection of utility theory to solve the problem of patient sorting in EDs. In this study, patients were ranked on the basis of an emergency severity index and three descriptive variables: age, gender, and pain level. However, the small sample size of 21 patients and the determinant, such as pain level, may have affected the accuracy. Furthermore, The study did not consider the conflict between the data and the resolution. Another study by Ashour and Kremer[32] adopted a dynamic grouping and prioritization (DGP) algorithm to identify appropriate patient groups. These groups were then prioritized on the basis of patient and system benefits. Upon discrete event simulation, the results provided statistical evidence that the DGP system outperformed alternative prioritization methods in all the performance measures. However, the algorithm did not improve patient throughput over "big data" on the basis of multiple performance measures.

Mills[33] proposed the "floating patient" method for optimizing the scheduling of patients' ED examinations. However, this study was applied in the ED setting without consideration of multiple evaluations. This approach can affect the optimization of the scheduling of patients on the basis of their states. Childers *et al.*[34] aimed to improve the patient prioritization during complete evacuations in healthcare facilities. The authors proposed a dynamic model for patient evacuations in the ED. They concluded that continuous discussions should be held among healthcare workers on ethical dilemmas associated with evacuation decision making in triage and prioritization processes. Sung and Lee[35] presented an algorithm with a column generation approach. However, the study was applied in a disaster situation and restricted to the allocation of emergency medical resources. A dynamic programming scheduling algorithm was proposed by Elalouf and Wachtel[36] and included termination, and a simulation method was applied to crowded patients inside the ED. However, the studies did not consider the problem of "big-data" patient prioritization on the basis of emergency cases using multimeasurement attributes.

Claudio and Okudan[37] revealed a hypothetical example that involves patient prioritization in an ED using a methodology, as well as multiattribute utility analysis in healthcare. Another study by Claudio *et al.*[38] investigated the possibility of integrating technology and multiattribute utility theory in developing a dynamic decision support system for patient prioritization in the ED. The attributes in the study complied with utility independence and preferential with one another. Nevertheless, this condition might not hold true when other attributes, such as complaints, are considered. In addition, both studies did not consider multiple attributes that are related to the "big-data" patient's emergency state.

Polk and Walker[39] described a model of global system for the mobile communication interface of an existing telemedicine system. The implementation enables the care provider to remotely ask for data from the local network. All information and requests are conveyed using the short message service protocol. In addition, the system is enriched by adding a priority message layer to the routing protocol. Another routing protocol study[40] proposed a data-centric congestion protocol called HOCA for avoiding congestion in the first step (routing phase) through QoS-aware and multipath routing. Nonetheless, the main limitations of the studies by Rezaee and Yaghmaee,[40] and Polk and Walker[39] are related to the establishment of the priority message, such as how messages are created, what vital signs of the patients are used in prioritization, and what the medical guidelines are. Moreover, the accuracy of priority levels, which were set for the sending of messages and the type of healthcare services provided by the server as "big data", was not addressed.

The study by Zvikhachevskaya and Markarian[41] defined the QoS improvement in telemedicine as the ability to assign different priority levels to various cases to guarantee a certain performance level to a data flow. The study presented novel scenarios for QoS provision in emergency telemedicine for the wireless network protocol IEEE 802.11. However, the authors only mentioned these scenarios as recommended solutions for future research direction. A method for determining G treatment plans for chronic heart disease and the patient schedules in prehospital care under a telemedicine environment was proposed by Kashiyama and Uchiyama.[42] The method helped increase the number of patients expected to be saved under limited medical resources. The proposed heuristic algorithm depends on depth-limited search. The study results showed that the average number of saved patients is 10% larger than that when greedy methods were used. Nevertheless, the algorithm could not calculate patient priority for the big data "of patients"; the priority level was only assumed in the simulation.

A system that uses the electronic triage tag in telemedicine was proposed by Mizumoto *et al.*[43] This system enables emergency medical technicians to identify patients' locations and conditions. Moreover, Vohra and Sarkar[44] introduced a priority-based media access control (MAC) protocol for WBANs. The main characteristics of the proposed dynamic MAC protocol are the minimal end-to-end delays, prioritized scheduling of emergency data, high throughput, and effective bandwidth usage compared with the existing standard of the IEEE 802.15.4 protocol. However, the number of patients in the proposed protocol is limited because the system cannot be used with "big data". Otherwise, the system would shut down and result in a network fail error.

In Kateretse and Lee,[45] the proposed method is limited from the coordinators to the Gate Way, and the issue of patient triage among healthcare service providers is not addressed. In addition, the triage processes demonstrated in Ref. 5 are insufficient because the triage officers could not triage casualties quickly when mass casualties occur or when healthcare providers do not arrive early at the scene. The order of casualties for treatment and transportation is also not determined. The framework presented in Seising and Tabacchi[11] is given without considering priority, and this framework is applicable for implementation inside a hospital. A telemedicine platform based on medical sensors and wireless communication is not addressed in this framework. Nonetheless, vital signs are used in data processing. Crowdsourced and Weaver[46] proposed a heuristic algorithm technique based on depth-limited search. However, patient prioritization is not considered although the patients are already triaged at the disaster sites. The server is also not aware of the number of patients who can be treated or transported in each area.

The above-mentioned methods involve disadvantages, and no particular study for any chronic disease type is available. Meanwhile, Salman and Rasid[7] proposed a multisource healthcare architecture (MSHA) to enhance healthcare scalability by improving the remote triaging and prioritization of chronic heart disease patients. The mathematical model of MSHA is a data fusion method and prioritization technique. MSHA is currently considered as the most relevant study in this research area. Nevertheless, MSHA exhibits two disadvantages: (1) The general scheme of telemedicine systems includes three tiers (sensors/sources, base station, and server). Thus, the simulation of the MSHA method is implemented only in the base station (Tier 2). This description means that physically present patients in the hospital (server side, Tier 3) are not addressed. The exclusion of in-hospital patients raises an ethical healthcare issue. This problem is related to the need to consider all patients (i.e., in-hospital and telemedicine patients) in the prioritization process and in the provision of compatible healthcare services on the basis of each patient's emergency level. This point leads us to the second disadvantage (2) related to data size. The inclusion of in-hospital patients along with telemedicine patients in prioritizing emergency patients requires a robust method that can accommodate an increasing number of patients and consequently handle the increasing data size. The triage and prioritization processes among patients involve the simultaneous regard of multiple attributes (vital signs) and assignment of proper weight for each feature. This method would then score patients on the basis of the urgency of their conditions. Therefore, this process can be considered a multicriteria decision problem. Moreover, multisensory sources are available. Hence, for each sensor source, the subset of features displays a range of different conflicting data from various triage levels for "big data." Therefore, the process remains a difficult task.

To overcome the drawbacks in Salman and Rasid,[7] a computational method that can solve the "big-data" problem in patient prioritization should be developed. Moreover, the prioritization should consider all patients requesting services from the same hospital regardless of location.



## 3. Methodology

### 3.1. *Conceptual framework*

This paper presents a comprehensive overview of the alternative big data of patients with chronic heart disease. These data involve a set of measures obtained from the infrequently performed actual measurement of patient data and the reporting of hands-on evaluation results derived from ECG and $SpO_2$ sensors as well as other sources. The input to this section (sources and related features) is discussed in later subsections.

The ranking for the big data of patients with chronic heart disease is derived from medical guidelines, medical-sensor evaluation, and text-frame sources. The output ranks the patients on the basis of a set of features in accordance with the integrated BFAWC and TOPSIS methods. All components of our study are illustrated in the conceptual framework in Fig. 2.

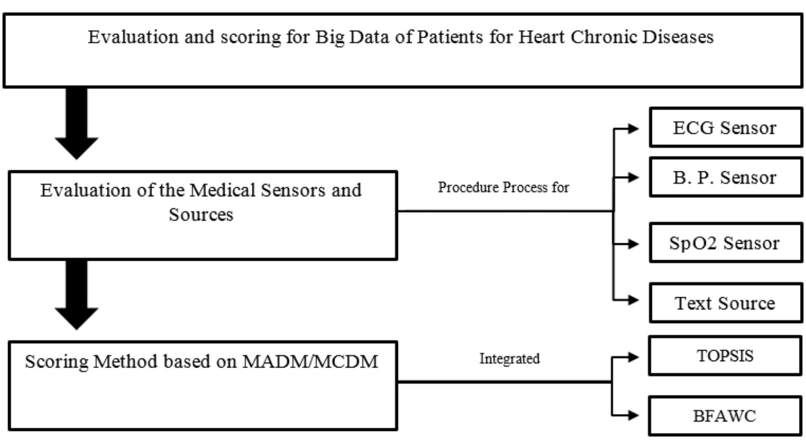



Fig. 2. Conceptual framework.

### 3.2. *Evaluation of medical sensors and sources*

Several medical devices are used to measure the patient's vital signs. The number and type of sensors depend on the type of disease that the patient should be monitored for. This research focuses on chronic heart disease; hence, this section evaluates four relevant medical sources that demonstrate cardiac performance and reflect the medical symptoms of patients with chronic heart disease. The three sensors used as signal sources and one text source are shown in Table 1. In an early stage, the input data are processed and analyzed using logically defined medical guidelines. The medical guidelines consider the rules defined and validated not only by research evidence but also by the experience of medical doctors and experts. These guidelines are then used to support decisions on user's emergency level. Medical guidelines demonstrate the relation among the user input vital sign as input data and the medical diagnosis as output data. Additional details about the medical guidelines for each source are presented in the next section.

In this study, 11 features from four heterogeneous sources are modeled. These features are considered criteria in the proposed decision-making algorithm. These features are distributed in the four sources, and the procedure is described in the following sections:

#### 3.2.1. *Procedure processes for the ECG sensor*

The ECG signal includes several features.[7] ECG feature detection is crucial for the diagnosis of cardiac diseases. The cardiac cycle in an ECG comprises P-QRS-T waves considered as ECG features. Each feature is used as a diagnostic reference for certain heart diseases. In this study, the four main ECG features used include rhythm, QRS width, peak-to-peak distance, and ST elevation.

According to medical guidelines,[7] ECG rhythm is only considered normal when its value ranges within 60–100 beats per minute; otherwise, the value is considered abnormal. Furthermore, the QRS width in an ECG signal is considered normal when the value ranges within 0.06–0.12 ms but abnormal in other ranges. The normal ST

Table 1. Description of four relevant medical sources used to monitor patients.

| Medical measuring source | Description |
|---|---|
| ECG Sensor | Measures the electrical representation of contractile activity of the heart over time. This device is helpful for the short-term assessment of cardiovascular diseases, particularly for patients with chronic heart problems. |
| $SpO_2$ Sensor | Pulse oximeter used to measure the blood oxygen saturation level of a patient. |
| Blood Pressure Sensor | Measures the physiological data of the systolic and diastolic blood pressures of a patient. |
| Text | Non-sensory measurements, such as chest pain and breathing, used by triage nurses in the hospital (ED) to prioritize patients into several categories. |

elevation is also considered normal when the ST segment is straight. However, this value is abnormal when the ST segment is evaluated to be upright or directed downward. Finally, the regular pattern of the peak-to-peak interval is considered normal, and the irregular pattern is considered abnormal.

A real-time data processing algorithm was designed to extract the four ECG features. An ECG signal is represented by an array of two columns as follows: time in ms and voltage in mv. We used these values to extract the features. An ECG signal also involves many cycles. One ECG cycle possesses various ECG features, namely, rhythm, QRS width, peak-to-peak distance, and ST elevation. For each cycle, the signal values vary around the zero line with time. We employed these values to divide the ECG cycle to up and down halves. Then, we sorted the upper half on the basis of the applied voltage values to determine the maximum point, designated as the R point. Finally, the upper half of the ECG cycle was divided in half by certain functions, as shown in Fig. 3.

To sort the values in the ECG cycle for each half (Up_Left and Up_Right) on the basis of the $t$ and $v$ values, one may locate the sites of the Q and S points. Moreover, the ST elevation can be determined through subtraction functions based on the differences of the $t$ and $v$ values. The $SpO_2$ and blood pressure (BP) values were also calculated.

### 3.2.2. *Processes for the BP sensor procedure*

BP measurements are commonly classified into normal and abnormal cases on the basis of the measurement of high and low BP levels for the patient.[47] According to medical guidelines,[7] the normal value for high BP is limited to between 11 and 14 mmHg, whereas all other values are considered abnormal. Moreover, values between 6 and 9 mmHg for low BP are considered normal, whereas other values are

**Inputs:**

- Array of ECG elements signal (ECG) for 1 minute.

**Outputs:**

- Rhythm, QRS width, ST-Elevation and regularity for ECG.

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

Fig. 3. Processes in the ECG procedure.

**Inputs:**

- Array of Blood Pressure elements signal (B) for 1 minute.

**Outputs:**

- Spo2 level.

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

Fig. 4. BP sensor procedure.



considered abnormal. The feature extraction algorithm for the BP feature is described in Fig. 4.

### 3.2.3. *Procedure processes for blood oxygen saturation sensor*

The accelerometer ($SpO_2$) value can be changed for the same user in different activities. According to medical guidelines,[48] $SpO_2$ levels range depending on different types of chronic heart disease. The normal value of $SpO_2$ ranges within 96–100%; otherwise, the value is considered abnormal. The feature extraction algorithm for the $SpO_2$ feature is described in Fig. 5.

### 3.2.4. *Processes for the text source procedure*

A series of discussions with doctors concluded that text features are essential for chronic heart disease according to medical guidelines.[7] These features show muscle activity surrounding the heart. In addition, doctors stated that abnormal text features are shared by all heart diseases regardless of abnormal or normal ECG features.[7] The presence of abnormal ECG features indicates that abnormal features are also acquired from the texts. Therefore, a patient is considered an urgent case. By contrast, when the ECG is normal and the text features are abnormal, a certain heart

**Inputs:**

- Array of Spo2 elements signal (S) for 1 minute.

**Outputs:**

- High and low blood pressure value for B.P.

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

Fig. 5. $SpO_2$ sensor procedure.

disease type has not been classified as urgent and has never been classified previously is reflected. A remarkable absence of these features was noted in telemedical applications, specifically in the remote triage setting. The text feature comprises the following sources:

- Non-sensory data;
- New sources that supply the context of the user/patient.

Salman and Rasid[7] addressed this concern by using four text measures in healthcare telemonitoring systems. These measures include chest pain, shortness of breath, palpitation, and rest or exercise. The array of text features is $1 \times 4$ because four variables represent four non-sensory features, as described in Fig. 6.

The evaluation results for each patient were generated by four sources (ECG, BP, $SpO_2$, and text). The findings also tacitly included 11 subsets of vital features: 4, 2, 1, and 4 for ECG, BP (high and low), $SpO_2$, and text, respectively. The data are summarized in Table 2 on the basis of such measures.

As stated in the evaluation result, the subsequent assumption is improved:

- According to medical guidelines, the vital feature for each source ranges in two triage levels. In our dataset, we noted that for one user (i.e., patient), the vital features simultaneously indicated more than one triage level 0 for normal, 1 for abnormal. Notably, Patient Number 1 was in the normal triage level on the basis of shortness of breath and peak-to-peak feature. However, this patient was in abnormal. on the basis of $SpO_2$ data and at the abnormal triage level on the basis of the low BP feature. As a result, the triage nurse was unable to assess the triage level of Patient Number 1. Therefore, reaching a final decision that represents the triage level of the patient is difficult under the paper-based triage system, which is normally used in the hospital by the doctor and triage nurse. A computational algorithm and a computer-based approach are urgently needed to solve complex situations in patient triage and prioritization.

**Inputs:**
- Text Variables (T).

**Outputs:**
- Text feature

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

Fig. 6. Text source procedure.

Table 2. Evaluation matrix for five random patient samples from 500 patients.

| Patient index in the decision-making matrix | $SpO_2$ sensor | BP sensor | | Text features | | | | ECG sensor | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | SpO2 level % | High BP level | Low BP level | Chest Pain | Shortness of Breath | Palpitation | Patient at Rest? | Rhythms per minute | QRS width | Peak-to-peak Interval | ST Elevation |
| 1 | 90 | 12 | 12 | True | False | True | True | 77 | 0.065 | Regular | True |
| 2 | 90 | 14 | 11 | False | False | True | False | 120 | 0.047 | Irregular | True |
| 3 | 90 | 18 | 10 | False | False | True | False | 112 | 0.047 | Irregular | True |
| 4 | 96 | 19 | 9 | True | True | False | False | 58 | 0.047 | Irregular | False |
| 5 | 85 | 23 | 10 | True | True | False | False | 60 | 0.065 | Regular | False |

- The different sources employed in this study are displayed in Table 2. For each source, a subset of features has a range of different conflicting data in various triage levels. Thus, the use of a decision-making algorithm that solves complex situations to address the problem of conflicting data in patient records is needed.

### 3.2.5. *Ranking the patients for chronic heart disease*

Multicriterion analysis is "a sub-discipline of operational research and explicitly considers multiple criteria in decision-making environments, which occur in several actual situations of medical diagnosis".[49] Several useful techniques can be adopted to address multiattribute or multicriterion decision-making (MADM/MCDM) issues in the real world.[70–76] These methods help DMs organize the problems to be solved and analyze, rank, and score alternatives.[49,50] Alternative(s) are then subsequently scored. MADM/MCDM methods can solve the scoring problem of big data for patients with chronic heart disease on the basis of the most urgent cases in a telemedicine environment. In any MADM/MCDM ranking, fundamental terms should be defined. These terms include evaluation matrix (EM), decision, criteria, and alternatives.[8] An EM that consists of $m$ alternatives and $n$ criteria must be constructed. Considering the crossing of each criteria and alternative as $x_{ij}$, we obtain the matrix $(x_{ij})_{m*n}$ as follows[86]:

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

where $A_1, A_2, \dots, A_m$ possible alternatives are scored by DMs (i.e., patients with chronic heart disease). $C_1, C_2, \dots, C_n$ are criteria against which each alternative performance is conducted (i.e., ECG, $SpO_2$ sensor, BP sensor, and text). Finally, $x_{ij}$ is the rating of alternative $A_i$ with respect to criterion $C_j$, and $W_j$ is the weight of criterion $C_j$. Certain processes, such as addition of weights, maximization of indicators, normalization, and other processes that rely on the method, must be completed to score the alternatives.

Patients with chronic heart disease were evaluated by several criteria, including ECG, $SpO_2$, and BP sensors, as well as non-sensory measurement (text frame). Another problem emerged because each patient with a chronic heart disease exhibited a number of attributes, and each DM assigned various weights to these attributes. Thus, patient prioritization based on the urgency of condition was difficult. Additionally, a server who aims to score one kind of patient might give more weight to the ECG, $SpO_2$, and BP sensors, as well as to the non-sensory measurement (text frame), than to other sources of lower interest. By contrast, developers who want to implement this software for actual healthcare providers may target different sources. The ranking of patients with chronic heart disease (particularly, for developing software) is a multiattribute problem. To solve this problem, one develops the BFAWC method to determine the weight of each feature. Most recommended MADM/MCDM methods are used to score the available alternatives. Given the integration of the most recommended MADM/MCDM methods and BFAWC method, the proposed algorithm was used to settle the multiattribute complex ranking issues in various medical diseases. The ranking scheme is explained below:

**Step 1:** Weights are allocated for each main feature in the criteria hierarchy through the BFAWC method. Each main feature is rated in the hierarchy for every patient involved in the evaluation. The BFAWC method was utilized to obtain the ratio scales from the balancing procedure. The set and test procedures were used for 50 patients when the triage system had five levels. Each level represented a certain emergency level for the patient, that is, risk, urgent, sick, cold state, and normal, as shown in Table 3 and demonstrated in Ref. 7.

In this procedure, the five tested types of chronic heart disease were selected from the five different triage levels. This procedure aims to obtain an accurate weight for

Table 3. Relationships between the emergency triage levels and selected types of chronic heart disease.

| Triage level | | | | Chronic heart disease |
|---|---|---|---|---|
| Color | Name | PC | Status | |
| | Red | 66–100 | Risk | Heart attack |
| | Orange | 51–65 | Urgent | Arrhythmia, apnea |
| | Yellow | 26–50 | Sick | Chest infection |
| | Blue | 03–25 | Cold state | Muscular pain |
| | Green | 0–2 | Normal | No disease |

each feature that can represent the patient diagnostics in all five triage levels. Table 3 presents the relationships between the emergency triage levels of the selected types of chronic heart disease from all four sources.

To establish the weight for each vital feature, the maximum score of 100% (which represents the most urgent case at the risk level) was divided into four categories: text and ECG, $SpO_2$, and BP sensors. Furthermore, the weight for each category was divided and randomly distributed over its related features. The summation of all weighted values from all four sources was checked before the tests were started. The tests were started when the summation was 100; otherwise, the weights for all the features were redistributed and optimized. Each test started with the following sequential steps:

(1) The features from all the four sources (ECG, BP, $SpO_2$, and text) are extracted.
(2) The weight is distributed:
   (a) If the feature is within the abnormal range ($\surd$), the value of the weight is set to a certain decimal number.
   (b) If the feature is within the normal range ($x$), the weight is set to zero (0).
(3) The summation of all weights is calculated.
(4) The value of the total weight with the triage level based on Table 4 is calculated.
(5) If the comparison is (FALSE), the weight is reset, and the tests are repeated.
(6) If the comparison is (TRUE), the next test proceeds, or if the test number is 5, the weight is saved for each feature.

These weights were considered the final weights for each feature and were saved only when the same scoring points for all the features have passed and completed all five tests. The procedure was then finished. Otherwise, the weights ware reset, and the procedure continued. Obviously, the outcome of the set and test procedures is a weight for each feature that is evaluated and validated for different types of chronic heart disease from varying emergency triage levels. Table 4 demonstrates the weight distribution for each feature in the five tests and the normal case (when the patient is within the normal situation) within the set and test procedures.

The set and test procedures were repeated for 50 patients with different emergency triage levels until the weight of all the features was set to certain integer values that indicate the right triage level for the symptoms of all the tested diseases. Thus, the results indicate the proper triage level if the same weight is used for every feature to triage patients in the five diseases. After attaining the responses on the weighted scale, the reciprocal weight percentage for each weight was collected from the balancing procedure, as indicated in Table 4. Lastly, the weights were calculated, the result of which indicated the importance of the feature (Table 5).

**Step 2:** Several MCDM or multicriteria decision-making theories are explored.[65–69] The most common MADM methods that use various concepts include weighted product method (WPM), weighted sum model (WSM), multiplicative

Table 4. Weight distribution for each feature in the five tests and the normal case.

| Source | Feature | Test 1 | | Test 2 | | Test 3 | | Test 4 | | Test 5 | | Normal case | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Abnormal? | Heart attack | Abnormal? | Arrhythmia | Abnormal? | Chest infection | Abnormal? | Apnea | Abnormal? | Muscular pain | Abnormal? | Normal |
| Text | Chest pain | √ | 18% | √ | 18% | √ | 18% | X | 0% | √ | 18% | X | 0 |
| | Shortness of breath | √ | 12% | √ | 12% | √ | 12% | √ | 12% | X | 0 | X | 0 |
| | Palpitation | X | 0 | √ | 6% | √ | 6% | √ | 6% | X | 0 | X | 0 |
| | Patient at rest? | √ | 2% | √ | 2% | √ | 2% | √ | 2% | X | 0 | √ | 2% |
| Sensor 1: ECG | Straight | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | ST segment | √ | 20% | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | Rhythm | X | 0 | √ | 10% | X | 0 | √ | 10% | X | 0 | X | 0 |
| | | X | 0 | X | 0 | √ | 10% | X | 0 | X | 0 | X | 0 |
| | P-to-P distance | √ | 4% | √ | 4% | X | 0 | X | 0 | X | 0 | X | 0 |
| | QRS width | X | 0 | √ | 4% | X | 0 | √ | 4% | X | 0 | X | 0 |
| Sensor 2 $SpO_2$ | ≥96 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | (90–95) | √ | 6% | X | 0 | X | 0 | √ | 6% | X | 0 | X | 0 |
| | (0–89) | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| Sensor 3 BP: high | (22–up) | X | 0 | X | 0 | X | 0 | √ | 7% | X | 0 | X | 0 |
| | (14–21.9) | √ | 3.5% | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | (11–14) | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| Sensor 3 BP: low | (≥11) | √ | 2.5% | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | (9–11) | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 | X | 0 |
| | (6–9) | X | 0 | X | 0 | X | 0 | √ | 5% | X | 0 | X | 0 |
| Output | PC | | 68% | | 56% | | 48% | | 52% | | 18% | | 2% |
| | Triage level | | Risk | | Urgent | | Sick | | Urgent | | Cold state | | Normal |
| | Triage color | | | | | | | | | | | | |

Table 5. Results of weights calculated from the set and test procedures on the BFAWC method.

| Source | Feature | Normal value | | Abnormal value | |
|---|---|---|---|---|---|
| | | Normal case | Weight % | Abnormal case | Weight % |
| Text | Chest pain | "No" | 0 | "Yes" | 0.18 |
| | Shortness of breath | "No" | 0 | "Yes" | 0.12 |
| | Palpitation | "No" | 0 | "Yes" | 0.06 |
| | Patient at rest? | "No" | 0 | "Yes" | 0.02 |
| ECG sensor | Straight | | 0 | Flatline | 0.38 |
| | ST segment | Straight | 0 | Up | 0.20 |
| | | | 0 | Down | 0.20 |
| | Rhythm | 60<R<100 | 0 | (R<60) | 0.10 |
| | | | | (R>100) | 0.10 |
| | P-to-P distance | Regular | 0 | Irregular | 0.04 |
| | QRS width (sec.) | 0.06<QRS < 0.12 | 0 | QRS<0.06 | 0.04 |
| | | | | QRS>0.12 | |
| $SpO_2$ sensor | Peak value | (≥96) | 0 | (90–95) | 0.06 |
| | | | | (0–89) | 0.12 |
| BP sensor | High BP | (11–14) | 0 | (≥22) | 0.07 |
| | | | | (18–22) | 0.035 |
| | | | | (14–18) | |
| | Low BP | (6–9) | 0 | (9–11) | 0.025 |
| | | | | (≥11) | 0.05 |

exponential weighting (MEW), simple additive weighting (SAW), hierarchical adaptive weighting (HAW), analytic network process (ANP), analytic hierarchy process (AHP), and TOPSIS.[50] To our knowledge, none of these methods have been used to score "big data" for patients with chronic heart disease. The advantages, shortcomings, and recommendations for popular MCDM methods are presented as follows on the basis of the literature.[51–55]

HAW and WSM are easy to understand and use. However, the attribute weights are assigned arbitrarily, and both methods are hard to adopt in case of numerous criteria. An additional drawback of these methods is that common numerical scaling is used to calculate the final score. The advantages of WPM and MEW are their capability to eliminate any item to be measured and the use of relative values rather than actual ones. On the other contrary, these two methods do not offer any solution with equal decision matrix weight. SAW considers all criteria, provides simple calculation, and makes decisions intuitively. Nevertheless, all criteria values must be positive and maximum. In addition, SAW does not usually reveal the real situation. AHP allows DMs to structure the decision-making problem into a hierarchy, which simplifies and facilitates understanding of the problem. However, this method is time consuming owing to the number of pairwise comparisons and required mathematical calculations, which increase as the number of criteria and alternatives increase or change. Scoring in AHP relies on the alternatives considered for evaluation. The deletion and addition of alternatives may alter the final ranking (rank reversal problem). The TOPSIS method is connected to discrete alternative issues. This method is one of the best approaches to solving real-world problems. The important merit of TOPSIS is its capability to rapidly recognize the most suitable alternative. Conversely, the major drawbacks of TOPSIS include lack of provision to weigh elicitation and check judgments' consistency. The use of AHP is significantly restrained by human's capacity for information processing; thus, $7 \pm 2$ is regarded as the ceiling for comparison.[56] By contrast, the ANP method provides complete understanding of the significance level that a criterion can take regarding its interrelationship with other criteria. The advantage of the ANP method is that it allows measurement of the judgments' consistency, which is impossible to evaluate in the method that assigns weights by compromise. Another advantage of the ANP model is that it helps assign weights by breaking up the problem into smaller parts so that a group of academics can have a manageable discussion, where only two criteria are compared in assigning judgments.[85] Conversely, ANP has two disadvantages. First, providing correct network structure among criteria is difficult even for experts, and different structures lead to different results. Second, the formation of a super matrix requires pairwise comparison of all criteria with all other criteria, which is both difficult and unnatural.[57,58] Based on this perspective, TOPSIS decreases the pairwise comparisons required, and the capacity limitation may not significantly dominate the process. Consequently, TOPSIS is applicable for cases with numerous alternatives and criteria; the method is also specifically convenient to use when quantitative or objective data are given.

The MCDM methods described in this section are used to score the big data of patients with chronic heart disease and prioritize the most urgent cases. However, these techniques lack indicators of how well a certain healthcare service can satisfy the patient's needs. An additional issue of these methods is that the requirement-driven approach is not adopted, which makes them insufficient for priority scoring based on decision making.[49] Moreover, the TOPSIS method is recommended for use because it is widely adopted in ranking matter on medical scatter.[49,50]

The available alternatives are scored in descending orders, and the most urgent patients are scored based on TOPSIS, as shown in Fig. 7. Aggregate scores provide an idea of which patients are more urgent than the others. Individuals can always be relied on to rank the most urgent, as in other ranking options.[77] TOPSIS assigns the rank to each patient on the basis of their geometric distance from negative and positive ideal solutions. With this technique, the most urgent patient would have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution, as illustrated in the following steps:

- **1:** Create the normalized decision matrix.

This step attempts to transform the dimensions of different attributes (vital features) into nondimensional attributes and permits comparison through the attributes. The matrix $[(x_{ij})]_{(m^*n)}$ is normalized from $[(x_{ij})]_{(m*n)}$ to the matrix

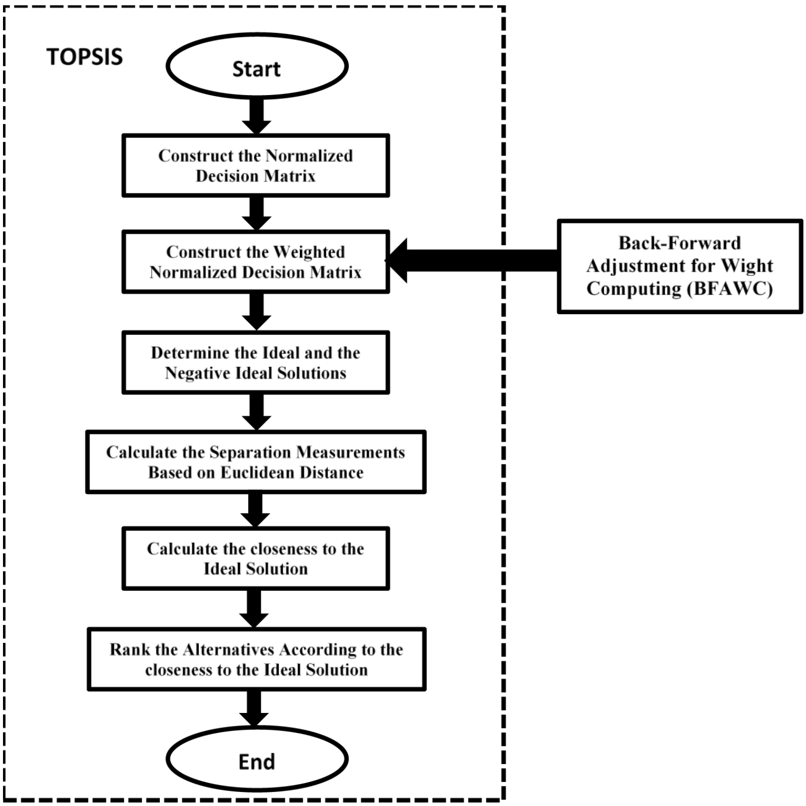



Fig. 7. Integrated BFAWC–TOPSIS model for patient prioritization.

$R = [(r_{ij})]_{(m*n)}$ using the normalizing method:

$$r_{ij} = \boldsymbol{x}_{ij} \Bigg/ \sqrt{\sum_{i=1}^{m} \boldsymbol{x}_{ij}^2}. \tag{1}$$

This step will produce a new matrix $R$, where $R$ is

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

- **2:** Build the weighted (scoring points), normalized decision matrix.

In this step, the weights for each attribute are computed based on the BFAWC model. A set of weights "$w = w_1, w_2, w_3, \ldots, w_j, \ldots, w_n$" from the DM is accommodated to the normalized decision matrix. The resulting matrix can be obtained by multiplying each column of the normalized decision matrix R to its associated weight $w_j$. Moreover, the set of the weights is equal to 1:

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

This process will produce a new matrix $V$, where $V$ is

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

- **3:** Determine the ideal and negative ideal solutions.

In this step, the two artificial alternatives, namely, A$^*$ (ideal alternative) and A$^-$ (negative ideal alternative), are defined as follows:

$$\begin{aligned} A^* &= \{((\max_i v_{ij} | j \in J), (\min_i v_{ij} | j \in J^-) | i = 1, 2, \dots, m)\} \\ &= \{v_1^*, v_2^*, \dots, v_j^*, \dots, v_n^*\}, \end{aligned} \tag{3}$$

$$\begin{aligned} A^- &= \{((\min_i v_{ij} | j \in J), (\max_i v_{ij} | j \in J^-) | i = 1, 2, \dots, m)\} \\ &= \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\}. \end{aligned} \tag{4}$$

Notably, $J$ is a subset of $\{i = 1, 2, \dots, m\}$, which presents the beneficial attributes, whereas $J^-$ is the complement set of $J$ and can be noted as $J^c$; $J^c$, which is the set of cost attributes.

- **4:** Calculate the separation measurement using the Euclidean distance.

In this step, measurement separation is performed by obtaining the distance among each alternative in $V$ and the ideal vector A$^*$ with the Euclidean distance, which is determined through the following:

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

Similarly, the separation measurement for each alternative in $V$ from the negative ideal A$^-$ is obtained as follows:

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

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

- **5:** Calculate the closeness to the ideal solution.

In the step, the closeness of $\mathrm{A}_i$ to the ideal solution $\mathrm{A}^*$ is defined as follows:

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

Obviously, $C_{(i^*)} = 1$, if and only if $(A_i = \mathrm{A}^*)$. Similarly, $C_{(i^*)} = 0$, if and only if $(A_i = A^-)$.

- **6:** Rank the alternatives based on their closeness to the ideal solution.

The set of alternatives $[A]_i$ can now be ranked based on the descending order of $[C]_{(i^*)}$. The highest value indicates the optimal performance.

## 4. Result Discussion

The discussion is divided into two parts, namely, the results and validation of the proposed method, and the characterization of the proposed method for the "big data" of patients on the basis of the "4Vs".

### 4.1. *Results and validation of the proposed method*

The proposed system was simulated using JAVA because of its many benefits, such as real-time implementation, parallel execution, usage from anywhere by all interested parties, ability to run JAVA-based applications on different platforms (e.g., PC and mobile phone devices), and compatibility with different operating systems (e.g., Android, Windows, and Linux).[59] Figure 8 shows that XAMMP was used on the server side (Tier 3). XAMPP is a light and small Apache distribution tool that contains the most common web development technologies in a single package. XAMPP is a free/open-source software, and the letters of its acronym stand for the following: X, cross platform for web server; A, HTTP Apache server; M, MySQL database; P, PHP script writing language; and P, Perl programming language. The content, size, and portability of XAMPP make it the ideal tool for researchers to develop and test applications.[60] In the simulation, JAVA was used as the programming language.[61]

The sent data from Tier 2 to Tier 3 consider the user's vital signs that are further used in Tier 3 by doctors to provide the user with personalized healthcare services. The improvement in remote triage, prioritization, and healthcare services with the use of these data has been previously demonstrated. However, this section shows how the addition of these data affects the total message size and how these data are considered big data in the server (Tier 3). The size of the user's sending message can reach the big data challenge by considering many factors (number of users, number of requests for one user per day, telemedicine users, and in-hospital users for many departments, such as ED, inside the hospital). Figure 9 shows the increasing measured data size in the healthcare server (Tier 3) for several users per day when the size of the sending message, which includes three sensory signals with 1 min length

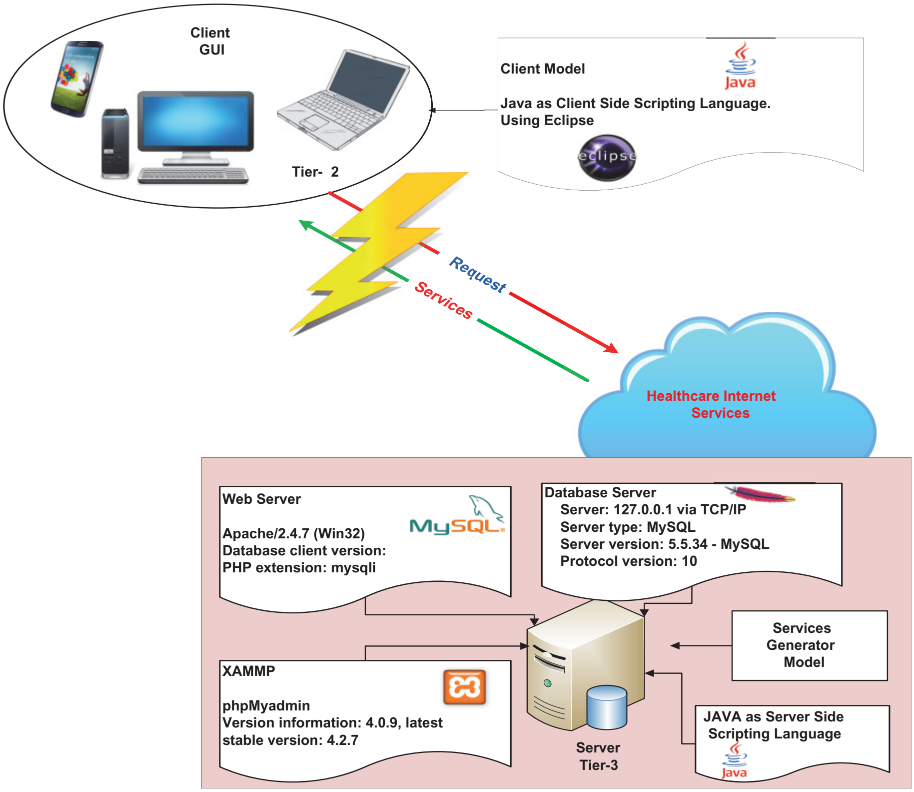



Fig. 8. Block diagram scheme of the simulation architecture of the proposed system.

(ECG, SpO2, and BP) and text features, is equal to 314.647460 KB. Furthermore, if the user updates his/her profile in the hospital server every 5 min, then the total size of the data in the server for one day becomes almost equal to 91 MB. In addition, we considered about 1000 telemedicine users who are physically in the hospital. Consequently, the total size reaches almost 2.2 TB for one day.

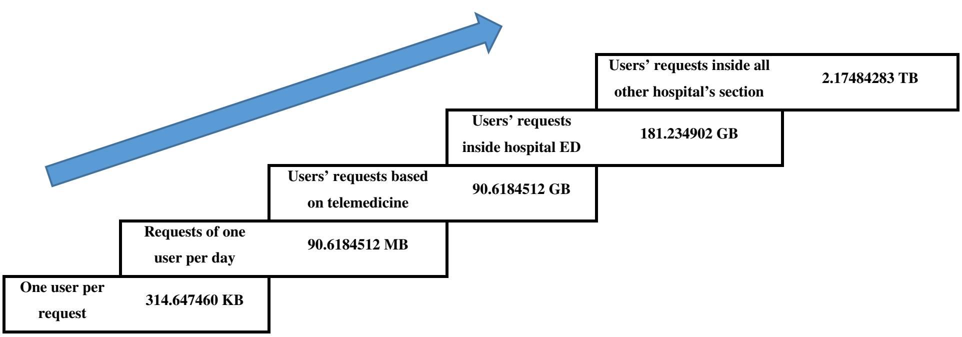



Fig. 9. Calculation of the data size.

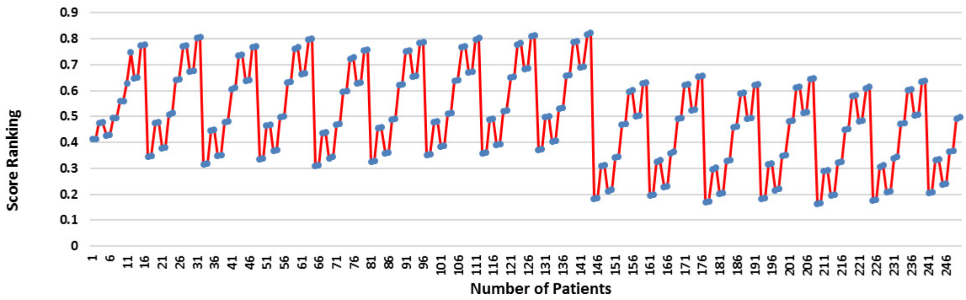
Current technologies introduce new Internet and mobile cellular communication protocols that can easily and successfully handle the increase in message size between Tiers 2 and 3. However, the computation for the big data in Tier 3 to extract the knowledge on the users' emergency level is a challenge.

The input dataset is used to evaluate the proposed model varied in different aspects, such as gender, age, patient location, and medical history availability in the hospital's server. For all the dataset used, the proportions of male and female were 60% and 40%, respectively. About 50% of the patients were 40–65 years old, 40% of them were more than 65 years old, and 10% of them were below 40 years old. In addition, 50% of the patients already had medical records, and the other 50% had none.

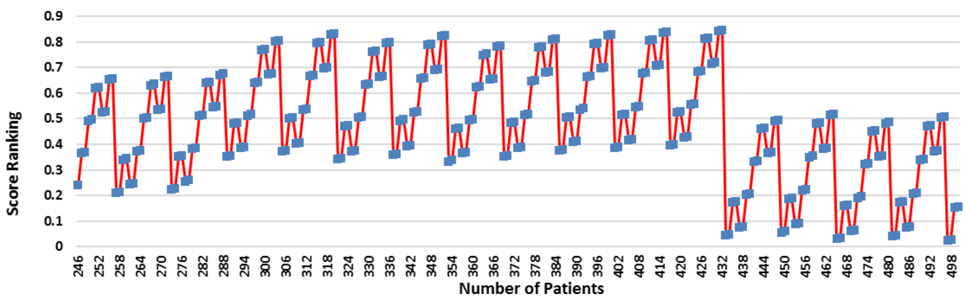
In the evaluation, the evaluation metric values were presented as follows: ECG, $SpO_2$, and BP sensors and non-sensory measurement (text frame). The data are presented as either normal or abnormal. An experiment based on the evaluation metric was conducted by integrating BFAWC and TOPSIS to calculate the weight and to score patients with chronic heart disease in terms of the most urgent patients, respectively, as displayed in Table 4. For both parts, the same dataset was used. The dataset presented different symptoms that had been defined by doctors. These symptoms were related to chronic heart disease. The standard ECG, $SpO_2$, and BP datasets from different data packages were used to validate and determine the reliable standard dataset.[62] Each package included the symptoms of chronic heart disease for one user. All users were considered at different emergency levels. Majority of the users exhibited abnormal emergency levels, and many showed symptoms of chronic heart disease on the basis of the abnormal ranges of ECG, $SpO_2$, and BP, as well as text features. The result of each iteration in the $x$-axis represents a patient (user) with certain symptoms of chronic heart disease. The corresponding value in the $y$-axis denotes the priority value. A total of 500 simulation iterations were used. Figures 10(a) and 10(b) illustrate the output results.

To validate the results, six patients were selected on the basis of the score ranking results and were evaluated by a medical committee (two triage doctors and one cardiologist). These patients were the first three (155, 156, and 158) and last three (91, 92, and 95). The medical committee ensured that the patients with the most urgent cases received the highest priority level (first three patients) whereas those with the least urgent cases were given the lowest priority levels (last three patients) compared with other patients' scores over the telemedicine environment.

The first three patients were considered as the patients with the highest priority level and who needed a fast response from the server. Based on the medical classification of all 11 features used in our proposed algorithm, the first three patients showed seven common abnormal features (SpO2, high BP, low BP, chest pain, shortness of breath, palpitation, and ECG ST elevation) and one common normal feature (ECG rhythm). Nevertheless, the three other features (patient at rest, QRS width, and peak-to-peak interval) showed different medical classifications. All three features were abnormal for Patient Number 155. Thus, this patient was the first in




(a)




(b)

Fig. 10. (a) Score ranking results of the patients (patient numbers 1–250) based on the proposed method. (b) Score ranking results of the patients (patient numbers 251–500) based on the proposed method.

the decision-making ranking and the urgent triage level. Patient Number 156 exhibited two abnormal features (QRS width and peak-to-peak interval) and one normal feature (patient at rest). Patient Number 158 showed two abnormal features (patient at rest and peak-to-peak interval) and one normal feature (QRS width). Although Patient Numbers 156 and 158 displayed the same number of abnormal features, they differed in the type of features and consequently in medical assessment and weight for each feature. Patient Number 156 was ranked higher than Patient Number 158 because the total weight for the two abnormal features of the former was higher than that of the latter.

The last three patients displayed eight common normal features ($SpO_2$ level, chest pain, shortness of breath, palpitation, ECG rhythm per minute, QRS width, peak-to-peak interval, and ST elevation). However, the three other features (high and low blood levels and patient at rest) displayed varying medical classifications. Patient Number 95 was ranked in the last index of the decision-making matrix and triaged in the normal triage level because the three features were normal. Patient number 92 only showed one abnormal feature (patient at rest), and the two other features (high and low blood levels) were normal. Moreover, Patient Number 91 presented two abnormal features (high and low blood levels) and one normal feature (patient at rest). Given that the total weight of high and low blood levels was higher than that of the "patient at rest" feature, Patient Number 91 was ranked an index higher than Patient Number 92.

According to the medical committee, the first three patients exhibited the most urgent cases and received the highest priority levels, whereas the last three patients showed the least emergency cases and were given the lowest priority levels compared with the other patients. This result was similar to the systematic ranking result outcomes.

### 4.2. *Characterization of the proposed method for the "Big Data" of patients on the basis of the "4 Vs"*

#### 4.2.1. *Data volume*

In the research environment, the data volume increases owing to the following reasons: (1) increase in the number of remote users (far from hospital) per unit area, (2) provide continuous 24/7 monitoring service for the user, and (3) increase in the number of users from different departments inside the hospital. Consequently, considering that the data volume represents one of the "4Vs" of big data, we describe in this section, the evaluation of the proposed method in handling the increased data volume.

The ability to handle the increase in data volume represents the scalable performance of the proposed method. Hence, our proposed method was evaluated and benchmarked with the relevant study based on the scalability performance in Tier 3.

An experimental process of the proposed scalability mechanism in healthcare monitoring requires the use of appropriate measurement metrics. Throughput is considered as one of the main parameters in the measurement of scalability performance.[63] It is defined as the rate at which requests (from the users) are processed by the healthcare services provider system. In the proposed method, throughput was measured in terms of requests per minute. According to Little's law,[63] in healthcare service provisioning scenario, when a number $(N)$ of average users wait for services and the average user spends $(R)$ seconds in waiting for services, then the throughput of the service provider $(X)$ is calculated as follows:

$$X = N/R. \tag{8}$$

The proposed algorithm exploited the triage and priority level generated in MCDM based on the integration of TOPSIS and medical guidelines; the benchmark algorithm exploits the triage level generated in MSHA based on the data fusion module.[7] In general, doctors spend a median of 13–16 min to provide services per patient.[64] We assumed that a doctor needs 10 min to analyze and evaluate the data and provide services for each patient in the server side (Tier 3). We also neglected the time required for the doctor to listen to the patient. Remote (telemedicine users) and in-hospital patients were considered in the scalability evaluation. According to the MSHA framework in Ref. 7, a doctor needs 10 min to analyze the data and provide services for remote patients who are already triaged and prioritized using PC code.

Thus, we assumed that the required time to prioritize and provide services for telemedicine patients in our proposed model and MSHA is 10 min. In our proposed model, we further assumed that the required time to provide services for in-hospital patients is 5 min, which is half of the 10 min mentioned earlier. The patients are already in the hospital; consequently, they have been admitted in the appropriate department, and their vital data have already been collected by the medical staff: (1) doctor and (2) nurses. By contrast, the in-hospital patients within MSHA were excluded from the prioritization processes. To overcome this drawback and improve the performance of the MSHA framework, we assumed that the medical staff needs 4 min to collect the data of the in-hospital patients and generate PC for them. Consequently, the service provisioning time for in-hospital patients becomes $(5 + 4 = 9)$ min.

The input dataset used to evaluate the scalability performance of the proposed model is the same dataset used earlier in the priority process, as shown as in Figs. 10(a) and 10(b). The dataset has varied aspects, such as ECG, $SpO_2$, and BP records; gender; age; patient's location (i.e., telemedicine or in-hospital patients); and medical history availability in the hospital's server. Thus, the main aspect of the dataset profile affecting the scalability performance was the patients' location. Five percent of the patients used telemedicine, and the remaining 95% of the patients were distributed in the different hospital departments. All users were considered at different emergency levels. A total of 500 users participated in the simulation. Initially, different data packages from the datasets were created. Each package included the symptoms for one user. The achievement of a highly accurate triage level based on MSHA and our proposed model was assumed. In addition, XAMMP was used as the software simulation environment on the server side (Tier 3). In our proposed scenario, the throughput (i.e., the rate of service provisioning per unit time) varied depending on the user's location. Figure 11 exhibits the scalability efficiency from the user's point of view, which focuses on response per unit time.

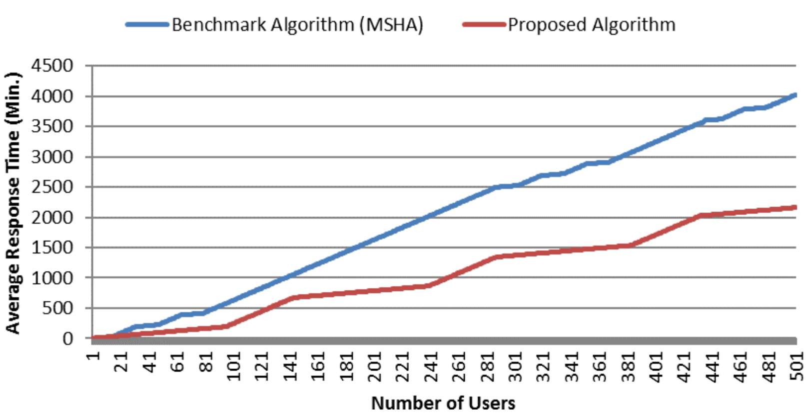



Fig. 11. Response time rate as a function of time (in minutes) per user for the proposed algorithm compared with the benchmark algorithm.

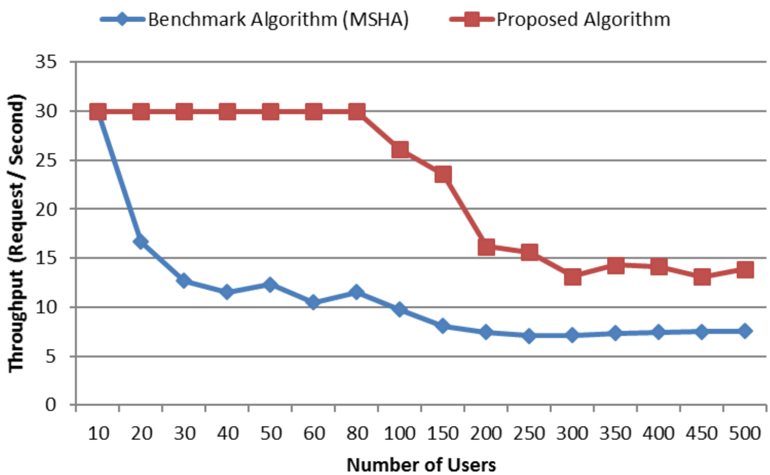



Fig. 12. Throughput as a function of the number of requests (user) served per second for the proposed algorithm compared with the benchmark algorithm.

When the number of users increased, the response time from the server based on our proposed algorithm was considerably less than that of the benchmark algorithm. Figure 12 shows the throughput of the proposed algorithm compared with that of the benchmark algorithm based on Eq. (1). Although the throughput was defined previously as the number of request served per minutes, Fig. 12 illustrates the throughput as a function of requests per second and shows the scalability efficiency from the server's point of view, which focuses on productivity (work performed per time unit). The results of the proposed algorithm started to deviate from linear scalability after about 100 users, and they started to deviate before the 10th user in the benchmark algorithm. Furthermore, the throughput values based on our proposed algorithm were higher than those of the benchmark algorithm.

As displayed in Figs. 11 and 12, the simulation results and analyses demonstrated that the proposed algorithm improves the scalability efficiency of the healthcare service by accommodating the increasing request number. Overall, the proposed MCDM model overcomes the weakness points of the most relevant study[7] through the following: (1) proposing one approach, which includes the remote patients in telemedicine and in-hospital patients, and (2) handling the increasing data size from large-scale patients. Technically, we use the same four sources and vital features found in the relevant study; our improvement aims to modify the mathematical model using MCDM. In our MCDM proposed model, the integrated use of medical guidelines with the TOPSIS method handles the increasing data size and solves the conflicting problem in the patients' data, as shown in Figs. 10(a) and 10(b).

### 4.2.2. *Data variety*

In our proposed scenario, data variety was achieved by collecting the data from the user in different forms. The user's data comprises sensory data from wearable medical sensors (ECG, BP, and $SpO_2$ signals) and non-sensory data representing in-text format. The text data added more context on the user's symptoms of chronic heart disease. In future studies, data variety in healthcare applications can be addressed by considering the data from different sources in a wide range of forms, such as video streaming, audio signal, GPS signal, wearable sensors, and images. Data variety paved the connection of big data with Internet of Things in healthcare systems.

#### 4.2.3. *Data velocity*

Patients who have chronic heart disease need 24/7 monitoring. Thus, in the proposed scenario, the user is attached to or wears medical sensors that send the text data all the time. The velocity of sending the data to the server depends on (1) the data processing in Tier 1 considering that the sampling rate of the sensor's signal is 10 samples per second, (2) sending the data from Tier 1 to Tier 2 and then to Tier 3 using Internet and wireless communication protocols, and (3) analyzing the data in the Tier 3 records.

#### 4.2.4. *Data veracity*

Healthcare data veracity encounters many common challenges, such as whether or not the patient or hospital is correct, and challenges that are unique to healthcare, for example, whether or not the diagnosis, treatment, prescription, procedure, or outcome is captured correctly.[30] In the present study, we had overcome those issues by (1) using a reliable dataset that represents the wearable medical sensors in the simulation,[62] (2) considering the medical guidelines in triaging and prioritizing patients, and (3) validating the outcome results.

## 5. Summary Points

- *What is Already Known?*
  - Triage setting and prioritization processes for remote "big data" of patients with chronic heart disease are more complex in telemedicine than in actual ED situations.
  - Patients with chronic heart disease display several attributes during the evaluation process, and each DM assigns these attributes with different weights. Another issue is that a server aiming to score one type of patient might give more weight attributes compared with others who have less interesting attributes than those mentioned. The ranking of patients with chronic heart disease is a multiattribute problem.
  - Traditionally, patients who are physically at the hospital's ED are prioritized by triage nurses using the paper-based triage system. Making a final decision that represents the triage level of the patients is difficult.

- *What Does This Study Contribute?*
  - This study presents a new methodology to evaluate and score the "big data" of patients with chronic heart disease and who displays the most urgent cases based on multicriteria decision making in telemedicine environment.
  - The BFAWC method was developed to calculate the attribute weights for each patient with chronic heart disease. Subsequently, TOPSIS was used to score the available alternatives that could be considered. The proposed algorithms were utilized to solve complex multiattribute ranking issues in patients with chronic heart disease.
  - On the basis of the proposed integration methods in telemedicine applications, a final decision indicated that the patients with the most urgent cases achieved the highest priority level, whereas those with the least urgent cases obtained the lowest priority levels among all patients' scores.

## 6. Conclusion

The evaluation and scoring for the big data of patients with chronic heart disease in telemedicine are a multicriteria decision problem that includes different issues. This study presented a new methodology to assist the processes of decision making in triaging and prioritizing patients with chronic heart disease over the telemedicine environment. An integrated model was established to evaluate and score the patients on the basis of BFAWC and TOPSIS. A hands-on study was performed, and a set of 498 patients with different symptoms and emergency levels of chronic heart disease were separately evaluated on the basis of four main measurements: ECG, $SpO_2$, BP sensors, and non-sensory data (text frame). The patients were ranked on the basis of a set of measurement outcomes using integrated methods. Results showed that patients with the most urgent cases obtained the highest priority level, whereas those with the least urgent cases obtained the lowest priority levels among all patients' scores. In addition, the throughput values based on our proposed algorithm were higher than those of the benchmark algorithm. In future works, a considerable number of studies are needed to elaborate on the architecture of an adaptive and integrated decision-making platform for different chronic diseases (heart attack, diabetes, and high or low BP), which can be used for patient prioritization, considering the different diseases and emergency levels of each patient. Moreover, the use of many sources (e.g., video, audio, image, medical sensor, and GPS) to triage, prioritize, and provide a compatible emergency level to patients remains an open research issue. Finally, the challenge on combining several integrated hospital servers and distributed database into one general model to triage and prioritize patients is one of the future research directions that need further studies, analyses, and justifications.

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## References

1. T. Nguyen *et al.*, Classification of healthcare data using genetic fuzzy logic system and wavelets, *Expert Systems with Applications* **42**(4) (2015) 2184–2197.
2. H. Westergren, M. Ferm and P. Häggström, First evaluation of the paediatric version of the Swedish rapid emergency triage and treatment system shows good reliability, *Acta Paediatrica* **103**(3) (2014) 305–308.
3. D. Christensen *et al.*, Nurse-administered early warning score system can be used for emergency department triage, *Danish Medical Bulletin* **58** (2011) A4221.
4. A. Zarabzadeh *et al.*, Variation in health care providers' perceptions: Decision making based on patient vital signs, *Journal of Decision Systems* **22**(3) (2013) 168–189.
5. K. Sakanushi *et al.*, Electronic triage system: Casualties monitoring system in the disaster scene, in *P2P, Parallel, Grid, Cloud and Internet Computing (3PGCIC), 2011 International Conference on* (2011).
6. D. Pinto Júnior, P. D. O. Salgado and T. C. M. Chianca, Predictive validity of the manchester triage system: Evaluation of outcomes of patients admitted to an emergency department, *Revista Latino-americana de Enfermagem* **20**(6) (2012) 1041–1047.
7. O. H. Salman *et al.*, Multi-sources data fusion framework for remote triage prioritization in telehealth, *Journal of Medical Systems* **38**(9) (2014) 1–23.
8. B. Godfrey *et al.*, *Emergency Medical Guidelines*, 3rd edn. (Sunshine Act of Florida, Florida, 2000), p. 245.
9. T. H. Sanders *et al.*, Remote smartphone monitoring for management of Parkinson's Disease, in *Proc. 6th Int. Conf. PErvasive Technologies Related to Assistive Environments* (ACM, 2013).
10. A. Rocha *et al.*, Innovations in health care services: The CAALYX system, *International Journal of Medical Informatics* **82**(11) (2013) e307–e320.
11. R. Seising and M. E. Tabacchi, *Fuzziness and Medicine: Philosophical Reflections and Application Systems in Health Care: A Companion Volume to Sadegh-Zadeh's Handbook of Analytical Philosophy of Medicine*, Vol. 302 (Springer, New York, 2013).
12. V. Yeguas and R. Casado, Big Data issues in computational chemistry, in *2014 Int. Conf. Future Internet of Things and Cloud (FiCloud)* (IEEE, 2014).
13. E. Dumbill, Making sense of big data, *Big Data* **1**(1) (2013) 1–2.
14. P. Russom, Big data analytics, *TDWI Best Practices Report, Fourth Quarter* (2011) 1–35.
15. C. Eaton *et al.*, *Understanding Big Data* (McGraw-Hill Companies, 2012).
16. O. Team, *Big Data Now: Current Perspectives from OReilly Radar* (OReilly Media, 2011).
17. P. Zikopoulos and C. Eaton, *Understanding big data: Analytics for enterprise class hadoop and streaming data* (McGraw-Hill Osborne Media, 2011).

18. P. Bellini *et al.*, Tassonomy and review of big data solutions navigation, *Big Data Computing* **8**(11) (2013) 1–31.
19. Y. Demchenko *et al.*, Addressing big data issues in scientific data infrastructure, in *Collaboration Technologies and Systems (CTS), 2013 Int. Conf.* (IEEE, 2013).
20. F. M. Megahed and L. A. Jones-Farmer, A statistical process monitoring perspective on big data, in *Frontiers in Statistical Quality Control*, eds. S. Knoth and W. Wolfgang, 11th edn. (Springer, New York, 2013).
21. M. Minelli, M. Chambers and A. Dhiraj, *Big Data, Big Analytics: Emerging Business Intelligence and Analytic Trends for Today'S Businesses* (John Wiley & Sons, New Jersey, 2012).
22. H. Rahman, S. Begum and M. U. Ahmed, Ins and outs of big data: A review, in *The 3rd EAI International Conference on IoT Technologies for HealthCare HealthyIoT'16*, 18 October 2016 (Sweden, 2017).
23. C. Auffray *et al.*, Making sense of big data in health research: Towards an EU action plan, *Genome Medicine* **8**(1) (2016) 71.
24. L. Wang and C. A. Alexander, Big data in medical applications and health care, *American Medical Journal* **6**(1) (2015) 1.
25. K. Priyanka and N. Kulennavar, A survey on big data analytics in health care, *International Journal of Computer Science and Information Technologies* **5**(4) (2014) 5865–5868.
26. S. C. Helm-Murtagh, Use of big data by blue cross and blue shield of North Carolina, *North Carolina Medical Journal* **75**(3) (2014) 195–197.
27. H. Jagadish *et al.*, Big data and its technical challenges, *Communications of the ACM* **57**(7) (2014) 86–94.
28. M. A. Chowdhury, W. Mciver and J. Light, Data association in remote health monitoring systems, *IEEE Communications Magazine* **50**(6) (2012) 144–149.
29. B. Feldman, E. M. Martin and T. Skotnes, *Big Data in Healthcare Hype and Hope* (Dr. Bonnie, 2012), p. 360.
30. W. Raghupathi and V. Raghupathi, Big data analytics in healthcare: Promise and potential, *Health Information Science and Systems* **2**(1) (2014) 1.
31. O. M. Ashour and G. E. Okudan, Patient sorting through emergency severity index and descriptive variables' utility, in *IIE Annual Conf. Proc.* (Institute of Industrial Engineers, 2010).
32. O. M. Ashour and G. E. O. Kremer, Dynamic patient grouping and prioritization: A new approach to emergency department flow improvement, *Health Care Management Science* **19**(2) (2016) 192–205.
33. A. F. Mills, A simple yet effective decision support policy for mass-casualty triage, *European Journal of Operational Research* **253**(3) (2016) 734–745.
34. A. K. Childers, M. E. Mayorga and K. M. Taaffe, Prioritization strategies for patient evacuations, *Health Care Management Science* **17**(1) (2014) 77–87.
35. I. Sung and T. Lee, Optimal allocation of emergency medical resources in a mass casualty incident: Patient prioritization by column generation, *European Journal of Operational Research* **252**(2) (2016) 623–634.
36. A. Elalouf and G. Wachtel, An alternative scheduling approach for improving patient-flow in emergency departments, *Operations Research for Health Care* **7** (2015) 94–102.
37. D. Claudio and G. E. Okudan, Utility function-based patient prioritisation in the emergency department, *European Journal of Industrial Engineering* **4**(1) (2010) 59–77.
38. D. Claudio *et al.*, A dynamic multi-attribute utility theory–based decision support system for patient prioritization in the emergency department, *IIE Transactions on Healthcare Systems Engineering* **4**(1) (2014) 1–15.

39. T. W. Polk, W. P. Walker and D. K. Bhatia, A wireless telemedicine system with extended reporting range and priority messaging, in *Engineering in Medicine and Biology Workshop* (IEEE, Dallas, 2007).
40. A. A. Rezaee *et al.*, HOCA: Healthcare aware optimized congestion avoidance and control protocol for wireless sensor networks, *Journal of Network and Computer Applications* **37** (2014) 216–228.
41. A. Zvikhachevskaya, G. Markarian and L. Mihaylova, Quality of service consideration for the wireless telemedicine and e-health services, in *WCNC* (2009).
42. A. Kashiyama, A. Uchiyama and T. Higashino, Depth limited treatment planning and scheduling for electronic triage system in MCI, in *Wireless Mobile Communication and Healthcare* (Springer, New York, 2012), pp. 224–233.
43. T. Mizumoto *et al.*, Emergency medical support system for visualizing locations and vital signs of patients in mass casualty incident, in *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2012 IEEE Int. Conf.* (IEEE, 2012).
44. A. Vohra, M. Sarkar and G. Lee, A smart transmission scheme for emergency data from a network of bio-sensors on the human body, in *Multisensor Fusion and Integration for Intelligent Systems (MFI), 2012 IEEE Conf.* (IEEE, 2012).
45. C. Kateretse, G.-W. Lee and E.-N. Huh, A practical traffic scheduling scheme for differentiated services of healthcare systems on wireless sensor networks, *Wireless Personal Communications* **71**(2) (2013) 909–927.
46. I. T. Crowdsourced and A. C. Weaver, Mobile electronic triaging for emergency response information, in *2013 IEEE/ACM Int. Conf. Advances in Social Networks Analysis and Mining* (2013), pp. 1092–1093.
47. A. H. Asssociation, Blood pressure tracked — Instructions, in *American Heart Asssociation* (San Diego, USA, 2012).
48. S.-L. Tan, J. García-Guzmán and F.-H. Villa-López, A wireless body area network for pervasive health monitoring within smart environments, in *Consumer Electronics-Berlin (ICCE-Berlin), 2012 IEEE Int. Conf.* (IEEE, 2012).
49. A. Zaidan *et al.*, Evaluation and selection of open-source EMR software packages based on integrated AHP and TOPSIS, *Journal of Biomedical Informatics* **53** (2015) 390–404.
50. A. Zaidan *et al.*, Multi-criteria analysis for OS-EMR software selection problem: A comparative study, *Decision Support Systems* **78** (2015) 15–27.
51. E. Triantaphyllou *et al.*, Multi-criteria decision making: An operations research approach, *Encyclopedia of Electrical and Electronics Engineering* **15** (1998) 175–186.
52. E. Triantaphyllou, Multi-criteria decision making methods, in *Multi-Criteria Decision Making Methods: A Comparative Study* (Springer, New York, 2000), pp. 5–21.
53. M. Aruldoss, T. M. Lakshmi and V. P. Venkatesan, A survey on multi criteria decision making methods and its applications, *American Journal of Information Systems* **1**(1) (2013) 31–43.
54. K. P. Yoon and C.-L. Hwang, *Multiple Attribute Decision Making: An Introduction*, Vol. 104 (Sage Publications, New York, 1995).
55. M. Mollaghasemi and J. Pet-Edwards, *Technical Briefing: Making Multiple Objective Decisions* (IEEE Computer Society Press, Los Alamitos, California, 1997).
56. T. L. Saaty and M. S. Ozdemir, Why the magic number seven plus or minus two, *Mathematical and Computer Modelling* **38**(3) (2003) 233–244.
57. D. Lesmes, M. Castillo and R. Zarama, Application of the analytic network process (ANP) to establish weights in order to re-accredit a program of a university, in *Proc. Int. Symp. Analytic Hierarchy Process* (2009).

58. T. L. Saaty, *The Analytic Hierarchy Process* (McGraw Hill, New York, 1980), International, Translated to Russian, Portuguesses and Chinese, Revised edition, Paperback (1996, 2000) (RWS Publications, Pittsburgh, 1980).
59. A. Zaidan *et al.*, Challenges, alternatives, and paths to sustainability: Better public health promotion using social networking pages as key tools, *Journal of Medical Systems* **39**(2) (2015) 1–14.
60. D. D. Dvorski, *Installing, Configuring, and Developing with Xampp* (Skills Canada, White Report, March Canada, Ontario University, 2007), pp. 1–10.
61. M. M. Kiah *et al.*, Design and develop a video conferencing framework for real-time telemedicine applications using secure group-based communication architecture, *Journal of Medical Systems* **38**(10) (2014) 1–11.
62. A. L. Goldberger *et al.*, Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals, *Circulation* **101**(23) (2000) e215–e220.
63. G. Barish, *Building Scalable and High-Performance Java Web Applications Using J2EE Technology* (Addison-Wesley Professional, 2002).
64. N. Ambulatory, M. Care, T. Cdc *et al.*, Medscape Physician Compensation Report New York, USA (2011) Available from: http://www.medscape.com/viewarticle/462656 [accessed on 30 November 2016].
65. N.-A. Belal, F.-E. Nur, M. Hazura, A. A. Zaidan and B. B. Zaidan, An evaluation and selection problems of OSS-LMS packages, *SpringerPlus* **5** (2016) 1–35.
66. M.-Y. Qahtan, A. A. Zadain, B. B. Zaidan, M. B. Lakulu and B. Rahmatullah, Towards on develop a framework for the evaluation and benchmarking of skin detectors based on artificial intelligent models using multi-criteria decision-making techniques, *International Journal of Pattern Recognition and Artifical Intelligence* **31**(3) (2017) 1–24.
67. B. B. Zaidan, A. A. Zaidan, H. A. Karim and N. N. Ahmad, A new digital watermarking evaluation and benchmarking methodology using an external group of evaluators and multi-criteria analysis based on 'large-scale data', *Software: Practice and Experience* **47**(7) (2016) 1–14.
68. B. B. Zaidan and A. A. Zaidan, Software and hardware FPGA-based digital watermarking and steganography approaches: Toward new methodology for evaluation and benchmarking using multi-criteria decision-making techniques, *Journal of Circuits, Systems and Computers* **26**(6) (2017) 1–27.
69. G. Kou, D. Ergu, C. Lin and Y. Chen, Pairwise comparison matrix in multiple criteria decision making, *Technological and Economic Development of Economy* **22**(5) (2016) 738–765.
70. G. Kou, Y. Peng and G. Wang, Evaluation of clustering algorithms for financial risk analysis using MCDM methods, *Information Sciences* **27** (2014) 1–12.
71. G. Kou, Y. lu, Y. Peng and Y. Shi, Evaluation of classification algorithms using MCDM and rank correlation, *International Journal of Information Technology & Decision Making* **11**(1) (2012) 197–225.
72. G. Kou and C. Lin, A cosine maximization method for the priority vector derivation in AHP, *European Journal of Operational Research* **235** (2014) 225–232.
73. G. Kou, D. Ergu and J. Shang, Enhancing data consistency in decision matrix: Adapting hadamard model to mitigate judgment contradiction, *European Journal of Operational Research* **236**(1) (2014) 261–271.
74. Y. Peng, G. Kou, Y. Shi and Z. Chen, A descriptive framework for the field of data mining and knowledge discovery, *International Journal of Information Technology & Decision Making* **7**(4) (2008) 639–682.
75. Y. Peng, G. Kou, G. Wang and Y. Shi, FAMCDM: A fusion approach of MCDM methods to rank multiclass classification algorithms, *Omega* **39**(6) (2011) 677–689.

76. G. Li, G. Kou, C. Lin, L. Xu and Y. Liao, Multi-attribute decision making with generalized fuzzy numbers, *Journal of the Operational Research Society* **66**(11) (2015) 1793–1803.
77. B. B. Zaidan, A. A. Zaidan, H. Abdul Karim and N. N. Ahmad, A new approach based on multi-dimensional evaluation and benchmarking for data hiding techniques, *International Journal of Information Technology & Decision Making* **16** (2017) 1–41.
78. B. B. Zaidan, A. Haiqi, A. A. Zaidan, M. Abdulnabi, M. L. Mat Kiah and H. Muzamel, A security framework for nationwide health information exchange based on telehealth strategy, *Journal of Medical Systems* **39**(5) (2015) 1–19.
79. H. O. Alanazi, A. A. Zaidan, B. B. Zaidan, M. L. Mat Kiah and S. H. Al-Bakri, Meeting the security requirements of electronic medical records in the ERA of high-speed computing, *Journal of Medical Systems* **39**(1) (2015) 1–14.
80. M. L. Mat Kiah, S. H. Al-Bakri, A. A. Zaidan, B. B. Zaidan and M. Hussain, Design and develop a video conferencing framework for real-time telemedicine applications using secure group-based communication architecture, *Journal of Medical Systems* **38**(10) (2014) 1–13.
81. M. L. Mat Kiah, B. B. Zaidan, A. A. Zaidan, M. Nabi and R. Ibraheem, MIRASS: Medical informatics research activity support system using information mashup network, *Journal of Medical Systems* **38**(4) 1–37.
82. H. O. Alanazi, G. M. Alam, B. B. Zaidan and A. A. Zaidan, Securing electronic medical records transmissions over unsecured communications: An overview for better medical governance, *Journal of Medicinal Plants Research* **4**(19) (2010) 2059–2074.
83. M. L. Mat Kiah, M. S. Nabi, B. B. Zaidan and A. A. Zaidan, An enhanced security solution for electronic medical records based on AES hybrid technique with SOAP/XML and SHA-1, *Journal of Medical Systems* **37**(5) (2013) 1–16.
84. B. B. Zaidan, A. A. Zaidan and M. L. Mat Kiah, Impact of data privacy and confidentiality on developing telemedicine applications: A review participates opinion and expert concerns, *International Journal of Pharmacol* **7**(3) (2011) 382–387.
85. M. S. A. Nabi, M. L. Mat Kiah, B. B. Zaidan, A. A. Zaidan and G. M. Alam, Suitability of SOAP protocol in securing transmissions of EMR database, *International Journal of Pharmacol* **6**(6) (2011) 959–964.
86. M. L. M. Kiah, A. Haiqi, B. B. Zaidan and A. A. Zaidan, Open source EMR software: Profiling, insights and hands-on analysis, *Computer Methods and Programs in Biomedicinem* **117**(2) (2014) 360–382.
87. D. Ergu, G. Kou, Y. Shi and Y. Shi, Analytic network process in risk assessment and decision analysis, *Computers & Operations Research* **42** (2014) 58–74.