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Particle Swarm Optimization-based Agent Negotiation Framework to Support Shared Decision-Making

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Abstract. *Shared decision-making (SDM) is a process by which patients and doctors make medical decisions together based on clinical evidence. It balances risk and expected outcomes with the preferences and values of patients. However, SDM is rarely employed in practice. Part of the reason for this is that the decision-making process is complex, takes long time, and the number of healthcare professionals trained in these techniques is limited. In this study, we first simplify the SDM preference negotiation problem as a multi-objective optimization (MOO) problem with bilateral treatment preferences. Then, we attempt to solve the MOO using an agent negotiation technique for bilateral MOO. We therefore propose a particle swarm optimization-based SDM-automated negotiation framework (PSOAN) that provides decision support for doctors and patients was proposed. The experimental results show that PSOAN obtains more overall satisfaction than other existing models by 11.1%–11.6%, indicating that it achieves higher social welfare. In addition, it reduces the satisfaction gap to 31.9%–34% and promotes social equity. It takes only 7.8 rounds to reach an agreement on average, which requires less than 1 minute. In summary, the proposed model can effectively improve agreement satisfaction and social welfare for both parties while reducing the time and space costs required for negotiation. The designed negotiation framework has bright future to assist and promote the implementation of SDM for both doctors and patients, and deserves more intensive studies.*

Keywords: Shared decision making, Agent negotiation, Meta-heuristic algorithms

1. **Introduction.**

With the advancement of medical science, there are typically varied treatments for many diseases. This gives options to patients with different preferences, but it also makes it difficult for patients to select proper treatment due to the limited medical literacy and inadequate doctor–patient communication time during traditional doctor visits. In particular, due to significant information asymmetry, most medical decisions are dominated by doctors in practice, and patients find it difficult to participate effectively. To respect the autonomy of personal health management and restrain the immoral behavior of doctors, researchers from philosophy and medicine have proposed a "shared decision-making" (SDM) model. which is defined as a process in which patients and doctors jointly participate in the medical decision-making process and agree on treatment decisions [1]. The potential benefits of implementing SDM include ethics, quality, informed decisions, patient satisfaction, the enhanced realization of patient self-management, improved adherence, and meaningful outcomes [2]. Currently, there are three main SDM process models in common use: the Makoul model [3], the three-step talk model [4], and the Stiggelbout model [5]. The Makoul model, also known as the integrative model, identifies the essential and ideal elements of SDM through a systematic review of articles addressing the conceptual definition of SDM. It includes nine essential elements: (1) define the problem, (2) present options, (3) discuss pros/cons, (4) patient preferences, (5) discuss patient ability/self-efficacy, (6) doctor knowledge/recommendations, (7) check/clarify understanding, (8) make or explicitly defer the decision, and (9) arrange follow-up. In 2012, Elwyn et al. translated conceptual descriptions into a three-step talk model by assigning the various steps to respective phases. In this model, the SDM process was organized as choice talk, option talk, and decision talk. The talk model is more practical for real-world applications and combines good communication skills with the use of patient decision support tools to make the process work [4]. Stiggelbout redesigned SDM as an easy memorized four-step model for easy implementation.

Although SDM has been advocated as a model for decision-making in preference-sensitive decisions since 1982, it is still not widely implemented in clinical practice [5, 6]. Therefore, there is an ongoing debate on how to improve its implementation, including strategies for doctors and patients and tools and instruments to assist SDM. Knowledge and awareness among both professionals and patients, as well as training in tools and communication skills, are important factors for SDM implementation [5]. Kunneman et al. [7] treated choice awareness as the first step in SDM and found that oncologists rarely express that a treatment decision needs to be made in consultation, missing a crucial opportunity to facilitate SDM. Shaoibi et al. [8] thought the accurate diagnosis of patient preferences is central to SDM and proposed a Bayesian collaborative filtering algorithm that combines pretreatment preferences and patient-reported outcomes to make treatment recommendations. Besides, many SDM implementation measurement instruments have been designed and used in surveys [9].

Few SDM tools have been developed to date to assist patients in understanding treatment options and participating in treatment decisions based on their values and preferences. Current technologies supporting SDM are focused on patient decision aids (PtDAs) and clinical decision support systems (CDSS). PtDAs (which may be flyers, videos or audiotapes, or interactive media) can help patients understand clinical evidence and determine their preferences by promoting a positive doctor–patient relationship [10, 11]. It is also helpful in informed medical decision-making that is consistent with the values and preferences of target objects. Meanwhile, CDSS aims to create human–computer interactive healthcare systems with data or models [12]. It matches patient characteristics with a computerized clinical knowledge base, and then patient-specific assessments or recommendations are presented to physicians or patients for decision-making [13]. However, the above approaches primarily use traditional media to guide patients in making issue-specific decisions. They do not consider or balance the values and preferences of doctors and patients to propose referable treatment protocols that support doctors and patients in making informed treatment decisions together.

Therefore, the main research objective of this study is to solve preference-sensitive decision-making problems through artificial intelligence (AI) technology, provide referable treatment plans, reduce the time and cost of decision-making, and balance the value preferences of doctors and patients. Agent negotiation technology is a widely used technology in the AI field currently. Automated agents can simulate human behavior, negotiate on behalf of human negotiators, and find better results than human negotiators. Jonker et al. [14] proposed a generic component-based agent architecture for multi-attribute (integrated) negotiation. The framework uses a distributed design, where each agent uses available information about an opponent's preferences to predict the opponent's preferences by introducing a "guessing" heuristic to improve the negotiation results. Hsu et al. [15] proposed an agent-based fuzzy-constrained directed negotiation mechanism for the scheduling problem of distributed job shops. The concept of using a fuzzy membership function was introduced to represent imprecise preferences. This increased information sharing accelerates convergence and achieves global consistency by repeatedly exchanging offers and counteroffers. These models are essential for improving the efficiency and effectiveness of agent negotiation.

In this study, we first simplify the SDM preference negotiation problem as a multi-objective optimization (MOO) problem with bilateral treatment preferences. Then, we attempt to solve the SDM preference negotiation problem using an agent negotiation technique for bilateral MOO.

The primary contributions of this study are summarized as follows.

(1) We propose an MOO-based agent bilateral preference negotiation framework to implement SDM. The proposed model creatively combines advanced SDM principles and agent negotiation techniques.

(2) We develop autonomous agents of doctors and patients based on their behaviors, including how they evaluate proposals, how to offer a proposal, and how to reach an agreement.

(3) We combine the multi-objective particle swarm optimization (MOPSO) algorithm and technique for order preference by similarity to ideal solution (TOPSIS) to implement MOO to generate a win–win protocol. This protocol can improve the satisfaction and social welfare of both patients and doctors.

The remainder of this paper is organized as follows. Section II describes the related work. Section III presents the proposed SDM agent negotiation model in detail. Section IV evaluates and discusses our proposed model from different perspectives. Section V concludes the study.

2. **Related Work.**

2.1. **SDM.**

SDM is a healthcare delivery model in which healthcare providers invite patients or their caregivers to participate in patient care decisions [16]. SDM must involve at least two participants (e.g., doctors and patients). The SDM process is characterized by clinical decision-making, information sharing, and the consideration of patients' preferences, and both parties must make consistent decisions [17]. Studies have shown that SDM can help improve patient participation in healthcare decision-making, improve the quality of care, and lower healthcare costs [18, 19].

2.2. **Decision Support Techniques.**

Several decision support technologies have been developed to facilitate SDM. The best-known technique is PtDAs [20, 21], and it can adequately inform patients of feasible treatment options and the risk–benefit relationship involved in various treatment options. However, these technologies do not help patients combine their values and preferences with information about the benefits and risks of choices to reach the best option.

Some researchers have also studied decision coaching. Trained health professionals guide patients through face-to-face consultations or by phone, email, or the Internet to help them access medical evidence, articulate their values and preferences, develop skills to consider options, and become more involved in SDM [22]. This approach can help patients understand their values and preferences and improve their decision-making experience, but it requires a significant amount of time and high labor costs [23].

In addition, some scholars have developed CDSS [24–26]. CDSS aims to improve healthcare delivery by enhancing medical decision-making with targeted clinical knowledge, patient information, and other health information [27]. There are two main types of CDSS: knowledge-based CDSS and non-knowledge-based CDSS. Most knowledge-based CDSSs consist of data repositories, inference engines, and communication mechanisms, where each data point is structured in the form of IF–THEN rules [28]. In CDSSs, an inference engine combines rules from a knowledge repository with a patient's data. The results are displayed to the user through a communication mechanism in the form of diagnostic recommendations, a series of treatment options, or a ranked list of possible solutions. Nevertheless, the final decision rests with the human expert [29]. Non-knowledge-based CDSS still requires data sources, but the decisions utilize AI, machine learning, or statistical pattern recognition rather than being programmed to follow specialized medical knowledge [30]. Both approaches can assist healthcare providers by analyzing patient data and using that information to help formulate a diagnosis. However, there are still issues such as high implementation costs and the lack of consideration of the user's value proposition or preferences.

2.3. **Agent Negotiation Techniques.**

Agents are software entities that simulate human behavior, and they are used in multiagent systems (MASs) to study the informational and dynamic behaviors of complex systems. Given the capabilities and characteristics of agents, the most widely used agent architecture is the belief–desire–intention (BDI) model. It provides practical reasoning by defining what is to be accomplished and how it should be accomplished. The BDI architecture consists of three basic components that define the state of an agent [31].

Belief: Information that agents possess about their environment, other agents, and themselves. This information forms the basis of all further decisions and plans.

Desire: An agent's motivations and goals. The goals an agent wants to pursue in each situation are dynamically determined.

Intention: Achieving specific goals through executable plans.

An agent can simulate the behaviors of negotiation participants and perform negotiations according to relevant protocols and frameworks to automate the negotiation process.

Agent-based auto-negotiation has been extensively used in service-level agreements (SLAs) [32], e-commerce, etc. Regarding research content, studies on agent negotiation primarily focus on the negotiation framework, negotiation or conflict resolution models, and negotiation strategies to seek a satisfactory solution. For example, Rajavel et al. [33] proposed an automated dynamic negotiation framework (ADSLANF) for SLAs that employs a bulk negotiation behavioral learning approach based on reinforcement learning techniques to optimize the negotiation strategy. Cao et al. [34] developed a theoretical model and algorithm for multi-strategy selection based on time-dependent and behavior-dependent strategies applied to e-commerce. Li et al. [35] proposed a genetic algorithm-based negotiation strategy that employs a genetic algorithm to investigate the preferences and utility functions of adversaries to achieve a win–win situation for customers and suppliers in the absence of incomplete information. These methods ensure their satisfaction and success rate through negotiation strategies and conflict resolution through behavioral learning, modified assessments, or concessions. They improve the success rate of the negotiating parties, optimizing performance in terms of negotiation rounds, total negotiation time, and communication overhead. However, these methods could be improved in terms of finding optimal solutions and prioritizing feasible solutions.

2.4. Summary of Related Work.

Currently, there are several barriers to healthcare providers implementing decision support technology in clinical practice, including lack of time, knowledge, and skills and inadequate training in decision coaching. There are also no studies in the literature that provide suggestions for solutions to support SDM. Previous research has shown that agent negotiation techniques can provide and achieve mutually beneficial solutions. Therefore, supporting SDM with agent-based negotiation techniques may be a proven way to reconcile values and preferences between healthcare providers and patients to provide feasible treatment options.

3. PSOAN for SDM.

In this section, we introduce the SDM problem formulation (Section 3.1) and design agents according to the SDM process (Section 3.2). Then, in Section 3.3, we describe how to solve the SDM preference negotiation problem using the MOO design negotiation framework for the bid strategy and how to map it to SDM negotiation. Finally, the negotiation protocol designed for the SDM negotiation framework is presented in Section 3.5.

3.1. Problem Definition.

3.1.1. *SDM Problem Definition.*

SDM is defined as a process with three main components: (1) sharing information, (2) discussing treatment options, and (3) reaching a mutual decision that both parties can agree on. In an actual clinical setting, more information cannot be shared between doctors and patients due to various constraints such as time, medical literacy, and beliefs. Therefore, we assume that doctor agents (DAs) and patient agents (PAs) operate in a limited information environment with fuzzy and imprecise information about their own and their opponent's preferences. We attempted to represent this inaccurate preference and information using a trapezoidal fuzzy membership function. A doctor and patient evaluation of a treatment protocol is defined as aggregate satisfaction values (ASVs) with negotiation content, which is expressed using the following function.

$$U(S) = \sum_{i=1}^{n} w_i \cdot M_i(S) \tag{1}$$

Here, $M_i(S)$ denotes the i^{th} membership degree of solution S. It can be obtained directly from a set of doctors and patients and will flexibly and efficiently represent their preferences for certain problems. In addition, n represents the number of issues to be negotiated by doctors and i^{th} issue.

3.1.2. *Convert to MOO Problem.*

Based on the above considerations, we reduce the SDM problem to an MOO problem with bilateral treatment preferences that follow the traditional SDM process.

We aim to achieve a win–win agreement for both physicians and patients, i.e., an agreement that results in the highest possible ASV for both parties. Here, an optimization problem with multi-objective functions is involved. Thus, the SDM bilateral preference negotiation problem can be converted into an MOO problem as follows.

$$max_o \; F(O) = \left(f_{doctor}(O), f_{patient}(O)\right), \tag{2}$$

$$f_{doctor} = U_{doctor}(O) = \sum_{i=1}^{n} w_i \cdot M_i(O), \tag{3}$$

$$f_{patient} = U_{patient}(O) = \sum_{i=1}^{n} \bar{h}_i^w \cdot \bar{h}_i^f(O). \tag{4}$$

The fitness function F has two objectives: the doctor's satisfaction value f_{doctor} and the patient's $f_{patient}$. O represents the agreement that they have reached.

Next, we use agent technology to construct bilateral agents (DA and PA) and use MOO to help these agents solve multi-issue (treatment protocol) problems.

3.1.3. *Agent Design.*

As shown in Figure 1, we can consider the direct participants of SDM as independent, interconnected, and environmentally retrained agents. Here, communication between doctors and patients is considered a negotiation between agents. In addition, the aggregate satisfaction of doctors and patients with the treatment protocol is considered the individual utility of an agent. Thus, agents can support the medical decision-making process for both doctors and patients.

First, we generate behavioral models of DAs and PAs based on the BDI architecture. Table 1 describes an example of the individual behavior of BDI-based DAs/PAs. Then, based on the behavioral model of DAs/PAs, an agent-based negotiation framework was constructed to simulate the SDM process between doctors and patients, as depicted in Figure 2. The specific process is described in detail in Section 3.4 Negotiation Protocol.

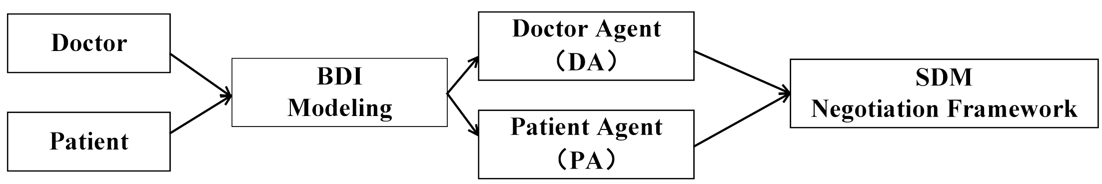

Figure 1. Conversion of doctor and patient to agent

3.2. **Bidding Strategy.**

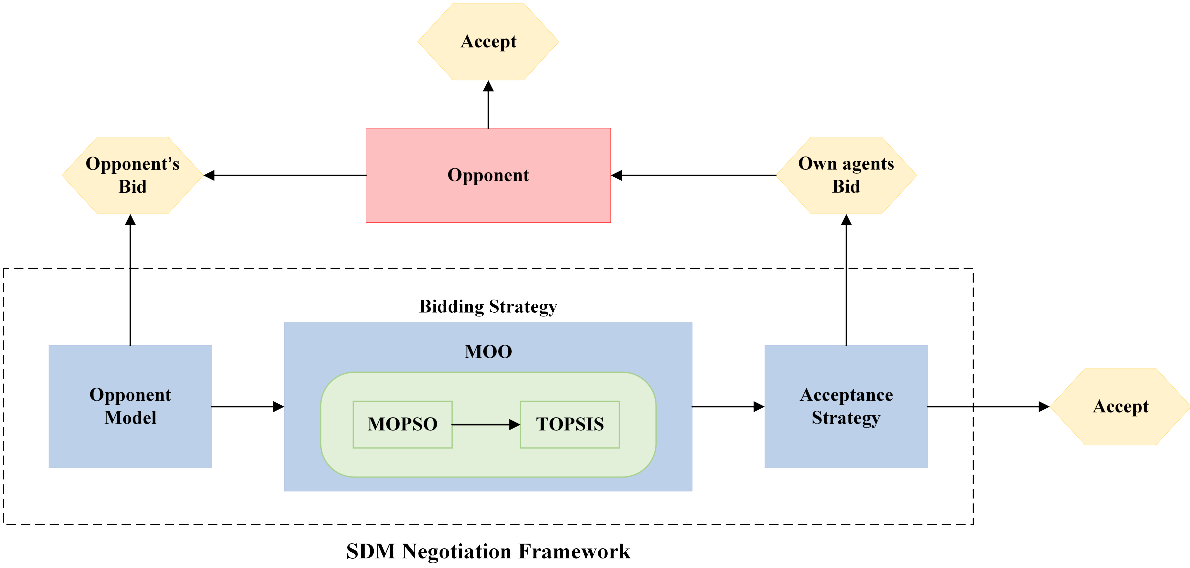

FIGURE 2. PSOAN to simulate the SDM process

TABLE 1. BDI-based example of individual behavior of DA/PA

Input	SDM
Belief	Number of humans: two (doctor and patient) Information: the content of treatment plan, own and others' preferences, communication history, etc.
Desire	Select the most mutually satisfactory treatment that can support SDM.
Intention	(1) Negotiate with the doctor/patient, and obtain their ideas or proposals for treatment. (2) Analyze each of their treatment preferences. (3) Select and propose the appropriate treatment plan.
Actions	(1) Propose treatment content. (2) Reject opponent's offer and propose counteroffer. (3) Accept opponent's offer and terminate negotiation. (4) Reject opponent's offer and terminate negotiation. (5) Terminate negotiation.

3.2.1. *MOO.*

Because the bilateral SDM problem has two objective functions (i.e., user and opponent utility functions) and SDM has imprecise information about user preferences and incomplete information about opponent preferences, in this model, user modeling (i.e., user utility function) uses a trapezoidal fuzzy membership function. The user needs to give the maximum acceptable range and desired range and weights for the treatment protocol issues. During the negotiation, opponent modeling uses a Bayesian learning-based opponent model. Therefore, we solve the bilateral SDM problem by solving the MOO problem that generates the Pareto optimal offer. This study combines MOPSO and TOPSIS to generate (near) optimal solutions in the bidding strategy. The method has two phases, as shown in Figure 3.

A. Phase I:

The MOPSO algorithm was proposed by Coello et al. [36] in 2004 to apply the principle of particle swarm optimization, which can only be used for a single objective, to multiple objectives to achieve MOO. The basic principles of the MOPSO algorithm are as follows:

1) Initialize the population particles in the initial population;
2) Calculate the fitness value to evaluate the solution quality given a certain velocity and position of the particles;
3) Continuously iterate through the velocity and position equations to find the optimal solution;
4) Output the optimal solution when the set number of iterations or the global optimal solution is reached.

These phases can be summarized as follows.

Stage 1 (initial population): Initialize a random population P. The population contains n particles. Each particle p_i has its position and velocity and is represented by a d-dimensional vector, as shown below. Copy the non-dominated particles of the current population to the archive set.

$$p_i = (p_{i1}, p_{i2}, \ldots, p_{id}) \tag{5}$$

$$p_i = q_L + Rand * (q_U - q_L) \tag{6}$$

Stage 2 (particle evaluation): The position of each particle is evaluated according to the fitness function of Equation 2. (1) Compare its fitness value with the current individual optimal $pBest$. if it is better than $pBest$, replace the current $pBest$ with the new position of the particle; otherwise, it remains unchanged. (2) Calculate the density information of particles in the archive set and select $gBest$ in the archive set.

Stage 3 (particle location updating): (1) Update the velocity v_{id} and position x_{id} of each particle according to the following equation. (2) Update the archive set and copy the non-dominated particles in the updated population P to the archive set. (3) When the number of particles in the archive set exceeds a specified number, the excess individuals should be removed to maintain a stable archive set size.

$$v_{id}^{k+1} = \omega \times v_{id}^{k} + c_1 \times rand \times \left(\mathrm{pBest}_{1d}^{k} - x_{id}^{k}\right) + c_2 \times rand \times \left(gBest_{d}^{k} - x_{id}^{k}\right) \tag{7}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{8}$$

Stage 4 (stopping criteria is satisfied): Output the set of non-dominated particles in the archive set as alternative solutions S when the set number of iterations or the global optimal solution is reached.

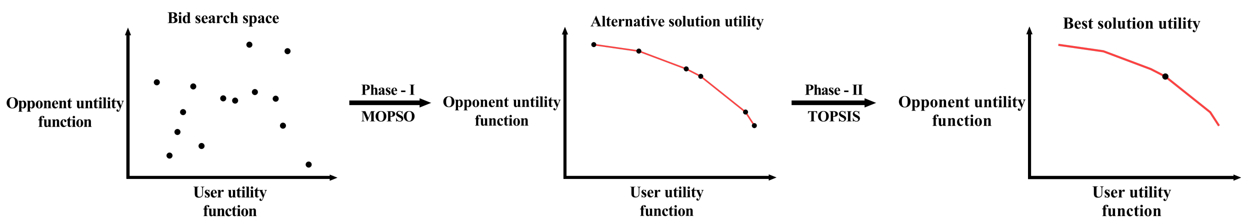

Figure 3. MOO generation offer process diagram

B. Phase 2:

We use TOPSIS to select the best solution from the set S output in MOPSO. In our SDM negotiation framework, we have three criteria ($m = 3$) or targets: our satisfaction value, the opponent satisfaction value predicted by the opponent model, and the satisfaction gap value between the two parties.

- A decision matrix $Z = n \times m$ is created consisting of alternatives n and criteria m. $m_1 = U(S_i)$, $m_2 = U_{opponent}(S_i)$, $m_3 = |m_1 - m_2|$, where $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$. z_{ij} denotes the value of the j^{th} criterion assigned to the i^{th} solution.
- If the j^{th} criterion in the matrix Z is not a very large index, forwarding is performed according to Equation 9.

$$z_{ij} = max\ [z_{i1}, z_{i2}, \ldots, z_{im}] - z_{ij}, \tag{9}$$

$$Z_{ij} = \frac{X_{ij}}{\sqrt{\sum_{k=1}^{n} (X_{ij})^2}}. \tag{10}$$

- The gap between each evaluation criterion and the optimal and inferior solutions is calculated and defined as D_{i+} and D_{i-}. Here, Z_{j+} and Z_{j-}denote the maximum and minimum values of the j^{th} evaluation criterion, respectively.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^+ - z_{ij}\right)^2}, \tag{11}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^- - z_{ij}\right)^2}, \tag{12}$$

$$Z^+ = \left(max\left\{z_{11}, z_{21}, \ldots, z_{n1}\right\}, max\left\{z_{12}, z_{22}, \ldots, z_{n2}\right\}, \cdots, max\left\{z_{1m}, z_{2m}, \ldots, z_{nm}\right\}\right) \tag{13}$$

$$Z^- = \left(min\left\{z_{11}, z_{21}, \ldots, z_{n1}\right\}, min\left\{z_{12}, z_{22}, \ldots, z_{n2}\right\}, \cdots, min\left\{z_{1m}, z_{2m}, \ldots, z_{nm}\right\}\right) \tag{14}$$

- Each alternative is ranked according to its relative proximity to the ideal solution, C_i.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{15}$$

- Finally, select the best solution based on the ranking and send it to the opponent as the offer for this round.

3.2.2. *SDM negotiation-mapping schema.*

In the MOO, the population of MOPSO consists of a set of possible offers for each negotiating agent party. Table 2 lists the negotiation mapping schema of SDM.

TABLE 2. SDM negotiation mapping schema

MOPSO	**SDM Negotiation**
Dimensional search space (D)	Set of negotiation issues (d)
Particle	Possible offer (P)
Population	Set of possible offers
Evolution of population	Computing new offers
Best solution	Counteroffer

The negotiating parties (i.e., DA and PA) calculate the offer through MOPSO and determine the best offer as a counteroffer exchange during the negotiation process. As depicted in Figure 4, each particle in the MOSPO population corresponds to a message containing the issues to be negotiated (e.g., offer O_1). More specifically, each particle contains the same number of issues as the negotiation issues. This setting is fixed for all negotiating sides, and the i^{th} negotiation issue is denoted $issue_i$. For each negotiation side, the population P of MOPSO is used to denote the subset of available offers.

Figure 5 shows an illustrative example of an offer O with five negotiation issues. The value of each negotiation issue is generated within the acceptable interval of DA/PA.

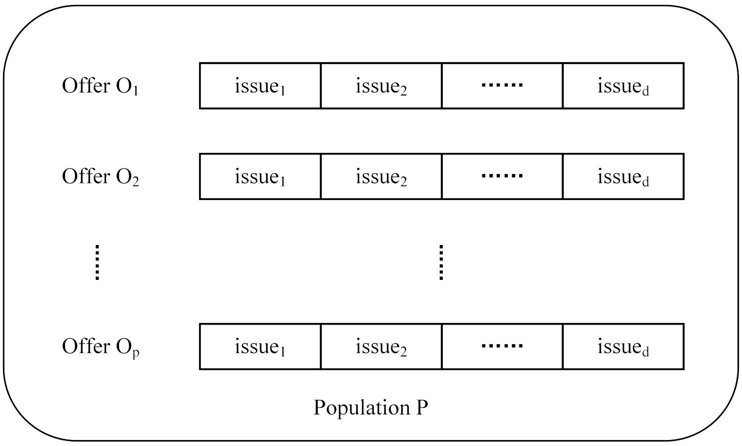

Figure 4. MOPSO-based negotiation representation

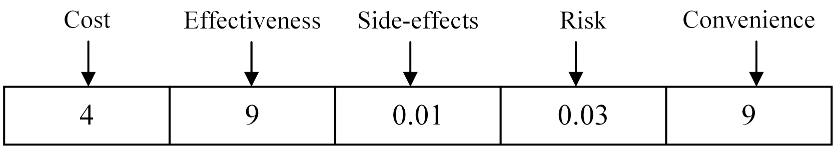

Figure 5. Illustrative example of offer O_1

3.3. **Opponent Model and Acceptance Strategies.**

Opponent model. The opponent model of the SDM negotiation framework uses a generic framework based on Bayesian learning [37] to learn the value preferences of opponents and the weights of the problem.

Acceptance strategies. Acceptance strategies can be considered utility-based, time-based, or a combination of both [38]. The acceptance conditions for our agents are shown below.

$$AC\left(r, O^r_{\text{opponent}}\right) = \begin{cases} \text{End} & \text{if } t > T, \\ \text{Accept} & \text{if } U\left(O^r_{\text{opponent}}\right) \geqslant U\left(O^{r-1}_{\text{counter}}\right) - t, \\ \text{Offer } \left(O^r_{\text{counter}}\right) & \text{otherwise.} \end{cases} \quad (16)$$

$$\text{t} = \alpha + (1-\alpha)\left(\frac{r}{N_{max}}\right)^{\beta} \quad (17)$$

3.4. **Negotiation Protocol.**

Because we are considering a bilateral SDM problem, the proposed model is designed for a bilateral (i.e., one-to-one) multi-issue, time-dependent function. Multiple bilateral (i.e., one-to-many) negotiations can also be applied to multilateral negotiations. The PSOAN for SDM has three stages, as described below.

Stage 1 (pre-negotiation stage): In this stage, DAs/PAs define their interval values of negotiation issues and expected intervals and assign weights to each negotiation issue according to their preferences. This stage also defines negotiation characteristics, such as negotiation deadline and time loss.

Stage 2 (negotiation stage): The negotiation process follows the alternate offer protocol and consists of the following steps.

- First, each party sends its most satisfactory target to the opponent as the first round of offers.
- The negotiating sides generate near-optimal solutions as exchange offers based on MOO (e.g., counteroffer $O_{counter}$).
- The negotiating sides then exchange offers until an agreement is reached or a deadline is met.

Stage 3 (negotiation result): At the end of the negotiation process, one action can be taken (acceptance, rejection, or meeting the deadline). If either party accepts the offer, the acceptance will be determined by mutual agreement. If its fitness value is less than the minimum acceptable value, either party can reject the offer. If the negotiation deadline is reached, the negotiation is over.

4. **Experimental Results and Discussions.**

In this section, to effectively validate the performance of our proposed SDM negotiation framework, we conduct comparative experiments with a fuzzy constraint-based agent-based negotiation framework (FCAN) [39] , which is also used for bilateral and multi-issue preference negotiation in SDM. Note that there are few preference negotiation problem frameworks using the agent method for solving SDM. Thus, the comparison experiments in this study are limited.

4.1. **Experimental Setup.**

Environment. The program is written in Java and runs on IntelliJ IDEA on a Windows 10 operating system. In addition, the SDM negotiation framework, proposed in this study, is implemented in the open-source negotiation software Genius [40].

Here, r represents the current negotiation round, N_{max} denotes the deadline of the negotiation, and t represents the time loss for the negotiation. α and β are constant; $1 > \beta > 0$ and $0 \leq \alpha \leq 1$.

Dataset. The experiment used data on the preferences of doctors and patients for childhood asthma treatment options collected by Lin et al. [39]. The preference negotiation questions involved in their treatment plans mainly include cost, effectiveness, side-effects, risk, convenience, etc. The preference data include value and weight preferences for issues.

Parameter setup. The parameters involved in the experiments and their settings are shown in Table 3. The data of DA and PA preferences in the experiments are shown in Tables 4 and 5. All experimental results of this study are the average values after 200 repetitions of the experiments.

4.2. **Performance Metrics.**

The proposed SDM negotiation framework is evaluated based on the following performance metrics.

Table 3. Experimental parameter setup

PSOAN parameter setup		**Negotiation experimental setup**	
Number of iterations ($Iter$)	5	The maximum negotiation round (N_{max})	20
Number of particles (P)	1000	Number of experiments negotiated (Neg_{total})	200
Number of Grids Divided ($nGrid$)	10×10	α	0.05
Acceleration factor 1 (c_1)	1.49	β	$\frac{1}{e}$
Acceleration factor 2 (c_2)	1.49		

Table 4. Preference data of DA

Preference / issue	Issue Value Range	Most Preferred Range	Minimum Preference Value	Maximum Preference Value	Weight Preference
Cost	0–8 k	4.5-7	3	7.5	0.15
Effectiveness	1–10 rank	7-8	4	10	0.3
Side-effects	1–100 %	10-15	1	20	0.25
Risk	1–100 %	10-20	5	25	0.2
Convenience	1–10 rank	7-8	7	10	0.1

Table 5. Preference data of PA

Preference / issue	Issue Value Range	Most Preferred Range	Minimum Preference Value	Maximum Preference Value	Weight Preference
Cost	0–8 k	1-4	1	5	0.3
Effectiveness	1–10 rank	9-10	8	10	0.25
Side-effects	1–100 %	0-1	0	15	0.2
Risk	1–100 %	0-4	0	15	0.15
Convenience	1–10 rank	9-10	10	10	0.1

- Average doctor ASV ($Avg.ASV_{\text{doctor}}$): This metric indicates the average ASV of the doctor with an agreement reached in all agreement reached negotiation experiments. It can be calculated as follows.

$$Avg.ASV_{\text{doctor}} = \sum_{i=1}^{Agr_{\text{total}}} U_{DA}\left(S_{agree}^{i}\right) \ / \ Agr_{\text{total},} \tag{18}$$

where Agr_{total} denotes the number of negotiation agreements. U_{DA} denotes the doctor's ASV function, calculated by Equation 1.

- Average patient ASV ($Avg.ASV_{\text{patient}}$): This metric indicates the average ASV of the patient with the agreement reached in all agreement reached negotiation experiments.

It can be calculated as follows.

$$Avg.ASV_{\text{patient}} = \sum_{i=1}^{Agr_{\text{total}}} U_{PA}\left(S_{agree}^{i}\right) \ / \ Agr_{\text{total}} \tag{19}$$

where U_{PA} denotes a patient's ASV function, calculated by Equation 1.

- The combination of ASV ($CASV$): This indicator represents the sum of $Avg.ASV_{\text{doctor}}$ and $Avg.ASV_{\text{patient}}$, representing the social welfare of the doctor and patient. It can be calculated as follows.

$$CASV = Avg.ASV_{\text{doctor}} + Avg.ASV_{\text{patient}} \tag{20}$$

- The disparate of ASV ($DASV$): This indicator represents the difference between $Avg.ASV_{\text{doctor}}$ and $Avg.ASV_{\text{patient}}$. The agreed solution may be mutually satisfactory and not extreme. It can be calculated as follows.

$$DASV = \mid Avg.ASV_{\text{doctor}} + Avg.ASV_{\text{patient}} \mid \tag{21}$$

- Agreement Ratio ($AgrR$): This metric represents the number of agreements reached as a percentage of the total number of negotiations.

$$AgrR(\%) = \frac{Agr_{\text{total}}}{Neg_{\text{total}}} \tag{22}$$

- Average negotiation rounds ($Avg.R$): This metric represents the average number of negotiation rounds. Average negotiation rounds ($Avg.R$): This metric represents the average number of negotiation rounds.

$$Avg.R = \sum_{i=1}^{Agr_{\text{total}}} R_i / Agr_{\text{total}} \tag{23}$$

where R_i denotes the number of rounds required to reach a mutual agreement about the negotiation process i between the doctor and patient.

- Average processing time ($Avg.T$): This metric represents the average time (in seconds) required to reach an agreement during a negotiation.

$$Avg.T = \sum_{i=1}^{Agr_{\text{total}}} T_i / Agr_{\text{total}} \tag{24}$$

where T_i denotes the time to complete the negotiation process i.

4.3. **Experimental results.**

Table 6 shows the comparative experimental results for doctors and patients using different negotiation frameworks. As presented in this table, although the $Avg.ASV_{\text{patient}}$ of PSOAN is slightly lower than that of FCAN, PSOAN is at least 0.111 higher than FCAN in $CASV$. This means that PSOAN can obtain better social welfare than FCAN. In addition, the $DASV$ of PSOAN is 0.044, which is at least 0.319 lower than that of FCAN. This indicates a smaller satisfaction gap between doctors and patients, promoting social fairness. In terms of $AgrR$, both parties could reach a 100% agreement. However, in terms of $Avg.R$ and $Avg.T$, PSOAN performs slightly worse than FCAN. This is because the heuristic search algorithm used by PSOAN needs to find near-optimal solutions in the solution space. Its search time increases with the number of negotiation issues.

To verify whether PSOAN achieves better social welfare and stable social fairness at different negotiation domain sizes than FCAN, we adjusted the number of negotiated questions and compared their performance. The experimental results are shown in Figures 6 and 7.

Table 6. Comparison of experimental results

Performance metrics	FCAN			PSOAN
	Collaborative	Win-win	Completive	
$Avg.ASV_{\text{doctor}}$	0.483	0.492	0.496	**0.755**
$Avg.ASV_{\text{patient}}$	**0.867**	0.861	0.859	0.711
$CASV$	1.35	1.353	1.355	**1.466**
$DASV$	0.384	0.369	0.363	**0.044**
$AgrR$	**100%**	**100%**	**100%**	**100%**
$Avg.R$	**7**	8	8	7.8
$Avg.T$	**0.056**	0.063	0.062	50.862

As shown in Figure 6, although PSOAN can obtain progressively decreasing $CASV$ as the number of negotiated problems increases, it still outperforms FCAN. In a small negotiation domain (the number of negotiation issues is 3), PSOAN can obtain a $CASV$ of 1.525, which is at least 0.098 greater than that of FCAN. In a large negotiation domain (the number of negotiation issues is 7), PSOAN can obtain a $CASV$ of 1.383, which is at least 0.128 greater than that of FCAN. In summary, PSOAN can obtain better social welfare than FCAN for different negotiation domain sizes.

Figure 7 shows the comparison of $DASV$ over different negotiation domain sizes. Although the $DASV$ of PSOAN increases with the size of the negotiation domain, it outperforms FCAN at all domain sizes. In the small negotiation domain, the $DASV$ of PSOAN is only 0.032. In addition, PSOAN maintains the disparity of ASV between doctors and patients at 0.107 in the large negotiation domain. In conclusion, PSOAN promotes social fairness and stabilizes the utility gap between the two sides better than FCAN.

In summary, previous auto-negotiation models for SDM can apply different negotiation strategies but are poor at improving the quality of negotiation results. Specifically, SDM has a large area to explore in terms of social welfare and equity. In the same configuration (with 5 issues), the previous work (FCAN) achieved a value of approximately 1.290–1.355 for social welfare (e.g., $CASV$) [39,41], whereas PSOAN achieved a value of up to 1.466. In social equity (e.g., $DASV$), the previous work maintained a value within 0.363–0.384 [39], whereas PSOAN reduced it to 0.044. In [41], the average number of negotiation rounds was 9, whereas PSOAN completed a negotiation in 7.8 rounds on average with high performance. Moreover, with the number of issues increasing and the negotiation result space becoming more complex and larger, PSOAN still exhibits good performance. The disadvantage of PSOAN is that it sacrifices the negotiation time while keeping the required time within an acceptable range (within 1 min).

5. **Conclusion.**

Previous related studies have focused on providing information for decision-making, either through supported decision-making tools or manual negotiations. But time and cost constraints have prevented widespread use. Therefore, supporting the process of negotiated communication between healthcare professionals and patients with relevant technologies and tools to reduce time and costs, which is the focus of this study. In this study, we propose an MOO-based bilateral preference negotiation framework to solve the bilateral SDM problem. Compared with the traditional manual SDM process, our proposed agent negotiation framework considers the preferences of both doctors and patients,

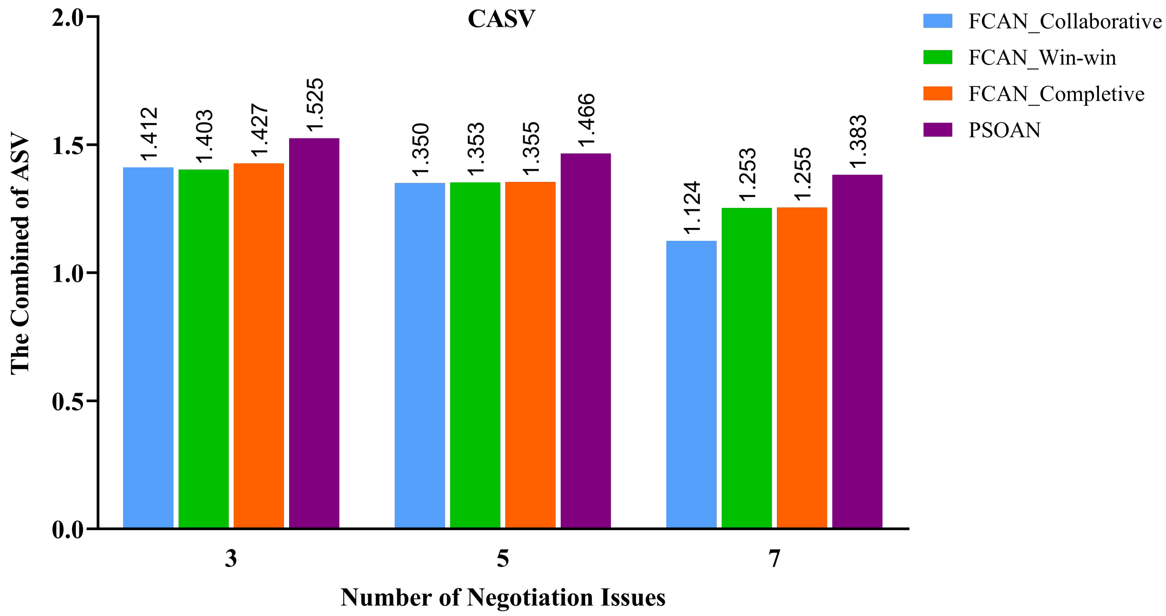

FIGURE 6. Comparison of CASV on different negotiation domains

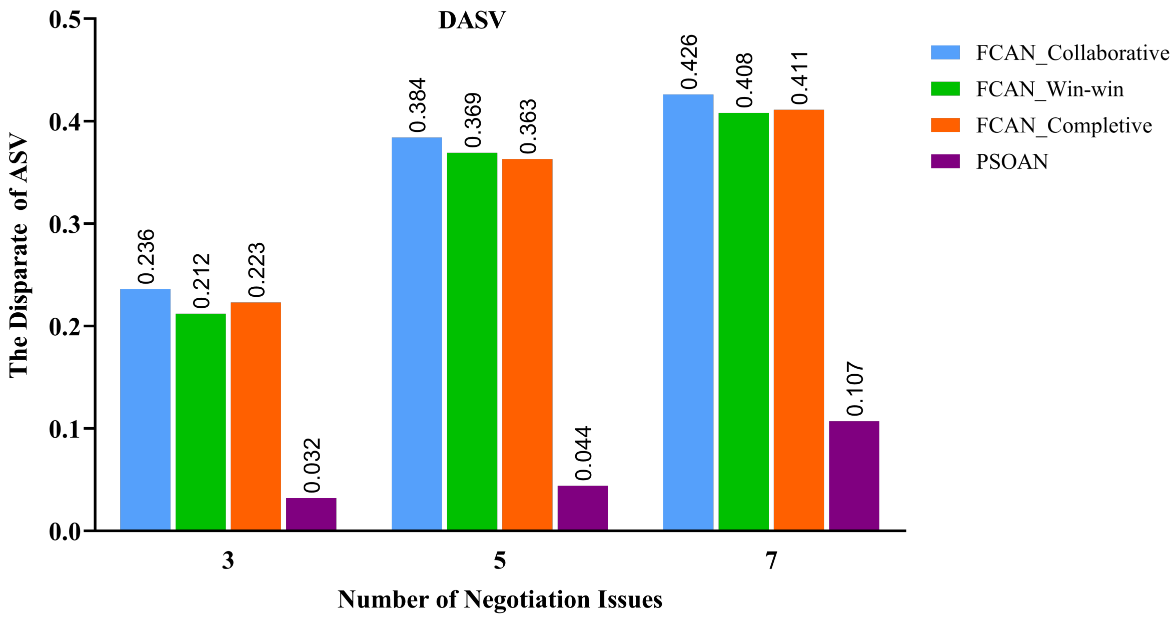

FIGURE 7. Comparison of DASV on different negotiation domains

reduces the satisfaction gap between the two parties on the negotiation results, and avoids potential conflicts.

The experimental results show that the proposed PSOAN can effectively support SDM scenarios and promote social welfare and fairness in SDM. It can effectively reduce the time required for doctor–patient communication, reduce the influence of emotions and biases on decision-making, and obtain satisfactory negotiation results while considering multiple value preferences of both parties.

In summary, the framework helps make suggestions for bilateral SDM preference negotiation, alleviating the problems of high cost, time-consuming, long response time, and decision fatigue. In addition, it improves the efficiency of SDM negotiations while considering the value preferences of both doctors and patients and avoiding potential conflicts, which is complementary to the clinical application of SDM.

Although agent negotiation-based SDM research is feasible and effective, it cannot be fully implemented in clinical SDM yet, and the following problems still need to be investigated in the future. (1) The complexity of the medical problem context is such that the decision-making of physicians and patients may be influenced by other social relationships. Therefore, considering the issue of group decision-making in the context of doctor–patient social relations is a future research priority. (2) The preferences of doctors and patients may change as the negotiation progresses and as medical knowledge changes. Such dynamic preferences are more in line with a real-world healthcare environment and can facilitate SDM research based on agent negotiations. (3) Due to the severity (significance) of medical decisions, we need additional empirical validation of the SDM negotiation model with real-world future decisions before it can be applied in real-world clinical scenarios.

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