



Hospital selection framework for remote MCD patients based on fuzzy q-rung orthopair environment

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Abstract

This research proposes a novel mobile health-based hospital selection framework for remote patients with multi-chronic diseases based on wearable body medical sensors that use the Internet of Things. The proposed framework uses two powerful multi-criteria decision-making (MCDM) methods, namely fuzzy-weighted zero-inconsistency and fuzzy decision by opinion score method for criteria weighting and hospital ranking. The development of both methods is based on a Q-rung orthopair fuzzy environment to address the uncertainty issues associated with the case study in this research. The other MCDM issues of multiple criteria, various levels of significance and data variation are also addressed. The proposed framework comprises two main phases, namely identification and development. The first phase discusses the telemedicine architecture selected, patient dataset used and decision matrix integrated. The development phase discusses criteria weighting by q-ROFWZIC and hospital ranking by q-ROFDOSM and their sub-associated processes. Weighting results by q-ROFWZIC indicate that the time of arrival criterion is the most significant across all experimental scenarios with $(0.1837, 0.183, 0.230, 0.276, 0.335)$ for $(q = 1, 3, 5, 7, 10)$, respectively. Ranking results indicate that Hospital (H-4) is the best-ranked hospital in all experimental scenarios. Both methods were evaluated based on systematic ranking and sensitivity analysis, thereby confirming the validity of the proposed framework.

Keywords Hospital selection · Internet of things · Mobile health · Remote multi-chronic disease patients · Multi-criteria decision-making · Wearable body medical sensors

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1 Introduction

Chronic diseases (CDs) are amongst the world's leading causes of death and disability, and they are predicted to account for a third of total global deaths [1–3]. Although CDs include many diseases, such as diabetes, hypertension and cardiovascular diseases (CVDs), some of them present more risks than others (in particular, CVD) [4, 5]. It presents risks for populations in terms of vitality and amongst the leading causes of disability [6]. CVD is a global concern because it results in conditions that affect heart functionality, including hypertension, arrhythmia, stroke, and heart attack, and it even causes death [7, 8]. CVD is a life-threatening disease, and its diagnosis, monitoring and treatment are needed [9, 10]. However, diagnosis and treatment can be hindered by issues, such as the unavailability of expert cardiologists or patients living in remote areas and are far from hospitals [11, 12]. To address such shortcomings, modern technologies are used to monitor

patients with CD; the Internet of Things (IoT) was a prominent example [6, 13]. IoT has paved the way for many applications, and its role in health care telemedicine services and managing remote patients has been remarkable [14]. Telemedicine care services empowered by IoT are based on a three-tier architecture, comprising the following: Tier 1, medical body sensors; Tier 2, mobile health (mHealth); and Tier 3, the medical centre server side, which connects and manages the distributed hospitals' servers. One part of the integration of telemedicine and IoT medical sensors is the consistent observation of health conditions, such as blood pressure, heartbeat and movement patterns [15]. These medical sensors can remotely monitor patient status and help provide health care details for diagnosis, treatment and monitoring patient activities. Despite the wide integration of medical sensors in telemedicine and IoT environments, many issues remain and are addressed differently. One main issue in managing and providing health care services is hospital selection. Demand for health care services has increased, especially for patients in remote areas, placing an unprecedented burden on medical health care centres [16, 17]. This issue was addressed in a previous study [18], where the authors used multi-criteria decision-making (MCDM) to propose smart real-time health monitoring based on wearable body health data sensors. The authors also proposed a new four-level remote triage and package localisation and used it to construct a decision matrix (DM) for hospital selection based on the crossover of 'multi-health care services' and 'hospital list.' Therefore, hospital rankings for each patient based on these health care services were achieved using MCDM techniques. The analytical hierarchy process (AHP) was applied to obtain the weights for each expert, and *ViseKriterijumska Optimizacija I Kompromisno Resenje* (VIKOR) was used to rank the alternatives. Another hospital selection problem occurs when IoT telemedicine sensors are subjected to service interruptions. This problem occurs when connected telemedicine architecture is interrupted due to scalability challenges, leading to network failure between Tiers 2 and 3. Amongst the main causes for such issues are disasters and mass casualty incidents, ageing population and network congestion [16, 19]. Service interruption also occurs when wearable body sensor failures fully or partially malfunction, thereby degrading the performance or destroying the stability of the overall telemedicine health care systems [20]. Thus, selecting a hospital is an issue worth considering. In response to these health care issues, authors in [21] proposed the use of an MCDM fault-tolerant mHealth framework in the context of IoT-based real-time wearable body health care data sensors. Their proposed framework can triage patients and detect their emergency cases. They directly connect with servers of distributed hospitals to

ascertain available health care services for the risk-level package in those hospitals. The framework also considers patient arrival time. Based on the two challenges discussed in [18, 21] for hospital selection in terms of distributing health care services and network failure, the authors elucidated situations in which both challenges occur simultaneously. When the connection with medical centres is interrupted and the use of mHealth is warranted, confusion ensues when patients select a particular hospital for its suitable health care services. However, both studies failed to mitigate the situation in health care service provision, in which all health care services used in evaluating hospitals were only based on yes/no value represented by 1/0. This representation is insufficient, because even with the existence of hospital services, such services might only be equipped for certain types of patients (*i.e., risk, urgent and sick*). In addition, despite the consideration of time of arrival (TAH), the representation was based on numerical values. The actual values measured in kilometres and those measured using the Global Positioning System (GPS) coordinates were not considered. Addressing these gaps was the aim of [22], where the authors developed a new mHealth framework for the evaluation and prioritisation of decentralised telemedicine hospitals based on the integrated techniques of Haversine-GPS and AHP-VIKOR. Another contribution of this study is that it presented a combined dataset related to health care service criteria and TAH using Haversine-based GPS for remote distance measurement. The major limitation of all previous studies was that their main discussions were only for patients with CHD. They did not consider hospital selection for patients who have multi-chronic diseases (MCDs). Subsequent research addressing this issue was proposed by [23], where the authors discussed the difficulty of hospitals receiving large numbers of critically ill or injured patients. In this situation, prioritisation is difficult, especially when the patients have MCDs. The authors proposed a novel decision technique to prioritise the patients with MCDs with a real-time remote health-monitoring system based on various triage levels. Results obtained using their method indicated that patients with the most severe MCD were treated first on the basis of their highest priority levels. The treatment for patients with less severe cases was delayed more than that for other patients. After discussing the major limitations of all previous studies, we found that they have their respective issues and challenges. The work by [22] addressed the issues of two previous studies [18, 21] in hospital selection in relation to the distribution of health care services and network failure. However, [22] has the shortcoming of focussing on only CHD and not considering MCD. Furthermore, [23] considered MCD but only focussed on prioritising patients; hospital selection in terms of health care services or fault tolerance was not applied.

The same group of authors extended their work in [24], where the main prioritisation problem for CHD was the big data generated from multiple disease conditions. However, hospital selection based on health care services was still not applied. Therefore, hospital selection for patients with MCD was identified as a clear research gap due to the complexity of the case study and due to the nature surrounding the criteria of MCDs, including multiple criteria presenting conflicts and trade-offs. To address these issues in the concept of hospital selection, a robust methodology that considers all previously mentioned issues is needed. MCDM was pioneered in the type of research that addresses a certain selection problem (*i.e.*, *Hospital Selection*). This type of research is most suited for this case study, because it deals with the main issues, such as the availability of many criteria (each disease has its own criteria), trade-offs and data variation [25–32]. Addressing all these issues requires a robust MCDM method [21, 33–44]. An examination of the literature shows that various techniques were proposed, and many of them are unique [23, 24, 45–50]. Nevertheless, a recently published technique has been proven to address most of the shortcomings of the previous ones; this method is known as the fuzzy decision by opinion score method (FDOSM), which has been presented by Salih et al. [51]. Since its release, the method has been intensively used in a variety of complex decision cases [52–57]. However, the method is prone to a certain limitation, namely criteria weighting. FDOSM weighs the criteria values of each application implicitly and is limited to weighting each criterion explicitly. To solve this issue, FDOSM was supported by fuzzy-weighted zero-inconsistency (FWZIC), which is a powerful weighting MCDM method for providing exact weights for criteria with zero inconsistencies [58–63]. FWZIC and FDOSM were used together to address the uncertainty and vagueness issues by integrating many fuzzy environments in complex case studies like COVID-19 vaccine distribution using Pythagorean fuzzy set [64], T-spherical fuzzy sets [65] and Q-rung orthopair fuzzy sets (q-ROFS) [66]. All the aforementioned environments supported FDOSM and FWZIC in dealing with complex decision problems, which were medically relevant and thus suitable for the current aim of this work.

However, the most recent version was developed under q-ROFS. Yager [67] invented a novel fuzzy idea known as the q-rung orthopair fuzzy set (q-ROFS) to overcome the drawbacks of information expression in conventional fuzzy sets (*i.e.*, *IFSs and PFSs*). In q-ROFSs, the constraint imposed by other fuzzy sets is eliminated, and the sum of the q powers of membership and non-membership grades is real numbers between [0, 1]. Thus, the DMs are permitted to freely select any grade for [0, 1] and [0, 1] [68]. When DM is asked for his or her preference about a particular

situation, he or she assigns a value of 0.9 for membership grade and a value of 0.8 for non-membership grade. In this instance, the IFS and PFS criteria cannot be met due to their restrictions. However, the membership and non-membership grades in the examples can be expressed using a q-ROFS with a q parameter equal to or greater than 4. When q equals 1, the q-ROFS becomes an IFS. When q = 2, the q-ROFS changes to PFSs. Considering the structure representation, the q-ROFS constraint is superior to the other constraints, because it provides more space and flexibility under unknown conditions and permits DMs to freely select membership and non-membership degrees [69]. Since its inception, a large number of scholars have intensively examined and utilised it to handle difficult and convoluted fuzzy issues from many aspects.

Therefore, FWZIC and FDOSM are to be integrated, while the latest version of fuzzy environment Q-rung orthopair is considered to be used to address the hospital selection problem in terms of health care services and service interruptions for case studies that involve MCD patients. The main contribution of this research is that it uses both techniques based on fuzzy environment Q-rung orthopair in a pioneering case study by creating an mHealth-based hospital selection framework for remote MCD patients based on IoT wearable body medical sensors.

2 Methodology

2.1 Identification

This work is proposed for the telemedicine and IoT contexts, but different architecture tiers exist [22]. The work is based on a mHealth client in Tier 2, which is prone to the disruption of service. Thus, it is considered in this study. This work addresses a gap for patient datasets identified from different studies. The first study is [22] for hospital selection and health care service datasets, and the second one is [23] for MCD patient datasets. From [22], a health care service package (HSP) for risk emergency level that includes different services, such as prepare surgery room (PSR), prepare surgery team (PST), prepare surgery doctor (PSD), prepare O2 supplier (POS), send ambulance (SA), provide medications (PM) and TAH, has been adopted. In [23], patient datasets are presented for remote patients with three diseases, as follows: CHD, high blood pressure (HBP) and low blood pressure (LBP). Each of these diseases has its own risk level ranging from Risk, Urgent, Sick, Cold State and Normal. However, only patients with consistent RL across all the MCDs are considered. They meet the inclusion criteria where all their MCDs' RLs are

at risk. The proposed matrix in this phase combining these aspects is presented in Table 1.

The values represented in these criteria represent the number of available services for those particular criteria, except for TAH, which represents the distance to each of the hospitals. The nature of all criteria is beneficial; the more they increase, the better. An exception is TAH, which is deemed a cost criterion; the more it decreases, the better. A DM is created to choose a suitable hospital for remote patients in a telemedicine environment.

2.2 Development

2.2.1 Criteria weighting by q-ROFWZIC

Q-ROFWZIC is used in weighting the evaluation criteria used in this study. It has different steps, as follows.

2.2.1.1 Criteria definition This step comprises the identification of the evaluation criteria to be used for ranking the hospitals for patients with MCD. Experts in charge of assigning proper importance levels for these criteria are discussed in the following phase.

2.2.1.2 Structured expert judgement (SEJ) This step discusses how different experts are selected based on their knowledge and expertise in telemedicine and IoT. Then, experts receive an evaluation form to collect their data using a five-point Likert scale. The last process converts the linguistic scale terms into their numerical equivalent in reference to [66], as presented in Table 2.

Table 1 Decision matrix

Criteria Hospital	PSR	PST	PSD	POS	SA	PM	TAH Value
H-1	14	23	2	28	5	100	18.00221
H-2	10	45	3	20	6	90	20.35723
H-3	5	28	5	10	4	75	42.41364
H-4	6	40	6	11	5	95	17.14394
H-5	12	30	4	25	7	150	23.88126
H-6	9	36	2	20	3	110	28.3679
H-7	4	29	3	10	4	45	20.5314
H-8	7	42	2	17	5	80	19.7176
H-9	3	45	2	8	4	50	19.1508
H-10	5	33	1	13	3	60	19.75615
H-11	5	19	2	14	8	40	22.26299
H-12	7	24	2	18	4	125	35.81598

Table 2 Linguistic terms, numerical scoring

Numerical scoring scale	Linguistic scoring scale	q-ROFS
1	Not important	(0.20, 0.90)
2	Slight important	(0.40, 0.60)
3	Moderately important	(0.65, 0.50)
4	Important	(0.80, 0.45)
5	Very important	(0.90, 0.20)

2.2.1.3 Expert decision matrix (EDM) This step includes creating an EDM comprising a crossover between selected evaluation criteria (HSP) and the SEJ panel. Each of the experts is intersected with each of the criteria to assign the level of importance.

2.2.1.4 Application of a fuzzy membership function Upon completion of the latter, data are transformed into q-ROF-EDM for additional precision. The q-ROFS is an objective with the form of [70] and defined in Eqs. (1) and (2), as follows:

$$P = \{ \langle m, (\mu_d(m), v_d(m)) \rangle \mid m \in M \}, \tag{1}$$

where $\mu_d : (M) \rightarrow [0, 1]$ is the membership function, and $v_d : (M) \rightarrow [0, 1]$ is the non-membership function of elements $m \in M$ to p ; it must fulfil the restriction seen in Eq. (2).

$$0 < (\mu_d(m))^q + (v_d(m))^q < 1, \text{ where } q > 1. \tag{2}$$

The degree of hesitancy is presented in Eq. (3), as follows:

$$\pi_m(m) = \sqrt[q]{(\mu_d(m))^q + (v_d(m))^q - (\mu_d(m))^q \cdot (v_d(m))^q}. \tag{3}$$

The applied q-rung orthopair fuzzy arithmetic mean (q-ROFA) aggregation operation is shown in Eq. (4), as follows:

$$q - \text{ROFA}(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \left\langle \left(1 - \prod_{k=1}^n (1 - \mu_k^q) \right)^{\frac{1}{q}}, \prod_{k=1}^n v_k \right\rangle. \tag{4}$$

Equation (5) shows the q-ROFS division operation, as follows:

$$\frac{p_1}{p_2} = \left(\frac{\mu_1}{\mu_2}, \sqrt[q]{\frac{v_1^q - v_2^q}{1 - v_2^q}} \right), \text{ if } \mu_1 \leq \min \left\{ \mu_2, \frac{\mu_2 \pi_1}{\pi_2} \right\}, v_1 \geq v_2. \tag{5}$$

Equation (6) shows the equation of q-ROFS division on a crisp value. The value of each linguistic term with q-ROFS is in reference to [66], as shown in Table 3.

$$p/\lambda = \left(\sqrt[q]{1 - (1 - (\mu_p)^q)^{\frac{1}{\lambda}}}, (v_p)^{\frac{1}{\lambda}} \right), \lambda \tag{6}$$

2.2.1.5 Computation of the final values of the weight coefficients of the evaluation criteria

In accordance with the defuzzification from the previous step, the final weight values of the evaluation criteria $(w_1, w_2, \dots, w_n)^T$ are calculated as follows.

- The fuzzification data ratio is calculated using Eqs. (3), (4) and (5).

The mean values for fuzzy values identification are calculated from the weight coefficients of the evaluation criteria $(\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)$. q-ROF-EDM is used to compute the weight value with Eqs. (3)–(6), where Eq. (7) symbolises the process.

$$\tilde{w}_j = \left(\frac{\sum_{i=1}^m \frac{\text{Imp}(\tilde{E}_{ij}/C_{ij})}{\sum_{j=1}^n \text{Imp}(\tilde{E}_{ij}/C_{ij})} \right) / m, \text{ for} \tag{7}$$

$$i = 1, 2, 3, \dots, m \text{ and } j = 1, 2, 3, \dots, n.$$

- Defuzzification is performed to determine the final weight using Eq. (8) while considering the weight for each criterion assigned given the sum of the weights of all the criteria for rescaling.

$$S_k = \mu_k^q - v_k^q, \text{ where } q \geq 1. \tag{8}$$

2.2.2 Formulation of q-ROFDOSM

Q-ROFDOSM is used to rank the alternatives based on the weight assigned for the evaluation criteria from the last step. Different stages, including data transformation and data processing, are needed to accomplish the ranking process. The details of the stages are as follows.

2.2.2.1 Data transformation unit This stage comprises the transformation of a DM into an opinion matrix. Firstly, the ideal solution of each sub-evaluation criterion is determined using Eq. (9).

$$A^* = \left\{ \left[\left(\max_i v_{ij} | j \in J \right), \left(\min_i v_{ij} | j \in J \right), (Op_{ij} \in I.J) | i = 1.2.3 \dots m \right] \right\}, \tag{9}$$

Max is the ideal value for benefit criteria, and min is the ideal value for the cost criteria. The Op_{ij} is the ideal value for critical criteria, when the ideal value lies between the max and min. The next step comprises selecting the ideal solution for every evaluation criteria and then performing a reference comparison using a five-point Likert scale. This comparison takes place between the ideal and other remaining values in each criterion, as presented by Eq. (10).

$$Op_{Lang} = \left\{ \left(\left(\tilde{v}_{ij} \otimes v_{ij} | j \in J \right) \cdot | i = 1.2.3 \dots m \right) \right\}, \tag{10}$$

where \otimes represents the reference comparison between the ideal solution and the value of alternatives in the same criterion. The final output of this block that indicates the linguistic term is the opinion matrix, which is ready to be transformed into a fuzzy opinion matrix by using q-ROFSs, as expressed in Eq. (11).

$$Op_Lang = \begin{matrix} A_1 & \begin{bmatrix} op_{11} & \dots & op_{1n} \\ \vdots & \ddots & \vdots \\ A_m & \begin{bmatrix} op_{m1} & \dots & op_{mn} \end{bmatrix} \end{matrix} \end{matrix} \tag{11}$$

2.2.2.2 Data processing unit In this stage, the opinion matrix is transformed into a q-ROF opinion matrix by converting linguistic terms into q-ROFSs using Table 4 based on [66]; when there is no difference in ideal linguistic term, the value is considered the highest. Therefore, the q-ROFS values are presented in ascending sequence.

The individual decision-making context begins by acquiring the weight generated by q-ROFWZIC to rank the alternatives. The opinion matrix from the previous step is aggregated using the q-rung orthopair fuzzy-weighted arithmetic mean (q-ROFWA) aggregation operation (12).

$$q - ROFWA(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \left\langle \left(1 - \prod_{k=1}^n (1 - \mu_k^q)^{w_k} \right)^{1/q}, \prod_{k=1}^n v_k^{w_k} \right\rangle \tag{12}$$

Then, defuzzification is performed using Eq. (8). After the completion of this process, alternatives can be ranked

Table 3 Linguistic terms and their equivalent Q-ROFS

Linguistic scale	q-ROFS
Not important	(0.20, 0.90)
Slight important	(0.40, 0.60)
Moderately important	(0.65, 0.50)
Important	(0.80, 0.45)
Very important	(0.90, 0.20)

Table 4 q-ROF opinion matrix

Linguistic scale	q-ROFSs
No difference	(0.90, 0.20)
Slight difference	(0.80, 0.45)
Difference	(0.65, 0.50)
Big difference	(0.40, 0.60)
Huge difference	(0.20, 0.90)

using individual q-ROFDOSM based on the assigned value. Although the group decision-making context discusses value in accordance with the variation resulting from many decision-makers' different ranks, their decisions are aggregated into a unified rank. The highest GDM score result indicates the best alternative, and the lowest score indicates the worst.

3 Results and discussion

3.1 Criteria weighting results

This section presents the criteria weighting results based on the q-ROFWZIC steps. After the steps are completed, distribution criteria are weighted according to the three experts' preferences without any inconsistency. Different weighting parameters will be considered (i.e., $q = 1, 3, 5, 7, 10$) in accordance with q-ROFS. The final weights of all the criteria are presented in Table 5.

In accordance with the fourth step of the q-ROFS membership function to convert crisp values to equivalent fuzzy numbers, fuzzification was achieved for the significance of all the seven selected criteria. The ratio value of criteria is calculated using Eqs. (3), (4) and (5). Then, the mean of the experts' preference for each criterion is calculated. Equations (7) and (8) are used to determine the final weight for each criterion. Across all the q parameters, TAH value (C7) consistently had the highest weight with (0.183790932, 0.183, 0.230, 0.276, 0.335) for ($q = 1, 3, 5, 7, 10$), respectively. PSD (C3) had the lowest weight with (0.114, 0.097, 0.061, 0.038, 0.017) for ($q = 1, 3, 5, 7, 10$), respectively, indicating the least importance. These weights along with the others are considered in q-ROFDOSM for the computation of ranking results for hospital selection.

3.2 Ranking results

After the weighting of each criterion, the ranking of hospitals was accomplished using q-ROFDOSM based on the individual and GDM contexts. The fuzzy opinion matrices were created for each DM to determine the ideal solution reflecting the hospital ranking. Then, q-ROFWA was

applied on the resulting fuzzy opinion matrices for all q values of 1, 3, 5, 7 and 10 to compute the individual ranking score based on each expert (E), as shown in Table 6.

Table 6 shows that the best hospital rank in q1 was (H-4) based on first and third experts and was third rank based on the second expert. This noticeable difference is shown in all other q values amongst the experts. The consensus of group decision-makers aggregates to compute the final ranking of GDM, as shown in Table 7.

According to Table 7, q-ROFDOSM ranking results are discussed for GDM context according to the q values of 3, 5, 7 and 10. For $q = 1$, the best ranking was attributed to (H-4) with a score value (0.322). The same hospital also ranked first in different q settings, including $q = 7$ and $q = 10$ with the score values (0.203 and 0.145), respectively. For the two remaining q values (3 and 5), the best hospital selection was attributed to (H-5) with score values of (0.367 and 0.280), respectively. For the worst hospital selection, most q values, including, 1, 3, 5 and 7, indicated that H-7 was the worst with different score values: $q = 1$ with (- 0.287), $q = 3$ with (- 0.231), $q = 5$ with (- 0.124) and $q = 7$ with (- 0.062). Only $q = 10$ indicated a different worst hospital selection for (H-3) with a score value of (- 0.028) score value. It is noticeable from the GDM that different q values presented different ranking results.

In Table 8, the variance percentage was calculated for each alternative (Hospital) rank across all q values. The average of the variance value over all hospitals was 64.16% (Table 8). This finding clearly indicates how the q value affected the rank for the GDM q-ROFDOSM. This ranking is the final one, and its evaluation is discussed in the following section.

4 Evaluation

Three evaluation methods are used in the process, including systematic ranking evaluation and sensitivity analysis. These evaluation approaches are used in many MCDM context cases [71] to ensure the validity of the ranking based on the GDM context.

Table 5 Criteria weighting results

Criteria	PSR (C1)	PST (C2)	PSD (C3)	POS (C4)	SA (C5)	PM (C6)	TAH value (C7)
$q = 1$	0.169	0.128	0.114	0.114	0.146	0.142	0.183
$q = 3$	0.177	0.118	0.097	0.097	0.168	0.157	0.183
$q = 5$	0.214	0.084	0.061	0.062	0.185	0.160	0.230
$q = 7$	0.245	0.055	0.038	0.039	0.190	0.154	0.276
$q = 10$	0.283	0.0272	0.017	0.0186	0.180	0.136	0.335

Table 6 Final ranking individual DM

H	Q1												Q3												Q5																													
	E1				E2				E3				E1				E2				E3				E1				E2				E3																					
	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R	S	R																		
H-1	0.345	2	0.238	2	0.285	3	0.388	3	0.281	3	0.363	2	0.296	2	0.224	3	0.292	1	0.345	2	0.238	2	0.285	3	0.388	3	0.281	3	0.363	2	0.296	2	0.224	3	0.292	1	0.345	2	0.238	2	0.285	3	0.388	3	0.281	3	0.363	2	0.296	2	0.224	3	0.292	1
H-2	0.341	4	0.210	4	0.317	2	0.380	4	0.248	4	0.362	3	0.254	4	0.164	4	0.248	4	0.341	4	0.210	4	0.317	2	0.380	4	0.248	4	0.362	3	0.254	4	0.164	4	0.248	4	0.341	4	0.210	4	0.317	2	0.380	4	0.248	4	0.362	3	0.254	4	0.164	4	0.248	4
H-3	-0.030	10	-0.255	11	-0.131	9	0.006	10	-0.205	11	-0.083	10	-0.003	10	-0.146	11	-0.050	10	-0.030	10	-0.255	11	-0.131	9	0.006	10	-0.205	11	-0.083	10	-0.003	10	-0.146	11	-0.050	10	-0.030	10	-0.255	11	-0.131	9	0.006	10	-0.205	11	-0.083	10	-0.003	10	-0.146	11	-0.050	10
H-4	0.368	1	0.234	3	0.368	1	0.389	2	0.285	2	0.389	1	0.284	3	0.237	2	0.284	2	0.368	1	0.234	3	0.368	1	0.389	2	0.285	2	0.389	1	0.284	3	0.237	2	0.284	2	0.368	1	0.234	3	0.368	1	0.389	2	0.285	2	0.389	1	0.284	3	0.237	2	0.284	2
H-5	0.344	3	0.284	1	0.250	4	0.411	1	0.354	1	0.338	4	0.304	1	0.271	1	0.267	3	0.344	3	0.284	1	0.250	4	0.411	1	0.354	1	0.338	4	0.304	1	0.271	1	0.267	3	0.344	3	0.284	1	0.250	4	0.411	1	0.354	1	0.338	4	0.304	1	0.271	1	0.267	3
H-6	0.104	5	-0.037	6	0.007	6	0.144	6	0.003	6	0.039	6	0.105	6	0.016	6	0.029	8	0.104	5	-0.037	6	0.007	6	0.144	6	0.003	6	0.039	6	0.105	6	0.016	6	0.029	8	0.104	5	-0.037	6	0.007	6	0.144	6	0.003	6	0.039	6	0.105	6	0.016	6	0.029	8
H-7	-0.144	12	-0.391	12	-0.327	12	-0.105	12	-0.326	12	-0.263	12	-0.049	12	-0.183	12	-0.140	12	-0.144	12	-0.391	12	-0.327	12	-0.105	12	-0.326	12	-0.263	12	-0.049	12	-0.183	12	-0.140	12	-0.144	12	-0.391	12	-0.327	12	-0.105	12	-0.326	12	-0.263	12	-0.049	12	-0.183	12	-0.140	12
H-8	0.101	6	-0.031	5	0.020	5	0.118	7	-0.003	7	0.047	5	0.070	8	0.011	7	0.039	6	0.101	6	-0.031	5	0.020	5	0.118	7	-0.003	7	0.047	5	0.070	8	0.011	7	0.039	6	0.101	6	-0.031	5	0.020	5	0.118	7	-0.003	7	0.047	5	0.070	8	0.011	7	0.039	6
H-9	0.007	9	-0.087	8	-0.034	7	0.065	9	-0.015	8	0.038	7	0.049	9	0.005	8	0.039	7	0.007	9	-0.087	8	-0.034	7	0.065	9	-0.015	8	0.038	7	0.049	9	0.005	8	0.039	7	0.007	9	-0.087	8	-0.034	7	0.065	9	-0.015	8	0.038	7	0.049	9	0.005	8	0.039	7
H-10	-0.129	11	-0.247	10	-0.253	11	-0.095	11	-0.199	10	-0.198	11	-0.037	11	-0.101	10	-0.095	11	-0.129	11	-0.247	10	-0.253	11	-0.095	11	-0.199	10	-0.198	11	-0.037	11	-0.101	10	-0.095	11	-0.129	11	-0.247	10	-0.253	11	-0.095	11	-0.199	10	-0.198	11	-0.037	11	-0.101	10	-0.095	11
H-11	0.089	7	-0.064	7	-0.139	10	0.178	5	0.061	5	0.003	8	0.175	5	0.120	5	0.082	5	0.089	7	-0.064	7	-0.139	10	0.178	5	0.061	5	0.003	8	0.175	5	0.120	5	0.082	5	0.089	7	-0.064	7	-0.139	10	0.178	5	0.061	5	0.003	8	0.175	5	0.120	5	0.082	5
H-12	0.061	8	-0.168	9	-0.042	8	0.098	8	-0.121	9	0.001	9	0.077	7	-0.069	9	0.009	9	0.061	8	-0.168	9	-0.042	8	0.098	8	-0.121	9	0.001	9	0.077	7	-0.069	9	0.009	9	0.061	8	-0.168	9	-0.042	8	0.098	8	-0.121	9	0.001	9	0.077	7	-0.069	9	0.009	9

Q7	Q10																																																			
	E1				E2				E3																																											
	S	R	S	R	S	R	S	R	S	R	S	R																																								
E1	0.216	1	0.174	3	0.216	1	0.141	2	0.141	2	0.123	2	0.141	2	0.141	2	0.216	1	0.174	3	0.216	1	0.141	2	0.141	2	0.123	2	0.141	2	0.141	2	0.216	1	0.174	3	0.216	1	0.141	2	0.141	2	0.123	2	0.141	2	0.141	2				
S	0.154	4	0.099	5	0.152	4	0.070	5	0.070	5	0.046	5	0.070	5	0.070	5	0.154	4	0.099	5	0.152	4	0.070	5	0.070	5	0.046	5	0.070	5	0.070	5	0.070	5	0.154	4	0.099	5	0.152	4	0.070	5	0.070	5	0.046	5	0.070	5	0.070	5	0.070	5
R	-0.006	10	-0.105	12	-0.029	10	-0.006	12	-0.006	12	-0.069	12	-0.069	12	-0.013	11	-0.006	10	-0.105	12	-0.029	10	-0.006	12	-0.006	12	-0.069	12	-0.069	12	-0.013	11	-0.013	11	-0.006	10	-0.105	12	-0.029	10	-0.006	12	-0.006	12	-0.069	12	-0.069	12	-0.013	11	-0.013	11
S	0.210	2	0.192	1	0.210	2	0.147	1	0.147	1	0.143	1	0.143	1	0.147	1	0.210	2	0.192	1	0.210	2	0.147	1	0.147	1	0.143	1	0.143	1	0.147	1	0.147	1	0.210	2	0.192	1	0.210	2	0.147	1	0.147	1	0.143	1	0.143	1	0.147	1	0.147	1
R	0.207	3	0.190	2	0.189	3	0.113	3	0.113	3	0.107	3	0.107	3	0.107	3	0.207	3	0.190	2	0.189	3	0.113	3	0.113	3	0.107	3	0.107	3	0.107	3	0.107	3	0.207	3	0.190	2	0.189	3	0.113	3	0.113	3	0.107	3	0.107	3	0.107	3	0.107	3
S	0.062	6	0.012	6	0.016	8	0.025	6	0.025	6	0.005	8	0.005	8	0.005	8	0.062	6	0.012	6	0.016	8	0.025	6	0.025	6	0.005	8	0.005	8	0.005	8	0.005	8	0.062	6	0.012	6	0.016	8	0.025	6	0.025	6	0.005	8	0.005	8	0.005	8	0.005	8
R	-0.020	12	-0.096	11	-0.070	12	-0.005	11	-0.005	11	-0.036	11	-0.036	11	-0.024	12	-0.020	12	-0.096	11	-0.070	12	-0.005	11	-0.005	11	-0.036	11	-0.036	11	-0.024	12	-0.024	12	-0.020	12	-0.096	11	-0.070	12	-0.005	11	-0.005	11	-0.036	11	-0.036	11	-0.024	12	-0.024	12
S	0.035	8	0.010	7	0.023	7	0.011	8	0.011	8	0.005	7	0.005	7	0.008	7	0.035	8	0.010	7	0.023	7	0.011	8	0.011	8	0.005	7	0.005	7	0.008	7	0.008	7	0.035	8	0.010	7	0.023	7	0.011	8	0.011	8	0.005	7	0.005	7	0.008	7	0.008	7
R	0.027	9	0.005	8	0.023	6	0.009	9	0.009	9	0.002	8	0.002	8	0.008	6	0.027	9	0.005	8	0.023	6	0.009	9	0.009	9	0.002	8	0.002	8	0.008	6	0.008	6	0.027	9	0.005	8	0.023	6	0.009	9	0.009	9	0.002	8	0.002	8	0.008	6	0.008	6
S	-0.011	11	-0.047	10	-0.041	11	-0.000	10	-0.000	10	-0.013	9	-0.013	9	-0.010	10	-0.011	11	-0.047	10	-0.041	11	-0.000	10	-0.000	10	-0.013	9	-0.013	9	-0.010	10	-0.010	10	-0.011	11	-0.047	10	-0.041	11	-0.000	10	-0.000	10	-0.013	9	-0.013	9	-0.010	10	-0.010	10
R	0.135	5	0.112	4	0.091	5	0.082	4	0.082	4	0.076	4	0.076	4	0.068	5	0.135	5	0.112	4	0.091	5	0.082	4	0.082	4	0.076	4	0.076	4	0.068	5	0.068	5	0.135	5	0.112	4	0.091	5	0.082	4	0.082	4	0.076	4	0.076	4	0.068	5	0.068	5
R	0.048	7	-0.037	9	0.005	9	0.005	9	0.020	7	0.020	7	-0.016	10	0.001	9	0.048	7	-0.037	9	0.005	9	0.005	9	0.020	7	0.020	7	-0.016	10	0.001	9	0.001	9	0.048	7	-0.037	9	0.005	9	0.005	9	0.020	7	0.020	7	-0.016	10	0.001	9	0.001	9

S = Score, R = Rank, H = Hospitals

Table 7 Final ranking GDM

Alternatives	$q = 1$		$q = 3$		$q = 5$		$q = 7$		$q = 10$	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
H-1	0.289	4	0.343	3	0.270	2	0.20199	2	0.135	2
H-2	0.289	3	0.329	4	0.221	4	0.135167	4	0.062	5
H-3	- 0.138	10	- 0.094	10	- 0.066	10	- 0.04657	11	- 0.028	12
H-4	0.322	1	0.354	2	0.268	3	0.203987	1	0.145	1
H-5	0.292	2	0.367	1	0.280	1	0.19567	3	0.108	3
H-6	0.025	6	0.062	6	0.050	6	0.030261	6	0.011727	6
H-7	- 0.287	12	- 0.231	12	- 0.124	12	- 0.06225	12	- 0.021	11
H-8	0.029	5	0.053	7	0.040	7	0.022654	7	0.007	7
H-9	- 0.037	7	0.029	8	0.030912	8	0.018212	8	0.006	8
H-10	- 0.209	11	- 0.163	11	- 0.077	11	- 0.0328	10	- 0.008	10
H-11	- 0.038	8	0.080	5	0.125	5	0.112968	5	0.075	4
H-12	- 0.049	9	- 0.007	9	0.005	9	0.005	9	0.001	9

Table 8 Variance percentage based on q values

Hospital	$q = 1$	$q = 3$	$q = 5$	$q = 7$	$q = 10$	VPQP
	Rank	Rank	Rank	Rank	Rank	
H-1	4	3	2	2	2	80
H-2	3	4	4	4	5	50
H-3	10	10	10	11	12	80
H-4	1	2	3	1	1	80
H-5	2	1	1	3	3	100
H-6	6	6	6	6	6	0
H-7	12	12	12	12	11	20
H-8	5	7	7	7	7	80
H-9	7	8	8	8	8	20
H-10	11	11	11	10	10	30
H-11	8	5	5	5	4	230
H-12	9	9	9	9	9	0

VPQP: Variance percentage per hospital over q values

4.1 Systematic ranking

The original data of all hospitals in the decision matrix are ordered based on their rank value and then divided based on four hospitals per group to compute the mean value for each group per q . In $q1$ for example, the three groups are as follows: (Group 1: H4, H5, H2 and H1), (Group 2: H8, H6, H9 and H11) and (Group 3: H12, H3, H10 and H9). The results of the systematic ranking based on the scenarios of three groups in Table 9 are as follows.

Table 9 clearly shows that each group’s mean value is smaller or equal to that of the following group. When these results are accomplished across all the q values, the validity

of the ranking is confirmed. Thus, the main concept of the systematic ranking is also confirmed. In our case study, our ranking is valid based on the results.

4.2 Sensitivity analysis

Another evaluation method is adopted by integrating sensitivity analysis. As a proof of concept, sensitivity analysis was carried out to measure the weight changes and their effect on the ranking of $q1$ only over nine scenarios using Eq. (13) [72]. The relative change for each criterion over the most important one (TAH) with respect to the $q1$ value was computed by using the elasticity coefficient (α_c), as shown in Table 10.

$$w_c = (1 - w_s) \times (w_c^o / W_c^0) = w_c^o - \Delta x \alpha_c, \tag{13}$$

For a q value,

- w_s is the higher significant contribution.
- w_c^o represents the original weight values computed using q -ROFWZIC.
- W_c^0 is the total of original weights for the changing criteria weight values.

Table 9 Systematic ranking

Group #	$q1$ Mean Value	$q3$	$q5$	$q7$	$q10$
Group 1	2.619	2.619	2.619	2.619	2.928
Group 2	3.559	3.559	3.559	3.559	3.25
Group 3	3.880	3.880	3.880	3.880	3.880

Table 10 Elasticity coefficient (α_c) for changing weights

T value	Criteria	C1	C2	C3	C4	C5	C6	C7
$q = 1$	α_c	0.207	0.157	0.140	0.140	0.179	0.174	0.225
$q = 3$	α_c	0.217	0.144	0.118	0.119	0.206	0.193	0.224
$q = 5$	α_c	0.278	0.110	0.080	0.081	0.240	0.208	0.299
$q = 7$	α_c	0.339	0.077	0.052	0.054	0.263	0.213	0.382
$q = 10$	α_c	0.427	0.040	0.026	0.028	0.272	0.204	0.504

- Δx is the range of change applied on the seven criteria weight values, which represents the limit values of the most significant criterion in this study (TAH) as follows:
- For $q = 1$, $-0.183 \leq \Delta x \leq 0.817$
- For $q = 3$, $-0.183 \leq \Delta x \leq 0.817$
- For $q = 5$, $-0.230 \leq \Delta x \leq 0.77$
- For $q = 7$, $-0.276 \leq \Delta x \leq 0.724$
- For $q = 10$, $-0.335 \leq \Delta x \leq 0.665$

All q values across the criteria presented slight changes in their weights according to Eq. (13). Table 10 clearly shows that for all α_c with respect to the q values, TAH (C7) received the highest weight in comparison with PSD (C3), which received the lowest weight. The interval range of Δx for q values was used in generating nine new weighting values for each criterion. That range was split into nine equal relative values according to the number of scenarios. Given that all the criteria are presented with the same level of importance across all q values, only q_1 as a proof of concept for sensitivity analysis results is discussed in Table 11.

Weights generated were used to assess the sensitivity of hospital ranking for MCD patients across nine scenarios. The first-ranked alternative ($H-4$) maintained its highest ranking with FWZIC in seven ($n = 7$) scenarios. The next alternative was ($H-11$), which maintained its ranking of eighth across five scenarios. Alternative ($H-8$) maintained the fifth rank consistently with FWZIC in four ($n = 4$) scenarios, and alternatives ($H-7$) and ($H-10$) only maintained three ranking scenarios. Alternative ($H-3$) maintained two ranking scenarios. The final maintained alternatives were ($H-2$), ($H-6$) and ($H-12$) which maintained their ranking in only one scenario. The worst alternatives were ($H-1$) and ($H-5$), which did not maintain their ranking with FWZIC in any scenario. Finally, Spearman’s rank correlation coefficient was used to statistically assess the relationship between the results of the nine scenarios [30]. Generally, high correlation was observed with a value of 1 for S_4 and between 0.94 and 0.96 for scenarios S_3 , S_5 and S_6 . S_2 presented a 0.88 correlation value, followed by S_7 with 0.89. S_1 , S_8

Table 11 Sensitivity analysis scenarios

Rec	q-ROFWZIC	S1	S2	S3	S4	S5	S6	S7	S8	S9
H-1	4	2	3	3	3	3	3	3	5	5
H-2	3	3	2	2	2	2	2	2	4	4
H-3	10	9	10	10	12	12	12	12	12	12
H-4	1	4	4	1	1	1	1	1	1	1
H-5	2	1	1	4	4	4	4	6	7	7
H-6	6	5	5	6	7	7	7	8	8	8
H-7	12	12	12	12	11	10	10	10	9	9
H-8	5	7	6	5	5	5	5	4	2	2
H-9	7	10	9	7	6	6	6	5	3	3
H-10	11	11	11	11	9	9	8	7	6	6
H-11	8	8	8	8	8	8	9	9	10	10
H-12	9	6	7	9	10	11	11	11	11	11

presented the same correlation value of 0.76. S_9 presented the lowest correlation value of 0.52.

4.3 Comparison analysis

To accentuate the present main contribution of this study, this section discusses comparisons of the proposed q -ROFDOSM and q -ROFWZIC with different MCDM methods. As mentioned earlier, the Q -rung orthopair fuzzy sets (q -ROFS) [66] proved its efficiency in comparison with other fuzzy environments in handling the vagueness and providing better representation to the membership degree in comparison with IFSs and PFSs. Theoretically, in MCDM, the proposed methods show superior performance and effectively handle the limitation of the other MCDM methods either in the weight approach or ranking approach. For instance, the q -ROFDOSM in comparison with TOPSIS and VIKOR could successfully overcome the limitation of the most common challenges found in the MCDM human approaches apart from the missing information and immeasurable criteria issues; it could also solve the ambiguous and vagueness issue [64, 65]. Although the q -ROFDOSM computed the weight implicitly, the proposed methodology used the integration formulation with

q-ROFWZIC to compute the criteria in a precise way due to the fuzzy environment and with zero inconsistency. In comparison with the most common weighting methods of AHP and BWM, the approach of the most recent extension of FWZIC succeeded in addressing the issue of uncertainty as a consequence of feedback of experts' subjectivity. In addition to reducing the number of comparison eight pair or reference comparison to zero, the inconsistency, which is main issue of weighting methods, was resolved [73, 74].

5 Conclusion

This study aimed to address the issue of hospital selection based on IoT wearable body medical sensors in health care services for patients with MCD. Various issues were considered in the process, as follows: (1) multiple evaluation criteria, (2) criteria importance and (3) data variation. A literature review presented various MCDM methods, each of which had its own shortcomings. Recent prominent and capable MCDM methods known as FDOSM and FWZIC were most suited for the case study in this research. The two integrated methods were presented based on a Q-rung orthopair fuzzy environment to address the uncertainty that resulted from DM in health care services and during service interruptions in our case study. The main contribution of this work was the use of both techniques for criterion weighting and hospital ranking. Thus, an integrated decision-making framework for hospital selection based on IoT wearable body medical sensors for remote MCD patients over a telemedicine environment was created. The framework's robustness was confirmed using systematic ranking assessment methods and sensitivity analysis.

However, this study has two main limitations that might be addressed in the future. The first limitation is the use of static selection procedure for outdoor patients without considering the dynamic nature associated with having multiple indoor MCD patients who might arrive first. For example, when a remote outdoor patient requests service, the service might be occupied by another indoor patient. This issue can be targeted in future research, in which the dynamically changing environment and the continuous synchronisation between indoor and outdoor patients and the health care centre can be considered. The second limitation is our reliance on only risk-level patients with MCD for hospital selection. This limitation can be addressed by considering different risk levels (i.e., urgent and sick) separately and in combination with the current risk level used in this study.

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Declarations

Conflict of interest The authors declare no conflict of interest.

References

1. Raad MW, Sheltami T, Shakshuki E (2015) Ubiquitous telehealth system for elderly patients with alzheimer's. *Procedia Comput Sci* 52:685–689
2. Albahri O et al (2018) Systematic review of real-time remote health monitoring system in triage and priority-based sensor technology: Taxonomy, open challenges, motivation and recommendations. *J Med Syst* 42(5):80
3. Kalid N et al (2018) Based on real time remote health monitoring systems: a new approach for prioritization "large scales data" patients with chronic heart diseases using body sensors and communication technology. *J med syst* 42(4):69
4. Albahri A et al (2018) Real-time fault-tolerant mHealth system: comprehensive review of healthcare services, opens issues, challenges and methodological aspects. *J Med Syst* 42(8):137
5. Hamid RA et al (2021) Dempster–Shafer theory for classification and hybridised models of multi-criteria decision analysis for prioritisation: a telemedicine framework for patients with heart diseases. *J Ambient Intell Humanized Comput* 13(9):1–35
6. Jabeen F et al (2019) An IoT based efficient hybrid recommender system for cardiovascular disease. *Peer-to-Peer Network Appl* 12(5):1263–1276
7. Bhatt A, Dubey S, Bhatt A (2018) Analytical study on cardiovascular health issues prediction using decision model-based predictive analytic techniques. In: Pant M, Ray K, Sharma T, Rawat S, Bandyopadhyay A (eds) *Soft Computing: Theories and Applications*. Springer, Singapore, pp 289–299
8. Albahri O et al (2018) Real-time remote health-monitoring systems in a medical centre: a review of the provision of healthcare services-based body sensor information, open challenges and methodological aspects. *J Med Syst* 42(9):164
9. Zheng T et al (2017) A machine learning-based framework to identify type 2 diabetes through electronic health records. *Int J Med Informatics* 97:120–127
10. Mohammed K et al (2019) Real-time remote-health monitoring systems: a review on patients prioritisation for multiple-chronic diseases, taxonomy analysis, concerns and solution procedure. *J Med Syst* 43(7):223
11. Sudhakar K, Manimekalai DM (2014) Study of heart disease prediction using data mining. *Int J Adv Res Comput Sci Softw Eng* 4(1):1157–1160
12. Napi NM et al (2019) Medical emergency triage and patient prioritisation in a telemedicine environment: a systematic review. *Heal Technol* 9(5):679–700. <https://doi.org/10.1007/s12553-019-00357-w>
13. Albahri AS et al (2021) Development of IoT-based mhealth framework for various cases of heart disease patients. *Health and Technol* 11(5):1013–1033. <https://doi.org/10.1007/s12553-021-00579-x>
14. Ray PP (2017) Understanding the role of internet of things towards smart e-healthcare services. *Biomed Res* 28(4):1604–1609
15. Albahri OS et al (2019) Fault-tolerant mHealth framework in the context of IoT-based real-time wearable health data sensors. *IEEE Access* 7:50052–50080
16. Salman O, Rasid MFA, Saripan MI, Subramaniam SK (2014) Multi-sources data fusion framework for remote triage prioritization in telehealth. *J Med Syst* 38(9):1–23

17. Rocha A et al (2013) Innovations in health care services: The CAALYX system. *Int J Med Informatics* 82(11):e307–e320
18. Albahri AS et al (2019) Based multiple heterogeneous wearable sensors: A smart real-time health monitoring structured for hospitals distributor. *IEEE access* 7:37269–37323
19. Van Dyk L (2014) A review of telehealth service implementation frameworks. *Int J Environ Res Public Health* 11(2):1279–1298
20. Dong J, Yang G-H (2014) Reliable state feedback control of T-S fuzzy systems with sensor faults. *IEEE Trans Fuzzy Syst* 23(2):421–433
21. Almahdi E et al (2019) Mobile patient monitoring systems from a benchmarking aspect: challenges, open issues and recommended solutions. *J Med Syst* 43(7):207
22. Albahri O et al (2021) New mHealth hospital selection framework supporting decentralised telemedicine architecture for out-patient cardiovascular disease-based integrated techniques: Haversine-GPS and AHP-VIKOR. *J Ambient Intell Humanized Comput* 13(1):1–21
23. Mohammed K et al (2020) Novel technique for reorganisation of opinion order to interval levels for solving several instances representing prioritisation in patients with multiple chronic diseases. *Comput Methods Programs Biomed* 185:105151
24. Mohammed K et al (2020) A uniform intelligent prioritisation for solving diverse and big data generated from multiple chronic diseases patients based on hybrid decision-making and voting method. *IEEE Access* 8:91521–91530
25. Zaidan A et al (2018) A review on smartphone skin cancer diagnosis apps in evaluation and benchmarking: coherent taxonomy, open issues and recommendation pathway solution. *Heal Technol* 8(4):223–238
26. Alsalem M et al (2018) Systematic review of an automated multiclass detection and classification system for acute Leukaemia in terms of evaluation and benchmarking, open challenges, issues and methodological aspects. *J Med Syst* 42(11):204
27. Alsalem M et al (2019) Multiclass benchmarking framework for automated acute Leukaemia detection and classification based on BWM and group-VIKOR. *J Med Syst* 43(7):212
28. Alaa M et al (2019) Assessment and ranking framework for the English skills of pre-service teachers based on fuzzy Delphi and TOPSIS methods. *IEEE Access* 7:126201–126223
29. Ibrahim N et al (2019) Multi-criteria evaluation and benchmarking for young learners' english language mobile applications in terms of LSRW skills. *IEEE Access* 7(7):146620–146651
30. Mohammed TJ et al (2021) Convalescent-plasma-transfusion intelligent framework for rescuing COVID-19 patients across centralised/decentralised telemedicine hospitals based on AHP-group TOPSIS and matching component. *Appl Intell* 51(5):1–32
31. Khatari M et al (2020) Multidimensional benchmarking framework for AQMs of network congestion control based on AHP and group-TOPSIS. *Int J Inf Technol Decis Mak* 20(5):1409–1446
32. Alamoodi A et al (2021) Machine learning-based imputation soft computing approach for large missing scale and non-reference data imputation. *Chaos, Solitons Fractals* 151:111236
33. Yager RR (2017) Multi-criteria decision making with interval criteria satisfactions using the golden rule representative value. *IEEE Trans Fuzzy Syst* 26(2):1023–1031
34. Khatari M et al (2019) Multi-criteria evaluation and benchmarking for active queue management methods: open issues, challenges and recommended pathway solutions. *Int J Inf Technol Decis Mak* 18(04):1187–1242
35. Almahdi E et al (2019) Mobile-based patient monitoring systems: A prioritisation framework using multi-criteria decision-making techniques. *J Med Syst* 43(7):219
36. Zaidan A et al (2020) Multi-agent learning neural network and Bayesian model for real-time IoT skin detectors: a new evaluation and benchmarking methodology. *Neural Comput Appl* 32(12):8315–8366
37. Albahri A et al (2020) Multi-biological laboratory examination framework for the prioritization of patients with COVID-19 based on integrated AHP and group VIKOR methods. *Int J Inf Technol Decis Mak* 19(05):1247–1269
38. Alamoodi A et al (2020) A systematic review into the assessment of medical apps: motivations, challenges, recommendations and methodological aspect. *Health Technol* 10(5):1–17
39. Albahri O et al (2020) Systematic review of artificial intelligence techniques in the detection and classification of COVID-19 medical images in terms of evaluation and benchmarking: Taxonomy analysis, challenges, future solutions and methodological aspects. *J Infect Public Health* 13(10):1381–1396
40. Albahri A et al (2020) Detection-based prioritisation: framework of multi-laboratory characteristics for asymptomatic COVID-19 carriers based on integrated entropy–TOPSIS methods. *Artif Intell Med* 111:101983
41. Zughoul O et al (2020) "Novel triplex procedure for ranking the ability of software engineering students based on two levels of AHP and group TOPSIS techniques. *Int J of Inf Technol Decis Mak* 20(01):67–135
42. Alsalem M et al (2022) Rescuing emergency cases of COVID-19 patients: an intelligent real-time MSC transfusion framework based on multicriteria decision-making methods. *Appl Intell* 52:1–25
43. Alamleh A et al (2022) Federated learning for IoMT applications: a standardisation and benchmarking framework of intrusion detection systems. *IEEE J Biomed Health Inf.* <https://doi.org/10.1109/JBHI.2022.31672562022>
44. Malik R et al (2021) Novel roadside unit positioning framework in the context of the vehicle-to-infrastructure communication system based on AHP—entropy for weighting and borda—VIKOR for uniform ranking. *Int J Inf Technol Decis Mak* 21(4):1–34
45. Abdulkareem KH et al (2020) A new standardisation and selection framework for real-time image dehazing algorithms from multi-foggy scenes based on fuzzy Delphi and hybrid multi-criteria decision analysis methods. *Neural Comput Appl.* <https://doi.org/10.1007/s00521-020-05020-4>
46. Abdulkareem KH et al (2020) A Novel multi-perspective benchmarking framework for selecting image dehazing intelligent algorithms based on BWM and group VIKOR techniques. *Int J Inf Technol Decis Mak* 19(3):909–957
47. Albahri O et al (2020) Helping doctors hasten COVID-19 treatment: towards a rescue framework for the transfusion of best convalescent plasma to the most critical patients based on biological requirements via ml and novel MCDM methods. *Comput Methods Programs Biomed* 196:105617
48. Alsalem MA et al (2021) Rise of multiattribute decision-making in combating COVID-19: a systematic review of the state-of-the-art literature. *Int J Intell Syst* 37(6):3514–3624
49. Alamleh A et al (2022) Multi-attribute Decision-Making for Intrusion Detection Systems: A Systematic Review. *Int J Inf Technol Decis Mak.* <https://doi.org/10.1142/S021962202230004X>
50. AlSereidi A et al (2022) Novel Federated Decision Making for Distribution of Anti-SARS-CoV-2 Monoclonal Antibody to Eligible High-Risk Patients. *Int J Inf Technol Decis Mak.* <https://doi.org/10.1142/S021962202250050X>
51. Salih MM et al (2020) Fuzzy decision by opinion score method. *Appl Soft Comput* 96:106595
52. Albahri OS et al (2021) Multidimensional benchmarking of the active queue management methods of network congestion control based on extension of fuzzy decision by opinion score method. *Int J Intell Syst* 36(2):796–831

53. Salih MM et al (2021) Benchmarking of AQM methods of network congestion control based on extension of interval type-2 trapezoidal fuzzy decision by opinion score method. *Telecommun Syst* 77(3):1–30
54. Al-Samarraay MS et al (2021) Extension of interval-valued Pythagorean FDOSM for evaluating and benchmarking real-time SLRSs based on multidimensional criteria of hand gesture recognition and sensor glove perspectives. *Appl Soft Comput* 116(2022):108284
55. Alamoodi A et al (2022) New extension of fuzzy-weighted zero-inconsistency and fuzzy decision by opinion score method based on cubic pythagorean fuzzy environment: a benchmarking case study of sign language recognition systems. *Int J Fuzzy Syst* 24:1–18
56. Alamoodi A et al (2022) Based on neutrosophic fuzzy environment: a new development of FWZIC and FDOSM for benchmarking smart e-tourism applications. *Complex Intell Syst* 8:1–25
57. Al-Samarraay MS et al (2022) A new extension of FDOSM based on Pythagorean fuzzy environment for evaluating and benchmarking sign language recognition systems. *Neural Comput Appl* 34(6):1–19
58. Qahtan S et al (2022) Novel multi security and privacy benchmarking framework for blockchain-based IoT healthcare industry 4.0 systems. *IEEE Trans Industr Inf* 18(9):6415–6423
59. Alsalem M et al (2022) Multi-criteria decision-making for coronavirus disease 2019 applications: a theoretical analysis review. *Artif Intell Rev* 55:1–84
60. Al-Humairi S et al (2022) Towards sustainable transportation: a pavement strategy selection based on the extension of dual-hesitant fuzzy multi-criteria decision-making methods. *IEEE Trans Fuzzy Syst*. <https://doi.org/10.1109/TFUZZ.2022.3168050>
61. Albahri O et al (2022) Combination of fuzzy-weighted zero-inconsistency and fuzzy decision by opinion score methods in pythagorean m-polar fuzzy environment: a case study of sign language recognition systems. *Int J Inf Technol Decis Mak*. <https://doi.org/10.1142/S0219622022500183>
62. Mahmoud U et al (2022) DAS benchmarking methodology based on FWZIC II and FDOSM II to support industrial community characteristics in the design and implementation of advanced driver assistance systems in vehicles. *J Ambient Intell Humaniz Comput*. <https://doi.org/10.1007/s12652-022-04201-4>
63. AlSattar H et al (2022) Integration of FDOSM and FWZIC under homogeneous fermatean fuzzy environment: a prioritisation of COVID-19 patients for mesenchymal stem cell transfusion. *Int J Inf Technol Decis Mak*. <https://doi.org/10.1142/S0219622022500511>
64. Albahri O et al (2021) Novel dynamic fuzzy decision-making framework for COVID-19 vaccine dose recipients. *J Adv Res* 37:147–168
65. Alsalem M et al (2021) Based on T-spherical Fuzzy environment: a combination of FWZIC and FDOSM for prioritising COVID-19 vaccine dose recipients. *J Infect Public Health* 14(10):1513–1559
66. Albahri A et al (2021) Integration of fuzzy-weighted zero-inconsistency and fuzzy decision by opinion score methods under a q-Rung orthopair environment: a distribution case study of COVID-19 vaccine doses. *Comput Stand Interfaces* 80(2022):103572
67. Yager RR (2016) Generalized orthopair fuzzy sets. *IEEE Trans Fuzzy Syst* 25(5):1222–1230
68. Hussain A, Ali M, Mahmood T (2020) Hesitant q-rung orthopair fuzzy aggregation operators with their applications in multi-criteria decision making. *Iran J Fuzzy Syst* 17(3):117–134
69. Liu Z, Li L, Li J (2019) q-Rung orthopair uncertain linguistic partitioned Bonferroni mean operators and its application to multiple attribute decision-making method. *Int J Intell Syst* 34(10):2490–2520
70. Liu P, Wang P (2018) Some q-rung orthopair fuzzy aggregation operators and their applications to multiple-attribute decision making. *Int J Intell Syst* 33(2):259–280
71. Khatari M et al (2021) Multidimensional benchmarking framework for AQMs of network congestion control based on AHP and group-TOPSIS. *Int J Inf Technol Decis Mak* 20(5):1–38
72. Pamucar D, Yazdani M, Obradovic R, Kumar A, Torres-Jiménez M (2020) A novel fuzzy hybrid neutrosophic decision-making approach for the resilient supplier selection problem. *Int J Intell Syst* 35(12):1934–1986
73. Mohammed R et al (2021) Determining importance of many-objective optimisation competitive algorithms evaluation criteria based on a novel fuzzy-weighted zero-inconsistency method. *Int J Inf Technol Decis Mak* 21(1):1–47
74. Krishnan E et al (2021) Interval type 2 trapezoidal-fuzzy weighted with zero inconsistency combined with VIKOR for evaluating smart e-tourism applications. *Int J Intell Syst* 36(9):4723–4774

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