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A multicriteria collaborative decision support system for multidisciplinary medical coordination meetings

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ABSTRACT

Multidisciplinary team meetings (MDTMs) are central to cancer care. However, consensus can be hard to reach because specialists rely on diverse expertise and uncertain, multi-criteria clinical data. In this paper, we propose a group decision support system (GDSS) that integrates a multi-agent system (MAS) with multi-criteria decision making (MCDM) to structure interactions, aggregate expert preferences, enable real-time evaluation of options based on criteria, and transparently prioritize patients for discussion and intervention. Each specialist is represented by an agent that evaluates cases against shared criteria, while an embedded negotiation protocol enables exchanges and concessions to resolve conflicts and build consensus. We evaluated the GDSS using simulated breast cancer MDTM scenarios generated from a synthetic dataset of MDTM records. Experimental results demonstrate rapid convergence toward a consensual patient prioritization within a few negotiation iterations; in our experiments, agreement on the highest risk patient was reached after four rounds. Sensitivity analysis on subjective inputs, including criteria weights and preference profiles, produced minor changes in the resulting ranking, indicating robustness and stability to preference variations. The system maintains low computational complexity and short execution times, improving the transparency and consistency of MDTM recommendations. These outcomes confirm effectiveness and scalability for complex multidisciplinary clinical decisions.

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1. INTRODUCTION

Patients' health and well-being are often linked to multiple, sometimes contradictory criteria. Medical decision-making is therefore a complex process, involving the management of critical cases, the allocation of resources, and the formulation of health policies. Multiple stakeholders, including nurses, healthcare administrators, patients, and their families, are expected to collaborate to ensure evidence-based, individualized, and sustainable outcomes. Multidisciplinary consultation meetings (MCMs), commonly known as multidisciplinary team meetings (MDTMs), are regular sessions that bring together medical specialists such as surgeons, oncologists, and radiologists. These meetings aim to review complex patient cases and define appropriate therapeutic strategies. Collective, team-based decision-making is achieved by integrating diverse expertise. MDTMs can enhance care quality, reduce medical errors, and support more effective treatment planning. However, given limited resources, including time and availability of technical facilities, prioritizing patients according to clinical severity and urgency becomes essential. In oncology, this prioritization within MDTMs can be viewed as a multi-criteria group decision-making problem. The key objectives are: i) to identify patients at highest risk, ii) to establish a fair and transparent prioritization process, and iii) to respect clinical, human, and logistical constraints.

Decision support systems (DSS) can generally be classified into two main categories: individual systems and collective systems. Individual decision support systems (IDSS) are designed to assist a single decision-maker in analyzing data, evaluating alternatives, and making well-informed decisions [1].

Group decision support systems (GDSS) aim to facilitate collaborative decision-making among multiple participants with heterogeneous preferences [2]. Several GDSS models have been proposed for distributed and asynchronous group decisions, for negotiation in resource management [3], and for coordination through dialogue-based systems such as DIAL [4]. General negotiation models for multi-agent systems (MAS) have also been introduced and illustrated through applications such as auctions and appointment scheduling platforms [5]. Hybrid approaches combining MAS and geographic information systems have been developed to support decision-making in environmental and territorial contexts [6].

Within this research area, several GDSS have been developed by the research team "Artificial Intelligence Tools in Support of Decision-Making Systems" of the laboratory LIO. These include a GDSS for territorial planning based on monotonic concession and multicriteria analysis [7], a multicriteria GDSS for industrial diagnosis [8], a spatial GDSS coupling multicriteria analysis and satisfactory game theory [9], and a negotiation platform for GDSS using web services and multicriteria methods [10]. Many GDSS rely on MAS to model interactions between decision-makers and to reach acceptable agreements through mechanisms such as voting, negotiation, and argumentation. Argumentation-based approaches have been proposed to structure reasoning and avoid non-intuitive outcomes in rule-based systems [11]. General frameworks for argumentation-based decision-making have been introduced to explain collective decisions derived from beliefs and preferences [12]. Concession-based negotiation strategies have also been studied, emphasizing minimal concession mechanisms that prioritize higher-ranked goals [13]. Additional works propose postulates for logic-based argumentation systems [14] and evaluate trust-aware argumentation tools in collaborative human-agent decision-making [15]. More recently, multi-agent multicriteria GDSS have been proposed for spatial decision problems, where agents negotiate to reach a compromise and a coordination mechanism ensures convergence before a deadline [16]. Web-intelligent multicriteria GDSS integrating MAS, geographic information systems, and multicriteria methods such as TOPSIS and AHP have also been introduced [17]. Ontology-based multicriteria GDSS have been proposed to address semantic heterogeneity and improve cooperation among decision-makers in site selection problems [18].

The application of GDSS in the medical field has gained increasing attention due to the collaborative nature of clinical decision-making, particularly during MDTMs. Several studies propose decision support frameworks to assist multidisciplinary medical teams by structuring clinical reasoning, aggregating expert knowledge, and coordinating the overall decision workflow [19]. Other approaches rely on multi-agent decision support based on medical ontologies, where specialized agents represent different medical domains and cooperate to generate consistent recommendations during MDTMs [20].

More recently, AI-based clinical decision support systems (CDSS) has been shown to support triage of breast cancer cases during MDTMs, allowing a substantial proportion of patients to be safely managed while reducing team workload and preserving concordance with clinical best practice [21]. Qualitative investigations highlight facilitators such as improved visualization of patient information and time-saving functionalities, as well as barriers related to data connectivity, accuracy of recommendations, guideline updates, and preservation of clinician responsibility during MDTMs [22]. Guideline-based decision support has also been investigated in oncological MDTMs, demonstrating high concordance with MDTM decisions when sufficient patient data are available, while also revealing limitations related to data completeness and workflow constraints in routine practice [23].

The objective of the current study is to develop a multicriteria group medical decision support system that improves the effectiveness of MDTMs. This is achieved by integrating MAS with multicriteria decision analysis methods. The proposed system structures expert discussions, supports the collective evaluation of patient cases, and promotes informed consensus. The case study focuses on identifying the cancer patient at highest risk in order to prioritize care during MDTMs.

The remainder of the paper is organized as follows: Section 1 presents the introduction, outlining the context, the addressed problem, the related works, and the contribution of the present study. Section 2 describes the methodology of the proposed system, including the formulation of the addressed decision-making problem. It explains the implemented negotiation protocol and presents the UML modeling of the system, followed by a description of the adopted decision-making process. Section 3 illustrates the overall approach through a case study, focusing on the problem formulation and the obtained results at the end of the negotiation process. Finally, Section 4 concludes and proposes extensions of the system.

Research gap and key contributions. To the best of our knowledge, none of the existing studies jointly integrate multicriteria decision-making methods and multi-agent negotiation within a unified framework specifically designed to support collaborative patient prioritization in MDTMs. This gap motivates the proposed approach, which contributes: i) a GDSS modeling MDTM decision-making using a Multi-Agent System and a structured negotiation protocol, ii) an integrated multicriteria decision process combining AHP, PROMETHEE II, and SCORAGE to support individual preference expression and collective convergence, and iii) a sensitivity and robustness analysis assessing the stability of the collaborative decision under variations in the preferences expressed by doctors.

2. METHOD

This section presents our proposed method, including the formulation of the medical decision-making problem, the system architecture, and the negotiation protocol for reaching a collaborative decision.

2.1. Formulation of the addressed decision-making problem

Objective**:** Identifying the patient most at risk and prioritizing his or her care. The global formulation of the problem is given by (A, F, PM, d, weight (d), SPi, T)

- A: the set actions (rows): each patient.
- F: the family of criteria (columns): the criteria identified to address this decision-making issue are described in Table 1.
- PM: consisting of an incidence matrix of actions and criteria.
- d: the number of the involved decision makers (doctors).
- weight (d): the weight of each doctor in the group decision process.
- SPi: preferences (subjective parameters) of each doctor according to the identified criteria (weight, preference, indifference)
- T: negotiation threshold.

Due to the lack of available real-world data, we propose an algorithm designed to generate synthetic data. This Algorithm 1 is carefully constructed to preserve the underlying logic of the relationships between the identified criteria, ensuring the coherence and relevance of the generated data. This approach provides a usable dataset for testing, validation, or modeling phases, while accurately reflecting the expected structure of the problem under study.

Algorithm1: Generation of a Performance Matrix for Patient Prioritization

```
Input: num_patients
Output: performance_matrix
Initialization:
Performance_matrix←[]
For i←1 to num_patients do
T← random value from {1, 2, 3, 4} ▷Tumor stage
N← random value from {0, 1, 2, 3} ▷Lymph nodes
If T≥ 3 and N≥ 2 then
 M←1 ▷ Presence of metastases
else
M← random value from {0,1}
endif
▷Calculation of OMS score
If T≤2 and M=0 then
oms_score← random value from {0,1}
elseif T=3 or N=1 then
oms_score← random value from {2,3}
else
oms_score← random value from {4,5}
endif
▷Calculation of Ki-67 score
If T≤2 and M=0 then
ki67←random number between 5 and 30
elseif T=3 or N=1then
ki67← random number between 31 and 60
else
ki67← random number between 61 and 90
endif
▷Determination of disease_phase
If M =1 or ki67 >30 then
```

```
 disease_phase←1       ▷Relapse
else
 disease_phase←0       ▷Initial phase
endif
Add(T, N, M, oms_score, ki67, disease_phase)
endfor
return performance_matrix
```

Table 1. Criteria of the performance matrix

Criteria	Description	Values
Tumor stage (T)	Tumor size and local extension	-1: Not assessed (Tx); 0: No tumor (T0); 0.1-0.2: In situ (Tis, Paget); 1.0-1.3: Small mass, no larger than 2 cm (T1mic, T1a-c); 2: Mass measuring between 2 and 5 cm (T2); 3: Mass greater than 5 cm (T3); 4.1-4.4: Involvement of adjacent structures (T4a-d).
Nodes (N)	Lymph node involvement	-1: Not assessed (Nx); 0.0-0.4: No nodes involved (N0, N0(i-, i+, mol-, mol+)); 0.5: Micro metastases (N1mi); 1.0-1.3: Moderate involvement of nearby lymph nodes (N1, N1a-c); 2.0–2.2: More advanced or internal lymph node involvement (N2, N2a–b); 3.0–3.3: Extensive lymph node involvement, especially supraclavicular or combined (N3, N3a–c).
Presence of metastases (M)	Indicates whether the cancer has progressed to other body regions, a sign of advanced stage.	-1: Not assessed (Mx); 0: No metastasis (M0); 1: Distant metastasis present (M1).
OMS	Patient's general condition	0: Able to walk and perform light or sedentary tasks, but limited in physically demanding activities. 1: Ambulatory and capable of all selfcare but unable to carry out any work activities; up and about more than 50% of waking hours. 2: Capable of only limited selfcare; confined to bed or chair more than 50% of waking hours. 3: Completely disabled; cannot carry on any selfcare; totally confined to bed or chair. 4: Dead.
Disease phase	Determine if the patient is in the initial phase (at the time of diagnosis) or in relapse (recurrence after treatment).	0: Initial; 1: Relapse.

2.2. The proposed system

The proposed group DSS is mainly composed of a web server, a MAS, and a negotiation protocol. The main components are described below:

2.2.1. The web server

It acts as the central platform for coordination and communication. It receives the final group decision and can serve as an interface for users or external systems (e.g., electronic medical records and hospital staff).

2.2.2. The multi-agent system

It models the medical GDSS and is structured around a Negotiator agent, Participant agents, and a negotiation protocol.

– Negotiator agent

This agent is autonomous and independent from the decision-makers. It orchestrates the negotiation process. The main functions of this agent are: i) Sending the performance matrix to the participating agents. ii) Collecting the local rankings of the patients produced by each participant. iii) Initiating and regulating the negotiation protocol between the participating agents. iv) Ensuring the consistency, fairness, and convergence of the decision-making process. v) Generating the collaborative decision.

– Participant agents (Doctors)

These agents represent the human decision-makers (doctors). Each agent includes: Personal preferences and multi-criteria decision analysis (MCDA) methods: AHP for criteria weighting, and PROMETHEE II for ranking the alternatives (patients). The main functions of each participant are:

i) Receiving a performance matrix sent by the negotiator agent. ii) Applying AHP to assign weights to the identified criteria. iii) Applying PROMETHEE II to generate a local ranking of the patients. iv) Participating in a negotiation through a multi-agent protocol.

2.2.3. Negotiation protocol

Constitutes a mechanism for interaction between participant agents, supervised by the negotiator agent. Its objective is to reach a consensus by taking into account the decision-makers' weights as well as their rankings of the patients according to their preferences. The description of this protocol is given in the next section.

Remark: The performance matrix represents the quantitative assessment of patients (alternatives) according to various medical criteria. This matrix is provided by the coordinator and used by each participant agent to generate its own ranking. The overall architecture of the proposed system is illustrated in the Figure 1.

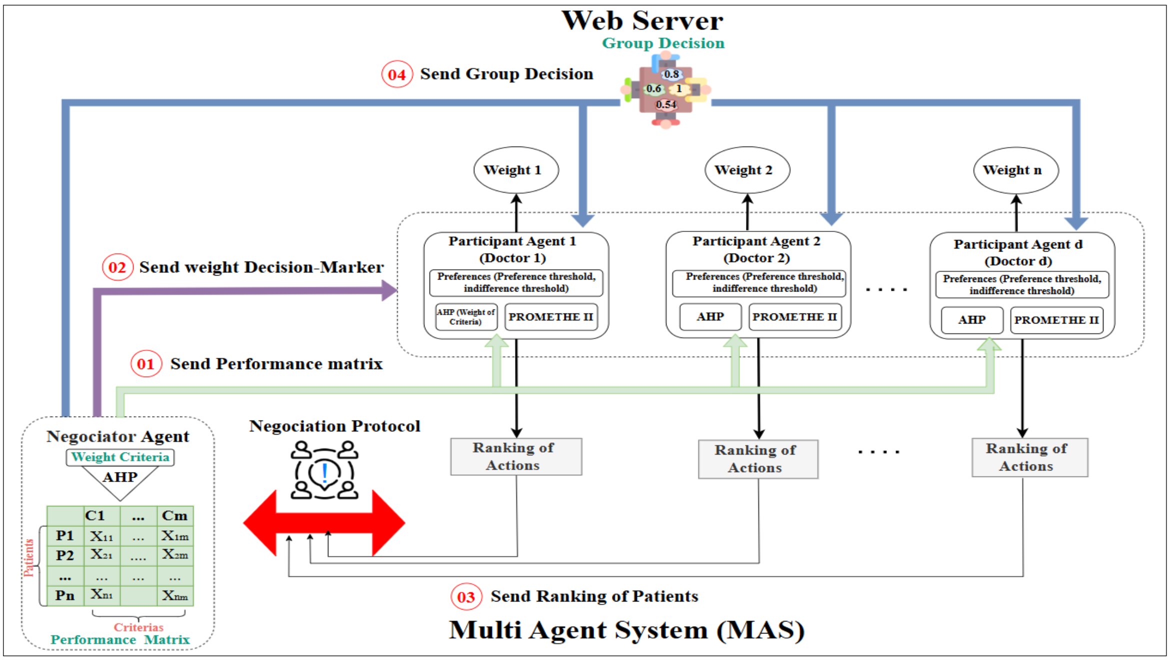


Figure 1. The overall architecture of the proposed system

2.3. The negotiation protocol

The protocol undergoes several stages to reach a group decision, as outlined below.

2.3.1. Steps of the protocol

STEP 1: Sending the decision problem (performance matrix (PM)): this phase of the protocol consists of formulating the decision problem in the form of a performance matrix, which evaluates the different possible alternatives (patients) according to several criteria.

STEP 2: Assigning weights to the decision-makers using AHP method: once this matrix is received by the various decision-makers, the negotiator assigns a weight to each decision in order to reflect their relative importance in the decision-making process. To do so, the negotiator uses the multicriteria method AHP [24], an approach developed by Thomas Saaty that allows pairwise comparisons of the decision-makers and calculates consistent weights reflecting their respective contributions to the decision process.

STEP 3: Ranking the actions (patients): is an essential part of the decision-making process, carried out by every decision-maker with the help of AHP and PROMETHEE II methods. First, AHP is used to assign weights to the criteria according to their relative importance. This method is based on pairwise comparisons, allowing for a normalized weighting of the criteria that influence the decision. Once the weights are defined, PROMETHEE II [25] is applied to assess and rank the different alternatives. This method compares the actions by taking into account the decision-makers' preferences, while considering thresholds (preference and indifference thresholds), and calculates positive and negative preference flows, leading to a final complete ranking of the alternatives. The combination of these two methods ensures more rational and well-justified decision-making by integrating both the decision- makers' priorities and a comparative analysis of the available actions.

STEP 4: Scoring the actions: carried out by the negotiator, this step consists of aggregating the individual rankings of all decision-makers in order to generate a global ranking of the alternatives. To do this, we use the following aggregation formula to affect a score to each patient (a_i),

$$Score(a_i)=\sum_{k=1}^{d} weight(participant\ k) * Rank(ai, participant\ k)) \quad (1)$$

Once the global scores calculated, the alternatives are ranked based on their obtained values.

STEP 5: Proposal of a deal: the proposal step is a key phase during which the negotiator proposes actions to the other participating agents (decision-makers) one by one, according to the scoring vector, over several successive rounds, and waits for the responses of the various decision-makers. This process allows the proposals to be progressively adjusted based on the feedback received.

STEP 6: Evaluation of responses: it takes place after receiving the responses from the various decision-makers. At this stage, the negotiator analyzes the feedback by counting the number of acceptances and rejections. If the number of acceptances exceeds a predefined threshold of negotiation, the collaborative decision is validated and adopted. Conversely, if this threshold is not reached, the decision-makers must begin a new round of negotiation. This process allows proposals to be refined and progressively leads to a consensus that is satisfactory for all parties involved.

STEP 7: Collaborative: the coordinator sends the final collaborative (group) decision to the various decision-makers. This decision step represents the final phase of the negotiation process. Once a consensus has been reached during the previous rounds, the initiator of the negotiation formalizes the final decision. It is then communicated to the different decision-makers involved so that it can be validated and implemented. This step marks the conclusion of the process, ensuring that all stakeholders have a clear and shared understanding of the decision that has been adopted.

2.3.2. UML modeling of the proposed system

Decision-makers communicate and negotiate by sending messages. We distinguish two types of messages: those exclusively used by the negotiator and those exclusively used by each decision-maker. The different messages exchanged in the protocol are described in the Tables 2 and 3.

Table 2. The messages used by the negotiator agent

Formulate (PM)	Formulation of the decisional problem and sending of the performance matrix to the participant agents (Doctors).
Weight_DM()	Assigning a weight to each decision-maker using the AHP method.
Request (Rank)	Asking participants to rank the actions using the PROMETHEE II method.
Propose_deal ()	Proposal of a deal (action) based on the scoring vector created by the negotiator and considering the different rankings of the decision-makers.
Confirm (Coldecision)	Success of the negotiation and sending the collaborative decision to all participants (doctors)
Failure_Negot()	All proposals made, but failure of the participants' negotiation

Table 3. The messages used by each participant agent

Accuse_Formulate (PM)	Acknowledgment of receipt of the performance matrix
Pref (w,p,q)	Expression of subjective parameters (Assigning weights to criteria using AHP(w), manual entry of preference and indifference thresholds p and q)
Send_Rank ()	Sending the rankings of actions performed using the Multicriteria analysis method PROMETHEE II
Accept (deal)	Accept the proposal
Refuse (deal)	Reject the proposal

The UML sequence model associated with the proposed system and the adopted decision making process are illustrated, respectively, in Figure 2 and Figure 3.

- We conducted a sensitivity and robustness analysis of the proposed protocol to assess its stability in the face of variations in decision-makers' preferences. To do this, we slightly modified the preferences expressed by the doctors and repeated the decision-making process several times. This approach allowed us to observe how these changes could affect the outcome of the collaborative decision. The analysis focused on both sensitivity to initial conditions and robustness to heterogeneous preferences.

The results provide valuable insights into the system's ability to maintain consistent and reliable decisions despite uncertainty or variability in individual expert opinions.

– Regarding convergence, negotiation may fail if all options (patients) have been proposed but no consensus is reached. This can be explained by the fact that the protocol relies more on mediation than on concession.

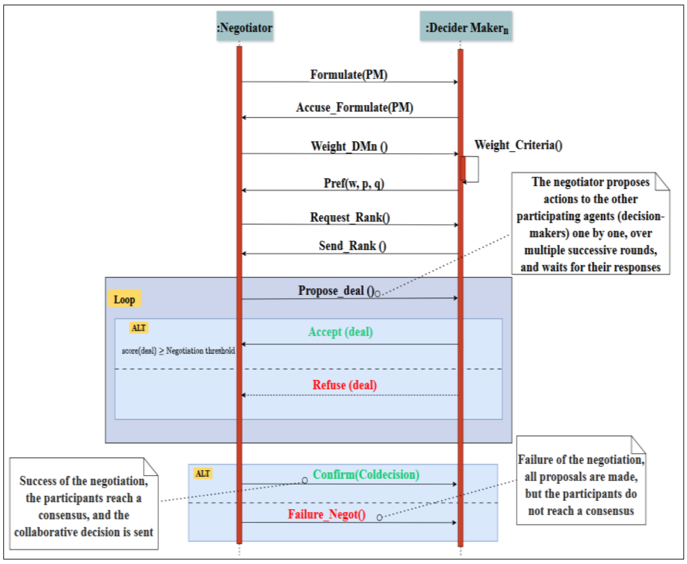


Figure 2. The UML sequence diagram

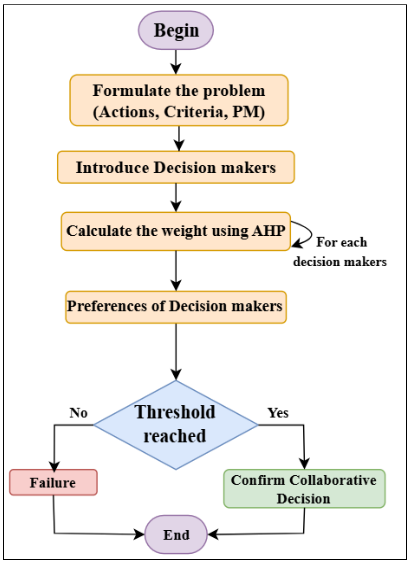
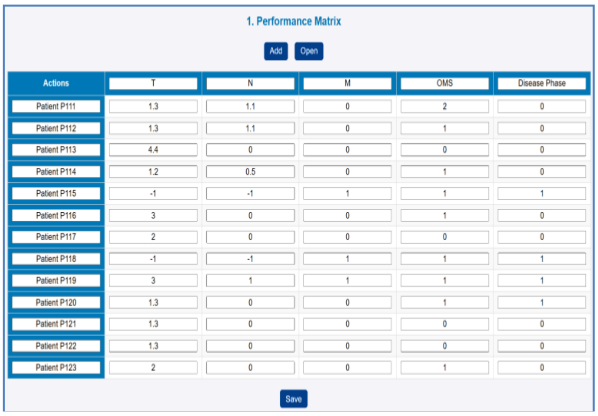


Figure 3. The decision-making process

3. RESULTS AND DISCUSSION

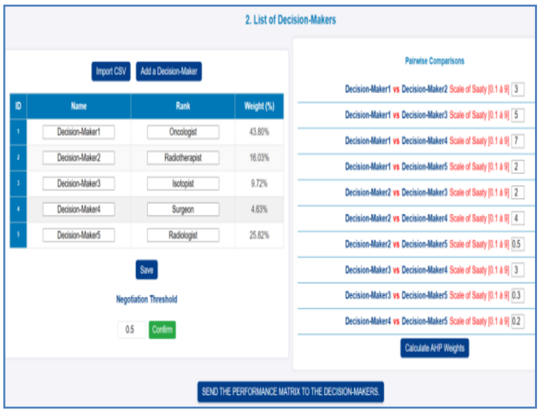
In this section, we present the results obtained by simulating a decision-making scenario within the framework of a MDTM in oncology. In order to experiment the proposed GDSS, the data supporting this study are freely accessible on the official portal data.gouv.fr. They are compiled under the title 'Synthetic records of MCMs (RCP)' and can be viewed at the following [26]. Although these are synthetic data, they have been developed to accurately reflect the structure, challenges, and underlying logic of MCMs in the medical field. Figure 4 illustrates the loading of the performance matrix (PM) by the negotiator. Figure 5 presents the involved decision-makers and their associated weights, as derived from the AHP method.

Five decision-makers are involved in this case study, namely: the surgeon, oncologist, radiotherapist, isotopist, and radiologist. The coordinator sends the performance matrix to the five decision-makers. After receiving the performance matrix, each decision-maker sets their preference and indifference thresholds, calculates the criteria weights using the AHP method, and performs the ranking using the PROMETHEEII method. The rankings performed by the five decision-makers are sent to the coordinator, as shown in the Figure 6.



Actions	T	N	M	OMS	Disease Phase
Patient P111	1.3	1.1	0	2	0
Patient P112	1.3	1.1	0	1	0
Patient P113	4.4	0	0	0	0
Patient P114	1.2	0.5	0	1	0
Patient P115	-1	-1	1	1	1
Patient P116	3	0	0	1	0
Patient P117	2	0	0	0	0
Patient P118	-1	-1	1	1	1
Patient P119	3	1	1	1	1
Patient P120	1.3	0	0	1	1
Patient P121	1.3	0	0	0	0
Patient P122	1.3	0	0	0	0
Patient P123	2	0	0	1	0

Figure 4. Loading the PM (negotiator)



ID	Name	Rank	Weight (%)
1	Decision-Maker1	Oncologist	43.80%
2	Decision-Maker2	Radiotherapist	16.03%
3	Decision-Maker3	Isotopist	9.72%
4	Decision-Maker4	Surgeon	4.63%
5	Decision-Maker5	Radiologist	25.82%

Figure 5. Decision-maker list (negotiator)

3. Rankings received from decision-makers

Decision-makers	Ranks	Rankings
D1	Oncologist	Patient P113 > Patient P119 > Patient P116 > Patient P111 > Patient P112 > Patient P114 > Patient P117 > Patient P120 > Patient P121 > Patient P122 > Patient P123 > Patient P115 > Patient P118
D4	Surgeon	Patient P119 > Patient P113 > Patient P116 > Patient P111 > Patient P112 > Patient P120 > Patient P117 > Patient P123 > Patient P114 > Patient P121 > Patient P122 > Patient P115 > Patient P118
D2	Radiotherapist	Patient P119 > Patient P115 > Patient P118 > Patient P116 > Patient P111 > Patient P120 > Patient P123 > Patient P113 > Patient P112 > Patient P114 > Patient P117 > Patient P121 > Patient P122
D5	Radiologist	Patient P119 > Patient P120 > Patient P113 > Patient P115 > Patient P118 > Patient P116 > Patient P117 > Patient P123 > Patient P111 > Patient P112 > Patient P121 > Patient P122 > Patient P114
D3	Isotopist	Patient P119 > Patient P115 > Patient P118 > Patient P120 > Patient P113 > Patient P116 > Patient P117 > Patient P123 > Patient P111 > Patient P112 > Patient P121 > Patient P122 > Patient P114

Figure 6. Negotiator: list of all received rankings

3.1. Negotiation process and consensus building

The negotiator performs the scoring by taking into account the received rankings as well as the decision-makers' weights, as shown in Figure 7. Then, it proposes patient 119 and waits for the decision-makers' responses (see Figure 8).

Consensus was not reached after three iterations. The consensus process was carried out in several steps. At first, the negotiator proposed patients one by one based on their aggregate scores (see Figure 9), receiving acceptance or rejection responses from all doctors according to their individual rankings. If the number of acceptances did not reach the negotiation threshold, the proposals were refined in subsequent iterations in order to reconcile divergent preferences without imposing concessions. Finally, patient 120 was accepted by all decision-makers at iteration 4 (see Figure 10), and the collective decision was communicated to all participants. Acceptance was influenced by the AHP-based weights of each decision-maker, the individual patient rankings determined by PROMETHEE II, the negotiation threshold, and compromises among the doctors' preferences.

Sorted scoring vector

Ranking	Action	Score	Propose
1	Patient P119	1.44	☑ 0.01 Confirm
2	Patient P113	3.07	☐
3	Patient P116	4.23	☐
4	Patient P120	5.65	☐
5	Patient P111	5.94	☐
6	Patient P115	7.36	☐
7	Patient P112	7.42	☐
8	Patient P117	7.64	☐
9	Patient P118	8.36	☐
10	Patient P123	9.15	☐
11	Patient P114	9.27	☐
12	Patient P121	10.24	☐
13	Patient P122	11.24	☐

Figure 7. Scoring vector and iteration 1 (negotiator)

Deciders' Responses for the Action: **Patient P119**

Decision Maker	Response
1	Rejected
4	Rejected
2	Rejected
3	Rejected
5	Rejected

Figure 8. Decision-makers' responses (negotiator)

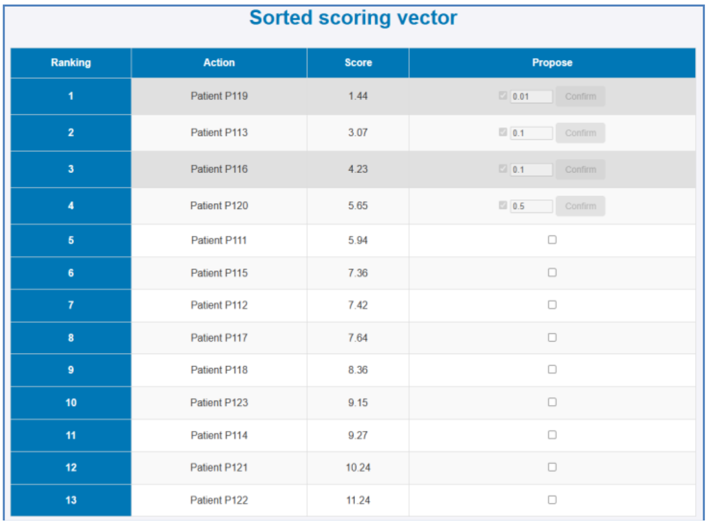


Figure 9. Scoring vector and iteration 4 (negotiator)

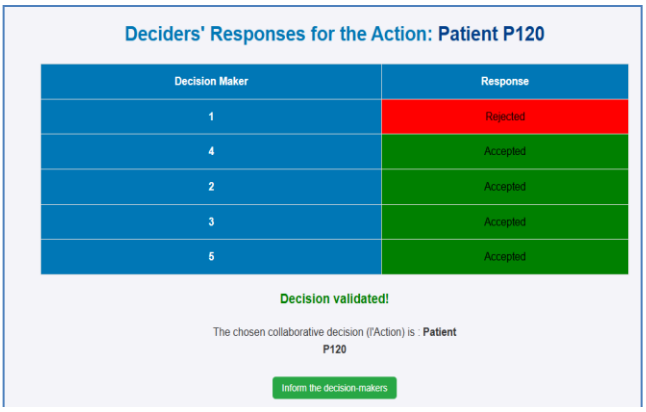


Figure 10. Decision-makers' responses (negotiator)

The negotiation history is recorded in a log, as illustrated in Figure 11. Then, the collaborative decision is sent to all decision-makers. Figure 12 shows the reception of the decision (the patient with the highest priority for hospitalization) by the surgeon.

In order to assess the robustness of the proposed collaborative decision-making approach, we conducted a thorough sensitivity analysis. This analysis aimed to examine the impact of variations in different subjective parameters on the obtained results, in order to verify the stability and reliability of the decision-making model. The results were very convincing: small changes in the parameters only led to slight variations in the respective rankings of the decision-makers (doctors). Therefore, we can conclude that the proposed approach demonstrates a satisfactorily robust performance.

3.2. Quantitative evaluation and system performance

The system was quantitatively evaluated in terms of decision quality, convergence time, and computational performance. The level of agreement among decision-makers significantly improved after negotiation, with Kendall's coefficient of concordance increasing from 0.61 to 0.84, indicating strong consensus. Robustness analysis showed high stability, with a 92% decision stability rate under variations in doctors' preferences. The negotiation protocol converged efficiently, requiring an average of 3.6 iterations and less than 30 seconds to reach a collective decision. From a computational perspective, the system demonstrated good scalability and low execution time, remaining below 1.5 seconds for 20 patients and 5 seconds for larger scenarios. Overall, the results confirm that the proposed system is accurate, robust, and suitable for real-time multidisciplinary medical decision-making. The computational performance of the proposed system was evaluated according to the problem size.

The algorithmic complexity of each component is as follows: i) AHP: $O(n^2)$ for criteria weighting. ii) PROMETHEE II: $O(m^2)$ for patient ranking. iii) Aggregation and negotiation: $O(m \times d)$. Where: n = number of criteria; m = number of patients (actions); d = number of decision-makers. The observed execution times were as follows: i) 10 patients / 5 doctors: < 0.5 seconds. ii) 20 patients / 5 doctors: ≈ 1.2 seconds. iii) 50 patients / 7 doctors: ≈ 4.5 seconds.

Memory usage remained below 200 MB in all scenarios. These results indicate that the system is efficient, scalable, and well suited to the typical size of clinical multidisciplinary meetings. For clarity and ease of analysis, the main results of the case study and the consensus-building process are summarized in Table 4.

The results of this study are particularly relevant for healthcare professionals involved in MDTMs, as well as for researchers in DSS and medical artificial intelligence. The proposed approach addresses a central challenge in modern clinical practice, namely collaborative decision-making in complex, uncertain, and multicriteria contexts. By integrating MAS, multicriteria decision-making methods (AHP and PROMETHEE II), and a structured negotiation protocol, the system formalizes heterogeneous medical preferences, reduces decision conflicts and ambiguity during group discussions, and enhances the transparency, traceability, and justification of collective medical decisions. Moreover, it enables a faster and more reliable identification of high-risk patients, thereby optimizing care prioritization. Sensitivity and robustness analyses further indicate that the obtained decisions remain stable despite variations in expert preferences, reinforcing the reliability of the proposed system in real-world clinical environments characterized by uncertainty and time pressure.

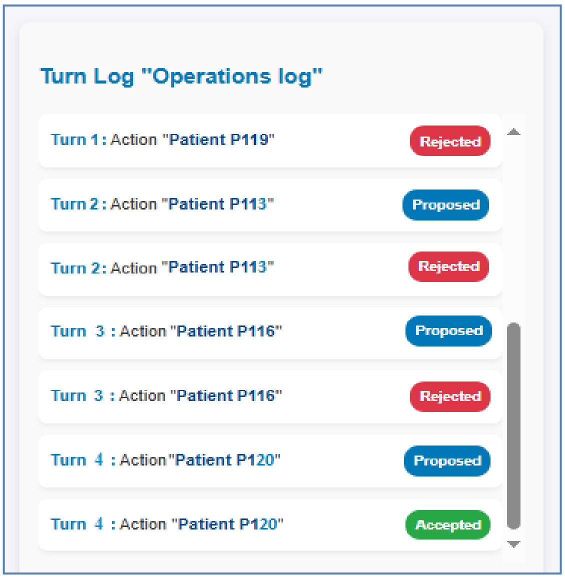


Figure 11. Negotiator: negotiation log

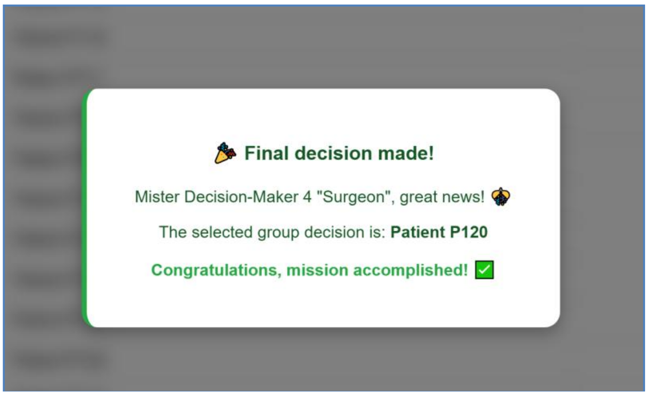


Figure 12. Decision-maker surgeon: reception of the collaborative decision

Table 4. Summary of the case study results

Step	Description	Quantitative indicators
Data Setup	Performance matrix generated for cancer patients using criteria	Patients characterized by 4 main criteria: Tumor stage (T), Nodes (N), Metastases (M), OMS score, Disease Phase
Decision-Makers (doctors)	5 doctors: Surgeon, Oncologist, Isotopist Radiotherapist, Radiologist	For each doctor, the coordinator assigned a weight using AHP method
Local Ranking	Each doctor applied PROMETHEE II for patient ranking	Rankings generated individually for all patients according to the preferences of the concerned doctor
Global Scoring	The negotiator aggregated rankings with decision-maker weights	Patient 119 proposed in iteration, rejected according to the negotiation threshold; Patient 120 proposed in iteration 4, accepted by all
Negotiation Iterations	Iterative proposal-response process	Consensus reached at iteration 4
Consensus Outcome	The GDSS identifies the patient with highest priority for hospitalization	Patient 120 selected
Robustness/Sensitivity analysis	Small variations in doctors' preferences tested	Minor changes in ranking indicates stable, robust decision-making
Convergence of the negotiation	Negotiation may fail if all actions (patients) explored without agreement	Emphasizes mediation-focused protocol rather than concession

3.3. Comparaison results

The AI-based CDSS proposed in [21] primarily aims at automating the clinical triage of patients in order to reduce the workload of MDTMs, relying on machine learning models. Although effective for routine decision-making tasks, such systems often suffer from limited explainability, which may hinder their acceptance in complex clinical decision contexts. In contrast, the multicriteria GDSS based on MAS, proposed in this paper, adopts a collaborative and explicitly formalized approach, integrating modeled expert decision-makers' preferences together with structured and formal negotiation mechanisms. This level of transparency significantly enhances the traceability, interpretability, and legitimacy of the resulting clinical decisions.

4. CONCLUSION

In this study, we proposed a GDSS that models the dynamics of MDTMs using a MAS and a structured negotiation protocol based on three multi-criteria decision-making methods: AHP, PROMETHEE II, and SCORAGE. The theoretical contribution lies in the integration of these methods within an agent-based negotiation framework, which supports both individual preference expression and collective decision convergence-a novel approach for medical decision support. Unlike existing GDSS approaches that rely either on multicriteria methods or agent-based negotiation, this work integrates both within a unified framework. This combination addresses a gap in the literature by jointly managing heterogeneous preferences and collaborative negotiation in medical decision-making. To evaluate the robustness and applicability of the system, we conducted a sensitivity and robustness analysis, which indicates that decisions remain stable despite variations in expert preferences, reinforcing the reliability of the system in real-world clinical environments, often marked by uncertainty and time pressure. However, the negotiation process may fail to converge when no consensus is reached after all options are explored. This limitation is due to the protocol's emphasis on mediation rather than concession, and it highlights an area for future improvement. Overall, the system optimizes workflow, saves time, and improves the quality of decisions in multidisciplinary medical teams, while providing a more structured and transparent collaborative decision-making process. From an ethical and user-acceptance perspective, the system is intended to support (not replace) clinicians' responsibility in MDTMs. In real clinical use, transparency, traceability, and justification of decisions are essential for trust and acceptance, and the elicitation of preferences and weights should be handled carefully, alongside secure handling of patient data. Future research directions include: i) Adopting cognitive agent models capable of learning and reasoning in context. ii) Validating the system in real-world clinical environments. iii) Enhancing decision support with machine learning to suggest compromises from past cases. iv) Using historical data from meetings to better predict. v) Including additional clinical, economic, or ethical criteria to make the model more representative of medical practice.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

Data are available at data.gouv.fr: https://www.data.gouv.fr/datasets/fiches-fictives-de-reunion-de-concertation-pluridisciplinaire-rcp/informations.

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