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An Intelligent Shared Decision-Making Model among One Patient and Multiple Doctors

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Abstract. *Shared decision-making (SDM) is an effective decision-making method in clinical practice. However, the pressure of negotiation and decision makes it difficult to apply widely. To alleviate the pressure of artificial SDM and promote the realization of clinical SDM, this article presents a fuzzy constraint-based negotiation and decision method for the patient-doctors SDM. The proposed method includes a negotiation model and a decision-making model. The negotiation model quantifies the negotiation process between patient agent (PA) and doctor agents (DAs) in SDM. It consists of the negotiation behavior and the negotiation protocol of agents. The decision-making model quantifies the decision process of SDM. It translates the negotiation results into treatment plans and assists PA in making decisions. The main contributions are as follows: 1) the agent technology is applied to make one-to-many SDM efficient and intelligent; 2) the distributed and fuzzy constraint theories are used to design an interconnected, autonomous, and distributed multi-agents negotiation system for SDM; 3) the decision-making model is presented to assist doctors and patients in making decisions. The evaluation results of the negotiation and decision models demonstrate that our method is feasible and effective.*
Keywords: Shared decision-making, One-to-many, Agent negotiation, Fuzzy constraint, Decision-making.

1. **Introduction.** Decision-making is the most important part of medical activities, directly affecting the quality of examination, diagnosis, treatment, and management of patients. In general, there are two decision-making methods in clinical practice: one is to make decisions according to effectiveness, the other is to make decisions according to preferences [1]. Specifically, the common decision approaches for patients and doctors including paternalistic decision-making, informed decision-making, and shared decision-making (SDM) [2]. However, paternalistic decision-making and informed decision-making have gradually become the fixed flow or process in clinical practice. The existence of patient preference and autonomy makes it questioned. By comparison, SDM integrates patient preferences and treatment effectiveness into the decision-making process. Thus, with the vigorous development of citizens' autonomy consciousness, SDM with higher participation and more autonomy has been entrusted with higher expectations.

The SDM is a health decision-making process made by doctors and patients. It needs to adopt the professional knowledge of doctors and consider the values, tendencies, and conditions of patients, so as to fully discuss the possible benefits and injuries [3]. As the method of medical decision most concerned and advocated, the theory and practice of SDM have been studied by many experts and scholars. However, compared to mature theoretical researches, there are many problems in clinical practical researches on SDM needed to be solved [4, 5]. For example, inadequate response of health care systems, shortage of medical knowledge of patients, lack of communication skills and treatment time of doctors, deficient participating awareness of doctors and patients, etc.

To solve these problems, experts and scholars conducted a lot of research work. For example, to solve these problems of health care systems and awareness, relevant laws and standards of SDM are attempted to establish in some countries [6], such as America and Britain. For the shortage of medical knowledge of patients, the patient decision aids [7, 8, 9] are researched and developed. It can help patients participate in healthcare choices, provide information about options, and help patients clarify and convey their personal values associated with the different functions of the options. In some researches, the trained communication skills [10, 11] of doctors have been effectively studying. Furthermore, some assessment tools [12, 13, 14] are developed to evaluate the decision process, results, and related structure to improve its clinical application. In summary, the researches of SDM in Europe and America are relatively complete and systematic, covering many aspects. But elsewhere, like China [15], the studies of SDM are still in the stage of theoretical reference and application exploration.

Although various tools and laws have been developed and established to tackle implementation problems of SDM, negotiation pressure or effective negotiation pressure still exists. These pressures include but are not limited to limited time, effective learning, incomplete information sharing, multiple negotiation issues, multiple negotiation parties. These pressures also exist in other fields, but instead, these problems in other fields have been solved by some computer technologies to a certain extent, such as agent negotiation used in e-commerce. Specifically, the Genetic algorithm [16, 17, 18], Bayesian algorithm [19, 20, 21, 22], Kernel Density Estimation method [23], Reinforcement learning [24, 25, 26] algorithm, and other algorithms [27] are applied to learn the knowledge of the opponent or environment in the agent negotiation process under incomplete information. The sequential negotiation [28, 29] and package deal negotiation [30] are proposed to deal with the pressure of increased negotiation issues. In addition, many multi-agent systems (MAS) [31] have been developed to solve the problems of negotiation and management among multiple agents. For SDM, the realization is mainly through negotiation, and the participants are knowledgeable, which meets the concept of the agent. In a system composed of multiple autonomous agents, negotiation enables the agents to reach an agreement on a belief, goal, or plan [32]. To be exact, agent negotiation is existed to solve complex and practical negotiation problems and make them intelligent. Thus, it is reasonable to use agent negotiation to realize and solve complex shared decision-making problems (SDMPs) among doctors and patients.

In addition, some studies suggested that the Internet of things has been widely applied in various areas [33, 34], especially in health or medical systems [35, 36, 37]. Thus, based on the Internet, it is feasible for this paper to use agent negotiation technology to design an SDM system for one patient and multiple doctors, as shown in Figure 1. It consists of multiple doctor agents, a patient agent, and multiple Graphic User Interfaces (GUIs). The referenced situation is one patient negotiating with many doctors to choose a better treatment. Although it is more common for one doctor to negotiate with multiple patients, the negotiation and decision model required is more complicated because of personalized diagnosis and treatment. Thus, the situation of one doctor and multiple patients is not considered in this paper.

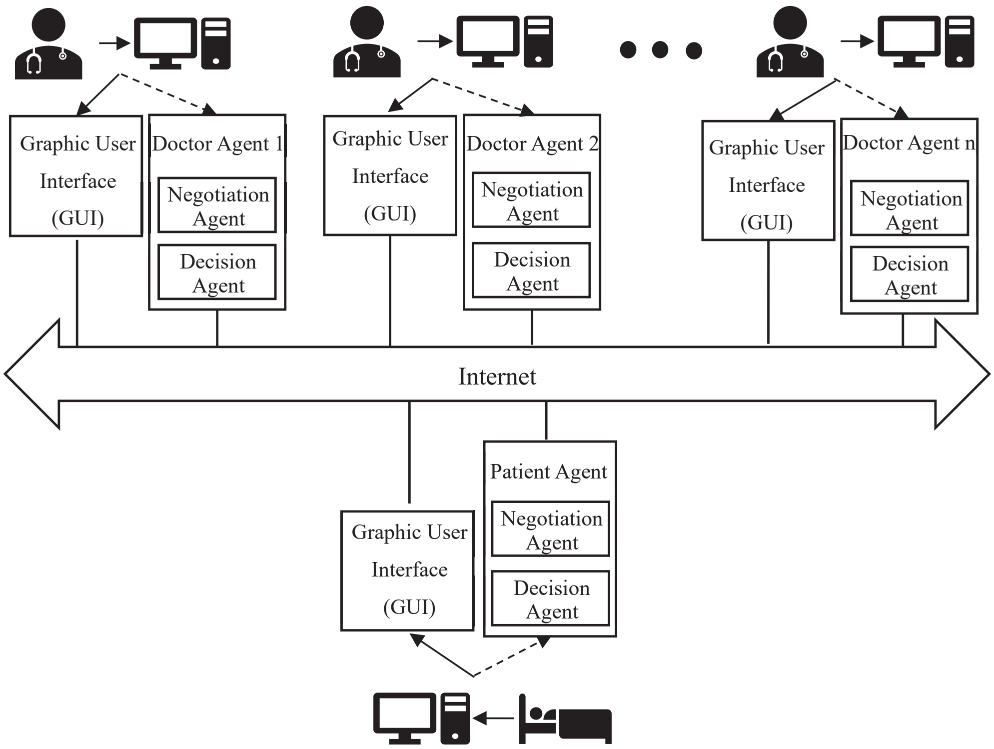

Figure 1. The distributed agent system architecture of SDM.

In response to the above considerations, this paper proposes an agent-based negotiation and decision model to realize one-to-many SDM and relieve the negotiation and decision pressure of it. The proposed negotiation model is a fuzzy constraint-directed agent-based negotiation model (FCAN). It represents preferences adopt fuzzy membership functions, achieves agreement through interactive negotiation, and satisfies different desires with negotiation strategies. The proposed decision-making model is a model that transforms the negotiation result into a treatment plan and assists patients and doctors in making decisions for treatment. The novelty of the proposed method is to adopt agent technology for efficient and intelligent one-to-many SDM. This method designed an interconnected, autonomous, and distributed multi-agent negotiation system and proposed a structured and auxiliary decision-making framework for SDM. In practice, it alleviates the pressures of artificial SDM and promotes the realization of clinical SDM. These pressures of artificial SDM include limited time, effective learning, incomplete information sharing, multiple negotiation issues, and multiple negotiation parties.

The remainder of this paper is structured as follows. In Section 2, the theoretical basis for modeling SDM into agent negotiation-decision and SDMPs into distributed fuzzy constraint satisfaction problems (DFCSPs) is described. In Section 3, we introduce the proposed one-to-many shared negotiation and decision system, including the negotiation process and protocol, the decision-making model, and the behavior model of different agents. In Section 4, the negotiation model and the decision model are evaluated from different points of view. In Section 5, the major work of this paper is concluded, and a prospect and plan for further studies are made.

2. **Modeling Shared Decision-Making with DFCSP.** This paper focuses on the common and simple scenario in SDM, that is, the negotiation and decision among one patient and multiple doctors. In actual medical practice, the patient will submit treatment requests and seek the help of multiple doctors to obtain the best treatment for the disease. These requests are the value requirements for some issues related to treatment, for example, issues related to the treatment of pediatric asthma: cost, effectiveness, side-effects, risk, convenience, etc [38].

In the SDM, patient-centered negotiation is a typical multi-agents and multi-issues negotiation scenario. Thus, in an SDMP, a set of issues is assigned to be negotiated by a set of PA and DAs. For flexible and decentralized negotiation, SDM is modeled as agent-based negotiation, which is the process of solving conflicts among one PA and many DAs in a MAS. That is, although both PA and DAs are agents with private interests, their ultimate goal is to reach a satisfactory agreement by solving conflicts. These conflicts may be that PA prefers to get the most effective treatment at the lowest cost, while DAs prefer to ensure that the treatment of PA is the most effective without considering the cost.

Definition 2.1. *The classic multiple shared decision-making problems (SDMPs) can be modeled as a MAS,* $(\mathcal{P}, \mathcal{D}, \mathcal{I})$.

$\mathcal{P}$ *is a set of* n *patient agents (PAs) representing patients. Each PA needs to propose some treatment requirements in order to negotiate with the DAs. It is noteworthy that the number of PAs in our set scene is one, that is,* n *equals one;*

$\mathcal{D}$ *is a set of* m *doctor agents (DAs) representing doctors. Each of those needs to respond to the requests of PAs and then negotiate with PAs. The value of* m *can be set as 1; and*

$\mathcal{I}$ *is a set of interrelations between the two classic agents. Each* $\mathcal{I}_{i,j}$ *specified the issues need be negotiated by* i^{th} *PA,* $\mathcal{P}_i$*, and* j^{th} *DA,* $\mathcal{D}_j$.

According to Definition 2.1, the SDMP is translated into a MAS, which is composed of one PA, many DAs, and the interrelations among them, as shown in Figure 2. Each PA is responsible for imposing time and priority constraints on the objective. These constraints further specify the negotiation time, deadline, and priority of each issue. Each DA is responsible for imposing capacity constraints, namely, value limits, which are specified by the treatment cost and clinical results. Then, SDMP can be expressed as DFCSP, which can make PA and DAs reach consensuses. The fuzzy constraints are used to model

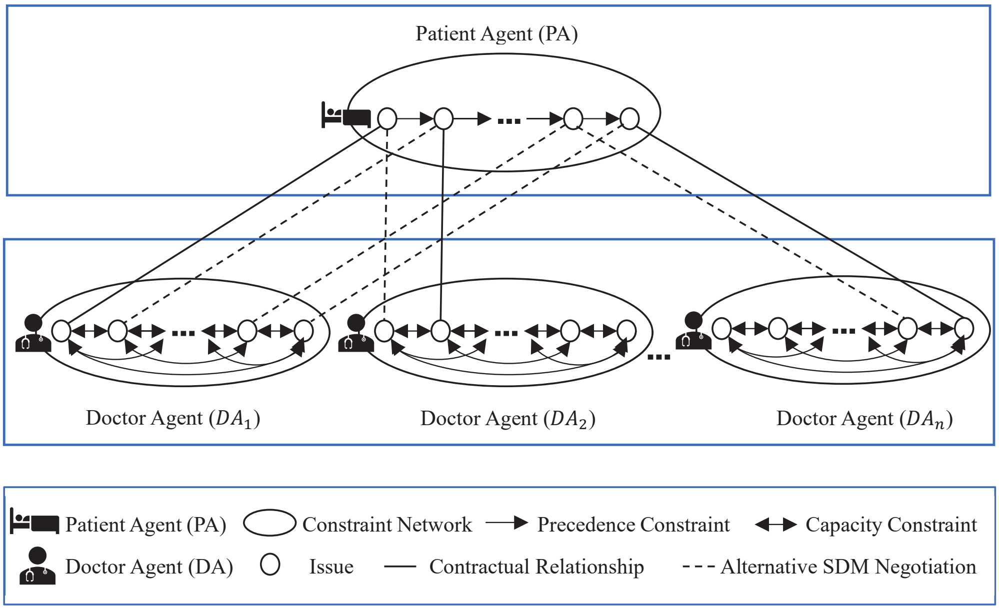

FIGURE 2. Shared decision-making with one PA and many DAs.

the objective of each agent, and the relationship between agents is regarded as the external constraints associated with each agent to determine whether the solutions satisfy all constraints in the DFCSP. A DFCSP can be expressed by a distributed fuzzy constraint network (DFCN) in which fuzzy relations for each agent and among agents are specified.

For a PA and m DAs, a DFCN $(U,\ X,\ C)$ for a SDMP is defined as a set of $1+m$ fuzzy constraint networks (FCNs) $\{N^1,\ N^2,\ ...,\ N^{1+m}\}$, where N^k is the FCN for agent $k\ \in\ (\mathcal{P},\mathcal{D})$.

Definition 2.2. *A DFCN $(U,\ X,\ C)$ in a SDM $(\mathcal{P},\mathcal{D},\mathcal{I})$ can be defined as a fuzzy constraint network (FCN) $N^k=(U^k,X^k,C^k)$, which is from agent k, where:*

U^k is the universe of discourse for FCN, N^k;

$X^k=(U_{i=1}^{n}X_i^k)$ is a tuple of n non-recurring objects; and

C^k is a set of fuzzy constraints in the FCN, which includes the internal constraints among objects in X^k and external constraints between agent and its opponent;

U is the universe of discourse for DFCN;

$X=(U_{k=1}^{K}X_l)$ is a tuple of all non-recurring objects; and

$C=(U_{k=1}^{K}C_l)$ is a set of all fuzzy constraints in the DFCN.

By Definition 2.2, the non-recurring object X^k represents attributes of agent k, for example, the beliefs, the environment cognition (e.g., the cognition of treatment deadline and medical resources). The fuzzy constraint set C^k of agent k consists of a set of internal fuzzy constraints among objects in X^k and a set of external fuzzy constraints between agent k and opponent agents. The internal fuzzy constraints involve priority constraints (e.g., the priority of issues), objective constraints (e.g., the desire for cost, effectiveness, and other objectives), etc. The external fuzzy constraints involve the relations and constraints of at least one object in X^k and another object not in X^k. The task of a DFCN in the SDM is to obtain a solution for X^k and FCN, which can be seen as intention Π_{N^k}, that is, Π_k. It expresses that the fuzzy set X^k of non-recurring objects satisfies all fuzzy constraints in C^k simultaneously.

3. **Negotiation-decision mechanism for the SDMP.** The fuzzy-based negotiation-decision mechanism is presented to solve the SDMPs. The mechanism consists of the negotiation model, the decision-making model, and the agent behavior model. They are described in Section 3.1, Section 3.2, and Section 3.3 separately. The negotiation model includes the specific behavior steps and the obeyed negotiation protocol of agents in the negotiation process. The decision-making model is utilized to assist PA and DAs in determining the final decision result, namely, the treatment plan. The behavioral models of an agent are illustrated to explain how the agent works to reach a consensus with its opponent agents.

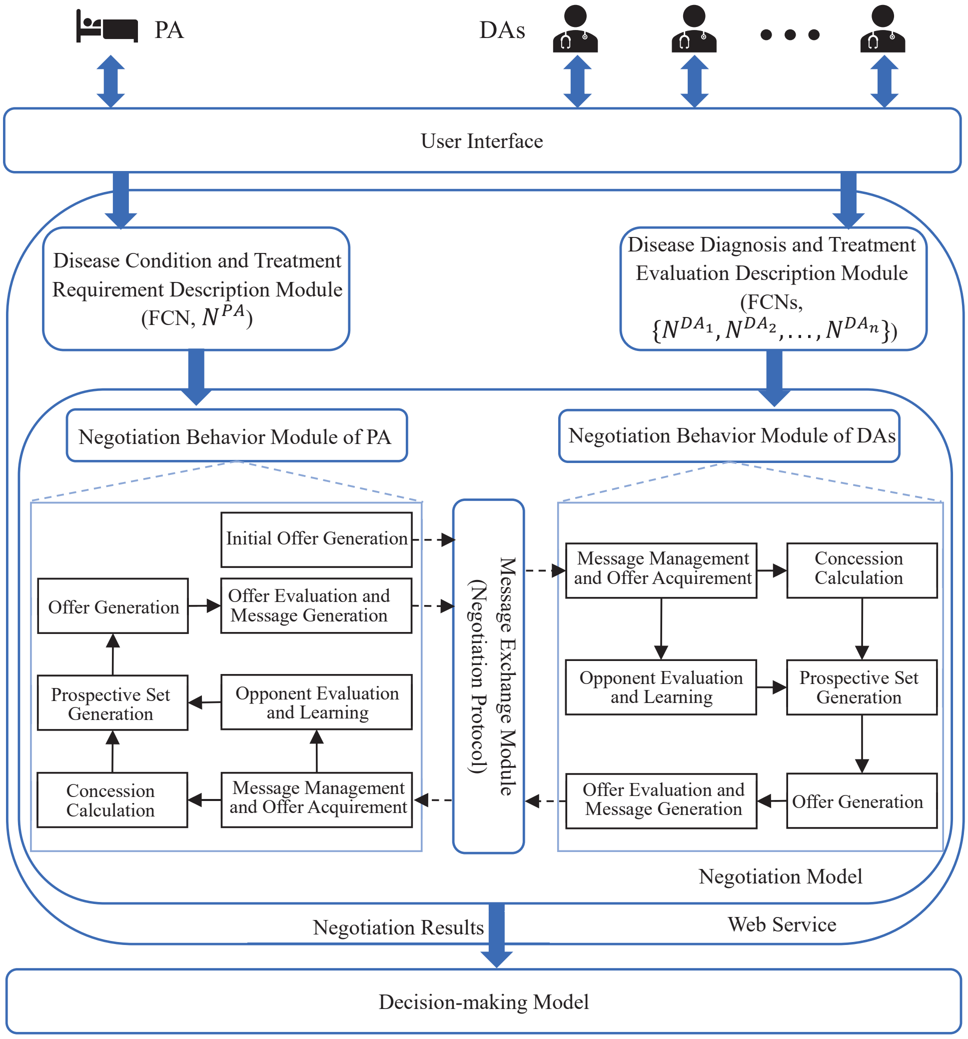

Figure 3. Negotiation model for SDM.

3.1. **Negotiation model.** The main contents of the negotiation model include the negotiation process and protocol, which describe in Sections 3.1.1 and 3.1.2, respectively. The negotiation process among PA and DAs is the exchange process of offer and counter-offer until an agreement is reached or no further offer/counter-offer is generated. The negotiation protocol defines the rules that agents obeyed and the type of message that agents sent. The negotiation model for SDM is shown in Figure 3.

3.1.1. *Negotiation process.* In the negotiation process, the negotiation steps of agents include opponent learning, concession evaluation, offer generation, and judgment of negotiation termination. Once received an offer from its opponent agent, the agent will learn the preference of the current opponent and evaluate the concession value in the next round. Based on the concession value, a new behavior state is determined, and a feasible set is generated. After that, a new offer or counter-offer is generated. Meanwhile, whether the negotiation is terminated will be judged to determine the type of message. These steps will be cycled until the agreement is reached or the negotiation is failed.

Assumed that a set of negotiation issues $I = \{I_1, I_2, \ldots, I_i, \ldots, I_n\}$ and a solution $S\epsilon\Pi_k$ is given, the aggregated satisfaction value (ASV) of agent k about S is:

$$\Psi(S) = \sum_{i=1}^{n} w_i * F_i(S) \tag{1}$$

Where $F_i(S)$ is the fuzzy membership function about issue I_i of S, which can be modeled by the formula (2) and represent the preferences for each issue flexibly and effectively. The main parameters can be obtained directly from the doctors and patients. Additionally, n is the total number of issues and w_i is the priority weight for issue I_i.

$$F_i(S) = \mu_i(x) = \begin{cases} 0, & \text{if } x \le a \\ 1 - \left(\frac{x-b}{b-a}\right)^2, & \text{if } a < x < b \\ 1, & \text{if } b \le x \le c \\ 1 - \left(\frac{x-c}{c-d}\right)^2, & \text{if } c < x < d \\ 0, & \text{if } x \ge d \end{cases} \tag{2}$$

Where, a is the smallest value of x which satisfies $x \le a$ and $\mu_i(a) = 0$, d is the largest value of x which satisfies $x \ge d$ and $\mu_i(d) = 0$. b and c is the interval boundary value of the most preferred value of variables and $\mu_i(b) = \mu_i(c) = 1$. The fuzzy membership function illustrated in Figure 4. Since the larger of the issue value, the higher of the satisfaction is when the issue value x changes in the range of a and b. Contrary to the situation in $[a, b]$, the satisfaction is decrease in the range of c and d. And the satisfaction of negotiated issue remains constant in $[b, c]$.

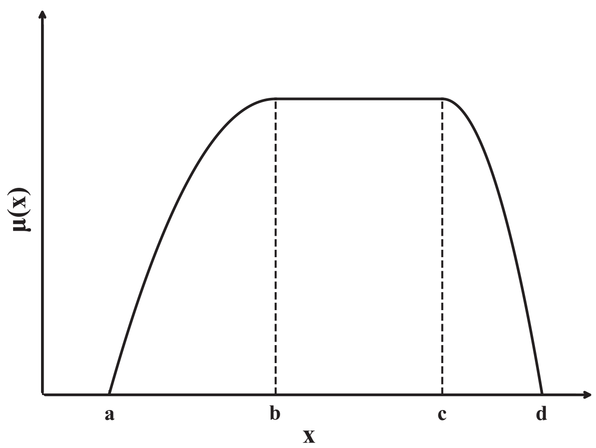

FIGURE 4. Illustration of membership functions.

Step 1: opponent learning

Since the preference of the opposing agent is unknown, the agent can build a linear function to fit it if the counter-offer received from the opponent can be differentiated. Thus, we suppose that the preference function of the current opposing agent $\bar{k}$ for the issue I_i can be represented as $F^{\bar{k}}{}_i\left(\bar{S}\right) = \mu^{\bar{k}}{}_i\left(x\right) = a*x+b$, where x is the value of counter-offer for i_{th} issue. Given the previous counter-offers $X = \{X_1, X_2, \ldots, X_j, \ldots, X_{r-1}\}, X_j = \{x_{j1}, x_{j2}, \ldots, x_{ji}, \ldots, x_{jn}\}$ of the opponent, as least two counter-offers, the parameters of the preference function of opponent about issue I_i at round r can be got by Least Squares Method as:

$$a = \frac{\sum_{j=1}^{r}\left(x_{ji} - \bar{x_i}\right)(\mu^{\bar{k}}{}_i\left(x_{ji}\right) - \overline{\mu^{\bar{k}}{}_i\left(x_i\right)})}{\sum_{j=1}^{r}\left(x_{ji} - \bar{x_i}\right)^2} \tag{3}$$

$$b = \overline{\mu^{\bar{k}}{}_i\left(x_i\right)} - a\bar{x_i} \tag{4}$$

Where r is the current negotiation round, x_{ji} is the value of issue I_i obtained from the counter-offer at round j, and $\mu^{\bar{k}}{}_i\left(x_{ji}\right)$ is the corresponding preference value, that is, satisfaction degree. In addition, $\bar{x_i}$ is the mean of x_{ji}, and $\overline{\mu^{\bar{k}}{}_i\left(x_i\right)}$ is the mean of $\mu^{\bar{k}}{}_i\left(x_{ji}\right)$.

Step 2: concession evaluation

The main purpose of negotiation is to move towards and explore the potential agreement in the common domain that agents are interested in. Thus, the agreement needs to satisfy the preference of negotiation parties as much as possible. For an agent, the mental state $\mathbf{M}$ reflects its own desires, and the external state reflects the constraints of the negotiation scenario, including the response state $\mathbf{R}$ and environment state $\mathbf{E}$. The response state reflects the intention of its opponent, and the environment state represents the constraints of the negotiation environment. Therefore, the agent can determine the value of the concession by evaluating the three states.

The mental state $\mathbf{M}$ includes a satisfaction level ρ and a tightness δ, which can be obtained by the offer A and the behavior state ε (that is, aggregated satisfaction threshold) in the last round, where:

$$\rho = \Psi(S^*) \tag{5}$$

$$\delta = 1 - (\rho - \varepsilon) \tag{6}$$

$\Psi\left(S^*\right)$ is the ASV of agent for $S^* \in \Pi$, S^* is the prospective solution of the agent in the last negotiation round.

The opponent responsive state $\mathbf{R} = \{\sigma\}$ is the difference degree between last offer A and most recently received counter-offer B, which can be calculated by:

$$\sigma = 1 - (G\left(A_0, B_0\right) - G\left(A, B\right))/G\left(A_0, B_0\right) \tag{7}$$

Where A_0 and B_0 is the first sent offer and received counter-offer. $G\left(A,\ B\right)$ is the distance measurement between offer A and counter-offer B on issue $I_i\epsilon X$. It can be defined as follows:

$$G\left(A, B\right) = \frac{\sqrt{\sum_{i=1}^{n} L(A_i, B_i)^2}}{n} \tag{8}$$

There A_i and B_i are the possibility distributions of offer A and counter-offer B on issue $I_i\epsilon I$, respectively.

Because, the major environmental constraints $\mathbf{E}$ of the PA and DAs in SDM are time constraints, so the constraints of time can be defined by the formula in [39] as:

$$\tau = \lambda + (1 - \lambda)\,(\frac{r}{r_{max}})^{\beta} \tag{9}$$

There, r is the current negotiation round, r_{max} is the deadline of negotiation, λ and β are constants, where $0 \leq \lambda \leq 1$ and $0 \leq \beta \leq 1$.

By formula (1)-(9), we can obtain the mental state $\mathbf{M} = \{\rho, \delta\}$ of the agent, the responsive state $\mathbf{R} = \{\sigma\}$ of the opponent agent and the environment state $\mathbf{E} = \{\tau\}$ of the negotiation scene. Thus, the concession value $\Delta\varepsilon$ of the agent can be defined as:

$$\Delta\varepsilon = (\mu_{\rho}\,(\rho)\ \Lambda\ \mu_{\delta}\,(\delta)\ \Lambda\ \mu_{\sigma}\,(\sigma)\ \Lambda\ \mu_{\tau}\,(\tau)\ )^{\omega} \tag{10}$$

Where $\mu_{\rho}(\rho)$, $\mu_{\delta}\,(\delta)$, $\mu_{\sigma}(\sigma)$, and $\mu_{\tau}\,(\tau)$ represent the desire for concession about the satisfaction level, degree of tightness, degree of difference, and time constraint, respectively. The parameter ω can be adopted to adjust the convergence speed of negotiation.

Finally, based on the concession value $\Delta\varepsilon$ and the last behavior state ε, the new behavior state ε^* of the agent is:

$$\varepsilon^* = \varepsilon - \Delta\varepsilon \tag{11}$$

Step 3: offer generation

Given the FCN N, intension Π, and a new behavior state ε^*, the feasible solutions P can be acquired by:

$$P = \Gamma(\Pi, \varepsilon^*) = \{S|(S\epsilon\Pi)\Lambda(\varepsilon \geq \Psi\,(S) \geq \varepsilon^*)\} \tag{12}$$

Where $\Psi\,(S)$ is the ASV of the agent about S. Suppose that counter-offer B and feasible solution P is known, the prospective solution S^* can be selected by follows:

$$S^* = arg(max_{S\in P}H(S,\ B)) \tag{13}$$

In the formula (13), the utility function $H(S,\ B)$ is used to evaluate the preference of feasible solution $S\epsilon P$, and the similarity of counter-offer B and feasible solution S. The calculation formula of it is:

$$H\,(S, B) = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(min(W_1(S_i)^{\omega_1} \wedge W_2(S_i, B_i)^{\omega_2})\right)^2} \tag{14}$$

$$W_2(S_i, B_i)\ =\ 1\ -\ D(\mu_i\,(S_i)\,,\ \mu^{\bar{K}}{}_i\,(B_i)) \tag{15}$$

There, W_1 and W_2 are the preference function and similarity function on issue I_i separately, and D is a distance measure function. In addition, ω_1 and ω_2 are the weights corresponding to the above two functions, which is also related to the negotiation strategy, defined as follows: i) Collaborative strategy: $\omega_1 < \omega_2$; ii) Win-Win strategy: $\omega_1 = \omega_2$; iii) Competitive strategy: $\omega_1 > \omega_2$, where $1 \geq \omega_1, \omega_2 \geq 0$.

The different negotiation strategies represent different negotiation attitudes of the agents. The most direct performance is the behavior of the agent when dealing with the offer of the opponent. If the agent adopts the collaborative strategy, the direct response to the opponent may be to make a concession. But if the agent adopts the competitive strategy, the direct response to the opponent may be to argue and not to compromise. The direct response of the agent who adopts a win-win strategy in dealing with the offer from its opponent is to try to find a solution that satisfies both its own interests and the opponent's desires.

Given feasible solution P and prospective solution S^*, the offers $A^* = \{A_1^*, A_2^*, \ldots A_i^*, \ldots, A_N^*\}$ over a set of issues $I \epsilon X$ can be generated by:

$$A^* = \wedge(P, S^*) \tag{16}$$

The element A_i^* in set A^* corresponds to the offer on issue $I_i \epsilon X$, and A_i^* is the marginal particularized possibility distribution of S_i^* in space X, which is defined as follows:

$$A_i^* = Proj_{X_q}(S^* \cap \bar{\Pi}_{X_1} \cap \bar{\Pi}_{X_2} \cap \ldots \cap \bar{\Pi}_{X_{i-1}} \cap \bar{\Pi}_{X_{i+1}} \cap \ldots \cap \bar{\Pi}_{X_{N_X}}) \tag{17}$$

Where $\bar{\Pi}_{X_i} = S_i^*$ is the cylindrical extension on space X, X_i is the object of issue I_i, and N_X is the number of negotiated objects.

Step 4: judgment on negotiation termination

Finally, judge whether the negotiation is terminated and determine the type of message. There are two states of negotiation termination, that is, success and failure. The judgment condition for a successful negotiation is the following:

$$\Psi(B) \geq \varepsilon^* \ and \ \Psi(S^*) \geq \varepsilon^* \tag{18}$$

and the judgment condition for negotiation failure is:

$$\varepsilon^* \leq 0 \ or \ P = \emptyset \tag{19}$$

If the ASV of the agent about the received counter-offer B is greater than or equal to the current aggregated satisfaction threshold ε^*, and the ASV of the next offer S^* is greater than or equal to the current aggregated satisfaction threshold ε^*, the negotiation is successful. Also, it indicates that the agreement is reached and the fuzzy constraint satisfaction problems (FCSPs) are solved. Otherwise, the negotiation fails because ε^* in the new round is less than or equal to zero, or the set of feasible solutions is empty.

3.1.2. *Negotiation protocol.* A negotiation protocol is presented to describe common rules and communication languages. It is mainly used to deal with the interactions between agents during the negotiation process. Concerning the different demands of DAs and PAs in the SDMP, various messages that DAs and PAs can send and receive in the process of negotiation are as follows:

Ask $((\mathcal{P}_i, \mathcal{D}_j), A_{i,j})$, PA send a message with an offer A to DA for asking;

Agree $((\mathcal{P}_i, \mathcal{D}_j), B_{i,j})$, PA agrees the counter-offer B form a DA and send an ***Agree*** () message to the DA;

Accept $((\mathcal{P}_i, \mathcal{D}_j), B_{i,j})$, PA send a message to DA to accept the counter-offer B;

Reject $((\mathcal{P}_i, \mathcal{D}_j), \emptyset)$, PA send a ***Reject*** () message to DA to reject reach an agreement with the opponent;

Tell $((\mathcal{D}_j, \mathcal{P}_i), B_{j,i})$, DA send a message with a counter-offer B to PA for telling;

Agree $((\mathcal{D}_j, \mathcal{P}_i), A_{j,i})$, DA agrees the offer A from PA and send an ***Agree*** () message to the PA;

Abort $((\mathcal{P}_i, \mathcal{D}_j), \ \emptyset)$ or ***Abort*** $((\mathcal{D}_j, \mathcal{P}_i), \ \emptyset)$, for some reason, the agent aborts the negotiation with an empty offer.

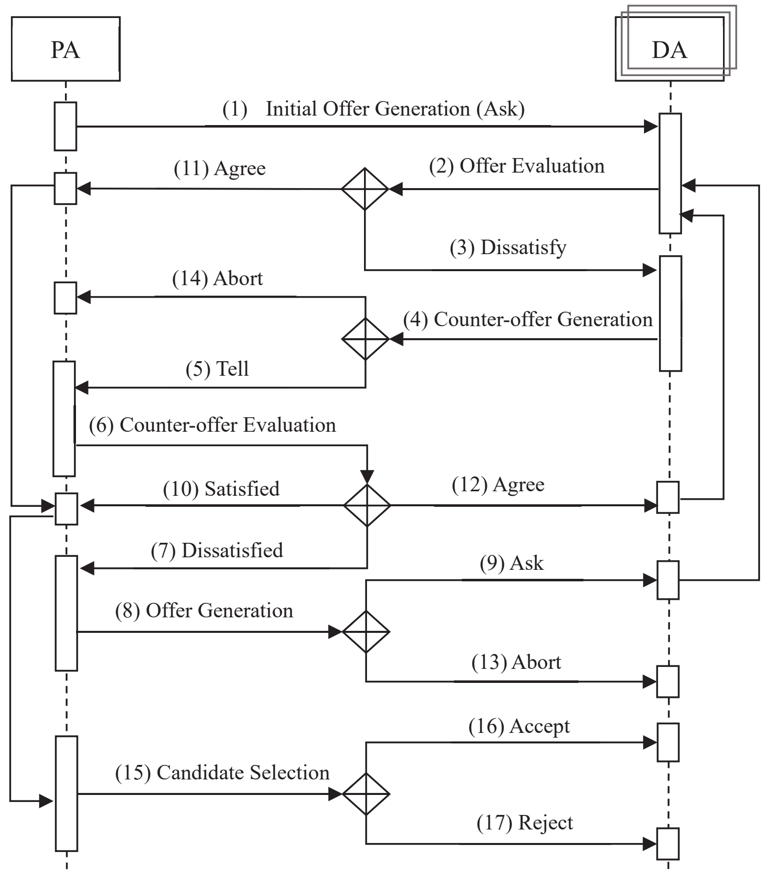

Figure 5. Negotiation protocol among one PA and many DAs.

Figure 5 illustrates the negotiation process among one PA and multiple DAs. At first, PA will send the ***Ask*** () message to all DAs with the initial offer of issues to start the negotiation. After that, DA will evaluate the offer received (step 2) using Eq. (18) and Eq. (19) to choose the next action. If the offer satisfies the constraints of DA, the ***Agree*** () message will be sent in step 11. If it does not satisfy the constraints, step 3 is executed, and a counter-offer is generated by Eq. (1)-(17) in step 4. Then, the basic preferences and beliefs of each issue decide whether the DA is able to respond to the PA. If the response can be done, a ***Tell*** () message with a counter-offer will be sent to the PA (step 5). Otherwise, there is no feasible solution existing and counter-offer generating, an ***Abort*** () message will be sent in step 14, which also means that the agent will withdraw from the negotiation process.

When PA receives a ***Tell*** () message from a DA, the carried counter-offer is evaluated (step 6) to determine whether the offer satisfy the requirement. If the counter-offer satisfy the requirements of issues, a ***Agree*** () will be sent (step 12) and the DA will become a candidate (step 10). Conversely, if the requirements cannot be satisfied, an ***Ask*** () message with a new offer will be generated (step 8 and 9) when the requirements of the issues adjusted based on Eq. (1) through Eq. (17). As shown in steps 2 through 9, the iterative exchange of offer and counter-offer among PA and DAs finished. Besides, the DA is also selected to be one of the candidates when PA received an ***Agree*** () message from DA. Next, the negotiation will be repeated according to the above steps until all DAs are the candidates or time is out. Finally, PA will select the best DA in the candidate DAs set in step 15 and send the ***Accept*** () message to it and the ***Reject*** () messages to other DAs.

The negotiation terminated successfully if PA has reached a consensus with all DAs, or the time is out and the candidates are not empty. However, if PA withdraws from the negotiation with all DAs or all DAs withdraw from the negotiation with PA, the state of negotiation is a failure. In addition, the negotiation terminated in a failure state if the negotiation time out and there no candidates existed.

3.2. **Decision-making model.** The ultimate purpose of SDM is to make the treatment as effective as possible for patients. Thus, the decision-making model is needed for PA to select the "best" treatment plan and the "optimal" opponent after negotiating with all opponents, DAs. In this section, we define the process of decision-making that can achieve the above goals based on the medical guidelines. First, the negotiation results should be transformed into treatment plans after the PA negotiating with all the DAs. And then, the "optimal" treatment plan will be selected according to some rules. Significantly, the "optimal" treatment plan is one in the medical guideline that most conform to patient's disease condition and negotiation results. As shown in Figure 6, the decision-making model is described.

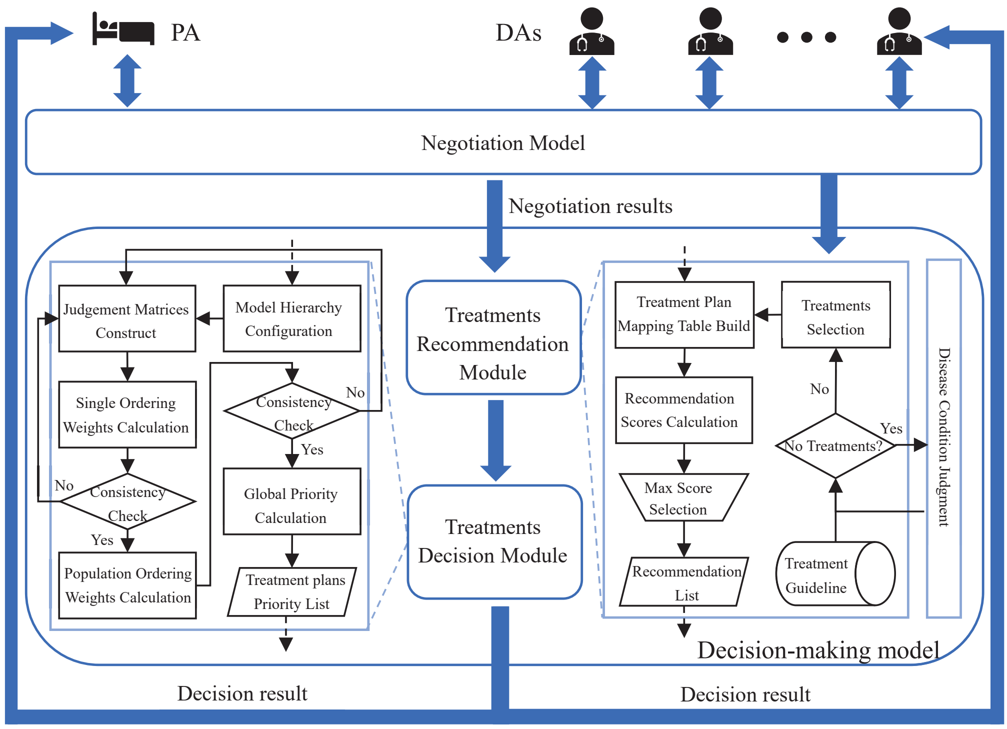

FIGURE 6. Decision-making model for SDM.

The presented decision-making model mainly includes two parts: the treatment recommendation module and the treatment decision-making module. The treatment recommendation module can transform the negotiation results of PA and DAs into the actual treatment plans by calculating recommendation scores based on the treatment plan mapping table, namely the treatment plan evaluation table. The treatment decision-making module can help PA make decisions using the analytic hierarchy process (AHP), which is a combination of qualitative and quantitative decision-analysis methods.

Step 1: treatment plans recommendation

According to the disease condition of the patient and the treatment guideline, alternative treatment plans can be selected, and then the treatment plans evaluation table will be built. Assume that PA and DA agree on the value of each issue. Then, based on the treatment plans evaluation table, we will calculate the recommendation scores for each agreement with the treatment plans selected from the treatment guidelines. The score is calculated as follows:

$$\Phi(S) = \sum_{i=1}^{n} w_i * R_i(S_i) \tag{20}$$

Where the w_i is the weight factor of relevant issues, S_i is the value of i_{th} issue in solution S, and R_i is the recommendation function that can forge links between negotiation result and treatment plans. In order to more clearly formulate, set $S_i = x$, thus the recommendation function $R(S_i)$ can be described as:

If $T_i = y$ is an accurate number, the recommendation function is the similarity function between two accurate number, that is,

$$R(S_i) = Sim(S_i, T_i) = 1 - \frac{|x-y|}{|b-a|}, x, y \in [a, b] \tag{21}$$

Else if $T_i = [\alpha, \beta]$ is an interval number, the recommendation function is the similarity function between an accurate number and an interval number, that is,

$$R(S_i) = Sim(S_i, T_i) = \frac{\int_{\alpha}^{\beta} exp - |x-u| du}{\beta - \alpha} = \begin{cases} \frac{exp(x-\alpha) - exp(x-\beta)}{\beta-\alpha}, & \text{if } x < \alpha \\ \frac{2 - exp(\alpha - x) - exp(x-\beta)}{\beta-\alpha}, & \text{if } \alpha \leq x \leq \beta \\ \frac{exp(\beta - x) - exp(\alpha - x)}{\beta-\alpha}, & \text{if } x > \beta \end{cases} \tag{22}$$

Where x, y, α, $\beta \in [a, b]$, a and b is the minimum value and maximum value of i_{th} issue. T_i is the value of i_{th} issue in the treatment plan T, which is obtained based on the treatment plans evaluation table given by some professional doctors.

Step 2: decision-making of the treatment plan

According to formula (20), the recommendation scores of all consensuses reached by the PA and DAs will be calculated, that is, the recommendation scores of all optional treatment plans of each DA will be obtained. After that, the treatment plan with the highest score will be recommended by each DA. Eventually, the PA needs to choose the "best" treatment plan from these recommendations, that is, makes decisions that finally satisfy the preference of the PA. For this question, the AHP method is used to help PA make decisions. It can decompose complex multi-criteria or multi-factor decision problems into a hierarchical structure [40, 41]. The AHP of the selection of the "best" treatment plan involves four steps; these steps are as follows:

a. The decision-making problem is decomposed into a hierarchical structure composed of multiple decision elements, including objectives, factors and treatment plans.

b. According to the characteristics of decision elements, the method of pairwise comparison is used to judge the relative importance of elements and construct the judgment matrices. In addition, the pairwise comparison method is calculated based on the 1-9 scale (see Table 1) proposed by Santy et. al. [41].

c. Executing the hierarchical single ranking and calculating the relative weight of the lower-level factors to the upper-level factors. In this process, it is necessary to check the consistency of each weight vector.

Table 1. Pairwise comparison scale for preference.

Scale	Definition and Description
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	Intermediate important

The consistency check is an operation to eliminate possible logical errors in the construction of the judgment matrices and check the coordination between the importance of each element. The index of consistency is the consistency ratio (C.R.), the smaller the value of C.R., the closer the judgment matrix is to complete consistency, and the final weight meets the decision requirements. The definition of C.R. is shown:

$$C.R. \;=\; \frac{C.I.}{R.I.}, \;\; C.I. \;=\; \frac{\lambda_{max} - n}{n-1} \tag{23}$$

Where, R.I. is the random consistency index and obtained from Table 2. N is the number of elements, that is, the dimension of the judgment matrix, and λ_{Max} is the largest eigenvalue of the judgment matrices obtained by the judgment matrices and relative weights.

Table 2. The value of average random consistency index RI.

n	1	2	3	4	5	6	7	8	9	10
R.I.	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

If C.R. is 0.1 or less, the estimation is accepted. Otherwise, a new judgment matrix is constructed until the condition of C.R. is satisfied.

d. Executing the hierarchical whole ranking and calculating the overall recommendation score $W(T)$ of each treatment plan based on the relative weight of the hierarchical single ranking. Finally, the "best" treatment plan with the maximum score or weight W_T is selected and the criterion of the selection is:

$$W(T) = \frac{f_i \;\; * w_{T_i}}{\sum_{i=1}^{m} f_i \;\; * w_{T_i}} \tag{24}$$

Where,f_i is the recommended times of the i th treatment plan, w_{T_i} is the total weight of each level element corresponding to the treatment plan, and m is the number of treatment plans. The larger the value $W(T)$, the more the treatment plan conforms to the agent's preference.

3.3. **Agent behavioral model.** Originally, a PA starts the negotiation by proposing its ideal solution to the issues to all DAs. Afterward, the PA and DAs will follow a certain behavior model, described below, to interact and reach agreements. The interaction among PA and DAs is the exchange of an offer and counter-offer about the values of issues.

3.3.1. *PA behavior.* Algorithm 1 describes the behavior of the i_{th} PA, $\mathcal{P}_i$, when it interacting with the corresponding DAs, $\mathcal{D}$, to deal with the treatment issues. Initially, $\mathcal{P}_i$ proposes its prospective solution $\mathbf{S}_i^*$ using Eq. (13) and generates the initial offers using Eq. (16) to all DAs. Then, the initial offers will be transformed into ***Ask*** () messages and sent to all DAs. Next, PA needs to select certain and specified actions in order to respond to the corresponding DAs after receiving messages from these DAs. These actions to respond to DAs will be repeated until the negotiation is terminated.

If the messages received from DAs are all ***Abort*** (), which means that all DAs withdraw from the negotiation with the PA, then the negotiation among the i_{th} PA, $\mathcal{P}_i$ and DAs, $\mathcal{D}$ are terminated in a failure state (in lines 8 and 9). Otherwise, PA will adjust its feasible solutions according to Eq. (12) and based on the new behavioral state ε^* (in lines 11 and 12). For each DA, $\mathcal{D}_j$, it will be judged whether reaches a consensus with the PA, either the ***Agree*** () message is generated by PA or sent by DA, if the consensus reached, the counter-offer $B_{j,i}$ will be added to the candidate set (in lines 14 to 19). Otherwise, generating the offers using Eq. (16) based on every counter-offer $B_{j,i}$ in $\mathbf{B}_i$ that received from the corresponding DAs (in lines 21 and 22). Next, determine whether each generated offer $A_{i,j}^*$ in the $\mathbf{A}_i^*$ is empty, and send ***Abort*** () message to corresponding DA (in line 25), otherwise ***Ask*** () message with new offer $A_{i,j}^*$ is sent (in line 24). Of course, the negotiation will be failed when PA quit the negotiations with all DAs.

PA, $\mathcal{P}_i$ continues negotiate with the DAs until it reaches a consensus with all DAs or timeout occurs. If one of the above two conditions is satisfied, the best counter-offer $B_{j\prime,i}$ is selected from the candidate counter-offers set $\mathbf{B}_i^*$ based on the decision-making model. Thus, an agreement is reached, and the ***Accept*** () message is generated and sent to the corresponding DA, and ***Reject*** () messages are sent to the others DAs (in lines 30 to 36). Finally, the negotiation is terminated in a success state, because PA has reached a satisfactory agreement with a DA.

Algorithm 1 Behavior of PA

1: Procedure Patient Agent ($\mathcal{P}_i$)
2: state $\leftarrow$ "*normal*"
3: activate Timer $\mathcal{T}_i$
4: Generate initial offers $\mathbf{A}_i$ for each opposing Doctor Agent $\mathcal{D}_j \in \hat{\mathcal{P}}_i$
5: $\forall A_{i,j} \in \mathbf{A}_i$, send $M_{i,j}$ = "***Ask*** $((\mathcal{P}_i, \mathcal{D}_j), A_{i,j})$"
6: **repeat**
7:     Receive $\hat{\mathbf{M}}_\mathbf{i} = \{\hat{M}_{j,i} | \hat{M}_{j,i}=$"***Tell*** $((\mathcal{D}_j, \mathcal{P}_i), B_{j,i})$" or "***Agree*** $((\mathcal{D}_j, \mathcal{P}_i), B_{j,i})$" or "***Abort*** $((\mathcal{D}_j, \mathcal{P}_i), \emptyset)$", $\mathcal{D}_j \in \hat{\mathcal{P}}_i\}$
8:     **if** $\forall \hat{M}_{j,i} \in \hat{\mathbf{M}}_\mathbf{i}, (\hat{M}_{j,i}$ is "***Abort***") **then**
9:         state $\leftarrow$ "*failure*"
10:     **else**
11:         Get counter-offer set $\mathbf{B}_i$ from ***Tell*** message
12:         Generate new feasible solution set P_i
13:         **for** each $\mathcal{D}_j \in \hat{\mathcal{P}}_i$ **do**
14:             **if** $\mathcal{P}_i$ and $\mathcal{D}_j$ reach a consensus **then**
15:                 **if** $\mathcal{P}_i$ reach a consensus with $\mathcal{D}_j$ about counter-offer $B_{j,i}$ **then**
16:                     Send = "***Agree*** $((\mathcal{P}_i, \mathcal{D}_j), B_{j,i})$"
17:                 **end if**
18:                 Remove $B_{j,i}$ from $\mathbf{B}_i$ and add it to candidate set $\mathbf{B}_i^*$
19:             **end if**
20:         **end for**

if $(\exists \mathcal{D}_j \in \hat{\mathcal{P}}_i, \mathcal{P}_i$ and $\mathcal{D}_j$ not reach a consensus) and (Timer $\mathcal{T}_i$ is counting) **then**
Generate offers $\mathbf{A}_i^*$ for each $B_{j,i}$ in $\mathbf{B}_i$
for each $A_{i,j}^* \in \mathbf{A}_i^*$ **do**
if $(A_{i,j}^* \neq \emptyset)$ **then** Send = "***Ask*** $((\mathcal{P}_i, \mathcal{D}_j), A_{i,j}^*)$"
if $(A_{i,j}^* = \emptyset)$ **then** Send = "***Abort*** $(((\mathcal{P}_i, \mathcal{D}_j)), \emptyset)$"
end for
if $\forall \mathcal{D}_j \in \hat{\mathcal{P}}_i, (\hat{M}_{j,i}$ is "***Abort***") or $(M_{i,j}$ is "***Abort***") **then**
state $\leftarrow$ "*failure*"
end if
else Timer $\mathcal{T}_i$ is timeout or $\mathcal{P}_i$ reaches a consensus with all $\mathcal{D}_j$ **then**
Select the best counter-offer $B_{j\prime,i} \in \mathbf{B}_i^*$ based on the "**Decision-Making Model**"
Generate agreement S_i^* according to $B_{j\prime,i}$
Send $M_{i,j\prime}$ = "***Accept*** $((\mathcal{P}_i, \mathcal{D}_{j\prime}), S_i^*)$"
$\forall B_{j,i} \in \mathbf{B}_i^*,\ j \neq j\prime$, send $M_{i,j}$ = "***Reject*** $((\mathcal{P}_i, \mathcal{D}_j), \emptyset)$"
state $\leftarrow$ "*success*"
end if
end if
until state is "*success*" or "*failure*"

3.3.2. *DA behavior.* Algorithm 2 describes the behavior of a DA $\mathcal{D}_j$ when contracting to issues with the related PA $\mathcal{P}_i$. The negotiation of DA will begin when it received message from the PA. If all messages received from the PA are ***Abort*** () or ***Reject*** (), the negotiation is failed for this DA (in lines 4 and 5). If the message received from the PA is ***Accept*** (), the negotiation with this PA is in the state of success (in lines 6 and 7).

Otherwise, the feasible solutions will be generated according to the new behavior state ε^* of itself (in lines 9 and 10). The new behavior state ε^* is determined by the use of Eq. (1) through Eq. (11). Then, if DA reaches a consensus with the PA, the ***Agree*** () message with an agreement S_j^* is sent (in lines 11 to 13). Otherwise, the new counter-offers $\mathbf{B}_j^*$ for each received offer $A_{i,j} \in \mathbf{A}_j$ is generated (in line 15). By judging whether each counter-offer $B_{j,i}^*$ in the $\mathbf{B}_j^*$ is empty or not, the accordingly messages are generated and sent. If the new counter-offer $B_{j,i}^*$ is none, an ***Abort*** () message is sent, otherwise, a ***Tell*** () message with the counter-offer is generated and sent (in lines 16 to 19).

Algorithm 2 Behavior of DA

1: **Procedure** Doctor Agent $(\mathcal{D}_j)$
2: **repeat**
3: Receive $\hat{\mathbf{M}}_j = \{\hat{M}_{i,j} | \hat{M}_{i,j} =$ "***Ask*** $((\mathcal{P}_i, \mathcal{D}_j), A_{i,j})$" or "***Agree*** $((\mathcal{P}_i, \mathcal{D}_j), A_{i,j})$" or "***Abort*** $((\mathcal{P}_i, \mathcal{D}_j),\ \emptyset)$" or "***Accept*** $((\mathcal{P}_i, \mathcal{D}_j), A_{i,j})$" or "***Reject*** $((\mathcal{P}_i, \mathcal{D}_j),\ \emptyset)$", $\mathcal{D}_j \in \hat{\mathcal{P}}_i\}$
4: **if** $\hat{M}_{i,j} \in \hat{\mathbf{M}}_j$, $(\hat{M}_{i,j}$ is "***Abort***") or $(\hat{M}_{i,j}$ is "***Reject***") **then**
5: state $\leftarrow$ "*failure*"
6: **else if** $\hat{M}_{i,j} \in \hat{\mathbf{M}}_j$, $(\hat{M}_{i,j}$ is "***Accept***") **then**
7: state $\leftarrow$ "*success*"
8: **else**
9: Get the offer set $\mathbf{A}_j$ from ***Ask*** message
10: Generate new feasible solution set P_j
11: **if** $\mathcal{P}_i \in \hat{\mathcal{D}}_j$, $\mathcal{D}_j$ and $\mathcal{P}_i$ have reached a consensus **then**
12: Generate agreement S_j^* according to $\mathbf{A}_j$
13: $A_{i,j} \in \mathbf{A}_j^*$, send $M_{j,i}$ = "***Agree*** $((\mathcal{D}_j, \mathcal{P}_i), S_j^*)$"

else
Generate counter-offer $\mathbf{B}_j^*$ for $A_{i,j} \in \mathbf{A}_j$
for $B_{j,i}^* \in \mathbf{B}_j^*$ **do**
if $(B_{j,i}^* \neq \emptyset)$ **then** send $M_{j,i}$ = "***Tell*** $((\mathcal{D}_j, \mathcal{P}_i), B_{j,i}^*)$"
if $(B_{j,i}^* = \emptyset)$ **then** send $M_{j,i}$ = "***Abort*** $((\mathcal{D}_j, \mathcal{P}_i), \emptyset)$"
end for
end if
end if
until state is "*success*" or "*failure*"

4. **Experimental results.** To explain the operation process of our presented negotiation and decision-making mechanism and exhibit its practicality, we have generated an example of childhood asthma SDM for evaluation. In this instance, assume that there are one PA and many DAs representing one patient and many doctors, respectively. Such a scenario is typical of incomplete information and a semi-competitive environment. That is, all parties in the negotiation attempt to share more information, but they cannot do it, and their opponents cannot fully understand it. They try to acquire the best deal, but conflicts of interest and time often arise.

4.1. **Experimental settings.** The negotiation issues related to the treatment of childhood asthma including cost, effectiveness, side-effects, risk, and convenience [35]. We define the ranges of issues value as following:

Cost (in thousand RMB): min = 0, max = 8; Effectiveness (in rank): min = 1, max = 10; Side-effects (in percentage): min = 0, max = 100; Risk (in percentage): min = 0, max = 100; Convenience (in rank): min = 1, max = 10.

The value range of each issue is defined based on the suggestions of doctors and the analysis of treatments. The value range of issue only limits the scope of discussed problem and does not affect the evaluation index. All preferences of patient and doctors related to the experiment were obtained through questionnaires. These preferences are personalized, which is also the necessary of the discussed problem in this paper. Although these preferences are personalized, the proposed method in this paper is adaptive. That is, the set-up of personalized preferences will not affect the evaluation of the model. In addition, the maximum negotiation round of negotiation is set at 15. If the negotiation round exceeds the setting, the negotiation is terminated. The values of parameters λ and β in Eq. 9 are set as 0.1 and 0.25 respectively, which consist with the relevant comparison model.

4.2. **Negotiation performance comparisons.** The SDMP is a comprehensive problem that requires PAs and DAs to weigh the values of negotiation issues, and it does not need to give the optimal solution to a certain issue. Thus, we can evaluate the performance of our negotiation model by the running time, negotiation round, the combined ASV, and the final ASV of PA. By varying the number of DAs from 2 to 10, the performance of our negotiation model with three different strategies (that is, collaborative, win-win, and competitive) are compared with the classic and related model, namely the time-consider negotiation model proposed by Zulkernine et al [39], expressed as Time model ($\lambda = 0.1, \beta = 0.25$). The parameters of the Time model are set based on the common phenomenon that participants may make larger concessions when the negotiation round is more than half. In addition, the parameters ω_1 and ω_2 are set to (i) collaborative strategy, when $\omega_1 = 0$ and $\omega_2 = 1$; (ii) win-win strategy, when $\omega_1 = \omega_2 = 1$; (iii) competitive strategy, when $\omega_1 = 1$ and $\omega_2 = 0$. In addition, all results are the average values obtained after repeating the experiment 200 times.

When the number of DAs increases, the change of negotiation run time (in seconds) and negotiation rounds are shown in Figure 7 and Figure 8, respectively. From Figure 7, the negotiation run time increases with increasing DA number. Compared to Time, the FCAN needs more run time because it needs to explore more solution space. For FCAN, a competitive strategy needs more run time than the other strategies. However, the run time is counted in seconds; the negotiation of FCAN is still fast compared to human-based negotiation. Figure 8 shows the speed of convergence of negotiation among PA and DAs. The negotiation rounds increase when the number of DAs is increasing for all methods. Compared with Time, our negotiation model FCAN takes fewer negotiation rounds, no matter which negotiation strategy is used. The number of negotiation rounds required for the competitive strategy is greater than that required for the win-win strategy, and the number of negotiation rounds needed for the collaborative strategy is the lowest.

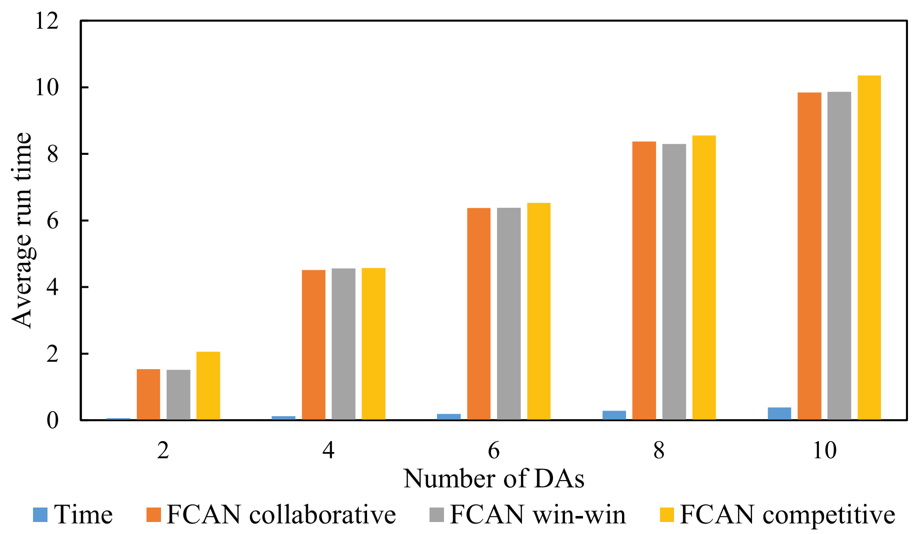

FIGURE 7. Performance comparisons in terms of run time in second.

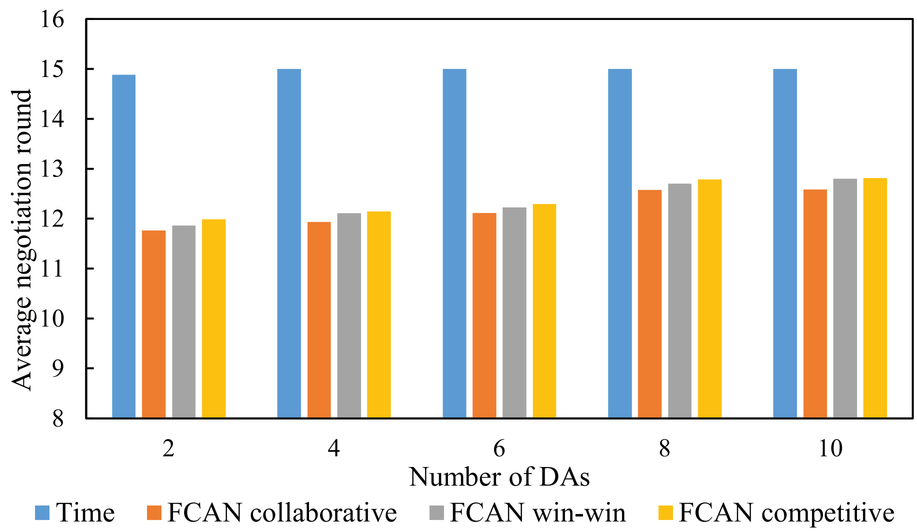

FIGURE 8. Performance comparisons in terms of negotiation round.

Figure 9 shows the average combined ASV of successful negotiations when the number of DA increases from 2 to 10 and the number of PA is fixed at 1. The maximum combined

ASV is 2 (that is, the maximum ASV of PA is 1, and the maximum ASV of DA is 1). The higher the combined ASV, the more likely the final negotiation is that the parties are satisfied. From this table, the changing trend of the combined ASV is not fixed, which means that with increasing DA numbers, combined ASV may rise or fall. Because it is not clear to what extent the PA will reach an agreement with the new rival DAs. However, regardless of the type of strategy used by FCAN, it can be observed that the FCAN model obtains a higher combined ASV than the Time model. In addition, the combined ASV of FCAN with competitive strategy or win-win strategy is higher than the FCAN with collaborative strategy. When the numbers of DAs are small, the FCAN with a competitive strategy achieves the best performance in terms of the combined ASV. Instead, as the number of DAs increases, the FCAN with a win-win strategy outperforms other strategies. Combined with Figure 8 and Figure 9, it can be concluded that the FCAN with a win-win strategy tends to balance the benefits for both sides when the number of DA increases as it achieves a higher combined ASV with the lower number of negotiation rounds.

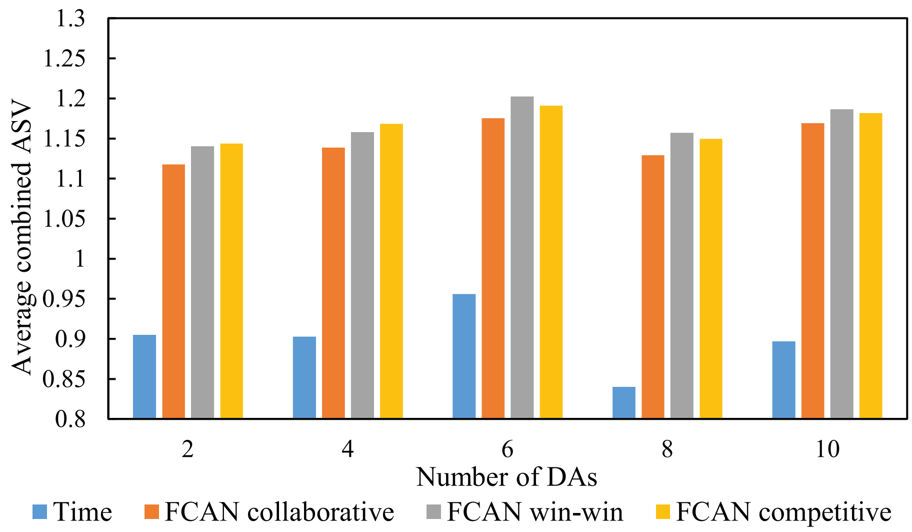

FIGURE 9. Performance comparisons in terms of combined ASV.

In addition, assuming that there is no decision-making model, we can evaluate the performance of the negotiation model simply with the final satisfaction of PA. Figure 10 shows the final ASV of PA if the satisfaction of PA is the selection condition. It can be observed that the overall trend of the final ASV of PA increases as the number of DA increases. The FCAN model can make PA obtain higher ASV compared with the Time model. The PA will get the higher ASV if it uses the FCAN model with a competitive strategy for negotiation, and the lower ASV is obtained if PA uses the FCAN model with a collaborative strategy for negotiation. The conclusion is logical and practical, which also shows the feasibility of our negotiation model.

4.3. **Decision-making for treatment.** In order to describe the process and functions of our presented decision-making model in detail, this section proposes an instance to explain. We consider a real SDM scenario consisting of one patient and five doctors, that is, one PA and five DAs. The requirement of this clinical decision-making scene is that PA obtains a satisfactory treatment plan after negotiating with all DAs. Assume that the patient is a 9-year-old child whose asthma severity reached grade 4. In the negotiation process, the preferences of PA and DAs are often different, including the value of issues

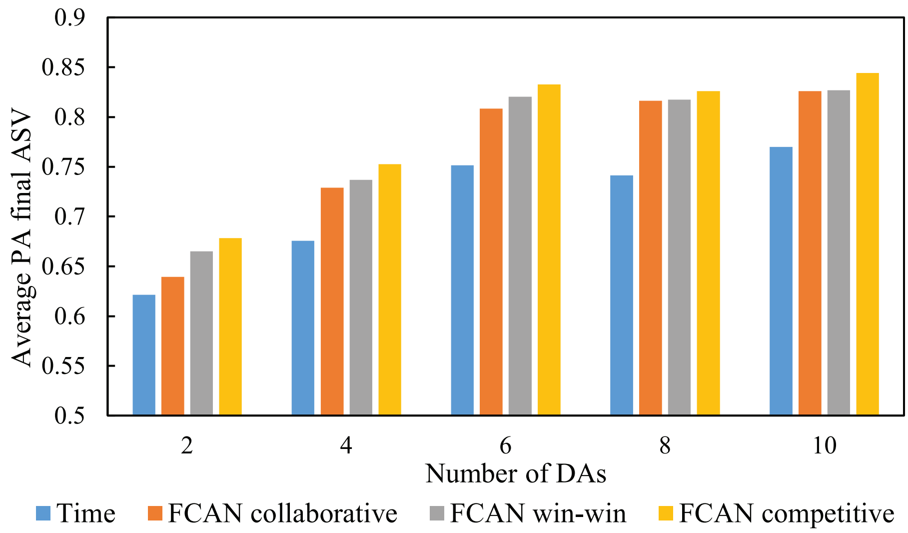

Figure 10. Performance comparisons in terms of PA final ASV.

and the priority of issues. What needs to be explained is that the issue preferences of PA on treatment are given based on the personal circumstances, the issue preferences of DA on treatment are given based on professional knowledge. The preferences for negotiation issues of one PA and five DAs are listed in Table 3 and Table 4

Table 3. The preference of issues value of all parties.

Parties \ Issue	Cost	Effective	Side-effect	Risk	Convenience
PA	[0,1,3,5]	[8,9,10,10]	[1,3,4,6]	[0,0.2,0.5,1.5]	[8,9,10,10]
DA1	[3,4.5,5,5.5]	[6,7,8,9]	[0,1,1.5,2]	[0,2,2.5,3]	[7,7,8,10]
DA2	[4,5,6.5,7]	[6,6,7,9]	[0,1,2,3]	[1,2,2.5,3]	[6,7,8,9]
DA3	[3,4.2,5,5.7]	[4,5,6,9]	[5,6,9,10]	[0,1.5,2,2.5]	[5,6,7,9]
DA4	[3.5,6,7.5,8]	[6,7,8,10]	[4,5.5,6,7]	[0.5,1.5,2,2.5]	[5,6,7,9]
DA5	[3.5,5,6,6.5]	[7,7,8,9]	[5,6,8,9]	[1,1.5,2,3]	[6,6,7,10]

Table 4. The preference of issues weight of all parties.

Parties \ Issue	Cost	Effective	Side-effect	Risk	Convenience
PA	0.3	0.25	0.15	0.2	0.1
DA1	0.25	0.3	0.2	0.15	0.1
DA2	0.23	0.3	0.27	0.15	0.05
DA3	0.1	0.4	0.2	0.2	0.1
DA4	0.3	0.3	0.15	0.15	0.1
DA5	0.15	0.3	0.25	0.2	0.1

The performance of our negotiation model is demonstrated in Section 4.2. Thus, PA can negotiate with DAs effectively based on the given negotiation model. Assuming that the negotiation strategies adopted by PA and DAs are win-win, PA can reach agreements

Table 5. Negotiation results for PA and different DAs.

Opponents \ Issue	Cost (k)	Effective	Side-effect	Risk	Convenience
DA1	3.57	8	1.81	0.92	9
DA2	4.41	9	1.59	1.21	9
DA3	4.26	9	5.41	1.21	9
DA4	4.25	9	5.1	1.12	9
DA5	3.94	8	5.29	2.71	9

with all DAs after full and efficient negotiation, the negotiation results are shown in Table 5.

Although PA has reached an agreement with all DAs through negotiation, it is not the ultimate goal of SDM in the given clinical environments. The purpose of SDM is to enable the patient to obtain effective treatment plans, and it also needs to conform with the preference of patients and doctors. Therefore, it is necessary to use our decision-making model to help the patient and doctors make a treatment decision. The details of the optional treatment plans according to the condition of the patient in the treatment guidelines [42] are shown in Table 6. Based on the first step in the decision-making model and the content of Table 6, the treatment recommendation list is: [DA1: "En-High Dose ICS/LABA", DA2: "En-High Dose ICS/LABA + Sustained-Release THP", DA3: "En-High Dose ICS/LABA", DA4: "En-High Dose ICS/LABA + Sustained-Release THP", DA5: "En-High Dose ICS/LABA + Sustained-Release THP"], and the recommendation scores of it are: [0.6068, 0.6298, 0.6116, 0.4867, 0.6220].

Table 6. The evaluation values of treatment plans according to the negotiation issues.

Treatments \ Issue	Cost	Effective	Side-effect	Risk	Convenience
En-High Dose ICS/LABA [1]	2.7-4.5 (3.6)	8-9 (8.5)	1-1.5 (1.25)	1-2 (1.5)	9.5-10 (9.75)
En-High Dose ICS [2]+ LTRA [3]	4.3-6.5 (5.4)	7-8 (7.5)	2-3 (2.5)	1.5-2.5 (2)	9-9.5 (9.25)
En-High Dose ICS + Sustained-Release THP [4]	2-4.2 (3.1)	6-7 (6.5)	6-10 (8)	2-2.5 (2.25)	8-8.5 (8.25)
En-High Dose ICS/LABA + LTRA	5.7-7.3 (6.5)	9-10 (9.5)	5-6 (5.5)	1-1 (1)	7.5-8 (7.75)
En-High Dose ICS/LABA + Sustained-Release THP	3.5-5 (4.25)	9-10 (9.5)	6-8 (7)	1-1 (1)	7.5-8 (7.75)

[1] A combination of inhaled corticosteroids and long-acting beta2-agonists.
[2] Inhaled corticosteroid.
[3] Leukotriene receptor antagonists.
[4] Theophylline.

In order to assist the patient and the doctors in decision-making, the "optimal" treatment plan can be selected by adopting AHP. In this case, the decision hierarchy for the selection of treatment plans, based on the five issues and four alternatives as shown in Figure 11.

By definition as Table 1, comparing an attribute with itself gives an equal importance value of 1. In addition, the value of the reciprocal comparison is the reciprocal of the

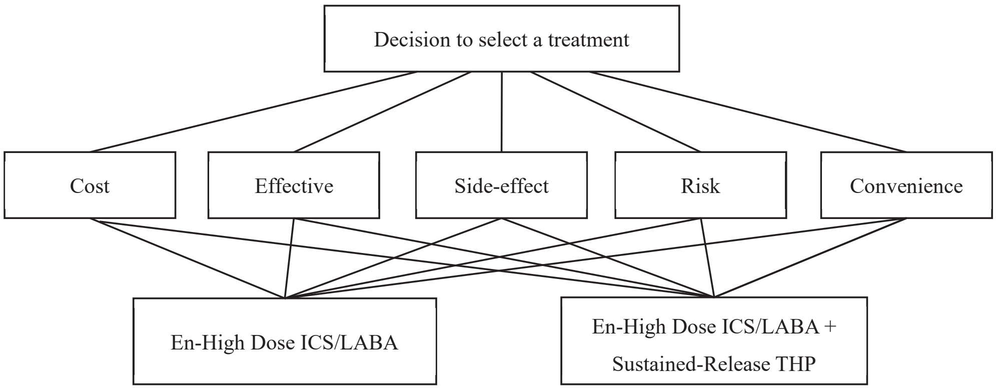

FIGURE 11. Hierarchy configuration model for treatment decision.

relative importance value. Thus, the 5×5 pairwise comparison matrix for level 2 can be built according to the priority preference of the negotiation issue of PA. For the two treatment plans obtained from the first step of the decision-making model, the 2×2 pairwise comparison matrix for level 3 can be built according to the treatment plans.

TABLE 7. The preference of issues weight of all parties.

Factors	Level 2 Priorities	Treatment plans	Level 3 Priorities
Cost	0.5028	En-High Dose ICS/LABA	0.6667
		En-High Dose ICS/LABA + Sustained-Release THP	0.3333
Effective	0.2602	En-High Dose ICS/LABA	0.8
		En-High Dose ICS/LABA + Sustained-Release THP	0.2
Side-effect	0.0677	En-High Dose ICS/LABA	0.8889
		En-High Dose ICS/LABA + Sustained-Release THP	0.1111
Risk	0.1346	En-High Dose ICS/LABA	0.2
		En-High Dose ICS/LABA + Sustained-Release THP	0.8
Convenience	0.0348	En-High Dose ICS/LABA	0.1
		En-High Dose ICS/LABA + Sustained-Release THP	0.9

All required consistency tests have passed, and the priority vectors for the decision hierarchy are shown in Table 7. Finally, all weights are integrated to determine the overall preferences of the treatment plans. The overall weight of En-High Dose ICS/LABA is the sum of the product of level 2 weight and level 3 weight, that is (0.5028*0.6667 + 0.2602*0.8 + 0.0677*0.8889 + 0.1346*0.2 + 0.0348*0.1) = 0.6339. Combine the recommended frequency with the overall weight, the recommendation score of En-High Dose ICS/LABA is 0.5358, and the recommendation score of En-High Dose ICS/LABA + Sustained-Release THP is 0.4642. That means En-High Dose ICS/LABA has a higher weight and is the most preferred treatment plan among all optional treatment plans.

5. **Conclusion.** This study proposes a fuzzy constraint-based negotiation model FCAN and a treatment decision-making model for the implementation of patient-to-doctors SDM. By employing agent technology, the FCAN model the behavior of patient and doctors, and simulate the interaction and negotiation among them. It can not only make human-oriented clinical decisions intelligent and efficient but also learn the preference of opponents and avoid potential conflicts to effectively reach a satisfactory agreement. The

treatment decision-making model can transform the negotiation results into related treatment plans. It can recommend personalized treatment plans, provide assistant decision-making for patients and doctors, and reduce the burden of patients and doctors. Compared with other methods, the agent-based negotiation and decision-making method provides a new idea, which can not only realize intelligent medical assistant decision-making but also consider the preferences of doctors and patients for personalized treatment. The experimental results show that the presented negotiation model is effective in terms of convergence speed, combined ASV, and the final satisfaction of the PA in negotiation, and the proposed decision-making model is feasible in treatment decisions.

Although the proposed negotiation and decision-making method is promising, it still can be improved. For example, the robustness and convergence of our negotiation model can be further studied and personalized treatment recommendations based on data can be added. Additionally, the proposed negotiation and decision method used in other dynamic medical environments, such as multiple doctors and multiple patients, can be researched.

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