Modeling Doctor-patient Shared Decision-making as Fuzzy Constraint-based Agent Negotiation

Yong Liu[1][a], Ping Lu[1][b], Yimin Yang[2][c], Feiping Hong[3][d] and Kaibiao Lin[1,*][e]
[1]School of Computer and Information Engineering, Xiamen University of Technology, Xiamen, China
[2]Department of Pediatrics, Xiamen Hospital of Traditional Chinese Medicine, Xiamen, China
[3]Department of Neonates, Xiamen Humanity Hospital, Xiamen, China

Keywords: Shared Decision-Making, Fuzzy Constraints, System Structure, Agent Negotiation, Recommendation.

Abstract: Shared decision-making (SDM) has been widely advocated as a new medical decision-making model, but limited time, uncertain information, and individual differences constrain its application and development. To facilitate the application of SDM, a multi-issue agent negotiation approach based on fuzzy constraints is proposed to solve the SDM problem between doctors and patients. The advantages of our approach can be summarized into three points: 1) a general framework for knowledge representation and problem-solving in SDM simulation; 2) a feasible system structure that includes negotiation and recommendation model, which can simulate a real clinical scenario to complete SDM; 3) an efficient negotiation model that can improve the negotiation efficiency of SDM by alleviating the constraints of issues and time and reducing the impact of space and emotion. To verify the feasibility and effectiveness of our method, we simulated and solved the asthma SDM between doctors and patients and then validated its performance under different deadlines and issues constraints.

1 INTRODUCTION

Evidence-based medicine encourages patients to participate actively in discussions of diagnosis, treatment, and follow-up (Hoffmann et al. 2014). On this premise, as a new medical decision-making model in which doctors and patients participate and fully negotiate about diagnosis and treatment, shared decision-making (SDM) has received extensive attention. Different from the paternalistic medical decision-making model and informed consent decision-making model, SDM is a patient-centered decision-making model (Weston 2001). It aims to make decision-making consistent with patients' values to improve their compliance and strengthen doctor-patient communication to promote the harmony of the doctor-patient relationship (Stiggelbout et al. 2015).

The studies on SDM mainly focus on the establishment of theory and the development of the application. The concept of SDM was first proposed by Reimann (Reimann 1968) in 1968, defined by Veatch (Veatch 1972) in 1972, and then perfected by the American government in 1982 (States 1982). Since then, many scholars have begun to enrich and improve relevant theories, such as the Makoul model (Makoul and Clayman 2006), the Talking model (Elwyn et al., 2013), and the Stiggelbout model (Stiggelbout et al. 2015). To promote the clinical application of SDM, patient decision aids (O'Connor 2000, Poprzeczny et al. 2020), evaluation tools (Scholl et al. 2012, Barr et al. 2014), auxiliary standards, and laws (Holmes-Rovner 2007) have been studied and developed.

Although the theoretical system of SDM has been mature and widely used in the clinic, there are still many problems to be solved (Pieterse et al. 2019). For example, uneven distribution of medical resources, lack of awareness of doctor-patient communication, limited time of doctors, lack of medical knowledge of patients, etc. These problems cannot be completely solved, and we can only

[a] https://orcid.org/0000-0002-6839-4769
[b] https://orcid.org/0000-0001-5666-0348
[c] https://orcid.org/0000-0002-1830-5190
[d] https://orcid.org/0000-0002-9453-1173
[e] https://orcid.org/0000-0003-2648-2960

Liu, Y., Lu, P., Yang, Y., Hong, F. and Lin, K.
Modeling Doctor-patient Shared Decision-making as Fuzzy Constraint-based Agent Negotiation.
DOI: 10.5220/0011228100003438
In *Proceedings of the 1st International Conference on Health Big Data and Intelligent Healthcare (ICHIH 2022)*, pages 48-55
ISBN: 978-989-758-596-8

reduce the impact of these uncertain factors on the clinical application of SDM.

The negotiations involved in SDM mainly take place between doctors and patients. To make SDM in-network and promote the theoretical study and clinical application of SDM, a fuzzy constraint-directed agent-based negotiation (FCAN) model and a recommendation model for bilateral SDM are proposed in this paper. We model the shared decision-making problems (SDMPs) as distributed fuzzy constraint satisfaction problems (DFCSPs) to implement SDM and achieve treatment plan recommendations to objectify SDM. The doctor agent (DA) and the patient agent (PA) are designed to interact in the form of offer and counteroffer until they reach an agreement or withdraw from negotiations. Then, we match the agreement with the existing treatment plans by calculating the recommendation score to achieve the recommendation of the treatment plans.

The main advantages of this paper can be summarized into three points. First, it provides a general framework for knowledge representation and problem-solving for SDM simulation. Second, a distributed computing model including negotiation algorithm and recommendation algorithm is established, which simulates SDM in the real world more closely and naturally. Thirdly, an efficient negotiation model is proposed to relax the constraints of negotiation issues and time and improve the negotiation efficiency. In addition, the negotiation model can effectively reduce the influence of space and the negotiator's emotions on negotiation because of its automaticity.

The rest of this paper is organized as follows. Section 2 generalizes the proposed methods. Section 3 describes the complete process of solving the SDM problem with the proposed method. It includes the problem formulation, negotiation and recommendation strategies, interaction mechanism, and system structure. Section 4 proves the feasibility and effectiveness of our method applied to SDM by an example and comparative test. Section 5 summarizes this paper.

2 METHODS

Study Subjects

The subjects were doctors and patients attending the treatment for chronic diseases. Significantly, the eligible patients with light or moderate conditions.

Ethical Requirement

This study was approved by the Medical Ethics Committee of Xiamen Hospital of Traditional Chinese Medicine, China, and the approval number is 2021-K065-01. In addition, all participants provided written informed consent after a complete description of the study. There was no financial compensation for the doctors and the patients.

Study Design

This study was designed as an exploratory study to solve the problems of doctor-patient SDM according to the agent negotiation and fuzzy constraints. Thus, it is necessary to establish an agent negotiation and recommendation method based on fuzzy constraints for SDM (Section 3) and validate it by experiments (Section 4). The proposed method includes four parts: problem formulation (Section 3.1), negotiation and recommendation strategies (Section 3.2), interaction mechanism (Section 3.3), and system structure (Section 3.4). The experiments consist of two parts: an illustration for judging its feasibility (Section 4.1) and a negotiation performance comparison for evaluating its effectiveness (Section 4.2).

Data Collection

The experimental data in this paper was related to childhood asthma and were obtained from the Department of Pediatrics at Xiamen Hospital of Traditional Chinese Medicine. It consists of the preference data of doctors and patients on issues and the evaluation data of treatment plans provided by doctors. In addition, the treatment plans come from the Diagnosis and Treatment Guidelines of Asthma published in 2016 (The Respiratory Group 2016).

Results Evaluation

The evaluation index of treatment recommendation is the recommendation score. The evaluation indicators of negotiation performance are the combined ASV (the sum of DA's ASV and PA's ASV) and the number of negotiation rounds.

3 FUZZY CONSTRAINT-BASED AGENT NEGOTIATION FOR SDM

In this section, we will introduce our proposed method in detail. Our problem formulation is summarized in Section 3.1. It describes the theoretical basis of modeling SDM as DFCAN. Section 3.2 introduces the negotiation and recommendation strategies of our method that is the behavior framework of the DA and PA. Section 3.3

presents the interaction mechanism between the DA and PA. Section 3.4 develops a system structure for a prototyped agent-based SDM simulator.

3.1 Problem Formulation

Agent-based negotiation technology has been successfully applied to solve the problems of resource allocation (Voos 2006), e-commerce (Ateib 2010), cloud computing (Shojaiemehr et al. 2019), etc. In clinical practice, SDMP is actually a problem that needs to be negotiated by doctors and patients. Thus, based on the agent concept (Wooldridge and Jennings 1995), SDMP can be transformed into the agent negotiation problems shown in Figure 1.

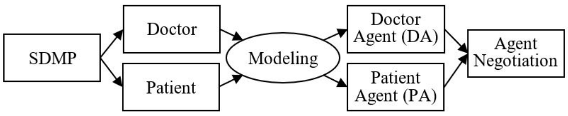

Figure 1: Problem conversion.

Furthermore, the real-world clinical environment is heterogeneous, distributed, and with a great deal of uncertain and inaccurate information. Therefore, in our work, SDMP can be modeled as DFCSP. The task of SDM simulation is to explore a satisfactory agreement that meets all constraints and then make a decision on treatment plans. A negotiation for treatment in SDM can be modeled as a triple $(\mathcal{D},\mathcal{P},\mathcal{I})$, where $\mathcal{D}$ and $\mathcal{P}$ represent the DA and PA, respectively, and $\mathcal{I}$ is the inter-relationships between the two types of agents. The distributed fuzzy constraint networks (DFCNs) are defined as follows.

Definition 1: A DFCN (U,X,C) in a SDM $(\mathcal{D},\mathcal{P},\mathcal{I})$ can be defined as a set of fuzzy constraint networks (FCN) $\{N^1,\ldots,N^l,\ldots,N^L\}$, where $N^l = (U^l,X^l,C^l)$ belongs to agent l, and

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

$X^l = \{X_1^l,\ldots,X_i^l,\ldots,X_n^l\}$ is a tuple of n non-recurring objects; and

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

U is the universe of discourse for DFCN;

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

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

As stated in **Definition 1**, the solution to X^l, FCN, can be regarded as an intention Π_{N^l} or Π_l, indicating that fuzzy set X^l of non-recurring objects satisfies all fuzzy constraints C^l.

3.2 Negotiation and Recommendation Strategies

Following the description of FCSP of SDM, the FCAN model and recommendation model for SDM can be described as follows.

Given an issue set $I = \{I_1, I_2, \ldots, I_i, \ldots, I_n\}$ and an offer (or a counteroffer) $S\epsilon\Pi_l$, the aggregated satisfaction value (ASV) about S of agent l is:

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

Where $\mu_i(S)$ is the i_{th} satisfaction degree function of S, fuzzy membership function, n is the number of issues, and w_i is the weight factor for i_{th} issue.

For an auto-negotiation, the agent will determine its new behavior state and generate a set of feasible solutions by reducing its demands to reach an agreement with its opponent. The feasible solution set is the solution space, in which agents can explore to a satisfactory consensus. Given FCN N, intention Π, and a new behavior state $\varepsilon^* = \varepsilon - \Delta\varepsilon$, a set of feasible solutions P can be acquired by:

$$P = \Gamma(\Pi,\varepsilon^*) = \{S|(S\epsilon\Pi)\Lambda(\varepsilon \geq \Psi(S) \geq \varepsilon^*)\} \tag{2}$$

Where, ε is the behavior state in the last round, and $\Delta\varepsilon$ is the concession value.

In the offer exchange round, the agent trends to select an "optimal" offer from the feasible solution set to maximize their individual interest. The selection condition can be defined as:

$$S^* = arg(max_{S\in P} H(S,B)) \tag{3}$$

Where $H(S,B)$ is a utility function that can evaluate the similarity between counteroffer B and feasible solution S. It can be calculated by:

$$(S,B) = 1 - \frac{1}{n}\sqrt{\sum\nolimits_{i=1}^{n} (1 - D(A_i,B_i))^2} \tag{4}$$

Where A_i and B_i are the possibility distributions of offer A and counteroffer B over the issue $I_i\epsilon I$, respectively, and D is the distance measure between a feasible solution $A \in S$ (i.e., A_i) and a counteroffer B (i.e., B_i).

The negotiation result between the DA and PA is an agreement on the value of all issues. However, the purpose of real SDM is to obtain a treatment plan that meets the preferences of both sides and conforms to the patient's condition. Therefore, we need to translate the results of the negotiations into treatment plans for doctors and patients to make decisions. The conversion method is as follows.

$$(S,B) = 1 - \frac{1}{n}\sqrt{\sum\nolimits_{i=1}^{n} (1 - D(A_i, B_i))^2} \qquad (5)$$

Where w_i is the weight of the relevant issues concerning treatment plans, and $R_i(S) \in [0,1]$ is the similarity calculation on the negotiation issue level, that is, the fuzzy membership function related to the treatment plans.

3.3 Interaction Mechanism

The above-mentioned negotiation process can be summarized as a universal negotiation and recommendation algorithm for the DA and PA, which describes the method adopted by the DA and PA in the negotiation process. Therefore, based on the strategies given in Section 3.2, Algorithm 1 presents the details of the interaction process between the DA and PA.

Initially, the negotiator will send a message with the initial offer to its opponent. When its opponent receives the message, it first determines the type of the message. If it is an "Abort" message, it means that the other party withdraws from the negotiation, and the negotiation fails. If it is an "Accept" message, it means that the other party agrees to reach an agreement, and the negotiation is terminated in a successful state. Otherwise, the opponent will generate a set of feasible solutions and judge whether it can reach an agreement with the other party. If it can, it will send an "Accept" message; if not, it will decide whether to generate the "Ask" message with a new offer according to the current time state. For another negotiator, the response process is similar. The above negotiation process will be repeated until the negotiation status is failed or successful.

Algorithm 1: Interaction Algorithm

```
negotiation state ← "normal"
activate Timer T
generate an initial offer A_0 or B_0 and send it in "Ask" to the opponent agent
Repeat
  receive a message from its opponent
  if the message is an "Abort", then
    negotiation state ← "failure"
  else if the message is an "Accept", then
    negotiation state ← "success"
  else
    get a counteroffer B or A from the received message
    generate a new feasible set P
    if D and P reach an agreement, then
      send an "Accept" message with the agreement S
      negotiation state ← "success"
    else if Timer T is counting, then
      generate a new offer A or B based on feasible set P
      send an "Ask" message with the new offer A or B
    else
      negotiation state ← "failure"
    end if
  end if
until the state is "success" or "failure"
```

3.4 System Structure

In the clinical environment, fuzzy-directed agent-based automatic negotiation is an open simulation platform for simulating SDM between doctors and patients. Figure 2 shows the structure of agent-based negotiation for simulating SDM. In this figure, based on the fuzzy description, the SDM Environment Description Module can transform the clinical environment (including the description of clinical situations, disciplines, and rules) into the fuzzy constraint network.

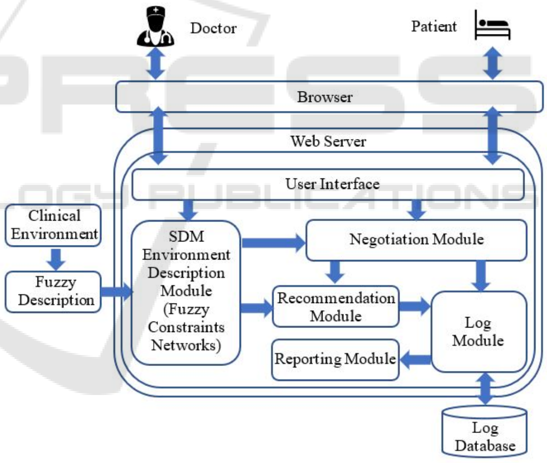

Figure 2: A system structure of SDM.

In the **Negotiation Module**, the DA and PA will comply with the negotiation protocols to solve their own FCSP by exchanging the offer and counteroffer in the transformed clinical environment. In the negotiation process, if the agent cannot reach an agreement with its opponent in the current round, it will relax its constraints, adopt a concession strategy, and explore alternative agreements. Meanwhile, the agent will update its cognition of the opponent and the environment and modify its negotiation status in the next round. The details can be seen in Sections 3.1 to 3.3.

When the DA and PA reach an agreement, the **Recommendation Module** is applied to convert the negotiation result into treatment plans and accomplish the recommendation of treatment plans. In this module, the recommendation scores of treatment plans will be calculated and ranked.

The **Log Module** records the relevant data of the Negotiation Module and Recommendation Module into log files. The negotiation data includes the process and results, and the recommendation data includes all the recommended results. The **Reporting Module** will generate a detailed report according to the results of negotiation and recommendation and send it to doctors and patients, respectively. Finally, doctors and patients can evaluate each other and make treatment decisions.

4 EXPERIMENTS

After defining the model and system structure, the next step is to evaluate it. Given the purpose of our work, we evaluated our method from the perspective of feasibility and effectiveness. On the one hand, we judged its feasibility by an illustration, as shown in Section 4.1; on the other hand, we evaluated its effectiveness by negotiation performance, as shown in Section 4.2. Additionally, the clinical decision-making scene used in the experiment was the SDM of doctors and patients on the treatment of childhood asthma. There are two roles, doctor and patient, corresponding to the DA and PA, respectively.

4.1 An Illustration for Agent-based SDM

The following content provides a case to illustrate the application of the framework proposed in this paper in simulating and solving SDM problems. For negotiation, the initial satisfaction threshold of both DA and PA is set to 1.0, the satisfaction retention value is 0.0, and the maximum number of rounds is 15. Negotiated issues include cost, effectiveness, side effects, risk, and convenience (Rivera-Spoljaric et al. 2014).

According to the negotiation algorithm, the negotiation is terminated when the DA and PA reach an agreement, or the negotiator withdraws from the negotiation, or the negotiation round is exceeded. After full negotiation, the negotiation result between the DA and PA is [Cost: 3.78, Effective: 9, Side-effects: 0.06, Risk: 0.07, Convenience: 9], because the ASV of DA for the received offer is greater than its satisfaction threshold.

As mentioned above, the negotiation result is not the real purpose of SDM. Thus, the Recommendation Module will be applied to address the problem of treatment recommendation. The final recommended results of treatment plans are shown in Figure 3.

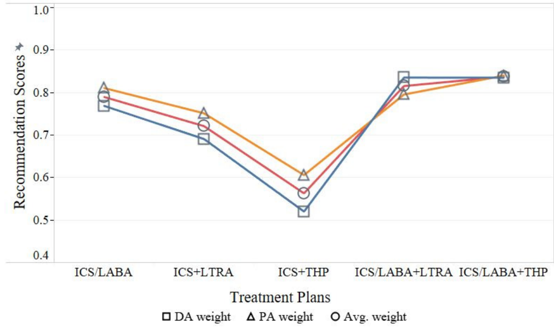

Figure 3: The recommendation scores of treatment plans in different priority constraints [with the weights of issues of DA, PA, and their average].

The recommended order of treatment plans is:

En-high dose ICS/LABA + Sustained-release THP ⩾ En-high dose ICS/LABA+LTRA ⩾ En-high dose ICS/ LABA ⩾ En-high dose ICS+LTRA ⩾ En-high dose ICS + Sustained-release THP.

Where ICS means inhaled corticosteroid, LABA is long-acting beta2-agonists, LTRA is leukotriene receptor antagonists, THP is theophylline, and ICS/LABA means a combination of inhaled corticosteroids and long-acting beta2-agonists.

4.2 Negotiation Evaluation

To evaluate the effectiveness of our SDM negotiation method, we compare it with the Time model (time-dependent negotiation model) (Faratin et al. 1998) in terms of negotiation rounds and combined ASV. All the experimental results were the average results of 200 repeated experiments. The first experiment compared the negotiation performance of agents on different issues but subjects to the same deadline. The second experiment compared the negotiation performance of agents on the same issues but subjects to different deadlines. Here, the negotiation environment is defined by the number of issues (between 1 and 9) and the number of deadlines (between 10 and 30). The range of these parameters is selected according to the experience of experts in the SDM field.

As shown in Figures 4 and 5, it can be seen that when the FCAN model and Time model negotiate on different issues (the number of issues is between 1 and 9) and subject to the same deadline constraints, the negotiation rounds required by the FCAN are lower than that of the Time model, and the combined ASV obtained are higher than that of the Time model. Figures 4-5 also show that when the number of issues increases, FCAN and Time usually need more negotiation rounds, but the combined ASV may decrease. This corresponds to a common phenomenon: when negotiation issues increase, negotiators need more rounds to explore and reach an agreement, and the final combined ASV does not necessarily increase.

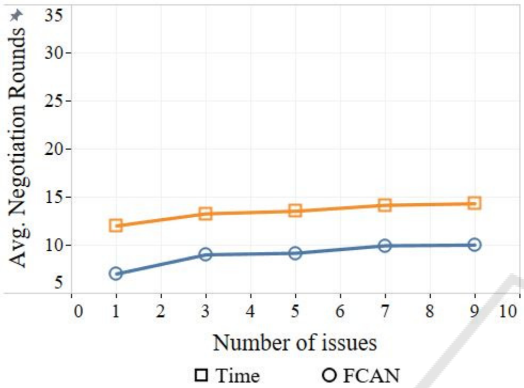

Figure 4: Average negotiation rounds of agents with different issues [deadline = 15].

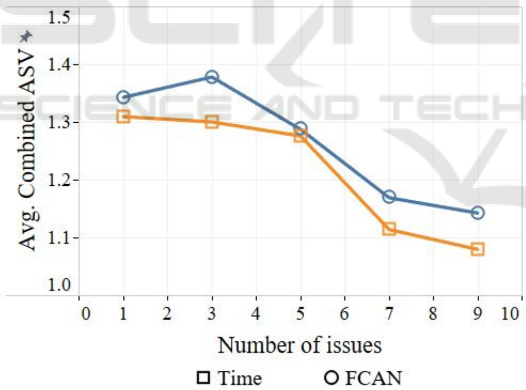

Figure 5: Average combined ASV of agents with different issues [deadline = 15].

As can be seen from Figures 6-7, when the negotiation is subject to the deadline constraints between 10 and 30 and is not affected by the number of negotiation issues, the number of rounds of the FACN model is usually lower than that of the Time model and the combined ASV is usually higher than that of the Time model. When the deadline is relaxed, the FCAN and Time can usually obtain a higher combined ASV after more rounds for negotiation. In addition, due to deadlines constraints, the combined ASV obtained by the FCAN and Time is close, but the number of negotiation rounds required shows a great difference. This corresponds to the common phenomenon that when agents negotiate purely based on time, they need more rounds to reach a satisfactory agreement.

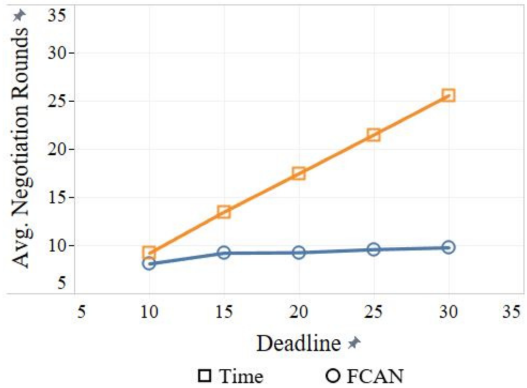

Figure 6: Average negotiation rounds of agents with different deadlines [the number of issues = 5].

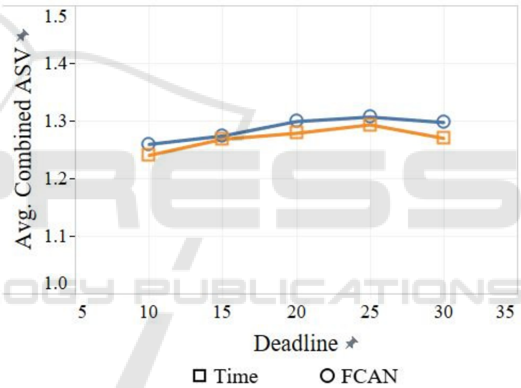

Figure 7: Average combined ASV of agents with different deadlines [the number of issues = 5].

In conclusion, when agents are eager to reach an agreement, whether they are under the pressure of deadlines or issues, the FCAN model performs better than the Time model because compared to the Time model, FCAN can obtain higher combined ASV in fewer negotiation rounds. This satisfies the general goal of automatic negotiation, that is, to obtain a higher combined ASV in fewer rounds. Therefore, the above experimental results fully validate the feasibility and effectiveness of our negotiation model.

5 CONCLUSIONS

A general framework and an open simulation platform for the fuzzy constraint-based agent negotiation of SDM are presented in this paper. Based on fuzzy constraints, we intuitively and effectively transformed SDMP into DFCSP. Then, in the Negotiation Module, the DA and PA were designed to simulate the negotiation between doctors and patients. After that, the Recommendation Module converted the negotiation results into treatment plans. Finally, the Reporting Module provides a detailed report of negotiations and recommendations to doctors and patients.

Experimental results demonstrate that our proposed method can successfully implement the negotiation and recommendation of SDM based on fuzzy constraints and obtain higher combined ASV in fewer rounds. Specifically, the presented method effectively alleviates the constraints of issues and time on negotiation and significantly improves negotiation efficiency. Although our method has received some feasible and effective results, further exploration is needed, such as the learning capabilities and convergence analysis and the negotiation of our proposed method in more complex scenarios.

ACKNOWLEDGEMENTS

This research was funded by the Science Foundation of Fujian Province (No. 2021J011188), the Xiamen Science and Technology Planning Project (No. 3502Z20206073), the Research Project of Xiamen Overseas Students (No. XRS202017206), and the Scientific Research Project of Xiamen University of Technology (No. YKJCX2019108).

REFERENCES

ATEIB, M. T. 2010. Agent based negotiation in e-commerce. *2010 International Symposium on Information Technology*. Kuala Lumpur, Malaysia: IEEE.

BARR, P. J., THOMPSON, R., WALSH, T., GRANDE, S. W. & ELWYN, G. (2014). The psychometric properties of collaboRATE: A fast and frugal patient-peported measure of the shared decision-making process. J. Journal of Medical Internet Research. 16, e2.

ELWYN, G., TSULUKIDZE, M., EDWARDS, A., LéGARé, F. & NEWCOMBE, R. (2013). Using a 'talk' model of shared decision making to propose an observation-based measure: Observer OPTION 5 Item. J. Patient Education and Counseling. 93, 265-271.

FARATIN, P., SIERRA, C. & JENNINGS, N. R. (1998). Negotiation decision functions for autonomous agents. J. Robotics and Autonomous Systems. 24, 159-182.

HOFFMANN, T. C., MONTORI, V. M. & MAR, C. D. (2014). The connection between evidence-based medicine and shared decision making. J. The Journal of the American Medical Association. 312, 1295-6.

HOLMES-ROVNER, M. (2007). International patient decision aid standards (IPDAS): Beyond decision aids to usual design of patient education materials. J. Health Expectations. 10, 103-107.

MAKOUL, G. & CLAYMAN, M. L. (2006). An integrative model of shared decision making in medical encounters. J. Patient Education and Counseling. 60, 301-312.

O'CONNOR, A. (2000). Using patient decision aids to promote evidence-based decision making. J. Acp Journal Club. 135, A11-2.

PIETERSE, A. H., STIGGELBOUT, A. M. & MONTORI, V. M. (2019). Shared decision making and the importance of time. J. The Journal of the American Medical Association.

POPRZECZNY, A. J., STOCKING, K., SHOWELL, M. & DUFFY, J. (2020). Patient decision aids to facilitate shared decision making in obstetrics and gynecology: A systematic review and meta-analysis. J. Obstetrics & Gynecology. 135.

REIMANN, H. (1968). Shared decision making and shared responsibility-a problem of modern educational establishments. J. Die Agnes Karll-schwester, der Krankenpfleger. 22, 102-103.

RIVERA-SPOLJARIC, K., HALLEY, M. & WILSON, S. R. (2014). Shared clinician-patient decision-making about treatment of pediatric asthma: What do we know and how can we use it? J. Current Opinion in Allergy and Clinical Immunology. 14.

SCHOLL, I., KRISTON, L., DIRMAIER, J. R., BUCHHOLZ, A. & HäRTER, M. (2012). Development and psychometric properties of the shared decision making questionnaire--physician version (SDM-Q-Doc). J. Patient Education and Counseling. 88, 284-290.

SHOJAIEMEHR, B., RAHMANI, A. M. & QADER, N. N. (2019). A three-phase process for SLA negotiation of composite cloud services. J. Computer Standards & Interfaces. 64.

STATES, U. (1982). Making health care decisions: a report on the ethical and legal implications of informed consent in the patient-practitioner relationship; volume one, report. J. Psychiatric Services. 34, 465.

STIGGELBOUT, A. M., PIETERSE, A. H. & DE HAES, J. C. (2015). Shared decision making: concepts, evidence, and practice. J. Patient Education and Counseling. 98, 1172-1179.

THE RESPIRATORY GROUP, T. S. O. P., CHINESE MEDICAL ASSOCIATION (2016). Guidelines for diagnosis, prevention and treatment of bronchial asthma in children (2016 Edition). J. Chinese Journal of Pediatrics. 15.

VEATCH, R. M. (1972). Models for ethical medicine in a revolutionary age. What physician-patient roles foster the most ethical realtionship? J. Hastings Center Report. 2**,** 5.

VOOS, H. 2006. Agent-based distributed resource allocation in technical dynamic systems. *IEEE Workshop on Distributed Intelligent Systems: Collective Intelligence and Its Applications (DIS'06).* Prague, Czech Republic: IEEE.

WESTON, W. W. (2001). Informed and shared decision-making: the crux of patient-centred care. J. Canadian Medical Association Journal. 165**,** 438-439.

WOOLDRIDGE, M. & JENNINGS, N. R. (1995). Intelligent agents: theory and practice. J. Knowledge Engineering Review. 10**,** 115-152.