A Uniform Intelligent Prioritisation for Solving Diverse and Big Data Generated From Multiple Chronic Diseases Patients Based on Hybrid Decision-Making and Voting Method

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ABSTRACT Telemedicine is increasingly used in the modern health care system because it provides health care services to patients amidst distant locations. However, the prioritisation process for patients with multiple chronic diseases (MCDs) over telemedicine is becoming increasingly complex due to diverse and big data generated from multiple disease conditions. To solve such a problem, massive datasets must be collected, and high velocity must be acquired, specifically in real-time processing. This process requires decision-making (DM) regarding the emergency degree of each chronic disease for every patient. Multi-criteria decision-making (MCDM) approaches (i.e. direct aggregation, distance measurement and compromise ranking) are the main solutions for dealing with this complex situation. However, each MCDM approach provides a unique rank from those of other methods. By far, the preferred DM approach that can provide an ideal rank better than other approaches has not been established. This study proposes an extension of the technique for reorganising opinion order to interval levels (TROOIL). Such an extension is called Hybrid DM and Voting Method (HDMVM) which is based on different DM approaches (i.e. direct aggregation, distance measurement and compromise ranking). HDMVM is used to prioritise big data of patients with MCDs in real-time through the remote health-monitoring procedure. In this paper, we propose a methodology that is based on three sequential stages. The first stage illustrates how the big data of patients with MCDs can be recognised in the telemedicine environment and identifies the target telemedicine tier in this study. The second stage describes the steps of the proposed HDMVM sequentially. The third stage applies the proposed method by prioritising the case study of big data of patients with MCDs based on the above DM approaches. Moreover, dataset of remote patients with MCDs (n = 500) is adopted, which contains three diseases, namely, chronic heart diseases and high and low blood pressures. The prioritisation results vary among direct aggregation, distance measurement and compromise approaches. The proposed HDMVM effectively provides a uniform and final ranking result for big data of patients with MCDs. A statistical method (i.e. mean) is performed to objectively validate the ranking results. Significant differences between the scores of the groups are identified in the objective validation, signifying identical ranking results. The evaluation of the proposed work with the benchmark study indicates that this study has tackled issues relevant to big data and diversity of MCDM approaches in the prioritisation of patients with MCDs.

INDEX TERMS Telemedicine, prioritisation, chronic disease, big data, intelligent, decision-making, HDMVM.
I. INTRODUCTION

Telemedicine is a medical practice that enables care providers to cooperate and perform collaborative efforts to diagnose or treat various diseases remotely [1]. It aims to remotely enable the delivery of medical services via telecommunication technologies [2]. Patients, specifically those in far isolated areas and far-flung regions, can benefit from remote health care services through telemedicine [3]. The reason behind this objective is the professional specialists or physician care received for travelling with the purpose of paying them visits [2]. The telemedicine environment comprises three connected tiers [4]. These tiers include (1) sensor-based (Tier 1) used for data collection purposes [5], (2) gateway-based (Tier 2) used to represent the patients’ side that is mainly responsible for signal transferring [6] and (3) server-based (Tier 3) used to represent the remote server that mainly serve the remote monitoring processes for patients [7]. In telemedicine, triage is identified as the patients sorting concept for treating them based on their necessity within a large-scale emergency [4]. In a different context, triage is identified to assess and care for all patients and casualties [8]. Early identification of patients with critical conditions, alongside the stratification upon acceptance of the emergency department, is significantly needed to ensure the quality and integrity of immediate health care response [9]. Patient prioritisation aims to identify patients who can safely wait and those who have immediate concerns [10]. Prioritising patients will lead to fairness and minimise urgent patients’ waiting times [11]. This process can impact the distinctions amongst areas due to the efficient appropriation of existing resources within each region [12]. However, due to the highlighted importance of prioritisation process over telemedicine environment, the value of this process is expanded especially with complex scenarios, such as prioritisation of patients with multiple chronic diseases (MCDs) (e.g. chronic heart diseases [CHD] and high and low chronic blood pressures [BP]). In general, the prioritisation process is a challenging task, especially when multiple decision factors are involved [13]. Thus, the prioritisation process for remote patients with MCDs is considered a challenging task, given that it requires decision making (DM) for each disease. Each patient must have a multigroup triage of the mentioned diseases to assess their emergency conditions. The rapid progression of information and communication technology plays an increasingly important role in telemedicine, given that it improves patients’ quality of life and generates massive data, specifically in Tier 3 [14]. According to previous studies, patients with heart diseases who died from arrhythmia are considered ‘big data’. However, prioritisation based on the massive data, i.e. ‘big data’, has drawn more challenging process during peak times or when numerous patients are served at the same time. To solve such issues, understanding the technicalities of the current scenario in the big data environment within telemedicine is extremely momentous. Generally, database servers at medical centres holding the typical database management system (DBMS) cannot deal with a maximised number of daily basis produced data [15]. Medical sensors measure the vital signs of patients, who are provided with health care services, by processing several sensor data attached to their bodies [16]. These data are produced in various form types, and they are very unstructured, diversified and complicated [17], [18]. Thus, efficiently dealing with such data is extremely challenging for DBMSs in Tier 3. The challenge of utilising big data for care improvements becomes complicated when providers start handling a large-scale number of patients whilst prioritising them remotely. The differences between process (i.e. gathered from sensory data) and outcome (i.e. prioritisation of patients in Tier 3) are considered. This study provides the medical and health industry with the right approach to solve big data challenges faced when evaluating patients with MCDs in telemedicine environments. Big data refers to three main aspects, i.e. high-volume, high-velocity and high-variety form of data [19], which are explained as follows [14]–[16]. High volume refers to the quantity of data generated by wearable sensors and devices for each chronic disease (e.g. heart, systolic and diastolic) in Tier 1 and data stored in the cloud server in Tier 3. Real-time monitoring of a large scale of patients with MCDs increases the value and potential insights into the generated data. In addition, the provision of health care services to patients in Tier 3 produces massive amounts of information that can be considered a physician’s reaction after effective planning and monitoring. High variety refers to the data type and nature. The type and number of sensors that are required for patient monitoring differ from one disease to another. High variety is associated with patients with MCDs for prioritisation to use the resulting insights effectively. Big data in MCDs are obtained from heterogeneous wearable sources and sensor data, such as oxygen saturation (SpO2), electrocardiography (ECG), blood pressure (BP), text, images, audios and videos. High velocity refers to the speed at which data are generated and processed to meet the prioritisation demands. Medical sensors and devices designed to monitor patients with MCDs produce data, such as vital signs. These data are analysed to fulfil prioritisation for emergency cases. Patient prioritisation can reduce urgent patients’ waiting times as well as improve fairness. In this context, prioritisation increases the velocity of big data related to MCDs. Prioritisation of patients with MCDs becomes increasingly complex, specifically with the emergence of the big data era. The best way to prioritise patients based on related MCDs data is to dispose a data lifecycle from creation to destruction. Big data lifecycle (BDLC) can be split into different stages, including collection of data, cleaning of data, classification of data modelling and its delivery [20]. In every phase of the BDLC, certain aspects must be included, such as data integrity and access control. We present a study of reshaping BDLC to support and prioritise large-scale patients with MCDs into the telemedicine environment. Figure 1 shows the BDLC for the MCDs context.

Data collection refers to the preparation and collection of data from wearable sensors in Tier 1 for patients with MCDs. This phase deals with a large scale of patients’ data at all time.
This phase also includes the clarification of data integrity amongst heterogeneous sources, followed by operational and access control procedures by Tier 2 to transmit the integrated data to the server-side in Tier 3. Data collection aims to obtain sensory information to prepare decisions about the prioritisation process and pass the required feedback to patients with MCDs. Data cleaning confirms if the obtained MCDs data are correct, consistent and usable in all tiers by identifying, correcting and omitting any errors or corruption in the data. Processing is used to check the integrity of large-scale data when accessed and stored in Tier 3 and prevent errors from occurring again. In general, data classification is related to the organisation of gathered MCDs data from the server-side into multigroup triage levels. Each group is composed of five levels of patients’ emergency case data. Data for each group must be processed separately and simultaneously to obtain reliable and efficient prioritisation. Complexity arises when patients’ health statuses continuously change during real-time monitoring, thereby affecting prioritisation. In this context, data classification is important when big data can be classified for several reasons, including ease of access and facilitating prioritisation, based on the type of data being retrieved for each triage group. Data modelling is a representation of MCDs data structures in a set of rules for several levels to reach the final prioritisation requirements. In addition, this process describes the structures, associations and constraints relevant to available MCDs data flow and encodes these rules into a reusable standard. Subsequently, the data delivery phase integrates MCDs data in process with benefits throughout priority guidelines for all patients in all phases. The need for medical data increases, specifically for MCDs data in process (i.e. computation and transmission), as a result of telemedicine progress. The number of MCDs data required by medical institutions for operation and storage also increases.

The remaining parts of this study are composed of five sections. The ‘Literature review’ section discussed previous studies in patient prioritisation over telemedicine. The ‘Study contributions’ section explains the contribution of the proposed work. The ‘Methodology’ section provides the research methodology description that contains phases of the methodology. The ‘Results and discussion’ section displays the results and discussion. The ‘Validation and evaluation’ section deliberates the results of the validation and evaluation of the proposed framework. The ‘Conclusion’ section discusses the conclusion and recommendations for future work.

II. LITERATURE REVIEW

This section presents an overview of previous studies related to patient prioritisation over telemedicine environment. Various methodologies are proposed for patient prioritisation. These methodologies are based on two perspectives. Firstly, previous studies have explored patient prioritisation based on a single disease, such as CHD through environmental telemedicine [4], [14].

Existing works have offered a new approach by using large-scale information from body sensors during disasters and peak seasons to give priority to patients with CHD. Patients’ scores have been produced by using each of integrated analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) methods. However, the method in existing studies can only prioritise patients with single chronic diseases. Thus, the emergency degree of each chronic condition cannot be assessed individually to appropriately prioritise patients with MCDs. Secondly, existing have explored patient prioritisation by considering MCDs, such as [21]. Previous study [21] has attempted to solve the prioritisation of patients with MCDs by proposing a novel MCDM method called ‘technique for reorganising opinion order to interval levels’ (TROOIL). TROOIL can easily calculate the priorities of patients with MCDs based on different triage rates. However, this work has failed to involve big data generated from MCDs, and only one MCDM approach (i.e. direct aggregation based on arithmetic mean) has been established to rank and prioritise patients. Other MCDM approaches, such as distance measurement and compromise ranking, are important to obtain insight and understand the variety in the ranking procedure. These approaches can engage in complex health problems when evaluating the prioritisation of MCDs. These approaches are essential in communicating complex diseases to reach the optimum solution for ranking patients with MCDs. In sum, existing studies have considered two main issues. From a technical point of view, the issue of prioritisation has been addressed based on big data but with single chronic disease (e.g. [4] and [14]). From theoretical perspective, the issue of prioritisation with MCDs has been addressed without considering the issues relevant to the generated big data (e.g. [21]). This study aims to present a solution that tackles the issues of prioritisation based on big data in MCDs. TROOIL [21] used a direct
aggregation approach. However, changing from direct to
distance measurement and compromise approaches ranking
will produce a different rank. Distance measurement, such as
TOPSIS, is a famous classical MCDM method based on the
ideal alternative concept. The ideal alternative possesses
the best level across all considered attributes. By contrast,
the negative ideal has the worst attribute values. According
to TOPSIS, the solution is defined as points that are simulta-
neously farthest from the negative-ideal point and closest
to the ideal point. Compromise ranking method, also known
as the všeukriterijumska optimizacija i kompromisno resenje
(VIKOR) method, introduces the multi-criteria ranking index
according to the particular measure of ‘closeness’ to the
‘ideal’ solution as an extension to the TOPSIS method. Direct
aggregation (TROOIL), distance measurement (TOPSIS) and
compromise rank (VIKOR) provide varying ranks for patient
prioritisation when utilising MCDs. In this context, the alter-
native solution must prioritise patients by using all these
DM approaches. Thus, voting must be used to aggregate
the produced ranks from each of the three approaches into
the hybrid and uniform final rank. Voting methods in DM
are useful because of their capability of aggregating indi-
vidual rankings into hybrid and final ranks. These methods
have evident implications for certain MCDM situations. Final
ranks imply that the notion of the best alternative, given a set
of criteria and information about the ordinal ranking of the
alternatives, can be essentially considered as arbitrary vot-
ing methods. These methods include plurality [22], majority
method (instant or two-round runoff) [23], pairwise compari-
son (Condorcet paradox or Copeland method) [24] and Borda
rank [25]. Ref. [26] utilised a voting method (i.e. pairwise
comparison) with a group of experts to determine the priority
of criteria, and they applied the voting method with TOPSIS
to solve real problems in disaster-damaged areas. The weight
for group decision-makers is calculated to achieve a commit-
tee consensus. In Ref. [27], TOPSIS is used as a classifier for
a UK dataset of nonbankrupt and bankrupt companies, and
the voting method is used to classify the criteria of alterna-
tives depending on the preferences of decision-makers. These
criteria must have the majority of voting results. Ref. [28]
tried to solve the problem of selecting the best employee
in a hotel by evaluating their performance to improve offer-
ings to the staff. The evaluation is conducted by group DM,
and each expert has rated each employee depending on the set
criteria. TOPSIS is then utilised for ranking. Borda method is
also used to combine the ranks from each expert and yield
the final rank. Ref. [29] selected the best web services based
on their qualities. Different MCDM methods are applied to
determine the accuracy of the selection and evaluate the best
solution. Experts have evaluated each criterion and presented
the priority by assigning the criterion weights. The subjec-
tive weights of the criteria are obtained using best-worst
method, which has performed fewer comparisons of criteria
than AHP. Ranks are determined using different methods (i.e.
TOPSIS, VIKOR, COPRAS and SAW), which have required
the weights to determine the final rank. Borda voting method

is used to obtain the best solution. Ref. [30] successfully
applied different MCDM methods to address groundwater
management scenario selection problem. SAW, TOPSIS and
PROMETHEE-II are adopted to rank four groundwater man-
gagement scenarios in wet and dry periods based on four
criteria. The weight of each criterion is obtained using direct
weighting and AHP methods. The ranks from these three
methods are aggregated via Borda method which is used to
determine the final rank for groundwater management
scenarios.

III. STUDY CONTRIBUTIONS

In sum, the contributions of this study are as follows:

1) Understanding and representation of the big data anal-
yses for MCDs in the telemedicine environment.
The link between big data characteristics and telemedicine environment is described. The issues rele-
vant with patient prioritisation are then discussed based
on big data generated from patients with MCDs.
2) Tackling the issues with existing MCDM methods.
A new intelligent prioritisation uniform is presented
based on the proposed HDMVM to prioritise patients
with MCDs effectively. Such a method has utilised
direct aggregation, distance measurement and compro-
mise rank approaches, and it has then applied voting
solution to deal with multiple DM problems for patients
with MCDs. The proposed method for big data scenario
has provided a final decision as follows. Patients with
the most urgent cases have achieved the highest priority
level. By contrast, those with the least urgent cases
obtained the lowest priority levels among all patients’
scores.

IV. METHODOLOGY

The methodology of this study is divided into three main
stages. The first stage illustrates the telemedicine environ-
ment and the target telemedicine tier in our study. The second
stage explains the steps of the proposed HDMVM. The third
and last stage illustrates the case study of big data of patients
with MCDs.

A. TELEMEDICINE ENVIRONMENT

BDLC can be recognised in telemedicine environment
within three tiers. Basically, this environment is based on
client-server approach (Tier-1, Tier-2, and Tier-3); thus,
it could be applicable for any of the three layers of computing
(i.e. cloud, fog, and edge) depending on the scenario used.
The client is represented by Tiers 1 and 2, whereas the server
is represented by Tier 3. Tier 3 plays an important role in
the remote monitoring environment, given that it is respon-
sible for the analysis of patients’ health data and healthcare
services based on their conditions and priority needs. Thus,
Tier 3 is selected as a targeted tier in this research. The high-
level abstract of the telemedicine environment is pre-
sented in Figure 2.
Patients generally exhibit specific signals, which are captured in various medical sensors. Patients also provide a picture of their situations to their doctors by manually completing a form describing pathological conditions, including the symptoms they are experiencing. In this way, a data (i.e., big data) will be collected from the medical sensors and manual inputs (i.e., text). The server receives three biomedical sensors representing these sensors’ vital signals and reliable datasets (i.e., ECG, SpO2 and BP). Text inputs related to CHD include chest pain, shortness of breath, palpitation and physical condition (i.e., rest or exercise) of patients. The transferred features from the users to the server may result in a yes (if abnormal) or no (if normal).

The user device, such as a laptop, smartphone or workstation, is also considered a base station. The Tier 2 device is responsible for the transfer of medical sensor/source signals from Tier 1 (user) to Tier 3 (server) using the mobile cellular network or other communication protocols. Tiers 1 (i.e., big data collection) and 2 (i.e., base station) are considered the client in the client–server structure wherein the big data is generated and collected then transferred to the target server.

2) TIER 3 (REMOTE SERVER)

On the server, the data from the sensors are analysed by the target analytical models. Tier 3 incorporates in real-time a remote monitoring portion. Remote monitoring helps doctors examine data in real time and provides compatible facilities for priority patients. The server usually contains medical records, reports on user history and database [31].

Figure 2 shows the flow of data from the user in the data collection (Tier 1) to the base station (Tier 2) and then to the server (Tier 3) for remote patients in sequential steps. Given that the server is considered the part in which all processes and decisions are made, resolving several problems are necessary. Amongst these issues and as stated in the problems of this research, the prioritisation requirement in Tier 3 must be fulfilled. Patient prioritisation is the ability to rank and order the patients according to their emergency status and show them in a queue. Thus, the prioritisation process for big data patients with MCDs will be conducted in Tier 3.

Three aspects relevant with big data are covered in three tiers. Firstly, the volume of the data can be seen when the number of patients’ data generated by medical sensors in Tier 1 have increased. The same data will then be transferred by Tier 2 to the sever side (Tier 3). Secondly, the huge volume of the data is usually generated from multiple heterogeneous sources (i.e., different kinds of data), which identify the variety aspect in the big data. Finally, patients’ data are usually generated, collected, transferred and analysed in a quick process, in which the velocity aspect in the big data is recognised.

B. PROPOSAL OF HDMVM

This section explains an extended TROOIL technique to propose a new HDMVM according to different DM approaches (i.e., direct aggregation, distance measurement and compromise ranking). HDMVM prioritises big data of patients with MCDs through the remote health-monitoring in real-time. We firstly review the TROOIL technique to aid in the elucidation of the proposed method. The TROOIL technique is composed of six steps, as shown in Figure 3.

In Step 6 of TROOIL technique, evaluation criteria can be weighted. Alternatives are then ranked based on direct aggregation approach. However, as mentioned before, in the DM context, changing from direct aggregation approach to different ranking approach (e.g., distance measurement and compromise approaches) may provide different ranks for alternatives (i.e., MCDs). To solve this issue, HDMVM has been ranked alternatives by using different DM approaches.

The voting approach is then used to aggregate the produced ranks from each of the three approaches into the hybrid final rank, as shown in Figure 3. In this study, the last step of TROOIL is discussed in the proposed HDMVM. This step is based on three aspects, namely, distance measurement, compromise ranking and voting approach.

HDMVM involves an objective ranking process of the alternatives according to the calculated weight as described in TROOIL [21]. The score that is comprehensive for each alternative within each rule according to the calculated weights may be obtained. A decision matrix will be constructed based on a crossover of multiple criteria and alternatives.

Equation (1) will be used to determine the weighted matrix: $\text{WM} = [\text{wm}_{ij}]_{m \times n}$.

$$\text{WM} = \sum_{j=1}^{n} \text{r}_{ij}\text{w}_{j}. \quad (1)$$

Alternatives can then be ranked based on the mentioned DM approaches. The process of calculation of direct aggregation approach has been described in TROOIL [21]. The process of calculation of distance measurement, compromise ranking and solution of hybrid ranking based on voting approach is described as follows.

1) DISTANCE MEASUREMENT APPROACH

In this stage, alternatives are ranked by applying the distance measurement procedure to calculate the closest alternative to the optimal solution scoring. This approach is used to...
A measures the distance from the alternative to the positive value denoted as calculated based on the Euclidean distance. A new set of measurement between alternatives and the ideal solution is the negative ideal solution for the criteria. Secondly, distance ideal solutions are measured as follows:

\[ A = \{ \min_{j \in J} v_{ij} \mid i = 1, 2, \ldots, m \} \]  

\[ A^- = \{ \max_{j \in J^-} v_{ij} \mid i = 1, 2, \ldots, m \} \]  

A new set of value denoted as \( J \) is used as a subset of \( i = 1, 2, \ldots, m \) to represent the ideal solution for the criteria, whereas \( J^- \) is the complement set of \( J \) used to represent the negative ideal solution for the criteria. Secondly, distance measurement between alternatives and the ideal solution is calculated based on the Euclidean distance. A new set of value denoted as \( S^* \) is generated from this process. This set measures the distance from the alternative to the positive solution \( A^* \). This process is conducted using Equation (4).

\[ S^* = \sqrt{\sum_{j=1}^{n} (v_{mj} - v_{mji}^*)^2} \]  

Similarly, another new set of value denoted as \( S^- \) is generated from this process. This set measures the distance from the alternative to the negative ideal \( A^- \) as given by:

\[ S^- = \sqrt{\sum_{j=1}^{n} (v_{mj} - v_{mji}^-)^2} \]  

Thirdly, the closeness of \( A_i \) to the ideal solution \( A_* \) is defined as:

\[ C_i = S^-/(S^* + S^-) \]  

Fourthly, alternatives are ranked according to the closeness to the ideal solution. Alternatives can be ranked in descending order, wherein the solution is considered good if the value is high.

2) COMPROMISE RANKING APPROACH

Compromise ranking is utilised to obtain the compromise solution, which is the closest to the ideal. The best alternative is preferred by maximising the utility group and minimising the regret group. The method proposes a compromise solution with an advantage rate. In this stage, alternatives are ranked by applying compromise ranking procedure. Firstly, the compromise rank of the alternatives are determined by the values \( S, R \) and \( Q \). \( S_i \) and \( R_i \) are obtained from WM. In this process, \( S_i \) and \( R_i \) are measured as follows:

\[ S_i = \sum_{j=1}^{n} v_{ij} \]  

\[ R_i = \text{MAX}_j (v_{ij}) \]  

where \( S_i \) and \( R_i \) are used to express ranking measures.

Secondly, \( Q \) value, which is a set of distance from the alternative to the ideal solution, is determined. This process is conducted by Equation (9).

\[ Q = [v(S_i - S^*)/(S^- + S^*]] + [(1 - v) \times (R_i - R^*)/(R^- + R^*)] \]  

where \( S^* = \min S_i, S^- = \max S_i \) and \( R^* = \min R_i, R^- = \max R_i \).

The value \( v \) is presented as the strategy weight of the majority of criteria. In this study, \( v = 0.5 \). This compromise solution is unchanging in a DM procedure which could increase the \( v (v > 0.5) \) or decrease \( v (v < 0.5) \) or \( v = 0.5 \), as needed to obtain the compromise solution.

Thirdly, the group of alternatives can already be ranked by sorting the \( Q \) value in ascending order. The least value determines the optimal alternative.

3) HYBRID RANKING BASED ON VOTING APPROACH

Ref. [32] noted that no preferred DM approach can provide an ideal rank better than others. Depending on only one of the three DM approaches and omitting others is difficult. This study includes the voting approach for specifying the optimum DM rank based on the ranking results of direct
TABLE 1. Weights for each criterion for each rule.

| Rules | Criteria          | HBPD | LBPD | Spo2 | BP  | CP  | SH. Breath. | Palip. | Rest | P      | QRS width | P–P | ST EL |
|-------|-------------------|------|------|------|-----|-----|-------------|--------|------|--------|-----------|-----|-------|
| Rule 1| Entropy weights   | 0.000| 0.000| 0.028| 0.000| 0.007| 0.059       | 0.030  | 0.088| 0.235  | 0.235     | 0.082| 0.235 |
| Rule 2| Entropy weights   | 0.000| 0.000| 0.065| 0.000| 0.067| 0.091       | 0.082  | 0.078| 0.178  | 0.178     | 0.137| 0.125 |
| Rule 3| Entropy weights   | 0.000| 0.000| 0.082| 0.000| 0.197| 0.098       | 0.132  | 0.095| 0.127  | 0.127     | 0.088| 0.054 |
| Rule 4| Entropy weights   | 0.000| 0.000| 0.000| 0.000| 0.000| 0.000       | 0.000  | 1.000| 0.000  | 0.000     | 0.000| 0.000 |
| Rule 56| Entropy weights  | 0.000| 0.000| 0.017| 0.000| 0.000| 0.041       | 0.012  | 0.079| 0.264  | 0.264     | 0.059| 0.264 |
| Rule 121| Entropy weights | 0.000| 0.000| 0.027| 0.000| 0.000| 0.221       | 0.000  | 0.531| 0.000  | 0.000     | 0.221| 0.000 |
| Rule 57| Entropy weights   | 0.000| 0.000| 0.051| 0.000| 0.035| 0.086       | 0.071  | 0.076| 0.193  | 0.193     | 0.140| 0.156 |
| Rule 58| Entropy weights   | 0.000| 0.000| 0.079| 0.003| 0.154| 0.097       | 0.112  | 0.097| 0.141  | 0.141     | 0.100| 0.074 |
| Rule 59| Entropy weights   | 0.000| 0.000| 0.212| 0.000| 0.000| 0.212       | 0.000  | 0.106| 0.212  | 0.212     | 0.044| 0.000 |
| Rule 122| Entropy weights | 0.000| 0.000| 0.042| 0.000| 0.012| 0.074       | 0.051  | 0.074| 0.202  | 0.202     | 0.139| 0.202 |
| Rule 123| Entropy weights  | 0.000| 0.000| 0.063| 0.000| 0.134| 0.093       | 0.105  | 0.090| 0.122  | 0.122     | 0.147| 0.122 |
| Rule 124| Entropy weights  | 0.000| 0.000| 0.205| 0.000| 0.000| 0.205       | 0.205  | 0.084| 0.084  | 0.104     | 0.029|       |

HBPD: High Blood Pressure Disease; LBPD: Low Blood Pressure Disease; Spo2: Oxygen Saturation; CP: Chest Pain; BP: Blood Pressure; ECG: Electrocardiography; SH. Breath: Shortness of Breath; Palip: Palpitation; Rest: Patient at Rest; P: Peaks; P–P: Peak-to-peak Distance; and ST EL: ST Elevation.

aggregation, distance measurement and compromise ranking to unify the obtained rank. The rank is regarded as ballots for application in the voting approach, and alternatives are presented as candidates. Borda approach is one of the voting approaches that can obtain the rank without depending on the majority or Condorcet paradox. The ranks of the three DM approaches are considered three voters applied to Borda approach, which depends on the number of the candidates in the ballots. If \( n \) candidates are present, then the first one is multiplied by \( n \) number. The second one is multiplied by \( n - 1 \), and the third one is multiplied by \( n - 3 \) and so on. Consequently, the Borda rank of candidates is denoted as BS (Borda selection), which is calculated as follows:

\[
BS(A) = (n) \times [i | \text{rank fro the chose one}] \\
+ (n - 1) \times [i | \text{rank second chose} + \ldots] \\
+ 1 \times [i | \text{rank fro the last one}].
\]  

The winner of this selection is the one that has achieved the highest score.

C. CASE STUDY: PRIORITISATION OF BIG DATA OF PATIENTS WITH MCDS

This stage presents the prioritisation solution based on HDMVM for big data of patients with MCDs. In this study, Tier 3 is the targeted one, as mentioned in the first stage of the methodology. The server process is an estimation of the medical situations of patients with MCDs which results in prioritising them based on their urgent cases. In this study, the type and number of patients’ dataset have been specified as adopted from [32] which contains 500 patients. The dataset contains three diseases (i.e. CHD and high and low BP) presented in two parts. The first part is CHD, whereas the second part is diseases related to high and low BP.

V. RESULTS AND DISCUSSION

This section discusses the proposed prioritisation approach based on HDMVM. Section 1 introduces the criterion weighting and patient prioritisation result based on direct aggregation, distance measurement and compromise approaches. Section 2 presents the hybrid patient prioritisation results based on voting approach.

A. CRITERION WEIGHTING AND PATIENT PRIORITISATION

Decision matrices for patients within rules 1, 2, 3, 4, 56, 121, 57, 58, 59, 122, 123 and 124 are created based on the crossover of ‘multi-source for each disease’ and ‘patients list’. Table 1 shows the criterion weighting of each rule in this stage, as determined objectively in previous work [21].

Patients in every rule are prioritised according to these weights. Thereafter, as mentioned in this study, patients are ranked based on three DM approaches, namely, direct aggregation, distance measurement and compromise ranking. Table 2 presents the sample of the results of the DM solution for the sample patients within each rule, whereas Table A.1 in the Appendix presents the prioritisation ranking results of all patients within all rules.

As illustrated in Table 2, regarding rule 1, patient 15 was ranked as 35 based on direct aggregation and distance measurement approaches. Moreover, the patient was prioritised as 4 based on compromise approach. Patient 22 was ranked as 22 based on direct aggregation and ordered as 19 and 20 in distance measurement and compromise approaches, respectively. Patient 27 was ordered as 38 in direct aggregation and distance measurement approaches and 1 in compromise approach. Patient 28 was ordered as 29, 28 and 12 in direct aggregation, distance measurement and compromise approaches, respectively. Patient 31 was ordered 34 in direct aggregation and distance measurement approaches and 5 in
TABLE 2. Results of various dm approaches applied to sample patients within each rule.

| Rules | P. No | Direct aggregation | Distance measurement | Compromise |
|-------|-------|-------------------|---------------------|------------|
|       | Score | Priority          | Score               | Priority   |
| 1     | 15    | 0.058             | 0.135               | 0.099      |
|       | 16    | 0.015             | 0.230               | 0.219      |
|       | 27    | 0.004             | 0.073               | 0.000      |
|       | 28    | 0.012             | 0.184               | 0.193      |
|       | 31    | 0.009             | 0.137               | 0.103      |
|       | 8     | 0.021             | 0.398               | 0.217      |
|       | 10    | 0.012             | 0.253               | 0.085      |
|       | 11    | 0.012             | 0.237               | 0.196      |
|       | 12    | 0.019             | 0.284               | 0.162      |
|       | 13    | 0.013             | 0.250               | 0.159      |
|       | 1     | 0.006             | 0.074               | 0.000      |
|       | 2     | 0.008             | 0.218               | 0.316      |
|       | 3     | 0.011             | 0.286               | 0.440      |
|       | 4     | 0.019             | 0.342               | 0.515      |
|       | 5     | 0.008             | 0.225               | 0.328      |
|       | 433   | 0.000             | 0.000               | 0.000      |
|       | 434   | 0.083             | 1.000               | 1.000      |
|       | 63    | 0.055             | 0.085               | 0.066      |
|       | 64    | 0.012             | 0.164               | 0.188      |
|       | 123   | 0.020             | 0.204               | 0.040      |
|       | 124   | 0.009             | 0.151               | 0.170      |
|       | 127   | 0.006             | 0.099               | 0.071      |
|       | 121   | 0.021             | 0.278               | 0.000      |
|       | 122   | 0.063             | 0.723               | 0.853      |
|       | 383   | 0.038             | 0.370               | 0.138      |
|       | 384   | 0.082             | 0.979               | 0.991      |
|       | 395   | 0.021             | 0.278               | 0.000      |
|       | 43    | 0.009             | 0.178               | 0.086      |
|       | 44    | 0.015             | 0.235               | 0.154      |
|       | 46    | 0.016             | 0.252               | 0.198      |
|       | 47    | 0.016             | 0.247               | 0.195      |
|       | 48    | 0.022             | 0.286               | 0.245      |
|       | 33    | 0.000             | 0.007               | 0.000      |
|       | 34    | 0.008             | 0.229               | 0.382      |
|       | 35    | 0.010             | 0.258               | 0.443      |
|       | 36    | 0.018             | 0.267               | 0.512      |
|       | 37    | 0.008             | 0.229               | 0.383      |
|       | 177   | 0.035             | 0.483               | 0.891      |
|       | 178   | 0.023             | 0.532               | 1.000      |
|       | 465   | 0.046             | 0.091               | 0.000      |
|       | 466   | 0.013             | 0.213               | 0.294      |
|       | 469   | 0.031             | 0.317               | 0.718      |
|       | 79    | 0.011             | 0.190               | 0.113      |
|       | 80    | 0.018             | 0.236               | 0.161      |
|       | 122   | 0.007             | 0.125               | 0.000      |
|       | 92    | 0.013             | 0.195               | 0.127      |
|       | 67    | 0.009             | 0.245               | 0.373      |
|       | 68    | 0.016             | 0.508               | 0.439      |
|       | 69    | 0.008             | 0.221               | 0.311      |
|       | 70    | 0.015             | 0.291               | 0.377      |
|       | 71    | 0.017             | 0.317               | 0.441      |
|       | 65    | 0.013             | 0.000               | 0.000      |
|       | 66    | 0.007             | 0.178               | 0.293      |
|       | 124   | 0.016             | 0.245               | 0.410      |

B. HYBRID PATIENT PRIORITISATION RESULTS BASED ON VOTING APPROACH

This section presents the final rank results of patients, which are calculated based on the Borda voting approach, within different rules. The final prioritisation results are obtained based on such approach. In this way, patients are prioritised from best to worst emergency cases. Table 3 illustrates the final patient prioritisation for the sample patients within each rule, whereas Table A.2 in the Appendix shows the ranking results for all patients within all rules.

Table 3 shows the differences between the final hybrid and other ranking results (i.e., direct aggregation, distance measurement, and compromise results). The final result of patient prioritisation within rule 1 shows that patient (15) is prioritised as 36, 35 in the direct aggregation and distance measurement approaches and 4 in compromise approach. Patients 16, 27, 28 and 31 are prioritised as 19, 38, 27 and 34, respectively, in the direct aggregation approach; 19, 38, 28 and 34, respectively, in distance measurement approach; and 20, 1, 12 and 5, respectively, in compromise approach.

VI. VALIDATION AND EVALUATION

The validation process for the patient prioritisation outcomes is conducted objectively. Statistical approach (i.e., mean) has been introduced at this point to make sure patient prioritisation is ranked in systematic manner. Similar to other MCDM methods [4], the prioritisation ranking results are separated into different groups to validate the work. The result of each set may be split into several groups. The number
of alternatives within each group is varying depending on various situations. The validation result will not be affected by number of groups or alternatives within each group. The mean (\( \bar{x} \)) is calculated for each weighted data group. \( \bar{x} \) is the average of the sample and determined as the sum of all observed results divided by the total number presented in Equation (11) as follows:

\[
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i.
\]  

(11)

Each group is composed of numerous prioritised patients. The mean of the first group data must be greater than or equal to the next group. One example is when the result of ranking is divided into four groups under the same rule. The first group will therefore have the highest possible mean value to validate the ranking result. The mean result of the second group must be lower than or equal to that of the first group and higher or equal to that of the third group. Same strategy for other groups must be followed, wherein each group must be higher than or equal to the next group but lower than or equal to the previous group. Validation results have been presented in Table 4.

### TABLE 4. Validation results.

| Prioritisation patients’ within all rules | 1st group | 2nd group | 3rd group | 4th group |
|-----------------------------------------|-----------|-----------|-----------|-----------|
| Rule 1 Mean (\( \bar{x} \))            | 0.05      | 0.01      | 0.01      | 0.00      |
| Rule 2 Mean (\( \bar{x} \))            | 0.06      | 0.04      | 0.02      | 0.01      |
| Rule 3 Mean (\( \bar{x} \))            | 0.04      | 0.04      | 0.04      | 0.01      |
| Rule 4 Mean (\( \bar{x} \))            | 0.08      | 0.00      | /         | /         |
| Rule 56 Mean (\( \bar{x} \))           | 0.04      | 0.01      | 0.01      | 0.00      |
| Rule 121 Mean (\( \bar{x} \))          | 0.08      | 0.06      | 0.03      | 0.02      |
| Rule 57 Mean (\( \bar{x} \))           | 0.06      | 0.03      | 0.02      | 0.01      |
| Rule 58 Mean (\( \bar{x} \))           | 0.05      | 0.03      | 0.02      | 0.01      |
| Rule 59 Mean (\( \bar{x} \))           | 0.04      | 0.03      | 0.02      | 0.00      |
| Rule 122 Mean (\( \bar{x} \))          | 0.06      | 0.02      | 0.01      | 0.01      |
| Rule 123 Mean (\( \bar{x} \))          | 0.05      | 0.03      | 0.02      | 0.01      |
| Rule 124 Mean (\( \bar{x} \))          | 0.03      | 0.03      | 0.01      | 0.00      |

In Table 4, statistical analysis for each group is presented per rule. The analysis reveals that the first group has the highest scores and the best one in all rules in terms of achieved ranking results. The scores of the second, third and fourth groups are following the scores of the first group. Except for the rule 3, the first three groups have equal values. However, this result still indicates that the ranking result of this group is valid. The results of statistical method pointed out that prioritisation of big data patients with MCDs have systematically ranked.

For evaluation, however, the most relevant work on the prioritisation over telemedicine environment is found in study [21]. Compared with our proposed study, both studies followed prioritisation strategy based on MCDM ranking. In other words, these approaches assign patients a rank according to their circumstances of emergency. Moreover, both studies have presented an effective prioritisation solution for patients with MCDs. However, different from the benchmarked study, in terms of application level, this study has considered issues with big data in prioritisation of MCDs. In terms of MCDM theory/method level, direct aggregation, distance measurement and compromise ranking approaches are used in this study to handle complex health problems when evaluating the prioritisation of patients with MCDs. By contrast, the benchmarked study has considered only direct aggregation, which cannot handle such problems.

### VII. CONCLUSION AND FUTURE WORK

In this study, previous work [21] is criticised in terms of two different issues. Firstly, previous work has failed to consider big data for MCDs. Secondly, only one approach is provided amongst various MCDM approaches. In this study, HDMVM is proposed and used to tackle the issue of prioritisation of multiple DM based on big data of patients with MCDs. Three DM approaches (i.e. direct aggregation, distance measurement and compromise ranking) are used to prioritise the big data of patients with MCDs. Then, voting approach is used in the proposed HDMVM to unify and provide final ranking results and specify the optimum DM rank. Most cases with MCDs must be treated and prioritised, because these patients have the highest priority rates. Patients with less serious cases can be treated subsequently. HDMVM rapidly determines the prioritisation of patients with MCDs based on various DM approaches. In this study, the validity of the findings is conducted objectively. The proposed work has showed a clearly significant advantage over the benchmark study in terms of application and theory/method levels. Two recommendations are presented for future work. Firstly, different applications exist for MCDs, such as stroke, cancer, diabetes and arthritis. In future studies, researchers must consider patient prioritisation with these complications as another case study. Secondly, HDMVM extensions may be applied subsequently under fuzzy or rough conditions to address ambiguous and imprecise problems in different case studies.

### COMPLIANCE WITH ETHICAL STANDARDS

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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