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A large-scale group decision making method to select the ideal mobile health application for the hospital

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Abstract
Mobile health, which is not limited by time and space, can effectively alleviate the imbalance of medical resources. Currently, more and more hospitals begin to pay attention to online medical care and actively expand their mobile channels. Among of which, the cooperation with the third-party platform is an effective way to expand the online services of most hospitals. With the increasing number of mobile health applications (mHealth apps), it is difficult to select the ideal application. Most of the existing studies on mHealth app selection are conducted from the perspective of users who have health needs, which is insufficient. The views of multiple stakeholders should be taken into account. mHealth app selection can be regarded as a large-scale group decision making (LSGDM) problem. In this paper, a hybrid LSGDM method is proposed to select the mHealth app with the highest user satisfaction. First, the weights of criteria are obtained based on quality function deployment and 2-additive measure. Furthermore, a consensus model that considers cooperative and non-cooperative behaviors of decision makers is applied to select the ideal mHealth app. Finally, an illustrative example is implemented to exhibit the utility and validity of the proposed model.

Keywords mHealth app selection · Large-scale group decision making · Consensus reaching process · Non-cooperative behavior

1 Introduction

The rampant spread of the COVID-19 has brought marvelous opportunities for the development and utilization of mobile health applications (mHealth apps) [9]. In the first half of 2020, the number of mobile medical users in China has reached 590 million, and the market size of mobile medical treatment has reached 8.75 billion Yuan [3]. The mHealth apps have become the main way for patients to obtain medical services during epidemic prevention. In China, these apps mainly focus on information inquiry, telemedicine, online consultation, registration, appointment, and health management [18, 24, 47]. Users can access contactless medical services regardless of time or location through mHealth apps, which is beneficial to deal with a public health emergency. Importantly, the popularity of mHealth apps contributes to relieve the imbalance in the allocation of medical resources in China. Furthermore, mobile medicine developed with the advantages of mobile technology can not only meet people's medical needs but also effectively alleviate some medical dilemmas in China [24]. In this situation, the Chinese government has issued a series of policies to vigorously promote the development of mobile medicine [15, 37].

It is reported that the number of smartphone users in China may exceed 800 million and reach 812.9 million in 2021 [21]. The wide use of smartphones has a great impact on medical services. Traditional medical care no longer meets the requirements of consumers, and hospitals must promote medical reform. On the other hand, the fierce competition between hospitals has extended from offline to online. Thus, hospitals must expand mobile channels, building their platforms or cooperating with third-party platforms [22, 61], to provide diversified mobile healthcare. Nevertheless, the construction and operating costs of building the platform are very high. Additionally, it needs to recruit and establish professional teams to operate and maintain the platform. Most hospitals don't have enough manpower and resources to build a mobile platform. The cooperation with the third-party platform becomes the first choice of hospitals. In this mode, third-party platforms are responsible for the specific operation and maintenance of the platform, and hospitals concentrate on their core services [22]. The third-party platform without offline

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entities is not allowed to provide diagnostic services in China [29]. Only in cooperation with the physical hospital, the third-party platform can be eligible to prescribe drugs for patients, which forms a closed-loop of medical treatment. At present, Chunyu doctor, Good doctor online, and other well-known platforms have cooperated with physical hospitals. As for hospitals, the medical services are no longer restricted by time and location, and the cost of the hospital is lower than that of building their own platforms. Both the third-party platform and hospital can benefit from this mode. Consequently, cooperation with the third-party platform is the best choice for most hospitals.

At present, there are more than 100,000 mHealth apps in the mobile store of Android and IOS [38]. In view of the proliferation of mHealth apps, it is increasingly difficult to identify and select high-quality mHealth apps. There are few studies on the selection of mHealth apps. Rajak et al. [39] integrated AHP and fuzzy TOPSIS to choose the mHealth app. Li et al. [24] proposed an uncertain multiplicative linguistic decision method based on a group compromise framework to rank the mobile medical applications in China. Dawson et al. [10] examined previous tools for selecting the appropriate mHealth app. These studies on mHealth apps are limited. Most of them are from the perspective of users who have health needs. In fact, it is incomprehensive for mHealth app selection and the views of multiple stakeholders (such as health care providers and professionals) should be taken into account. Therefore, this study continues to research the selection of mHealth apps, which considers the opinions of mHealth app users including patients, healthcare providers, nurses, and professionals. In this situation, there are numerous decision makers (DMs) with diverse knowledge backgrounds involved in the mHealth app selection, which is in fact a large-scale group decision making (LSGDM) problem.

With the increasing complexity of the decision environment, more and more DMs participate in the decision process, and LSGDM has been widely concerned and applied [62, 63]. One object of LSGDM is to select the best alternative from finite ones according to the assessment information provided by DMs [11]. In LSGDM, it usually contains more than 20 DMs who provide assessment information for alternatives based on several criteria [27]. It is inevitable that the opinions or preferences of DMs are quite different [40, 53]. Therefore, the consensus reaching process (CRP), which is a dynamic and iterative process, is applied to assist DMs to adjust opinions and reach a consensus. However, it is difficult to achieve a full and unanimous agreement in real life [58]. Soft consensus that reflects partial agreements has been widely applied [8]. To solve LSGDM problems, Xu et al. [55] developed a two-stage consensus method to adjust the internal and external consensus levels of sub-clusters. Li et al. [25] introduced a LSGDM approach for healthcare management in the setting of hesitant fuzzy linguistic environment. Shi et al. [43] designed a CRP to classify modification behaviors of DMs into 3 categories by cooperative index and non-cooperative index and update DMs' weights based on the uninorm aggregation operator. Xu et al. [54] presented a confidence-based model to manage non-cooperative behaviors. To deal with the heterogeneous preference information and non-cooperative behaviors in LSGDM, Chao et al. [7] developed a novel consensus model. Li et al. [26] introduced a group consistency index which combines fuzzy preference values and cooperation degrees to detect the non-cooperative behaviors of DMs in LSGDM. Based on hesitant fuzzy preference relation, Liu et al. [32] proposed a reliability index-based consensus model to manage the non-cooperative clusters. In view of robust optimization, Lu et al. [34] presented a minimum cost consensus model to solve the LSGDM problem in social network. Gao et al. [14] introduced a *k*-core decomposition-based method to identify the opinion leader in social network and proposed a clustering-based consensus model to improve the consensus level of LSGDM problem.

Based on the above analysis of mHealth app selection and literature review, one can find that there are still some limitations as follows:

(i) Cooperation with the third-party platform is an effective way to expand the online services for most hospitals. How to select the ideal mHealth app is a difficult problem for the hospital. And there is no research on the mHealth app selection from the perspective of hospital.
(ii) Most LSGDM methods ignore the interdependence of criteria. The interactions among criteria commonly exist in decision problems. For example, when we buy a mobile phone, some criteria are considered including price, configuration and appearance. In addition, there is a positive interaction between price and configuration, namely, the better the mobile phone configuration, the higher the price.
(iii) Most consensus models only adjust the subgroup with the lowest consensus level, which causes the inefficiency of consensus reaching.
(iv) Some LSGDM methods adopt the consensus adjustment mechanism for subgroup decision matrices, which usually causes the over-adjustment.

To fill up these gaps, we propose a new LSGDM method that considers non-cooperative behaviors to select the mHealth app with the highest user satisfaction for the hospital. First, we construct the evaluation criteria for mHeath app selection and identify user requirements (URs). Then, considering the interdependence of criteria, we propose a hybrid method to obtain the weights of criteria by using analytic hierarchy process (AHP), quality function deployment (QFD) and 2-additive measure. Next, we provide different modification recommendations to improve the consensus level based on the group consensus level and the willingness of subgroups. Finally, we aggregate DMs' opinions by the 2-additive generalized Shapley aggregation (2AGSA) operator to select the ideal mHealth app. Figure 1 presents the research framework of this study.

The rest of this paper is organized as follows: Section 2 constructs the evaluation criteria for the mHealth app selection and reviews the characteristics about LSGDM. Section 3 proposes a hybrid method to determine the weights of criteria, which considers the interactions among criteria. Section 4 offers a LSGDM method that analyzes the consensus reaching. Section 5 illustrates the utility and validity of the proposed model by a case study. Section 6 provides a comparative analysis to show the advantages of the proposed model. Section 7 draws conclusions.

2 Preliminaries

This section constructs the evaluation criteria for mHeath app selection and recalls the characteristics of LSGDM.

2.1 The evaluation criteria for the evaluation of mHeath app

Based on the above analysis and previous reaserch of mHeath app selection, we construct the evaluation criteria for mHeath app selection which contains 5 criteria and 16 sub-criteria. Please see Table 1.

2.2 The characteristics of LSGDM

Traditional group decision making (GDM) [6, 51, 64, 65] is a powerful tool for many practical decision problems. With the increasing complexity of the decision environment, traditional GDM is surfing more and more restriction. To fill up this gap, scholars introduced LSGDM [52]. As a branch of GDM, LSGDM which usually involves a large number of DMs with diverse interests and knowledge has been paid more attention and applied to many real-world problems. Compared with traditional GDM, LSGDM views are more diverse and decision-making results are more objective and scientific. The characteristics of LSGDM can be described as follows:

(i) Decision events are complex and have multiple aims [11, 54].
(ii) The number of DMs in LSGDM is usually more than 20 [7, 14, 40].
(iii) Compared with traditional GDM, DMs in LSGDM have more different professional backgrounds and represent more different stakeholders [11, 43, 53].
(iv) Both the consensus levels of DMs and subgroups are considered [49, 55].

In LSGDM, DMs are required to provide assessment information for several alternatives based on multiple criteria. There are various preference expression formats such as real numbers [33, 53], linguistic variables [59], and fuzzy sets

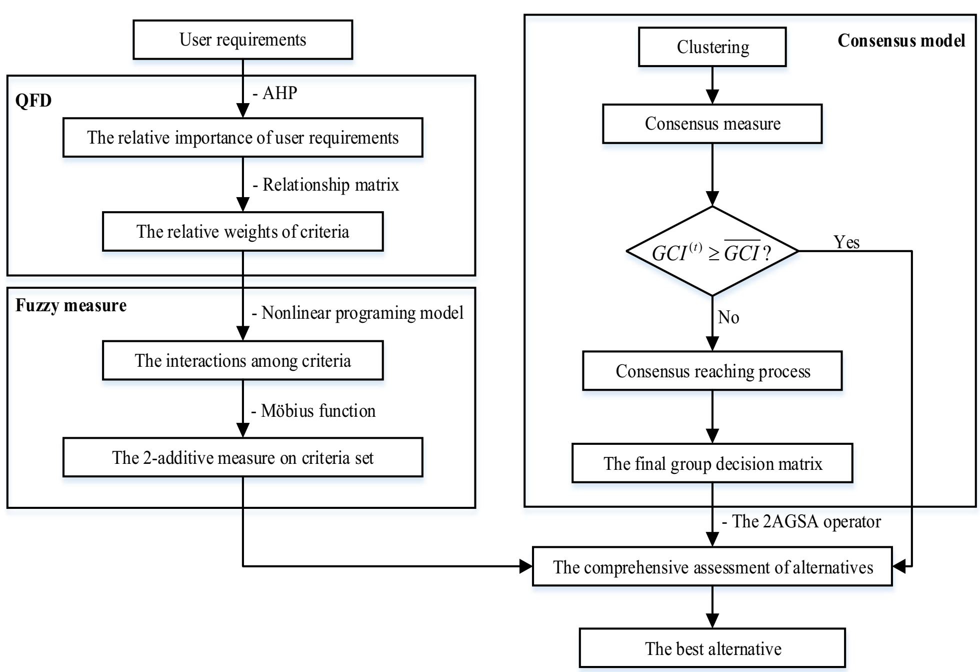


Fig. 1 The framework of the new method

Table 1 Evaluation criteria for mHealth app selection

Criteria	Sub-criteria	Explanations	References
Engagement (c_1)	Customization (c_{11})	Provide customized and personal service according to user needs	[4, 5, 39, 44, 45]
	Interactivity (c_{12})	Two-way transmission of information through the APP	[5, 39, 44, 45]
	Target group (c_{13})	Appropriateness of content for the target audience	[44, 45]
Functionality (c_2)	Performance (c_{21})	Response time of service process	[5, 35, 39, 44, 45]
	Ease of use (c_{22})	Ease in accessing information or services	[35, 39, 44, 45]
	Navigation (c_{23})	Guide users to get target information or services	[4, 44, 45]
Aesthetics (c_3)	Layout (c_{31})	The layout design of graphic, text, and navigation buttons in the user interface	[44, 45]
	Graphics (c_{32})	The quality of graphics	[4, 44, 45]
	Visual appeal (c_{33})	The overall visual appeal of the user interface	[44, 45]
Information (c_4)	Quality of information (c_{41})	The effectiveness, relevance, and understandability of information	[4, 5, 35, 39, 44, 45]
	Quantity of information (c_{42})	The richness and comprehensiveness of information	[44, 45]
	Visual information(c_{43})	The effectiveness and timeliness of information conveyed by visual elements	[44, 45]
	Credibility (c_{44})	The accuracy and reliability of information	[44, 45]
Technology (c_5)	Security (c_{51})	Protect users' data and privacy	[4, 5, 35, 44, 45, 48]
	Integration (c_{52})	Integration of data	[39]
	Connection and synchronization (c_{53})	Ability to connect the health equipment and automatically synchronize data	[48]

[28]. In this paper, DMs evaluate the alternatives by 1–10 scale.

3 A hybrid method to determine the weights of criteria

To obtain the weights of criteria, we propose a hybrid method in this section. First, key URs are identified by reviewing relevant literature and interviewing experienced users of the mHealth apps. Second, we obtain the final relative importance of URs based on the AHP. Third, the QFD is employed to determine the relationships among URs and criteria, which contributes to select the mHealth app with the highest user satisfaction for the hospital. Finally, we adopt the 2-additive measure to obtain the weights of criteria.

3.1 Analytic hierarchy process

The AHP [41] is an effective tool to deal with multi-criteria decision making (MCDM) problems. This method can derive the relative importance and ranking of alternatives or criteria. In this study, DMs are required to assess the relative importance ratings between pairs of URs based on the 1–9 ratio scale [41], see Table 2.

The main steps of AHP based decision making process include:

Step 1. Identify the key URs.
The key URs are obtained from literature review and interview.

Step 2. Construct the pairwise comparison matrix.
Each DM offers his/her individual pairwise comparison matrix based on Table 2.

Step 3. Check the consistency of each individual pairwise comparison matrix by

$$CR = CI/RI(n) \tag{1}$$

Table 2 1–9 ratio scale

Linguistic variables	Importance ratings
Equally significant	1
Weakly significant	3
Strongly significant	5
Very Strongly significant	7
Absolutely significant	9
Intermediate values between two adjacent judgments	2, 4, 6, 8

where $CI = (\lambda_{max} - n) / (n - 1)$ and λ_{max} is the largest eigenvalue of the pairwise comparison matrix, n is the order of the matrix, and $RI(n)$ is a random index listed in Table 3.

If $CR < 0.1$, the consistency is acceptable and go to the next step. Otherwise, the corresponding DM is required to revise the judgments until the consistency is met.

Step 4. Obtain the synthesized pairwise comparison matrix.
Step 5. Calculate the relative importance of URs.

3.2 Quality function deployment

Mizuno and Akao [1] introduced a useful tool that converts the requirement of customers into the technical criteria of products, called QFD. The core of QFD is the house of quality (HOQ), which translates customer requirements into technical requirements through the relationship matrix. The HOQ consists of the determination of customer requirements, the determination of criteria, the determination of the relationship matrix between customer requirements and criteria, and the determination of the relative importance of criteria. QFD has been applied to various areas [19, 56].

After obtaining the relative importance of URs from Subsection 3.1, DMs are required to construct the relationship matrix. The relationships among URs and criteria are denoted by graphical symbols, as shown in Fig. 2. If a UR is not relevant to any criterion, the corresponding squares are blank. Once the relationships between URs and criteria are identified, we calculate the relative weight $_i$ of criterion c_i by

$$\nu_i = \sum w_s s_{is} \tag{2}$$

for all $i = 1, 2, \ldots, n$, where w_s is the relative weight of UR s, s_{is} is the relationship level between UR s and criterion c_i. Then, we normalize the relative weights of criteria and get their weights, where

$$w_i = \nu_i / \sum_{i=1}^{n} \nu_i \tag{3}$$

for all $i = 1, 2, \ldots, n$.

3.3 The 2-additive measure on criteria set

It generally assumes that criteria are independent in MCDM. In fact, there are usually some interaction degrees among criteria, and this influence can't be ignored [16]. In this case,

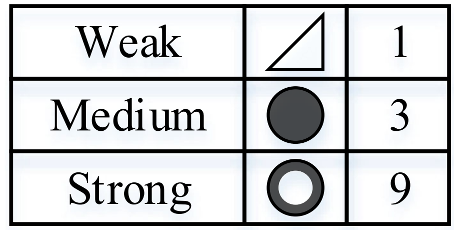


Fig. 2 Graphical symbols of QFD

it is unsuitable to aggregate the assessment information by additive measure [36]. As for the evaluation criteria for mhealth app selection, there are interactions among them too. For example, there is a positive interaction between engagement and functionality. With the powerful functions of mHealth app, users will have a high sense of participation. In addition, there is a positive interaction between customization and interactivity. The mHealth app that allows mass customization appears high interaction. To model the weights of criteria in MCDM problems, Sugeno [46] proposed the concept of fuzzy measure, which can flexibly describe the interactions among criteria and generalize the additive measure by replacing the additive property with monotonicity [16]. In this subsection, we present some definitions regarding fuzzy measure and apply the 2-additive measure to obtain the interactions among criteria.

Definition 1 [46] A fuzzy measure μ on N is a set function μ: $P(N) \rightarrow [0, 1]$ such that

(i) $\mu(\varnothing) = 0, \mu(N) = 1.$

(ii) $A_n \subseteq N, A \subseteq B \Rightarrow \lim_{n\to\infty} \mu(A_n) = \mu(A) \leq \mu(B).$

(iii) $A_n \nearrow A$ or $A_n \searrow A$, then $\lim_{n\to\infty} \mu(A_n) = \mu(A)$, where $A_n \subseteq N$ for all $n = 1, 2, \ldots$.

Definition 2 [17] Let $C = \{c_1, c_2, \ldots, c_n\}$ be a finite set of criteria, and μ be a fuzzy measure on C. Then, the Möbius function m of μ is defined as:

$$m(A) = \sum_{B\subseteq A} (-1)^{|A|-|B|} \mu(B) \forall A \subseteq C \tag{4}$$

where $|A|$ and $|B|$ are the cardinalities of the sets A and B, respectively.

Table 3 The value of the random index RI

n	3	4	5	6	7	8	9	10	11	12	13	14	15
$RI(n)$	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Furthermore, the fuzzy measure μ can be expressed by the Möbius function as follows:

$$\mu(S) = \sum_{T \subseteq S} m(T) \forall S \subseteq C \tag{5}$$

For a 2-additive measure μ on C, its Möbius representation is

$$\begin{cases} I(\varnothing) = m(\varnothing) + \frac{1}{2} \sum_{c_j \in C} m(c_i) + \frac{1}{3} \sum_{c_i, c_j \in C} m(c_i, c_j) \\ I(c_i) = m(c_i) + \frac{1}{2} \sum_{c_j \in C \setminus c_i} m(c_i, c_j) \\ I(c_i, c_j) = m(c_i, c_j) \\ I(A) = 0, A \subseteq C \text{ such that} |A| > 2 \end{cases} \tag{6}$$

where $I(\varnothing)$, $I(c_i, c_j)$ and $I(A)$ are the relative importance of the sets $\varnothing$, $\{c_i, c_j\}$ and A, $I(c_i)$ is the relative importance of criterion c_i, and $|A|$ is the cardinality of the set A.

Definition 3 [36, 42] Let $C = \{c_1, c_2, \ldots, c_n\}$ be a finite set of criteria, and μ be a 2-additive measure on C. The 2AGSA operator is defined as:

$$\text{2AGSA}(f(c_1), f(c_2), \ldots, f(c_n)) = \sum_{i=1}^{n} \phi_{c_i}(\mu, C) f(c_i) \tag{7}$$

where $\phi_{c_i}(\mu, C) = \sum_{T \subseteq C \setminus c_i} (|C| - |T| - 1) \frac{!|T|!}{|C|!(\mu(c_i \cup T)} - \mu(T))$ is the Shapley value of the criterion c_i such that $|C|$ and $|T|$ are separately the cardinalities of the sets C and T, and$f(c_i)$ is the assessment value for criterion c_i.

Currently, the theory and application of MCDM that considers the interaction characteristics have been researched by many scholars [50, 57]. However, with the number of criteria increasing, the coefficients of fuzzy measure will grow exponentially. When the number of criteria is n, it requires 2^{n-1} coefficients to determine a fuzzy measure. While the 2-additive measure only takes into account the interaction between the two criteria, it only needs $(n + 2)(n-1)/2$ coefficients. Considering this advantage of 2-additive measure, we employ it to measure the interactions among criteria and identify a 2-additive measure by Zhang et al.'s method [60]. The concrete steps are as follows:

Step 1. Obtain the relative importance$I(c_i)$of each criterion c_i, $i = 1, 2, \ldots, n$, by Subsection 3.2.

Step 2. Determine the interval of $I(c_i, c_j)$for the criteria c_i and c_j. According to Definition 2, we get

$$|I(c_i, c_j)| \leq \frac{2I(c_i)}{n-1} \quad |I(c_i, c_j)| \leq \frac{2I(c_j)}{n-1} \quad \forall \{c_i, c_j\} \subseteq C \tag{8}$$

Then, we set

$$t(c_i, c_j) = \min\{2I(c_i)/(n-1), 2I(c_j)/(n-1)\} \tag{9}$$

and define$I(c_i, c_j) \in [-t(c_i, c_j), t(c_i, c_j)]$. In this study, we divide the interval $[-t(c_i, c_j), t(c_i, c_j)]$ into$[-t(c_i, c_j), -\frac{1}{3}t(c_i, c_j)]$, $[-\frac{1}{3}t(c_i, c_j), \frac{1}{3}t(c_i, c_j)]$ and $[\frac{1}{3}t(c_i, c_j), t(c_i, c_j)]$, which represent the negative interaction, independence and positive interaction, respectively. According to the interactions between criteria c_i and c_j, DMs choose the interval$\bar{t}(c_i, c_j)$.

Step 3. Construct the following nonlinear programming model to obtain the interactions among criteria:

$$\max z = \sum_{i=1}^{n} \sum_{S \subseteq C \setminus c_i} \frac{(|C| - |S| - 1)!|S|!}{|C|!} \times h\left(I(c_i) - \frac{1}{2} \sum_{c_j \in C \setminus S} I(c_i, c_j) + \frac{1}{2} \sum_{c_j \in S} I(c_i, c_j)\right) \tag{10}$$
$$s.t. \begin{cases} I(c_i) = w_i \\ I(c_i, c_j) \in \bar{t}(c_i, c_j) \\ c_i, c_j \in C \end{cases}$$

for all $i, j = 1, 2, \ldots, n$ with $i \neq j$, where $|C|$ and $|S|$ are the cardinalities of the sets C and S, and the function h is an entropy measure, namely,$h(x) = -x ln(x)$for any positive real value x.

Step 4. Obtain the corresponding Möbius function m by Eq. (4).

Step 5. Determine the 2-additive measure μ on criteria set C by Eq. (5).

4 A new LSGDM method for mHealth app selection

The problem of mHealth app selection for the hospital needs to consider the opinions of multiple stakeholders with diverse knowledge backgrounds, which can be seen as a LSGDM problem. In this section, we propose a consensus model to deal with the LSGDM problem and select the best alternative. The model mainly consists of four parts: (i) clustering, (ii) consensus measure, (iii) CRP, and (iv) selection.

4.1 Basic notations of LSGDM

Let $X = \{x_1, x_2, \ldots, x_m\}$ be the set of alternatives, where x_i denotes the ith alternative, $i = 1, 2, \ldots, m$. Let $SC = \{sc_1, sc_2, \ldots, sc_n\}$ be the set of sub-criteria, where sc_j denotes the jth sub-criterion, $j = 1, 2, \ldots, n$. Let $C = \{c_1, c_2, \ldots, c_s\}$ be the set of criteria, where c_k denotes the kth criterion, $k = 1, 2, \ldots, s$. Furthermore, let $C_k = \{sc_{\gamma_1+\gamma_2+\ldots+\gamma_{k-1}+1}, sc_{\gamma_1+\gamma_2+\ldots+\gamma_{k-1}+2}, \ldots, sc_{\gamma_1+\gamma_2+\ldots+\gamma_{k-1}+\gamma_k}\}$ be the set of sub-criteria for the criterion

c_k, where γ_k is the number of sub-criteria for the criterion c_k such that $n = \sum_{k=1}^{s} \gamma_k$. Let $E = \{e_1, e_2, \ldots, e_l\}$ $(l \geq 20)$ be the set of DMs, where e_h denotes the hth DM, $h = 1, 2, \ldots, l$. $V^h = \left(v_{ij}^h\right)_{m\times n}$ is the individual decision matrix offered by the DM e_h, where v_{ij}^h is the assessment of the alternative x_i for the sub-criterion sc_j. $R^h = \left(r_{ij}^h\right)_{m\times n}$ is the normalized individual decision matrix, where $r_{ij}^h = \frac{1}{10} v_{ij}^h$ for all $h = 1, 2, \ldots, l$, and all $j = 1, 2, \ldots, n$. Let t be the tth iteration.

Let $G = \{g_1, g_2, \ldots, g_\kappa\}$ be the set of subgroups, where g_p is the pth subgroup, $p = 1, 2, \ldots, \kappa$. The weight vector on the subgroup set is $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_\kappa)$, where λ_p is the weight of the subgroup g_p, that $\sum_{p=1}^{\kappa} \lambda_p = 1$ and $0 \leq \lambda_p \leq 1$ for all $p = 1, 2, \ldots, \kappa$. The number of DMs in the subgroup g_p is denoted as n_p.

Let w_h^p be the weight of the DM e_h in the subgroup g_p, namely, $e_h \in g_p$, defined as:

$$w_h^p = \frac{1-d_h^p}{\sum_{h=1}^{n_p} 1-d_h^p} \tag{11}$$

where $d_h^p = \frac{1}{n_p-1} \sum_{u=1,h\neq u}^{n_p} \frac{1}{m\times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left| r_{ij}^h - r_{ij}^u \right|$ for all $p = 1, 2, \ldots, \kappa$ and all $h = 1, 2, \ldots, n_p$.

Eq. (11) shows that the smaller the value of d_h^p, the larger the weight of DM e_h. Let $R^p = \left(r_{ij}^p\right)_{m\times n}$ and $R^c = \left(r_{ij}^c\right)_{m\times n}$ be the subgroup decision matrix and the group decision matrix, where $r_{ij}^p = \sum_{h=1}^{n_p} w_h^p r_{ij}^h$ and $r_{ij}^c = \sum_{p=1}^{\kappa} \lambda_p r_{ij}^p$ for all $i = 1, 2, \ldots, m$, and all $j = 1, 2, \ldots, n$.

4.2 Clustering

Clustering methods are widely applied in LSGDM to reduce the dimensions of DMs, which can improve the efficiency of the CRP [11]. There are many clustering methods such as the k-means clustering method [34] and fuzzy c-means clustering method [23, 49]. In this study, we adopt the k-means clustering method to divide DMs into κ $(\kappa \geq 2)$ subgroups, which is described in Algorithm 1.

Algorithm 1 k-means clustering method.

Algorithm 1 k-means clustering method

Input: The normalized individual decision matrices $R^h = (r_{ij}^h)_{m\times n}$, $h = 1, 2, \ldots, l$ and the number of subgroups κ $(\kappa \geq 2)$.
Output: The clustering result.
Step 1. Select κ subgroup centers randomly from normalized individual decision matrices.
Step 2. Calculate the Euclidean distances between each individual decision matrix and each subgroup center. Cluster the DM to the subgroup with the smallest Euclidean distance.
Step 3. Calculate the mean of each updated subgroup as the new subgroup center.
Step 4. Repeat Steps 2-3 until all subgroup centers remain stable.

The weights of subgroups are determined by two indicators. (i) The standard deviation among subgroups. The smaller the standard deviation of the subgroup is, the larger the subgroup weight will be; (ii) The size of the subgroup. According to the majority principle, the subgroups with more DMs are assigned the larger weights. To make DMs express their opinions effectively and avoid the conformity behaviors of DMs, we set ω as the threshold of the subgroup cardinality weights. In view of the above analysis, the weight of the subgroup g_p is defined as:

$$\lambda_p = \frac{\varphi_p}{\sum_{p=1}^{\kappa} \varphi_p} \tag{12}$$

where $\varphi_p = \delta \times \frac{1/\sigma_p}{\sum_{p=1}^{\kappa} 1/\sigma_p} + (1-\delta) \times \tau_p$, $\sigma_p = \frac{1}{\kappa-1} \sum_{q=1,p\neq q}^{\kappa} \sqrt{\frac{1}{m\times n} \times \sum_{i=1}^{m} \sum_{j=1}^{n} \left(r_{ij}^p - r_{ij}^q\right)^2}$, $\tau_p = \begin{cases} \frac{n_p}{l} & \frac{n_p}{l} \leq \omega \\ \omega & \frac{n_p}{l} > \omega \end{cases}$ for all $p = 1, 2, \ldots, \kappa$, and δ is the preference coefficient of the standard deviation, which is usually determined by the organizer.

4.3 Consensus measure

To measure the consensus level of subgroup decision matrix, we here adopt the distance deviation between subgroup decision matrix and group decision matrix, where

$$CI\left(g_p\right) = 1 - \frac{1}{m\times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left| r_{ij}^p - r_{ij}^c \right| \tag{13}$$

for all $p = 1, 2, \ldots, \kappa$.

Moreover, the group consensus level GCI is defined as:

$$GCI = \sum_{p=1}^{\kappa} \lambda_p CI\left(g_p\right) \tag{14}$$

It is obvious that $0 \leq GCI \leq 1$. The larger the value of GCI, the higher the agreement degree between subgroups. Let $\overline{GCI}$ be the consensus threshold. If $GCI < \overline{GCI}$, we need to improve the consensus level. If $GCI \geq \overline{GCI}$, the selection process is applied directly.

4.4 Consensus reaching process

If the group consensus level does not meet the requirement, DMs need to be adjusted their judgments according to the recommendations. In the CRP, some DMs or subgroups show negative behaviors, which inhibits the process of consensus reaching [11]. Therefore, it is necessary to detect the non-cooperative behaviors and implement a punishment mechanism. In this section, we design a feedback mechanism to detect the cooperative and non-cooperative behaviors and provide modification recommendations based on the consensus level.

Step 1: Identifying the adjustment subgroups Based on the idea of TOPSIS method [20], we design a mechanism to detect subgroups that need to adjust their judgments. The higher the subgroup consensus level is, the closer the distance between the subgroup opinions and the group opinions will be. With this in mind, the subgroup with the maximum consensus level is considered as the positive ideal subgroup g^{+}, and the associated decision matrix is denoted by $R^{+} = \left(r_{ij}^{+}\right)_{m\times n}$. On the other hand, the subgroup with the minimum consensus level is regarded as the negative ideal subgroup g^{-}, and the associated decision matrix is denoted by $R^{-} = \left(r_{ij}^{-}\right)_{m\times n}$. The distances between the subgroup decision matrix $R^{p} = \left(r_{ij}^{p}\right)_{m\times n}$ and the positive ideal decision matrix $R^{+} = \left(r_{ij}^{+}\right)_{m\times n}$ as well as the subgroup decision matrix $R^{p} = \left(r_{ij}^{p}\right)_{m\times n}$ and the negative ideal decision matrix $R^{-} = \left(r_{ij}^{-}\right)_{m\times n}$ are separately defined as:

$$d_{p}^{+} = \sum_{i=1}^{m}\sum_{j=1}^{n}\left|r_{ij}^{p} - r_{ij}^{+}\right| \tag{15}$$

and

$$d_{p}^{-} = \sum_{i=1}^{m}\sum_{j=1}^{n}\left|r_{ij}^{p} - r_{ij}^{-}\right| \tag{16}$$

for all $p = 1, 2, \ldots, \kappa$.

Therefore, the closeness coefficient of each subgroup g_p is calculated as

$$\eta_{p} = \frac{d_{p}^{-}}{d_{p}^{+} + d_{p}^{-}} \tag{17}$$

where $p = 1, 2, \ldots, \kappa$. From Eq. (17), one can check that the bigger the value of η_p, the higher the consistency level of the corresponding subgroup. Let α be the given adjustment threshold. If $\eta_p < \alpha$, then g_p is identified as the adjustment subgroup.

Step 2: Modification mechanism According to the consensus level, this paper adopts different modification mechanisms. When the group consensus level is low, it can effectively shorten the number of iterations by adjusting the subgroup opinions. While the group consensus level reaches a certain level, too much adjustment will distort the opinions of DMs. In this case, we only adjust the opinions of part DMs in subgroups. Let ξ be the modification mechanism coefficient, which reflects the gap between the group consensus level and the consensus threshold, where

$$\xi = \frac{GCI}{\overline{GCI}} \tag{18}$$

It is obvious that $0 \leq \xi \leq 1$. The larger the value of ξ, the bigger the group consensus level. Let $\overline{\xi}$ be the threshold to determine which modification mechanism is adopted. When$\xi < \overline{\xi}$, we adopt the mechanism I, which adjusts the subgroup directly. Otherwise, we adopt the mechanism II that adjusts some DMs in subgroups to promote the consensus level.

Step 3: Cooperative and non-cooperative subgroups After determining the modification mechanism, we need to consider whether the subgroups or DMs are willing to accept the modification recommendation. The willingness of subgroups represents the willingness of its DMs. According to the willingness of subgroups or DMs, we divide them into two parts: cooperative subgroups $CG = \{g_p|\ p = 1_{Co}, 2_{Co}, \ldots, \kappa_{Co}\}$and non-cooperative subgroups$NG = \{g_p|\ p = 1_{Nc}, 2_{Nc}, \ldots, \kappa_{Nc}\}$.

Step 4: Adjustment measure Based on the modification mechanism coefficient ξ and the willingness of adjusted subgroups or DMs, the modification recommendations are classified into four cases, shown in Table 4.

Case i. When $\xi < \overline{\xi}$, for any cooperative subgroup$g_p \in CG$, we take the following measure to modify its opinions:

$$R^{p,(t+1)} = \frac{\beta\left(g_p\right)^{(t)}}{\sum_{g_p\in G}\beta\left(g_p\right)^{(t)}} R^{c,(t)} + \left(1 - \frac{\beta\left(g_p\right)^{(t)}}{\sum_{g_p\in G}\beta\left(g_p\right)^{(t)}}\right) R^{p,(t)} \tag{19}$$

where$\beta\left(g_p\right)^{(t)} = \left\{ \overline{GCI} - CI\left(g_p\right)^{(t)} \; CI\left(g_p\right)^{(t)} < \overline{GCI} \; 0 \; CI\left(g_p\right)^{(t)} \geq \overline{GCI} \right.$ for all $p = 1_{Co}, 2_{Co}, \ldots, \kappa_{Co}$. $\beta(g_p)^{(t)}$ reflects the gap between the subgroup consensus level and the consensus threshold in the tth iteration. Eq. (19) shows that the higher the subgroup consensus level, the smaller the adjustment.

Case ii. When $\xi \geq \overline{\xi}$, for any cooperative subgroup$g_p \in CG$, we first identify its DMs who need to adjust the judgments in each g_p, which is denoted as

Table 4 Modification recommendations

	$\xi < \overline{\xi}$	$\xi \geq \overline{\xi}$
Cooperation	Opinion adjustment (Subgroups)	Opinion adjustment (DMs)
Non-cooperation	Weight penalty (Subgroups)	Weight penalty (DMs)

$$CDM\left(g_p\right)^{(t)} = \left\{e_h | CI(e_h)^{(t)} < \sigma\left(g_p\right)^{(t)} \wedge e_h \in g_p\right\} \tag{20}$$

where $\sigma\left(g_p\right)^{(t)} = \frac{1}{n_p}\sum_{h=1}^{n_p} CI(e_h)^{(t)}$ and $CI(e_h)^{(t)} = 1 - \frac{1}{m \times n} \times \sum_{i=1}^{m}\sum_{j=1}^{n}\left|r_{ij}^{h,(t)} - r_{ij}^{c,(t)}\right|$ for all $h = 1, 2, \ldots, n_p$ and all $p = 1_{Co}, 2_{Co}, \ldots, \kappa_{Co}$.

For all DMs in the subgroup g_p whose consensus levels are smaller than the average consensus level of all DMs in g_p, we identify the positions of adjusted elements by

$$P\left(g_p\right)^{(t)} = \left\{r_{ij}^{h,(t)} \middle| \left|r_{ij}^{h,(t)} - r_{ij}^{c,(t)}\right| > \sigma(e_h)\right.$$

$^{(t)}$, ***where*** $e_h \in CDM\left(g_p\right)^{(t)}\}$ where $\sigma(e_h)^{(t)} = \frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left|r_{ij}^{h,(t)} - r_{ij}^{c,(t)}\right|$ for all $h = 1, 2, \ldots, |CDM(g_p)^{(t)}|$, and $|CDM(g_p)^{(t)}|$ is the cardinality of the set $CDM(g_p)^{(t)}$.

Finally, the identified opinion is adjusted by

$$r_{ij}^{h,(t+1)} = \frac{\beta\left(e^h\right)^{(t)}}{\sum_{e_h \in g_p}\beta\left(e^h\right)^{(t)}} r_{ij}^{c,(t)} + \left(1 - \frac{\beta\left(e^h\right)^{(t)}}{\sum_{e_h \in g_p}\beta\left(e^h\right)^{(t)}}\right) r_{ij}^{h,(t)} \tag{22}$$

where $\beta(e_h)^{(t)} = \{\overline{GCI} - CI(e_h)^{(t)} CI(e_h)^{(t)} < \overline{GCI} 0 CI(e_h)^{(t)} \geq \overline{GCI}$ and $r_{ij}^{h,(t)} \in P\left(g_p\right)^{(t)}$ for all $h = 1, 2, \ldots, |CDM(g_p)^{(t)}|$, all $i = 1, 2, \ldots, m$, and all $j = 1, 2, \ldots, n$.

Case iii. When $\xi < \overline{\xi}$, for any non-cooperative subgroup $g_p \in NG$, we adopt the following weight punishment mechanism:

$$\lambda_p^{(t+1)} = \left(1 - \frac{\beta\left(g_p\right)^{(t)}}{\sum_{g_p \in G}\beta\left(g_p\right)^{(t)}}\right) \times \lambda_p^{(t)} \tag{23}$$

for all $p = 1_{Nc}, 2_{Nc}, \ldots, \kappa_{Nc}$.

The weights of subgroups excluding the non-cooperative subgroups $g_p \in G \backslash NG$ are updated as:

$$\lambda_p^{(t+1)} = \frac{\sum_{g_p \in NG}\beta\left(g_p\right)^{(t)}\lambda_p^{(t)}}{\sum_{g_p \in G}\beta\left(g_p\right)^{(t)}} \times \frac{CI\left(g_p\right)^{(t)}}{\sum_{g_p \in G \backslash NG} CI\left(g_p\right)^{(t)}} + \lambda_p^{(t)} \tag{24}$$

for all $p = 1, 2, \ldots, |G \backslash NG|$, where $|G \backslash NG|$ is the cardinality of the set $G \backslash NG$.

Case iv. When $\xi \geq \overline{\xi}$, for any non-cooperative subgroup $g_p \in NG$, we first identify DMs who are carried out the weight punishment mechanism in each g_p by

$$NDM\left(g_p\right)^{(t)} = \left\{e_h | CI(e_h)^{(t)} < \sigma\left(g_p\right)^{(t)} \wedge e_h \in g_p\right\} \tag{25}$$

for all $h = 1, 2, \ldots, n_p$ and all $p = 1_{Nc}, 2_{Nc}, \ldots, \kappa_{Nc}$.

Then, we update the weights of these DMs by

$$w_h^{(t+1)} = \left(1 - \frac{\beta(e_h)^{(t)}}{\sum_{e_h \in g_p}\beta\left(e^h\right)^{(t)}}\right) \times w_h^{(t)} \tag{26}$$

for all $e_h \in NDM(g_p)^{(t)}$, all $h = 1, 2, \ldots, |NDM(g_p)^{(t)}|$, where $|NDM(g_p)^{(t)}|$ is the cardinality of the set $NDM(g_p)^{(t)}$.

The weights of DMs in $g_p \backslash NDM(g_p)^{(t)}$ are updated as:

$$w_h^{(t+1)} = \frac{\sum_{e_h \in NDM\left(g_p\right)^{(t)}}\beta(e_h)^{(t)}\lambda_h^{(t)}}{\sum_{e_h \in g_p}\beta(e_h)^{(t)}} \times \frac{CI(e_h)^{(t)}}{\sum CI(e_h)^{(t)}} + w_h^{(t)} \tag{27}$$

for all $h = 1, 2, \ldots, |g_p \backslash NDM(g_p)^{(t)}|$, where $|g_p \backslash NDM(g_p)^{(t)}|$ is the cardinality of the set $g_p \backslash NDM(g_p)^{(t)}$.

Repeat the above process until the consensus requirement is reached.

Step 5: Selection When the group consensus level meets the requirement, the 2AGSA operator is used to obtain the comprehensive assessment and then the best alternative is selected. Based on the Shapley value for 2-additive measure on criteria set, the assessment of alternative x_i for the criterion c_k is calculated as:

$$CE_{ik} = \sum_{j=\gamma_1+\ldots+\gamma_{k-1}+1}^{\gamma_1+\ldots+\gamma_{k-1}+\gamma_k} \phi_{sc_j}(\mu, C_k) r_{ij} \tag{28}$$

where $i = 1, 2, \ldots, m$ and $k = 1, 2, \ldots, s$.

Furthermore, the comprehensive assessment of alternative x_i is calculated as:

$$CE_i = \sum_{k=1}^{s} \phi_{c_k}(\mu, C) CE_{ik} \tag{29}$$

where $i = 1, 2, \ldots, m$.

To show the CRP intuitively, we offer the following Fig. 3.

5 A case study

Due to the fierce competition and the impact of mobile medical, a hospital in Changsha decides to cooperate with a mHealth app to expand its mobile services. The mHealth app is responsible for the specific operation and maintenance of the mobile platform. The hospital can concentrate on its core services. In order to select the mHealth app with the highest user satisfaction, the hospital invites 25 DMs including patients, health care providers, nurses, and professionals to select the best choice from Pingan good doctor, Good doctor

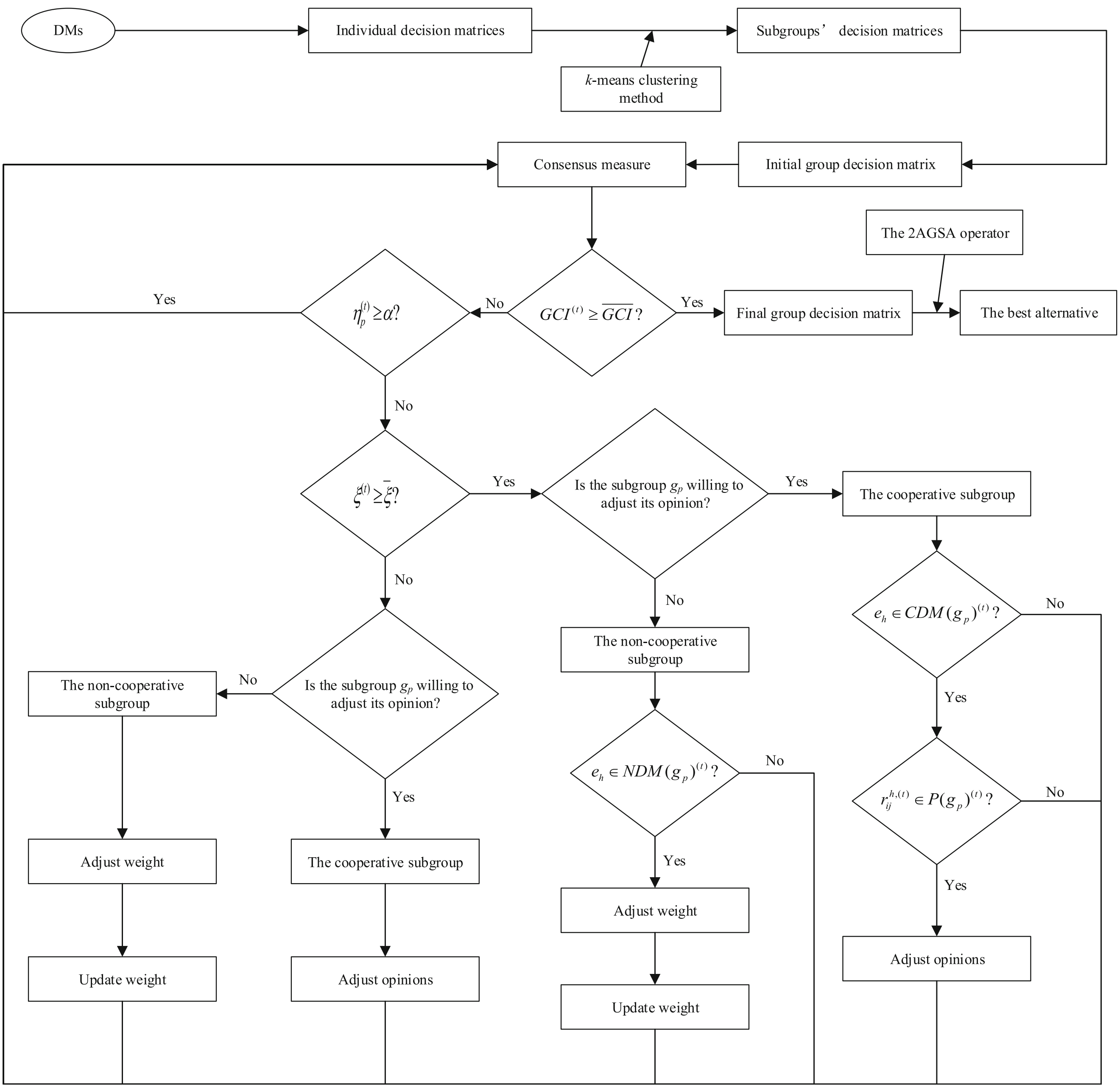


Fig. 3 The proposed consensus process

online, Dingxiang doctor and Chunyu doctor, denoted as $X = \{x_1,\ x_2,\ x_3,\ x_4\}$. These DMs are very familiar with the mHealth apps. In this paper, the selection process includes two stages, the first stage is the weight determination of criteria, and the second stage is the CRP.

Step 1. The weight determination of criteria Based on the hybrid method for determining the criteria weights proposed in Section 3, we offer the following process. First, through the literature review and interview, we summarize 15 key URs which excludes elementary URs (online consultation, registration, and so on), as shown in Table 5. DMs are required to carry out pairwise comparisons among URs. The last column shows the relative importance of URs, where UR_{10} is the most important UR, namely, users pay more attention to their privacy and security.

We check the consistency of each individual pairwise comparison matrix by Eq. (1). Then, we obtain the synthesized pairwise comparison matrix based on the arithmetic averaging operator, which is shown in Table 6.

Moreover, URs are translated into criteria based on HOQ, where the relationship matrix is shown in Fig. 4.

Furthermore, the relative weights of criteria are obtained by Eqs. (2) and (3) as shown in Table 7.

Based on the interaction types listed in the second and sixth columns in Table 8, we obtain the interaction intervals by Eqs. (8) and (9), as shown in the third and seventh columns in Table 8. By model (10), the interactions among criteria are derived as shown in the fourth and eighth columns in Table 8.

By Table 8, the corresponding Möbius values are obtained in Table 9.

Furthermore, the 2-additive measures on the criteria set and the sub-criteria set are separately shown in Table 10 and Table 11.

Step 2. The CRP DMs provide the evaluation for each alternative under the built criteria in Subsection 3.2 by the 1–10 scale. The initial individual decision matrices V_h (h = 1, 2, …, 25) are shown in Table 12. To save space, the normalized individual decision matrices are omitted. Assume that the threshold of the subgroup cardinality weight, the preference coefficient of the standard deviation, the consensus threshold, the adjustment coefficient, and the modification mechanism coefficient threshold are ω = 0.3, δ = 0.5, $\overline{GCI} = 0.85$, α = 0.55and $\overline{\xi} = 0.98$, respectively. Then, the consensus model proposed in Section 4 is applied to select the best alternative.

Based on the k-means clustering method, DMs are divided into 6 subgroups. The clustering results are shown in Table 13.

Using Eq. (12), the initial weights of subgroups are

$$\lambda_p^{(0)} = (0.1436, 0.1828, 0.1636, 0.1357, 0.2330, 0.1414).$$

Based on Eq. (11), the initial weights of DMs are obtained as shown in Table 14.

Furthermore, the subgroup decision matrices and group decision matrix are derived as follows:

$$\boldsymbol{R}^{1,(0)} = \begin{pmatrix} 0.3888 & 0.3418 & 0.8592 & 0.4075 & 0.6761 & 0.7732 & 0.8249 & 0.4502 & 0.7685 & 0.7897 & 0.3324 & 0.3408 & 0.8601 & 0.8019 & 0.3418 & 0.2362 \\ 0.1963 & 0.3056 & 0.7770 & 0.7592 & 0.7639 & 0.6888 & 0.3399 & 0.7418 & 0.2526 & 0.2667 & 0.9695 & 0.3230 & 0.3798 & 0.6723 & 0.2667 & 0.8427 \\ 0.8028 & 0.3807 & 0.7324 & 0.7981 & 0.8991 & 0.3770 & 0.1963 & 0.8695 & 0.3277 & 0.6981 & 0.7897 & 0.8963 & 0.4455 & 0.3418 & 0.3113 & 0.3362 \\ 0.8333 & 0.8953 & 0.7685 & 0.7685 & 0.2526 & 0.3211 & 1.0000 & 0.5056 & 0.8390 & 0.2362 & 0.6667 & 0.7028 & 0.2408 & 0.7695 & 0.3704 & 0.3418 \end{pmatrix}$$

$$\boldsymbol{R}^{2,(0)} = \begin{pmatrix} 0.8612 & 0.1605 & 0.4380 & 0.2953 & 0.7413 & 0.6987 & 0.7631 & 0.6980 & 0.8408 & 0.8193 & 0.3420 & 0.7965 & 0.2214 & 0.8175 & 0.2192 & 0.7802 \\ 0.3588 & 0.8419 & 0.3592 & 0.7981 & 0.8196 & 0.2213 & 0.3166 & 0.2826 & 0.2607 & 0.2592 & 0.4020 & 0.2000 & 0.8416 & 0.6770 & 0.8186 & 0.8210 \\ 0.3811 & 0.3788 & 0.2820 & 0.3601 & 0.3785 & 0.7415 & 0.7217 & 0.2809 & 0.6820 & 0.2195 & 0.8623 & 0.3607 & 0.7385 & 0.8572 & 0.1991 & 0.2005 \\ 0.3610 & 0.2961 & 0.8214 & 0.3423 & 0.6775 & 0.3007 & 0.8419 & 0.8812 & 0.2004 & 0.8416 & 0.7985 & 0.2991 & 0.7428 & 0.2971 & 0.8187 & 0.3005 \end{pmatrix}$$

$$\boldsymbol{R}^{3,(0)} = \begin{pmatrix} 0.8275 & 0.2311 & 0.3338 & 0.8746 & 0.2184 & 0.3701 & 0.3401 & 0.4165 & 0.2492 & 0.3813 & 0.4496 & 0.9507 & 0.3438 & 0.8419 & 0.2765 & 0.8125 \\ 0.2924 & 0.2184 & 0.9539 & 0.3200 & 0.3180 & 0.2041 & 0.7599 & 0.3028 & 0.2971 & 0.9001 & 0.8602 & 0.7531 & 0.8748 & 0.2492 & 0.7145 & 0.3487 \\ 0.3257 & 0.3115 & 0.8079 & 0.3042 & 0.9248 & 0.1540 & 0.8282 & 0.8483 & 0.7458 & 0.2010 & 0.3903 & 0.3861 & 0.9046 & 0.8517 & 0.8919 & 0.3185 \\ 0.2966 & 0.7085 & 0.2732 & 0.2959 & 0.7178 & 0.6761 & 0.3542 & 0.9264 & 0.7045 & 0.8524 & 0.3010 & 0.2258 & 0.3027 & 0.3082 & 0.8736 & 0.2678 \end{pmatrix}$$

Table 5 URs and their imporatnce

Code Number	User Requirements	The relative importance
UR_1	User-friendly, accessible, and aesthetic design of the user interface	0.0844
UR_2	Communication and information shared among users	0.0641
UR_3	Reminders and notifications	0.0302
UR_4	Ability to view previous images and recommendations of a particular patient	0.0943
UR_5	Daily, monthly, and yearly statistics	0.0299
UR_6	Data management	0.0835
UR_7	Provide comprehensiveness and professional information	0.1412
UR_8	Facility to support the financial information	0.0357
UR_9	Integration of existing electronic health records systems and applications	0.0364
UR_{10}	Data privacy and security	0.1709
UR_{11}	Storage and backup	0.0735
UR_{12}	Support equipment connection to obtain health data	0.0207
UR_{13}	Provide customized and personal service	0.0292
UR_{14}	Convenient and safe in-app payment	0.0668
UR_{15}	Fast response of service	0.0391

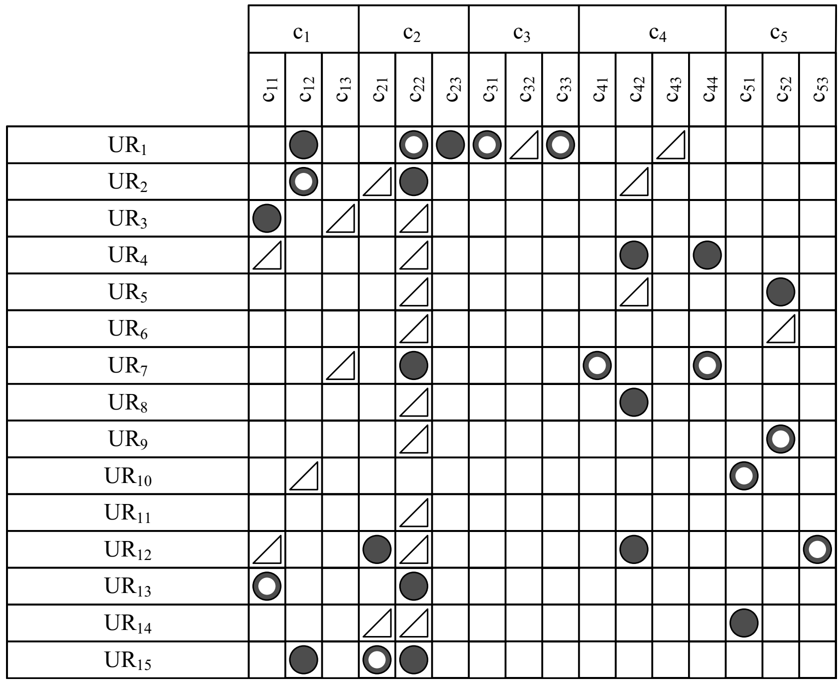
$$\boldsymbol{R}^{4,(0)} = \begin{pmatrix} \mathbf{0.8660} & \mathbf{0.9011} & \mathbf{0.9324} & \mathbf{0.3030} & \mathbf{0.7988} & \mathbf{0.3354} & \mathbf{0.1665} & \mathbf{0.8325} & \mathbf{0.2006} & \mathbf{0.8660} & \mathbf{0.9352} & \mathbf{0.2675} & \mathbf{0.8694} & \mathbf{0.1983} & \mathbf{0.8325} & \mathbf{0.8381} \\ \mathbf{0.8705} & \mathbf{0.1971} & \mathbf{0.2306} & \mathbf{0.8635} & \mathbf{0.9029} & \mathbf{0.6999} & \mathbf{0.8381} & \mathbf{0.7699} & \mathbf{0.8325} & \mathbf{0.9011} & \mathbf{1.0000} & \mathbf{0.7314} & \mathbf{0.3030} & \mathbf{0.2340} & \mathbf{0.2954} & \mathbf{0.2295} \\ \mathbf{0.2675} & \mathbf{0.7733} & \mathbf{0.8294} & \mathbf{0.9000} & \mathbf{0.3730} & \mathbf{0.8024} & \mathbf{0.2619} & \mathbf{0.7646} & \mathbf{0.2005} & \mathbf{0.8294} & \mathbf{0.3284} & \mathbf{0.8294} & \mathbf{0.9029} & \mathbf{0.3030} & \mathbf{0.9659} & \mathbf{0.9665} \\ \mathbf{0.2706} & \mathbf{0.8341} & \mathbf{0.3047} & \mathbf{0.2340} & \mathbf{0.1676} & \mathbf{0.7646} & \mathbf{0.2675} & \mathbf{0.1659} & \mathbf{0.1648} & \mathbf{0.8635} & \mathbf{0.2694} & \mathbf{0.2664} & \mathbf{0.2706} & \mathbf{0.8381} & \mathbf{0.3030} & \mathbf{0.1994} \end{pmatrix}$$

$$\boldsymbol{R}^{5,(0)} = \begin{pmatrix} \mathbf{0.4695} & \mathbf{0.7454} & \mathbf{0.4047} & \mathbf{0.7376} & \mathbf{0.3840} & \mathbf{0.7607} & \mathbf{0.4414} & \mathbf{0.7444} & \mathbf{0.7752} & \mathbf{0.4484} & \mathbf{0.3329} & \mathbf{0.8054} & \mathbf{0.7404} & \mathbf{0.4465} & \mathbf{0.7007} & \mathbf{0.3335} \\ \mathbf{0.7589} & \mathbf{0.3215} & \mathbf{0.7795} & \mathbf{0.4878} & \mathbf{0.7852} & \mathbf{0.5862} & \mathbf{0.7358} & \mathbf{0.6335} & \mathbf{0.8206} & \mathbf{0.8089} & \mathbf{0.4008} & \mathbf{0.3903} & \mathbf{0.7953} & \mathbf{0.6119} & \mathbf{0.4077} & \mathbf{0.3272} \\ \mathbf{0.7803} & \mathbf{0.6723} & \mathbf{0.3078} & \mathbf{0.4313} & \mathbf{0.4952} & \mathbf{0.6886} & \mathbf{0.4585} & \mathbf{0.3726} & \mathbf{0.2761} & \mathbf{0.6246} & \mathbf{0.3773} & \mathbf{0.4269} & \mathbf{0.4352} & \mathbf{0.4201} & \mathbf{0.4242} & \mathbf{0.3389} \\ \mathbf{0.8381} & \mathbf{0.2440} & \mathbf{0.3637} & \mathbf{0.3450} & \mathbf{0.3513} & \mathbf{0.3631} & \mathbf{0.2815} & \mathbf{0.8527} & \mathbf{0.5854} & \mathbf{0.4695} & \mathbf{0.3014} & \mathbf{0.6989} & \mathbf{0.6498} & \mathbf{0.6943} & \mathbf{0.4178} & \mathbf{0.7204} \end{pmatrix}$$

Table 6 Synthesized pairwise comparison matrix on URs

	UR_1	UR_2	UR_3	UR_4	UR_5	UR_6	UR_7	UR_8	UR_9	UR_{10}	UR_{11}	UR_{12}	UR_{13}	UR_{14}	UR_{15}
UR_1	1.0000	2.8249	1.4065	0.8396	3.4364	1.1416	0.3143	3.9841	2.0871	0.2717	2.2173	2.6954	3.4159	0.9107	3.2573
UR_2	0.3540	1.0000	2.8142	0.7598	2.7143	0.4829	0.2791	2.3117	1.9623	0.3265	0.6881	3.1596	5.0213	0.8692	2.3474
UR_3	0.7110	0.3553	1.0000	0.3968	0.5974	0.2786	0.2981	0.3018	0.8042	0.4016	0.5577	2.7123	1.1524	0.4272	0.3095
UR_4	1.1910	1.3161	2.5202	1.0000	3.3670	2.4155	0.7915	2.7023	2.7959	0.7021	0.6916	3.2678	2.8042	1.3175	2.6385
UR_5	0.2910	0.3684	1.6740	0.2970	1.0000	0.3432	0.2571	0.8268	0.6124	0.1977	0.3163	2.3751	1.6788	0.4055	0.4078
UR_6	0.8760	2.0708	3.5890	0.4140	2.9140	1.0000	0.4985	3.4321	3.2342	0.3756	1.2183	3.9141	1.2758	2.1785	2.1978
UR_7	3.1820	3.5829	3.3546	1.2634	3.8895	2.0060	1.0000	3.9155	3.2431	0.7634	1.9763	4.2318	3.4116	3.5842	3.3557
UR_8	0.2510	0.4326	3.3135	0.3701	1.2095	0.2914	0.2554	1.0000	0.8125	0.2409	0.4458	2.6142	1.6788	0.3662	0.8326
UR_9	0.4791	0.5096	1.2435	0.3577	1.6329	0.3092	0.3083	1.2308	1.0000	0.2483	0.2974	2.8902	0.4924	0.4664	1.8484
UR_{10}	3.6810	3.0628	2.4900	1.4243	5.0582	2.6624	1.3100	4.1510	4.0270	1.0000	3.2154	4.7230	4.5715	5.0761	5.3191
UR_{11}	0.4510	1.4533	1.7930	1.4460	3.1620	0.8208	0.5060	2.2430	3.3620	0.3110	1.0000	2.7652	2.2138	1.0941	2.0040
UR_{12}	0.3710	0.3165	0.3687	0.3060	0.4210	0.2555	0.2363	0.3825	0.3460	0.2117	0.3616	1.0000	0.5015	0.2642	0.8598
UR_{13}	0.2927	0.1992	0.8678	0.3566	0.5957	0.7838	0.2931	0.5957	2.0310	0.2187	0.4517	1.9940	1.0000	0.3871	0.2974
UR_{14}	1.0980	1.1505	2.3410	0.7590	2.4660	0.4590	0.2790	2.7310	2.1440	0.1970	0.9140	3.7850	2.5830	1.0000	2.2883
UR_{15}	0.3070	0.4260	3.2310	0.3790	2.4520	0.4550	0.2980	1.2010	0.5410	0.1880	0.4990	1.1630	3.3620	0.4370	1.0000

Fig. 4 The relationship matrix



$$\boldsymbol{R}^{\mathbf{6},(\mathbf{0})} = \begin{pmatrix} \mathbf{0.3191} & \mathbf{0.6839} & \mathbf{0.8244} & \mathbf{0.7892} & \mathbf{0.2755} & \mathbf{0.2404} & \mathbf{0.7190} & \mathbf{0.3053} & \mathbf{0.2244} & \mathbf{0.3000} & \mathbf{0.7350} & \mathbf{0.3595} & \mathbf{0.4053} & \mathbf{0.3809} & \mathbf{0.8595} & \mathbf{0.3107} \\ \mathbf{0.7297} & \mathbf{0.7702} & \mathbf{0.2702} & \mathbf{0.4191} & \mathbf{0.4511} & \mathbf{0.1595} & \mathbf{0.2404} & \mathbf{0.2755} & \mathbf{0.8297} & \mathbf{0.9999} & \mathbf{0.4351} & \mathbf{0.7648} & \mathbf{0.3702} & \mathbf{0.2755} & \mathbf{0.8595} & \mathbf{0.3053} \\ \mathbf{0.7702} & \mathbf{0.8106} & \mathbf{0.8701} & \mathbf{0.8244} & \mathbf{0.7915} & \mathbf{0.2351} & \mathbf{0.7053} & \mathbf{0.2244} & \mathbf{0.7702} & \mathbf{0.2053} & \mathbf{0.8648} & \mathbf{0.7350} & \mathbf{0.3351} & \mathbf{0.8946} & \mathbf{0.9350} & \mathbf{0.9297} \\ \mathbf{0.7946} & \mathbf{0.1351} & \mathbf{0.7541} & \mathbf{0.8648} & \mathbf{0.7564} & \mathbf{0.6946} & \mathbf{0.8946} & \mathbf{0.9648} & \mathbf{0.6648} & \mathbf{0.2404} & \mathbf{0.6999} & \mathbf{0.8244} & \mathbf{0.8159} & \mathbf{0.3458} & \mathbf{0.7892} & \mathbf{0.7702} \end{pmatrix}$$

Table 7 The relative weights of criteria

Criteria	The relative weight of criteria	Sub-criteria	The relative weight of sub-criteria
Engagement (c_1)	0.1454	Customization (c_{11})	0.2664
		Interactivity (c_{12})	0.6361
		Target group (c_{13})	0.0975
Functionality (c_2)	0.2357	Performance (c_{21})	0.1912
		Ease of use (c_{22})	0.7199
		Navigation (c_{23})	0.0889
Aesthetics (c_3)	0.1326	Layout (c_{31})	0.4737
		Graphics (c_{32})	0.0526
		Visual appeal (c_{33})	0.4737
Information (c_4)	0.2857	Quality of information (c_{41})	0.3678
		Quantity of information (c_{42})	0.1581
		Visual information(c_{43})	0.0244
		Credibility (c_{44})	0.4497
Technology (c_5)	0.2006	Security (c_{51})	0.7167
		Integration (c_{52})	0.2065
		Connection and synchronization (c_{53})	0.0768

Table 8 The interactions

S	Interaction	$\bar{t}(c_i, c_j)$	$I(c_i, c_j)$	S	Interaction	$\bar{t}(c_i, c_j)$	$I(c_i, c_j)$
$\{c_1, c_2\}$	Positive	[0.0242,0.0727]	0.0242	$\{c_1, c_3\}$	Positive	[0.0221,0.0663]	0.0221
$\{c_1, c_4\}$	Positive	[0.0242,0.0727]	0.0242	$\{c_1, c_5\}$	Positive	[0.0242,0.0727]	0.0242
$\{c_2, c_3\}$	Positive	[0.0221,0.0663]	0.0221	$\{c_2, c_4\}$	Positive	[0.0393,0.1179]	0.0393
$\{c_2, c_5\}$	Positive	[0.0334,0.1003]	0.0334	$\{c_3, c_4\}$	Positive	[0.0221,0.0663]	0.0221
$\{c_3, c_5\}$	Positive	[0.0221,0.0663]	0.0221	$\{c_4, c_5\}$	Positive	[0.0334,0.1003]	0.0334
$\{c_{11}, c_{12}\}$	Positive	[0.0888,0.2664]	0.0888	$\{c_{11}, c_{13}\}$	Positive	[0.0325,0.0975]	0.0325
$\{c_{12}, c_{13}\}$	Negative	[−0.0975,−0.0325]	-0.0325	$\{c_{21}, c_{22}\}$	Positive	[0.0637,0.1912]	0.0637
$\{c_{21}, c_{23}\}$	Negative	[−0.0889,- 0.0296]	−0.0296	$\{c_{22}, c_{23}\}$	Positive	[0.0296,0.0889]	0.0296
$\{c_{31}, c_{32}\}$	Positive	[0.0175,0.0526]	0.0175	$\{c_{31}, c_{33}\}$	Positive	[0.1579,0.4737]	0.1579
$\{c_{32}, c_{33}\}$	Positive	[0.0175, 0.0526]	0.0175	$\{c_{41}, c_{42}\}$	Positive	[0.0351,0.1054]	0.0351
$\{c_{41}, c_{43}\}$	Positive	[0.0054, 0.0163]	0.0054	$\{c_{41}, c_{44}\}$	Positive	[0.0817,0.2452]	0.0817
$\{c_{42}, c_{43}\}$	Negative	[−0.0163,−0.0054]	-0.0054	$\{c_{42}, c_{44}\}$	Negative	[−0.1054, −0.0351]	−0.0351
$\{c_{43}, c_{44}\}$	Positive	[0.0054,0.0163]	0.0054	$\{c_{51}, c_{52}\}$	Positive	[0.0688,0.2065]	0.0688
$\{c_{51}, c_{53}\}$	Positive	[0.0256,0.0768]	0.0265	$\{c_{52}, c_{53}\}$	Positive	[0.0256,0.0768]	0.0265

$$\boldsymbol{R}^{c,(0)} = \begin{pmatrix} \mathbf{0.6206} & \mathbf{0.5089} & \mathbf{0.5954} & \mathbf{0.5801} & \mathbf{0.5051} & \mathbf{0.5560} & \mathbf{0.5406} & \mathbf{0.5899} & \mathbf{0.5443} & \mathbf{0.5899} & \mathbf{0.4922} & \mathbf{0.6248} & \mathbf{0.5680} & \mathbf{0.5870} & \mathbf{0.5321} & \mathbf{0.5448} \\ \mathbf{0.5397} & \mathbf{0.4440} & \mathbf{0.5844} & \mathbf{0.5973} & \mathbf{0.6807} & \mathbf{0.4268} & \mathbf{0.5501} & \mathbf{0.4987} & \mathbf{0.5540} & \mathbf{0.6850} & \mathbf{0.6440} & \mathbf{0.5044} & \mathbf{0.6302} & \mathbf{0.4743} & \mathbf{0.5614} & \mathbf{0.4786} \\ \mathbf{0.5652} & \mathbf{0.5510} & \mathbf{0.5961} & \mathbf{0.5693} & \mathbf{0.6274} & \mathbf{0.5174} & \mathbf{0.5376} & \mathbf{0.5372} & \mathbf{0.4941} & \mathbf{0.4604} & \mathbf{0.5895} & \mathbf{0.5737} & \mathbf{0.6182} & \mathbf{0.6105} & \mathbf{0.5891} & \mathbf{0.4786} \\ \mathbf{0.5785} & \mathbf{0.4877} & \mathbf{0.5378} & \mathbf{0.4557} & \mathbf{0.4891} & \mathbf{0.4982} & \mathbf{0.5837} & \mathbf{0.7428} & \mathbf{0.5251} & \mathbf{0.5877} & \mathbf{0.4966} & \mathbf{0.5080} & \mathbf{0.5233} & \mathbf{0.5396} & \mathbf{0.5958} & \mathbf{0.4516} \end{pmatrix}$$

Table 9 The Möbius representation

S	m	S	m	S	m	S	m	S	m
$\{c_1\}$	0.0981	$\{c_2\}$	0.1762	$\{c_3\}$	0.0884	$\{c_4\}$	0.2262	$\{c_5\}$	0.1441
$\{c_1, c_2\}$	0.0242	$\{c_1, c_3\}$	0.0221	$\{c_1, c_4\}$	0.0242	$\{c_1, c_5\}$	0.0242	$\{c_2, c_3\}$	0.0221
$\{c_2, c_4\}$	0.0393	$\{c_2, c_5\}$	0.0334	$\{c_3, c_4\}$	0.0221	$\{c_3, c_5\}$	0.0221	$\{c_4, c_5\}$	0.0334
$\{c_{11}\}$	0.2058	$\{c_{12}\}$	0.6080	$\{c_{13}\}$	0.0975	$\{c_{11}, c_{12}\}$	0.0888	$\{c_{11}, c_{13}\}$	0.0325
$\{c_{12}, c_{13}\}$	−0.0325	$\{c_{21}\}$	0.1742	$\{c_{22}\}$	0.6733	$\{c_{23}\}$	0.0889	$\{c_{21}, c_{22}\}$	0.0637
$\{c_{21}, c_{23}\}$	−0.0296	$\{c_{22}, c_{23}\}$	0.0296	$\{c_{31}\}$	0.3860	$\{c_{32}\}$	0.0351	$\{c_{33}\}$	0.3860
$\{c_{31}, c_{32}\}$	0.0175	$\{c_{31}, c_{33}\}$	0.1579	$\{c_{32}, c_{33}\}$	0.0175	$\{c_{41}\}$	0.3067	$\{c_{42}\}$	0.1608
$\{c_{43}\}$	0.0271	$\{c_{44}\}$	0.4237	$\{c_{41}, c_{42}\}$	0.0351	$\{c_{41}, c_{43}\}$	0.0054	$\{c_{41}, c_{44}\}$	0.0817
$\{c_{42}, c_{43}\}$	−0.0054	$\{c_{42}, c_{44}\}$	−0.0351	$\{c_{43}, c_{44}\}$	0.0054	$\{c_{51}\}$	0.6691	$\{c_{52}\}$	0.1589
$\{c_{53}\}$	0.0503	$\{c_{51}, c_{52}\}$	0.0688	$\{c_{51}, c_{53}\}$	0.0265	$\{c_{52}, c_{53}\}$	0.0265		

Table 10 The 2-additive measure on criteria set

S	μ	S	μ	S	μ	S	μ	S	μ
$\{c_1\}$	0.0981	$\{c_2\}$	0.1762	$\{c_3\}$	0.0884	$\{c_4\}$	0.2262	$\{c_5\}$	0.1441
$\{c_1, c_2\}$	0.2985	$\{c_1, c_3\}$	0.2086	$\{c_1, c_4\}$	0.3485	$\{c_1, c_5\}$	0.2664	$\{c_2, c_3\}$	0.2867
$\{c_2, c_4\}$	0.4417	$\{c_2, c_5\}$	0.3537	$\{c_3, c_4\}$	0.3367	$\{c_3, c_5\}$	0.2546	$\{c_4, c_5\}$	0.4037

Table 11 The 2-additive measure on sub-criteria set

S	μ	S	μ	S	μ	S	μ	S	μ
$\{c_{11}\}$	0.2058	$\{c_{12}\}$	0.6080	$\{c_{13}\}$	0.0975	$\{c_{11}, c_{12}\}$	0.9026	$\{c_{11}, c_{13}\}$	0.3358
$\{c_{12}, c_{13}\}$	0.6730	$\{c_{21}\}$	0.1742	$\{c_{22}\}$	0.6733	$\{c_{23}\}$	0.0889	$\{c_{21}, c_{22}\}$	0.9112
$\{c_{21}, c_{23}\}$	0.2335	$\{c_{22}, c_{23}\}$	0.7918	$\{c_{31}\}$	0.3860	$\{c_{32}\}$	0.0351	$\{c_{33}\}$	0.3860
$\{c_{31}, c_{32}\}$	0.4386	$\{c_{31}, c_{33}\}$	0.9299	$\{c_{32}, c_{33}\}$	0.4386	$\{c_{41}\}$	0.3067	$\{c_{42}\}$	0.1608
$\{c_{43}\}$	0.0271	$\{c_{44}\}$	0.4237	$\{c_{41}, c_{42}\}$	0.5026	$\{c_{41}, c_{43}\}$	0.3392	$\{c_{41}, c_{44}\}$	0.8121
$\{c_{42}, c_{43}\}$	0.1825	$\{c_{42}, c_{44}\}$	0.5494	$\{c_{43}, c_{44}\}$	0.3392	$\{c_{51}\}$	0.6691	$\{c_{52}\}$	0.1589
$\{c_{53}\}$	0.0503	$\{c_{51}, c_{52}\}$	0.8968	$\{c_{51}, c_{53}\}$	0.7459	$\{c_{52}, c_{53}\}$	0.2357		

The consensus levels of subgroups are $CI(g_1)^{(0)} = 0.7611$, $CI(g_2)^{(0)} = 0.7649$, $CI(g_3)^{(0)} = 0.7617$, $CI(g_4)^{(0)} = 0.7023$, $CI(g_5)^{(0)} = 0.8312$ and $CI(g_6)^{(0)} = 0.7430$, and the group consensus level is $GCI^{(0)} = 0.7677$. As $GCI^{(0)} < \overline{GCI} = 0.85$, the CRP should be applied to improve the consensus level.

As $CI(g_5)^{(0)} = \max\{CI(g_p)^{(0)} | p = 1, 2, 3, 4, 5, 6\}$ and $CI(g_4)^{(0)} = \min\{CI(g_p)^{(0)} | p = 1, 2, 3, 4, 5, 6\}$, $R^{5,(0)}$ is identified as the positive ideal decision matrix, and $R^{4,(0)}$ is regarded as the negative ideal decision matrix. The closeness coefficients of each subgroup are shown in the third column for $t = 0$ in Table 15. Because $\xi^{(0)} = 0.9032 < \overline{\xi}$, we apply

Table 12 The initial individual decision matrices

		sc_1	sc_2	sc_3	sc_4	sc_5	sc_6	sc_7	sc_8	sc_9	sc_{10}	sc_{11}	sc_{12}	sc_{13}	sc_{14}	sc_{15}	sc_{16}
e_1	x_1	7	1	7	9	8	8	4	10	10	7	1	10	1	10	3	10
	x_2	5	6	2	10	9	2	7	1	1	4	4	1	8	10	10	7
	x_3	5	3	1	1	6	6	6	2	3	1	5	5	7	10	3	2
	x_4	1	6	9	3	10	2	6	7	2	6	9	3	6	6	10	1
e_2	x_1	3	8	1	10	1	3	1	10	10	9	5	10	3	5	10	7
	x_2	9	2	10	1	10	6	4	3	8	7	1	2	5	4	7	2
	x_3	10	3	1	8	8	9	6	3	2	10	7	7	2	2	1	2
	x_4	8	9	3	1	7	1	10	10	2	1	1	9	9	6	1	8
e_3	x_1	4	2	4	9	1	8	1	5	8	7	5	5	10	8	6	3
	x_2	9	6	4	8	10	10	9	8	7	10	3	4	10	4	6	4
	x_3	8	10	10	2	8	10	9	1	2	9	8	6	10	1	8	6
	x_4	9	1	2	6	9	1	2	10	5	9	2	9	6	6	6	1
…																	
e_{25}	x_1	1	9	9	9	7	10	1	10	1	3	1	3	10	6	10	7
	x_2	1	1	9	8	10	1	9	8	10	10	7	9	10	10	9	1
	x_3	10	3	1	1	1	10	1	1	2	1	1	1	3	1	1	1
	x_4	10	3	8	1	1	9	1	10	10	9	1	10	2	10	1	10

Table 13 Clustering result and the initial weights of subgroups ($\xi = 0.5$)

Subgroup	Size of subgroup	DMs	Initial weight of subgroup	Subgroup	Size of subgroup	DMs	Initial weight of subgroup
g_1	3	e_8, e_{12}, e_{13}	0.1436	g_2	5	$e_1, e_4, e_6, e_{16}, e_{20}$	0.1828
g_3	4	$e_9, e_{10}, e_{14}, e_{23}$	0.1636	g_4	3	e_7, e_{17}, e_{21}	0.1357
g_5	7	$e_2, e_3, e_{11}, e_{18}, e_{19}, e_{24}, e_{25}$	0.2330	g_6	3	e_5, e_{15}, e_{22}	0.1414

Table 14 The initial weights of DMs

Subgroup	DM	Initial weight of DM	Subgroup	DM	Initial weight of DM	Subgroup	DM	Initial weight of DM
g_1	e_8	0.3521	g_2	e_1	0.1936	g_3	e_9	0.2467
	e_{12}	0.3052		e_4	0.2043		e_{10}	0.2702
	e_{13}	0.3427		e_6	0.2023		e_{14}	0.2303
				e_{16}	0.1986		e_{23}	0.2528
				e_{20}	0.2012			
g_4	e_7	0.3350	g_5	e_2	0.1407	g_6	e_5	0.3512
	e_{17}	0.3238		e_3	0.1427		e_{15}	0.2977
	e_{21}	0.3412		e_{11}	0.1414		e_{22}	0.3512
				e_{18}	0.1535			
				e_{19}	0.1315			
				e_{24}	0.1330			
				e_{25}	0.1571			

the mechanism I to improve the consensus level. Suppose that the subgroups g_3 and g_4 are willing to modify their opinions, where$CG^{(0)} = \{g_3, g_4\}$. Then, we modify the opinions of subgroups g_3 and g_4 by Eq. (19). Furthermore, the consensus levels of the subgroups are $CI(g_1)^{(1)} = 0.7646$, $CI(g_2)^{(1)} = 0.7696$, $CI(g_3)^{(1)} = 0.7964$, $CI(g_4)^{(1)} = 0.7740$, $CI(g_5)^{(1)} = 0.8340$ and $CI(g_6)^{(1)} = 0.7461$, and the group consensus level is $GCI^{(1)} = 0.7855 < \overline{GCI}$. Therefore, we need to improve the consensus continuously.

After five iterations, the group consensus level has reached an acceptable level, $GCI^{(5)} = 0.8545 > \overline{GCI}$. The main results for the CRP are shown in Table 15.

The final group decision matrix R^{c^*} is obtained as follows:

$$
\boldsymbol{R}^{\mathbf{c}^*} = \begin{pmatrix}
\mathbf{0.6034} & \mathbf{0.5204} & \mathbf{0.5742} & \mathbf{0.6161} & \mathbf{0.4858} & \mathbf{0.5967} & \mathbf{0.5532} & \mathbf{0.6056} & \mathbf{0.6065} & \mathbf{0.5843} & \mathbf{0.4621} & \mathbf{0.6500} & \mathbf{0.6025} & \mathbf{0.5937} & \mathbf{0.5410} & \mathbf{0.4982} \\
\mathbf{0.5795} & \mathbf{0.4387} & \mathbf{0.5874} & \mathbf{0.5911} & \mathbf{0.7031} & \mathbf{0.4400} & \mathbf{0.5455} & \mathbf{0.5008} & \mathbf{0.5803} & \mathbf{0.6886} & \mathbf{0.5951} & \mathbf{0.4804} & \mathbf{0.6589} & \mathbf{0.4887} & \mathbf{0.5481} & \mathbf{0.4655} \\
\mathbf{0.5966} & \mathbf{0.5606} & \mathbf{0.5550} & \mathbf{0.5389} & \mathbf{0.6157} & \mathbf{0.5439} & \mathbf{0.5349} & \mathbf{0.5029} & \mathbf{0.4803} & \mathbf{0.4720} & \mathbf{0.5975} & \mathbf{0.5548} & \mathbf{0.5901} & \mathbf{0.6120} & \mathbf{0.5673} & \mathbf{0.4506} \\
\mathbf{0.6141} & \mathbf{0.4518} & \mathbf{0.5269} & \mathbf{0.4475} & \mathbf{0.4900} & \mathbf{0.4504} & \mathbf{0.5557} & \mathbf{0.7619} & \mathbf{0.5454} & \mathbf{0.5458} & \mathbf{0.4761} & \mathbf{0.5491} & \mathbf{0.5603} & \mathbf{0.5632} & \mathbf{0.5959} & \mathbf{0.4959}
\end{pmatrix}
$$

Table 15 The main results for the CRP

Iteration t	Ideal subgroup	Closeness coefficients	Modification mechanism	Cooperative subgroups	Non-cooperative subgroups	Final GCL
0	g^+: g_5 g^-: g_4	$\eta_1^{(0)} = 0.5613$, $\eta_2^{(0)} = 0.5882$ $\eta_3^{(0)} = 0.5276$, $\eta_4^{(0)} = 0.0000$ $\eta_5^{(0)} = 1.0000$, $\eta_6^{(0)} = 0.5648$	I	g_3, g_4		0.7677
1	g^+: g_5 g^-: g_6	$\eta_1^{(1)} = 0.5657$, $\eta_2^{(1)} = 0.5349$ $\eta_3^{(1)} = 0.5161$, $\eta_4^{(1)} = 0.5825$ $\eta_5^{(1)} = 1.0000$, $\eta_6^{(1)} = 0.0000$	I	g_2, g_6	g_3	0.7855
2	g^+: g_5 g^-: g_1	$\eta_1^{(2)} = 0.0000$, $\eta_2^{(2)} = 0.5170$ $\eta_3^{(2)} = 0.5569$, $\eta_4^{(2)} = 0.5451$ $\eta_5^{(2)} = 1.0000$, $\eta_6^{(2)} = 0.5548$	I	g_1, g_2, g_4		0.8032
3	g^+: g_5 g^-: g_3	$\eta_1^{(3)} = 0.5738$, $\eta_2^{(3)} = 0.4793$ $\eta_3^{(3)} = 0.0000$, $\eta_4^{(3)} = 0.5454$ $\eta_5^{(3)} = 1.0000$, $\eta_6^{(3)} = 0.4987$	I	g_2, g_4	g_3, g_6	0.8245
4	g^+: g_6 g^-: g_4	$\eta_1^{(4)} = 0.4823$, $\eta_2^{(4)} = 0.5479$ $\eta_3^{(4)} = 0.5262$, $\eta_4^{(4)} = 0.0000$ $\eta_5^{(4)} = 0.4856$, $\eta_6^{(4)} = 1.0000$	II	g_1 (e_{13}) g_4 (e_7)	g_2 (e_4, e_{16}, e_{20}) g_3 (e_{10}, e_{23}) g_5 (e_2, e_{11}, e_{18}, e_{25})	0.8419
5						0.8545

Table 16 The comprehensive assessment values of alternatives

	CE_{i1}	CE_{i2}	CE_{i3}	CE_{i4}	CE_{i5}	CE_i
x_1	0.7303	0.6941	0.7749	0.4965	0.7673	0.6683
x_2	0.6543	0.8778	0.7462	0.5804	0.6656	0.7003
x_3	0.7596	0.7929	0.6765	0.4843	0.7871	0.6833
x_4	0.6698	0.6378	0.7488	0.4736	0.7531	0.6334

By Eq. (29), the comprehensive assessment values of alternatives are shown in Table 16.

Therefore, the ranking of the alternatives is $x_2 \succ x_3 \succ x_1 \succ x_4$. Since x_2 is the best choice, the hospital prefers to cooperate with the Good doctor online.

6 Comparation analyses

This section carries out the comparation analaysis from three aspects: weight, adjustment measure and consensus model.

6.1 Comparation results with different weights

In order to show the stability of the decision results, a sensitivity analysis is conducted to explore the influence of the preference coefficient of the standard deviation δ on the ranking of alternatives. To facilitate the simulation analysis, suppose that all subgroups are willing to adjust their opinions. The results are shown in Table 17.

From the results listed in Table 17, we derivie the following conclusions:

(i) The initial and final GCLs decrease with the increase of the coefficient δ.

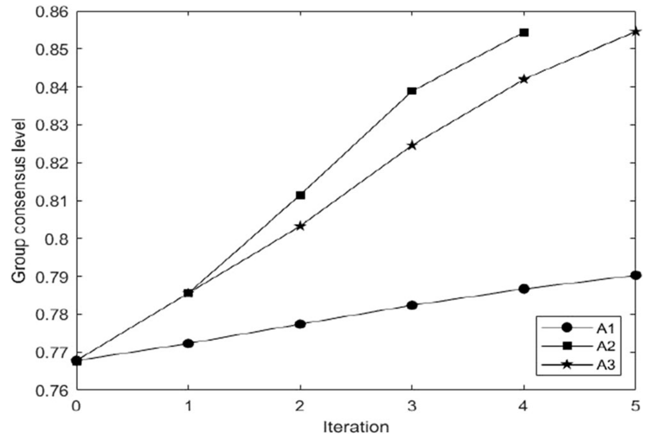


Fig. 5 Comparison of different adjustment measures

(ii) With the increase of the value of δ, the weights of subgroups g_2 and g_5 decrease and the weights of other subgroups increase. This is because that the influence of the sizes of subgroups on their initial weights decreases with the increase of the value of δ.

(iii) The final rankings of alternatives are same and x_2 is the best choice.

6.2 Comparisons of different adjustment measures

To show the superiority of the proposed model, this subsection compares the three types of adjustment measures: the weight penalty (A1), the opinion adjustment (A2), and the mixed adjustment (A3). Figure 5 intuitively shows their differences, where $\delta = 0.5$ and $\overline{\xi} = 0.98$. And we derive the following conclusions:

(i) After the first iteration, the group consensus level of the opinion adjustment (A2) is the highest while the weight penalty (A1) is the lowest among these three measures.

Table 17 Comparative results with different weights

Preference coefficient (δ)	Iterations	Initial weights of subgroups	Initial GCL	Final GCL	Ranking of alternatives
0.0	4	(0.1200, 0.2000, 0.1600, 0.1200, 0.2800, 0.1200)	0.7744	0.8635	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.1	4	(0.1247, 0.1966, 0.1607, 0.1231, 0.2706, 0.1243)	0.7730	0.8625	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.2	4	(0.1294, 0.1931, 0.1614, 0.1263, 0.2612, 0.1285)	0.7715	0.8561	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.3	4	(0.1341, 0.1897, 0.1622, 0.1294, 0.2518, 0.1328)	0.7702	0.8556	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.4	4	(0.1389, 0.1862, 0.1629, 0.1326, 0.2424, 0.1371)	0.7689	0.8550	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.5	4	(0.1436, 0.1828, 0.1636, 0.1357, 0.2330, 0.1414)	0.7677	0.8543	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.6	4	(0.1483,0.1793, 0.1643, 0.1389, 0.2236, 0.1456)	0.7665	0.8542	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.7	4	(0.1530, 0.1759, 0.1650, 0.1420, 0.2142, 0.1499)	0.7655	0.8533	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.8	4	(0.1577, 0.1724, 0.1657, 0.1451, 0.2048, 0.1542)	0.7644	0.8530	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.9	4	(0.1624, 0.1690, 0.1665, 0.1483, 0.1954, 0.1585)	0.7635	0.8525	$x_2 \succ x_3 \succ x_1 \succ x_4$
1.0	4	(0.1671, 0.1655, 0.1672, 0.1514, 0.1860, 0.1627)	0.7626	0.8523	$x_2 \succ x_3 \succ x_1 \succ x_4$

Table 18 Comparisons among three CRP models

Consensus model	Initial *GCL*	Final *GCL*	Iterations	Opinion adjustment amount	Ranking of alternatives
Du et al.'s model [13]	0.6808	0.8519	8	50.2081	$x_2 \succ x_3 \succ x_1 \succ x_4$
Liu et al.'s model [30]	0.6808	0.8544	30	49.0924	$x_2 \succ x_3 \succ x_1 \succ x_4$
The proposed model	0.7677	0.8545	5	36.8450	$x_2 \succ x_3 \succ x_1 \succ x_4$

Note: $\overline{GCL} = 0.85$

(ii) The opinion adjustment (A2) requires four iterations to reach consensus requirement while the mixed adjustment (A3) needs five iterations. This is because the willingness of the subgroups or DMs for adjusting their opinions increases the number of iterations.

6.3 Comparisons of different consensus models

To manage the non-cooperative behavior, Du et al. [13] developed a mixed consensus model, where a supervised consensus-reaching model was adopted, in which all subgroups were required to adjust their opinions. When the group consensus level reached a certain level, the independent consensus-reaching model eas used, in which just one subgroup's opinions were adjusted. Liu et al. [30] designed a feedback mechanism to detect the objects that need to be modified. First, the subgroup with the minimum subgroup consensus level was identified. Then, they detected the alternatives that need to be adjusted from the selected subgroup. Finally, they modified the preference values that didn't meet the consensus requirement. In this study, we propose a consensus model to detect the cooperative and non-cooperative behaviors and provide modification recommendations based on the consensus level. To show the merits of the proposed model, a comparative analysis is conducted between Du et al.'s model [13], Liu et al.'s model [30], and the proposed model. To facilitate the simulation analysis, suppose that all DMs in Liu et al.'s model are willing to change their opinions. Table 18 shows the main results.

Figure 6 visually shows that concrete changes of the related interactions of these three CPR models. Since Liu et al.'s model [30] requires 30 iterations to reach the threshold, only the results of the first eight iterations are shown in Fig. 6.

Next, we analyze the differences between Du et al.'s model [13], Liu et al.'s model [30], and the proposed model in detail.

(i) The initial group consensus levels are different. There are three reasons: (1) different consensus measures are adopted. The consensus measures used in [13, 30] are based on the distance among subgroups' opinions, in which a compromise appears between subgroups' consensus levels [54]. The group consensus measure of the proposed model is based on the distance between subgroup decision matrix and group decision matrix, where the subgroups with the larger weights make a bigger

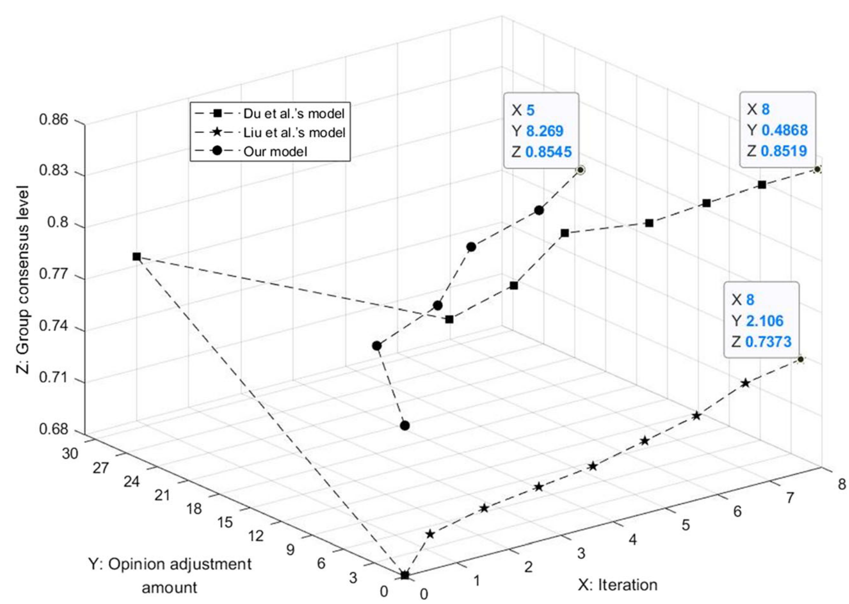


Fig. 6 Comparison among three CRP models

contribution to the group consensus level; (2) the weights of DMs are different. In the proposed model, DMs' weights are obtained by the distance between the opinions of DMs within the subgroup. While the weights of DMs are deemed as equal in Du et al.'s model [13] and Liu et al.'s model [30]; (3) the weights of subgroups are different. Three factors, including the number of DMs within subgroups, the subgroup consensus level and the internal consensus level of subgroups, are considered in Du et al.'s model [13]. Liu et al. [30] only considered the number of DMs within subgroups, which may lead to some DMs following blindly. In the proposed model, the weights of subgroups are determined by the standard deviation among subgroups and the number of DMs in subgroups.

(ii) The consensus iterations are different. In the case study, the number of criteria is relatively more and the individual decision matrices are complex. It is found that the proposed model has the shortest iterations and the smallest amount of opinion adjustments. The proposed model can precisely identify DMs who need to adjust opinions and provide recommendations based on their consensus levels. Du et al.'s model [13] also adopts different adjustment mechanisms according to the group consensus level. However, Du et al.'s model modifies the opinions on the subgroup level and requires a greater adjustment. As for Liu et al.'s model [30], it only adjusts the alternative with the lowest consensus level within the lowest consensus subgroup. This method accurately detects the evaluation information that needs to be modified, but it usually takes more time to reach the consensus threshold. In contrast, the proposed model is more suitable for dealing with decision-making problems with many criteria.

(iii) The management mechanisms for non-cooperative behavior are different. Du et al.'s model [13] identifies the non-cooperative behavior through the change rate of the subgroup consensus level and adopts the weight punishment and opinion punishment. The DMs who are unwilling to change their original evaluations are dropped out in Liu et al.'s model [30]. In the proposed model, the subgroups who are unwilling to modify their opinions are managed by the weight penalty.

(iv) The final rankings of alternatives are same. Regardless of which consensus model is adopted, x_2 is always the best alternative, which shows the stability of the results.

7 Conclusions

Based on the analysis of the cooperation with the third-party platform, we propose a hybrid method to deal with the problem of mHealth app selection, which can provide decision support for the hospital. The major contributions of this paper are summarized as:

(i) URs are converted into criteria by QFD, which contributes to select the mHealth app with the highest user satisfaction for the hospital.
(ii) A hybrid method is proposed to determine the weights of criteria, which takes the advantages of AHP, QFD and 2-additive measure.
(iii) A new method to determine the weights of subgroups is presented, which considers the size of subgroup and the standard deviation among subgroups.
(iv) A new mechanism to detect the inconsistent subgroup is designed that follows the idea of TOPSIS method. Multiple subgroups can be adjusted in each round of iteration.
(v) A new consensus model is developed, which provides different modification recommendations with respect to the group consensus level and the willingness of subgroups.

At the same time, there are some limitations and opportunities of this study

(i) The *k*-means clustering method is adopted to cluster DMs into several subgroups, in which the subgroup centers are selected randomly. The clustering results may be influenced by the initial subgroup centers. We can employ other clustering methods to deal with the classification problem in future studies such as the fuzzy c-means (FCM) clustering algorithm [2], the grey clustering algorithm [31] and the trust-score and similarity based clustering method [12].
(ii) The non-cooperative behaviors of DMs are diverse. In addition to the complete non-cooperative behavior, DMs/subgroups may accept to modify their opinions partly.
(iii) With the development of social media, it is common that DMs have complicated social relationships, which may influence the final results. Thus, the research on social network can be taken into account in the future.

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