SAMAC: Collaborating with Multi-Disciplinary Team for Adaptive Medical Decision-Making

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Abstract

Multi-agent large language model systems offer a promising paradigm for multidisciplinary medical decision support by integrating heterogeneous expert perspectives. However, existing frameworks often rely on loosely structured interactions, where disagreement is insufficiently diagnosed and discussion may collapse into superficial consensus or parallel opinion aggregation. We propose Structured Adaptive Multi-disciplinary Collaboration (SAMAC), a structured and strategy-aware multi-agent framework for adaptive MDT-style medical reasoning. SAMAC introduces Structured Deliberation to detect opinion disagreement and majority not confident, along with a Consensus Purification mechanism that transforms disagreement into constructive and collaborative refinement. When disagreement arises, SAMAC adaptively selects between Self-refinement and Counter-questioning to enable evidence-grounded negotiation. Experiments on three medical datasets—RADCURE, HANCOCK, and OSCCPI—show that SAMAC consistently improves overall performance and collaborative gains over existing multi-agent baselines. In particular, SAMAC improves the Average Score by 4.29 points on the RADCURE dataset and achieves higher Relative Self-Correction Scores (RSS), indicating more effective resolution of disagreement and stable collective decisions. These results highlight the importance of controlled and diverse interaction dynamics in multi-agent medical reasoning. Code will be released upon publication.

1 Introduction

Healthcare is increasingly improved by the quality, timeliness, and precision of its medical decisions. Clinical decision-making encompasses diagnostic evaluation and treatment strategy, which ultimately affect patients' survival and quality of life (Djulbegovic and Elqayam, 2017; Elwyn et al., 2012). At the same time, patients may have heterogeneous comorbidities, individualized risk profiles, and contextual factors that often fall outside the strict boundaries of individual clinicians (Boast et al., 2018; McDuff et al., 2025). As a result, clinical decision-making is no longer a straightforward application of evidence, but a process of fully interpreting, weighing, and reconciling competing considerations based on multidisciplinary teams (MDTs) (Bates et al., 2025; Hendriks et al., 2024; Taberna et al., 2020). In this work, we study this problem from the perspective of LLM-based MDT-style reasoning, focusing on how multiple expert agents should deliberate when their opinions or confidence levels diverge.

Recent large language model (LLM)-based MDT approaches aim to emulate this collaborative process by leveraging LLMs to integrate structured and unstructured clinical data and generate multi-disciplinary decision support in natural language (Clusmann et al., 2023; Kim et al., 2024a,b; Li et al., 2024; Tang et al., 2024; Wu et al., 2025; Yan et al., 2024). For example, MedAgents (Tang et al., 2024) proposes a role-playing-based (Li et al., 2023) MDT collaboration framework in which LLM agents representing different medical specialties iteratively discuss and refine their analyses until they reach a consensus report. In addition, MDAgents (Kim et al., 2024a) dynamically assigns individual or team-based configurations based on the estimated medical complexity of the query, emulating real-world medical decision-making flows. More recently, KAMAC (Wu et al., 2025) has proposed a knowledge-driven adaptive collaboration strategy, in which LLM agents dynamically detect knowledge gaps during discussion and recruit additional specialists to expand the expert team, allowing flexible cross-specialty reasoning in complex clinical scenarios.

Existing adaptive MDT-style systems mainly focus on adapting who participates in the collaboration, such as assigning individual or team-based

configurations or recruiting additional specialists when knowledge gaps are detected. However, after the expert team is formed, the interaction process itself remains under-controlled: agents are often asked to discuss, debate, or vote under a fixed protocol, regardless of the current disagreement state (Du et al., 2024; Liang et al., 2024).

To address these limitations, we propose Structured Adaptive Multi-disciplinary Collaboration (SAMAC), a structured framework for adaptive MDT-style medical reasoning with multi-disciplinary expert agents. SAMAC addresses this complementary problem by adapting when agents should deliberate and how disagreement should be resolved, thereby providing an explicit interaction-control layer for MDT-style reasoning. As shown in Fig. 1(b), disagreement within an MDT can arise from two complementary sources: opinion disagreement among experts and confidence disagreement defined as Majority Not Confident (MNC), where more than half of the agents report neutral or not confident. Based on this, we introduce a Structured Deliberation that systematically organizes expert opinions and confidence levels (Chen et al., 2024; Yang et al., 2024), providing explicit, interpretable guidance for disagreement diagnosis. By jointly examining opinion disagreement and MNC, the framework determines whether further discussion is necessary, guiding agents toward focused and meaningful deliberation rather than superficial exchanges. To further enhance collaboration quality, we propose a Consensus Purification mechanism that treats disagreement as a diagnostic trigger. When disagreements arise, SAMAC initiates differentiated behaviors that self-refine viewpoints, counter-question opinions, and update evidence, transforming superficial opinion exchange into structured multi-agent negotiation. Our contributions are threefold:

- We propose SAMAC, a structured interaction-control framework for LLM-based MDT-style medical reasoning. Rather than focusing only on expert recruitment or final aggregation, SAMAC explicitly models the collaboration state and regulates when and how agents deliberate.

- We design Structured Deliberation, a confidence-aware triggering mechanism that jointly captures answer-level disagreement and epistemic uncertainty, thereby preventing multi-agent collaboration from degenerating into implicit majority voting. We further introduce Consensus Purification, which routes disagreement resolution into two complementary behaviors—Self-refinement and Counter-questioning—to support evidence-grounded negotiation.

- Extensive experiments on three medical benchmarks, RADCURE, HANCOCK, and OSCCPI, demonstrate that our SAMAC consistently enhances multi-agent collaborative performance.

2 Related Work

Multidisciplinary decision-making with LLMs. LLM-based MDT-style medical reasoning has increasingly shifted from single-agent reasoning toward multidisciplinary collaboration. Recent MDT-style systems use LLM agents to represent different clinical specialties, enabling the integration of structured clinical variables, unstructured reports, and other patient evidence into natural-language decision support (Clusmann et al., 2023; Kim et al., 2024a,b; Li et al., 2024; Tang et al., 2024; Wu et al., 2025; Yan et al., 2024). This paradigm is particularly suitable for complex clinical tasks, where no single specialty may fully cover all relevant diagnostic, prognostic, and treatment-related factors. Representative work includes MedAgents (Tang et al., 2024), which builds a role-playing-based (Li et al., 2023) MDT framework for iterative expert discussion and consensus formation.

Adaptive collaboration in multi-agent medical reasoning. Recent multi-agent medical systems increasingly seek to move beyond static expert panels toward adaptive collaboration. One direction focuses on the dynamic composition of multidisciplinary teams (MDTs). For example, MDAgents (Kim et al., 2024a) dynamically assigns individual or team-based configurations according to the estimated complexity of the medical query, while KAMAC (Wu et al., 2025) further introduces a knowledge-driven adaptive collaboration framework that detects knowledge gaps during discussion and recruits additional specialists when necessary. Such methods make the expert team more flexible than fixed-role settings and allow the MDT structure to evolve with the diagnostic context.

Another important aspect of adaptivity lies in the interaction process among expert agents. Existing multi-agent reasoning frameworks usually

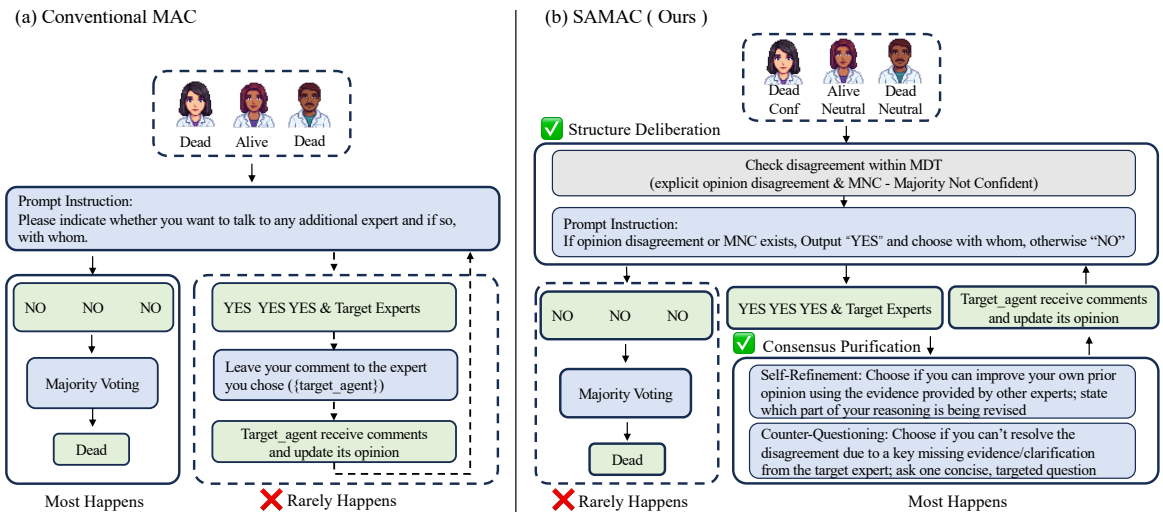

Figure 1: (a) Conventional multi-agent collaboration (MAC) relies on prompt-triggered discussion and majority voting. (b) Our SAMAC features Structured Deliberation and Consensus Purification for adaptive MDT-style reasoning. Blue boxes denote system-level instructions and green boxes mean agent actions during interaction.

rely on a single predefined interaction behavior throughout collaboration. For example, some methods aggregate agent outputs through majority voting or consensus-based decision-making (Kaesberg et al., 2025), while debate-based frameworks construct opposing roles or iterative argumentation to resolve conflicts (Du et al., 2024; Liang et al., 2024). Other medical multi-agent systems mainly adopt prompt-triggered discussion, where agents are asked whether further interaction or additional expertise is needed (Kim et al., 2024a; Wu et al., 2025). While these studies have substantially advanced LLM-based MDT collaboration, most of them focus either on expert composition or on a fixed interaction protocol. In contrast, SAMAC focuses on an interaction-control layer that diagnoses the current collaboration state and routes agents to different disagreement-resolution behaviors after expert opinions are available.

3 Method

3.1 Overview

As shown in Fig. 2, our SAMAC mainly includes five stages: (1) Recruit Stage: SAMAC is built on the dynamic recruitment framework of KAMAC (Wu et al., 2025) and inherits its recruitment backbone. We further extend this stage by requiring each recruited expert agent to produce not only an opinion but also an explicit confidence level and supporting evidence; (2) Structured Deliberation: SAMAC explicitly diagnoses disagreement by jointly evaluating opinion disagreement among experts and Majority Not Confident (MNC); (3) Consensus Purification and Opinion Update: When disagreement is detected, SAMAC initiates structured collaboration and adaptively selects between Self-refinement and Counter-questioning strategies to regulate how conflicts are resolved. The updated opinions and evidence are iteratively refined through this process; (4) Knowledge-Gap (KG) Identification: After discussion, SAMAC follows KAMAC (Wu et al., 2025) to examine whether unresolved knowledge gaps remain. If gaps are detected, SAMAC dynamically recruits additional specialists to address them and provide targeted clarification before the final decision. (5) Final Results: SAMAC aggregates refined opinions and evidence into a unified clinical recommendation.

3.2 Structured Deliberation through Explicit Guidance

A core component of SAMAC is explicit guidance that structures multi-agent deliberation and prevents collaboration from degenerating into independent reasoning followed by majority voting. Instead of allowing agents to observe peer responses only and implicitly conform to dominant opinions, SAMAC introduces Structured Deliberation that explicitly diagnoses disagreement and regulates when and how collaboration should proceed.

Specifically, Structured Deliberation aggregates all the latest experts' opinions and computes an objective "system disagreement signal" vector from the current opinions, including:

- **Opinion disagreement**: Whether multiple distinct answers exist among experts.

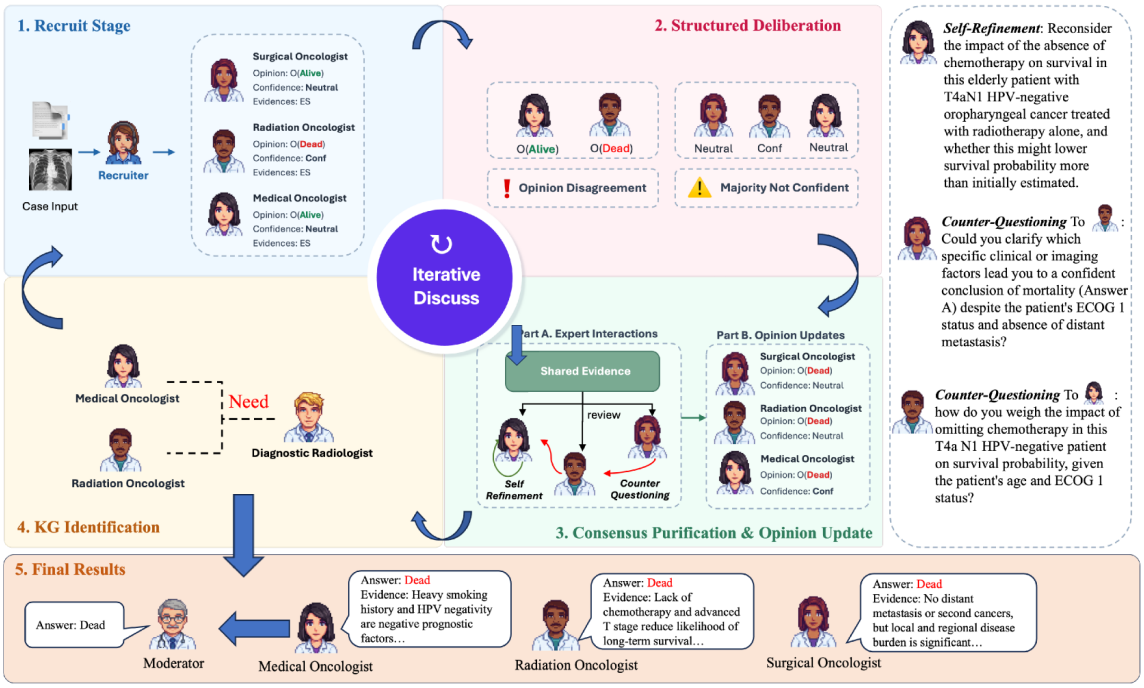

Figure 2: Overview of the proposed SAMAC framework for adaptive collaboration of multi-agent MDT-style medical reasoning. Given a clinical question and patient evidence, SAMAC first recruits a configurable number of domain-specific agents to provide independent predictions with confidence estimates. It then performs structured deliberation to identify opinion disagreement or insufficient consensus among agents, where insufficient consensus is determined when more than half of the agents provide Not-confident predictions. Once triggered, the agents enter an iterative collaboration process involving self-refinement, counter- questioning, and opinion updates, allowing them to reassess uncertain evidence and resolve conflicting judgments. When necessary, SAMAC further identifies missing knowledge and recruits an additional specialist before producing the final summarized decision.

- **Majority Not Confident (MNC)**: Whether more than half of the experts are not confident, determined through majority voting.

If neither substantive opinion disagreement nor insufficient confidence is identified, the system proceeds directly to generating the final answer. Otherwise, the disagreement is routed to the Consensus Purification module. These disagreement signals serve as explicit guidance for deliberation rather than passive observation. Agents are instructed to examine not only the final answers but also the confidence levels and underlying reasoning chains, thereby fostering proactive collaboration. By structurally guiding attention toward opinion divergence and epistemic uncertainty, Structured Deliberation prevents superficial consensus formation and mitigates premature convergence to majority voting.

3.3 Consensus Purification through Disagreement Diagnosis

Medical diagnosis requires structured reasoning grounded in established clinical evidence rather than purely empirical inference. Evidence-based agentic frameworks, such as MedAgent-Pro (Wang et al., 2025), emphasize aligning decision-making with retrieved clinical criteria to ensure reliability and interpretability. Inspired by this paradigm, we posit that disagreement in multi-agent collaboration may arise either from evidential insufficiency or from reasoning inconsistency. Meanwhile, recent studies have shown that agent generalization is closely related to the model's ability to perform self-refinement based on feedback (Fu et al., 2025; Madaan et al., 2023; Shinn et al., 2023). Motivated by these insights, we introduce a strategy-aware interaction mechanism that explicitly distinguishes between **Self-refinement** and **Counter-questioning** during multi-agent collaboration. Specifically, when disagreement signals are detected, SAMAC adaptively selects an appropriate interaction strategy from Self-refinement or Counter-questioning. The strategy is chosen from a predefined set based on the nature of the disagreement and the availability of evidence. The supported strategies include:

- **Self-refinement**: Applied if the Agent can im-

prove its own prior opinion using the evidence provided by other experts; Then state which part of its reasoning is being revised. After the current round of interaction concludes, the agent revises its assumptions or inference chain before updating its conclusion.

- **Counter-questioning**: Applied if the Agent can't resolve the disagreement due to a key missing evidence/clarification from the target expert; Then ask one concise, targeted question. After the current round of interaction concludes, the questioned expert provides an answer to the targeted question based on their own domain-specific expertise.

After each interaction round, expert opinions and confidence levels are updated, and disagreement signals are recomputed. The process iterates until consensus is reached or a maximum of three refinement rounds is reached.

Through this iterative consensus purification process, weakly supported arguments are progressively revised or discarded, hidden reasoning inconsistencies are exposed, and experts converge toward evidence-aligned conclusions. In the context of MDT-style medical reasoning, this mechanism reduces superficial disagreement, mitigates premature consensus, and promotes principled multi-agent negotiation.

4 Experiments and Results

4.1 Datasets

To comprehensively evaluate our framework under multi-modal clinical scenarios, we conducted experiments on three publicly available datasets: RADCURE (Welch et al., 2024), HANCOCK (Dörrich et al., 2025), and OSCCPI (Guan et al., 2025). For RADCURE, we use 750 cases from the official test split. Each case includes contrast-enhanced CT images along with demographic, clinical, and treatment information. We formulate the task as survival status prediction in a radiotherapy setting, requiring multi-modal reasoning over imaging and structured clinical variables. From the HANCOCK cohort, we select all 298 cases of oropharyngeal cancer. Each case provides hematoxylin–eosin (HE) stained whole-slide images, immunohistochemistry (IHC) images, structured clinical data, pathological reports, and tissue microarray measurements. Similarly to RADCURE, we evaluate survival status prediction in a multimodal oncology scenario. For OSCCPI, we used 200 cases from the OSCCPI test split. Each case contains high-resolution histopathology images covering both tumor core and edge regions. We formulate the task as recurrence prediction, enabling pathological reasoning evaluation.

4.2 Metrics

We evaluate the performance of our framework using a combination of standard classification metrics and collaboration-aware improvement metrics.

Classification Metrics. We report the following standard metrics: Accuracy (Acc), Specificity (Spec), Precision (Prec), and Recall (Rec). Also, we calculate the Average Score (Avg) for a clear presentation.

Collaboration-aware Correction Metrics. To quantify the effect of multi-agent discussion, we adopt and extend the framework of Yang et al. (2025) and report Confidence Level (CL), Critique Score (CS), and Relative Self-Correction Score (RSS). For each case i, let $a_i, b_i \in \{0, 1\}$ indicate whether the prediction is correct before and after collaboration. We define

$$\mathrm{Acc}_{\mathrm{pre}} = \frac{1}{N}\sum_i a_i, \quad \mathrm{Acc}_{\mathrm{post}} = \frac{1}{N}\sum_i b_i.$$

CL measures the proportion of initially correct predictions preserved after collaboration, while CS measures the proportion of initially incorrect predictions corrected after collaboration:

$$\mathrm{CL} = P(b = 1 \mid a = 1), \quad \mathrm{CS} = P(b = 1 \mid a = 0).$$

Accordingly, the post-collaboration accuracy can be decomposed as

$$\mathrm{Acc}_{\mathrm{post}} = \mathrm{CL} \cdot \mathrm{Acc}_{\mathrm{pre}} + \mathrm{CS} \cdot (1 - \mathrm{Acc}_{\mathrm{pre}}).$$

Following Yang et al. (2025), RSS further normalizes the collaborative gain by the available correction space:

$$\mathrm{RSS} = \frac{\mathrm{Acc}_{\mathrm{post}} - \mathrm{Acc}_{\mathrm{pre}}^2}{2\mathrm{Acc}_{\mathrm{pre}}(1 - \mathrm{Acc}_{\mathrm{pre}})}.$$

An RSS value of 0.5 corresponds to no net accuracy change after collaboration; $\mathrm{RSS} > 0.5$ indicates positive collaborative gain, while $\mathrm{RSS} < 0.5$ indicates performance degradation.

4.3 Image Analysis before Collaboration

Since the focus of this work is the collaboration protocol rather than medical image representation learning, we use a fixed image-to-text preprocessing pipeline to convert visual evidence into textual clinical findings. We first converted image information into textual evidence using GPT-4.1-mini. For each case, GPT-4.1-mini analyzed the associated medical images together with the corresponding bounding-box annotations, focusing on the regions of interest indicated by the bbox. The model extracted clinically relevant visual findings from both the global image context and the localized bbox regions. These image-derived findings were concatenated with the patient's structured clinical indicators to construct the final input question, which was then provided to the recruited expert agents for collaborative reasoning, confidence estimation, evidence extraction, and final decision-making. This design keeps the visual evidence extraction stage identical across all compared methods, allowing the evaluation to isolate the effect of the multi-agent collaboration mechanism.

4.4 Results

Comparison with Different LLM-based Methods. Table 1 presents the comparative results on three datasets. For fair comparison, the initial number of experts in the Majority Voting baseline is set to 3, consistent with KAMAC-3 and SAMAC-3. All experiments are conducted using GPT-4.1-mini (OpenAI, 2023) as the LLM backbone to ensure consistency across methods.

Overall, SAMAC-3 achieves the best Average Score on all three datasets, reaching 82.11 on RADCURE, 81.54 on HANCOCK, and 72.78 on OSCCPI. Compared with KAMAC-3, SAMAC-3 improves the Average Score by 4.29, 2.40, and 4.17 points, respectively. These consistent gains demonstrate the effectiveness and robustness of the proposed strategy-aware interaction mechanism across different clinical datasets. The improvements are particularly notable on RADCURE and OSCCPI, suggesting that SAMAC-3 is especially beneficial in clinically complex and heterogeneous scenarios where agents may need more targeted discussion to resolve disagreements.

In terms of individual metrics, although some baselines such as MDAgent and KAMAC-3 obtain slightly higher Recall on certain datasets, their relatively low Specificity leads to inferior overall performance. In contrast, SAMAC-3 substantially improves Specificity, especially on RADCURE, HANCOCK, and OSCCPI, indicating that it better balances sensitivity and specificity rather than simply favoring positive predictions.

Ablation Study. We conduct ablation experiments on RADCURE to evaluate the contribution of each component in SAMAC, as shown in Table 2. Starting from the KAMAC-3 baseline, enabling either opinion disagreement detection (OD) or majority-not-confident detection (MNC) improves both Average Score and RSS, indicating that answer-level disagreement and insufficient collective confidence are complementary signals for deciding when further deliberation is needed. Combining OD and MNC as Structured Deliberation (SD) further increases the discussion rate and improves the Average Score to 79.80, but the RSS does not consistently increase, suggesting that triggering more discussions alone is not sufficient.

Introducing resolution strategies further improves the effectiveness of collaboration. Self-refinement (SR) helps agents revise their own reasoning based on peer evidence, while Counter-questioning (CQ) encourages agents to request missing clarifications before updating their opinions. The full SAMAC integrating OD, MNC, SR, and CQ achieves the best overall performance, improving Avg from 77.82 to 82.11 and RSS from 0.480 to 0.577 over the baseline. These results indicate that SAMAC benefits from two complementary forms of interaction control: OD and MNC determine when discussion should be triggered, while SR and CQ determine how the triggered discussion should proceed. Thus the improvement of SAMAC is not merely due to more frequent discussion, but to the coordinated control of discussion triggering and disagreement resolution.

Effect of Initial Agent Number. Table 3 reports the impact of varying the initial number of participating agents ($N_{init} = 1, 3, 5$) on RADCURE dataset, examining its influence on expert recruitment (Rec.), discussion frequency (Dis.), and performance metrics (Avg and RSS). SAMAC consistently outperforms KAMAC on both Avg and RSS in all settings, demonstrating that our Structured Deliberation and Consensus Purification remain effective across varying collaboration scales. When increasing N_{init} from 1 to 3, SAMAC achieves its best performance. However, increasing the number of agents does not yield further gains, as additional

Datasets	Methods	Acc	Prec	Spec	Recall	Avg	RSS
RADCURE	SA_{CoT} (Wei et al., 2022)	86.80	88.82	33.62	96.53	76.44	–
	Majority voting (Wang et al., 2022)	88.40	89.93	40.52	97.16	79.00	–
	MDAgent (Kim et al., 2024a)	87.73	88.94	33.62	**97.63**	76.98	–
	KAMAC-3 (Wu et al., 2025)	88.13	89.32	36.21	**97.63**	77.82	0.480
	SAMAC-3 (Ours)	**89.87**	**91.39**	**50.00**	97.16	**82.11** (+4.29)	**0.577**
HANCOCK	SA_{CoT} (Wei et al., 2022)	82.71	86.87	35.85	92.98	74.60	–
	Majority voting (Wang et al., 2022)	82.83	87.26	37.74	92.62	75.11	–
	MDAgent (Kim et al., 2024a)	82.21	82.43	1.89	**99.59**	66.53	–
	KAMAC-3 (Wu et al., 2025)	88.93	88.41	39.62	**99.59**	79.14	0.482
	SAMAC-3 (Ours)	**89.26**	**89.89**	**49.06**	97.96	**81.54** (+2.4)	**0.549**
OSCCPI	SA_{CoT} (Wei et al., 2022)	78.28	78.42	12.77	**98.68**	67.04	–
	Majority voting (Wang et al., 2022)	78.00	79.14	17.02	96.73	67.72	–
	MDAgent (Kim et al., 2024a)	78.00	77.44	10.2	100	66.41	–
	KAMAC-3 (Wu et al., 2025)	77.50	79.12	22.45	95.36	68.61	0.439
	SAMAC-3 (Ours)	**80.00**	**81.71**	**34.69**	94.70	**72.78** (+4.17)	**0.530**

Table 1: Comparative experiments of different methods on three datasets. SA_{CoT} represents single-agent chain-of-thought reasoning; Majority voting aggregates multiple independent predictions by selecting the most frequent output; MDAgent uses multi-agent discussion to refine decisions; KAMAC-3 and SAMAC-3 both adopt an initial configuration of three agents, where KAMAC-3 follows a knowledge-aware collaboration framework and SAMAC-3 denotes our proposed self-adaptive multi-agent collaboration method. Results are reported on RADCURe, HANCOCK, and OSCCPI, with the best values highlighted in bold.

Methods	OD	MNC	SR	CQ	Acc	Prec	Spec	Recall	Avg	RSS
baseline	✗	✗	✗	✗	88.13	89.32	36.21	97.63	77.82	0.480
+OD	✓	✗	✗	✗	88.27	90.38	43.97	96.37	79.75	0.536
+MNC	✗	✓	✗	✗	88.27	90.27	43.10	96.53	79.54	0.536
+SD	✓	✓	✗	✗	88.00	90.48	44.83	95.90	79.80	0.524
SD+SR	✓	✓	✓	✗	88.40	90.76	46.55	96.06	80.44	0.543
SD+CQ	✓	✓	✗	✓	88.53	90.29	43.1	96.85	79.69	0.549
ours	✓	✓	✓	✓	**89.87**	**91.39**	**50.00**	**97.16**	**82.11**	**0.577**

Table 2: Ablation study of the key components in the proposed SAMAC framework on RADCURE. OD, MNC, SR, and CQ denote opinion disagreement detection, majority-not-confident detection, self-refinement, and counter-questioning, respectively. Starting from the baseline, different combinations of components are progressively enabled to evaluate their individual and joint contributions. The full model, which integrates all four components, achieves the best overall performance, obtaining the highest Average Score, and RSS.

opinions tend to be redundant, adding interaction complexity without improving correction quality. Interestingly, while KAMAC shows performance fluctuations and decreasing RSS as N_{init} grows, SAMAC maintains stable RSS in all settings. This suggests that structured and strategy-aware interaction mitigates the instability typically introduced by larger multi-agent groups.

Multi-run comparison analysis. The multi-run results in Table 4 further confirm the robustness of SAMAC-3 over KAMAC-3. Across all three datasets, SAMAC-3 consistently achieves higher Avg and RSS scores. Specifically, SAMAC-3 improves Avg by +4.60, +1.97, and +4.22 on RADCURE, HANCOCK, and OSCCPI, respectively, while the corresponding RSS improvements are +0.103, +0.050, and +0.091. These consistent gains indicate that SAMAC-3 provides more stable performance improvements across repeated independent runs. The results suggest that our structured deliberation and consensus purification mechanisms can enhance collaborative correction capability across different datasets. Overall, SAMAC-3 improves both predictive performance and collaborative reliability compared with KAMAC-3.

Backbone Robustness Analysis. To examine whether the effectiveness of SAMAC depends on a specific LLM backbone, we conduct additional experiments with DeepSeek and compare the results with GPT-4.1-mini. As shown in Table 5,

Method	Rec.	Dis.	Avg	RSS
KAMAC-1	67	0	76.39	0.512
SAMAC-1	141	104	78.18	0.570
KAMAC-3	36	27	77.82	0.480
SAMAC-3	3	153	**82.11**	**0.577**
KAMAC-5	24	27	78.39	0.448
SAMAC-5	36	261	80.03	0.500

Table 3: Effect of different initial agent numbers on RADCURE. KAMAC-n and SAMAC-n start with n initial agents. Rec. denotes the number of cases triggering additional expert recruitment, and Dis. denotes the number of cases entering the discussion process.

Dataset	Metric	KAMAC-3	SAMAC-3
RADCURE	Avg	$77.34_{\pm 0.49}$	$\mathbf{81.94}_{\pm 0.15}$
	RSS	$0.462_{\pm 0.016}$	$\mathbf{0.565}_{\pm 0.010}$
HANCOCK	Avg	$79.45_{\pm 0.45}$	$\mathbf{81.42}_{\pm 0.17}$
	RSS	$0.491_{\pm 0.012}$	$\mathbf{0.541}_{\pm 0.010}$
OSCCPI	Avg	$68.24_{\pm 0.52}$	$\mathbf{72.46}_{\pm 0.45}$
	RSS	$0.439_{\pm 0.001}$	$\mathbf{0.530}_{\pm 0.001}$

Table 4: Multi-run comparison of SAMAC-3 and KAMAC-3 across different datasets and metrics. Results are reported as mean$_{\pm}$standard deviation over repeated independent runs.

SAMAC-3 consistently improves over KAMAC-3 on all three datasets with both GPT-4.1-mini and DeepSeek backbones. Although the absolute scores differ between the two LLMs, SAMAC-3 maintains higher average performance and generally better RSS scores. These results indicate that the effectiveness of SAMAC is not limited to a specific backbone and demonstrates good robustness across different LLMs.

Consensus Analysis under Initial Disagreement. We further analyze cases where the initially recruited agents produce conflicting opinions, and evaluate whether the subsequent multi-agent process can resolve these disagreements into a correct consensus. For a fair comparison, SAMAC and KAMAC are initialized with the same agent opinions and then execute their respective reasoning pipelines. As shown in Fig. 3, KAMAC leaves many cases unresolved, especially with five initial agents, where 79.5% of cases end with no consensus and only 15.4% reach a correct consensus. In contrast, SAMAC resolves disagreements more effectively, achieving 50.0% correct consensus and reducing no-consensus cases to 21.8% in the five-agent setting. Although SAMAC produces more

Dataset	Metric	KAMAC-3		SAMAC-3	
		GPT	DS	GPT	DS
RADCURE	Avg	77.82	77.84	82.11	81.39
	RSS	0.480	0.445	0.577	0.557
HANCOCK	Avg	79.14	76.11	81.54	78.64
	RSS	0.482	0.479	0.549	0.521
OSCCPI	Avg	68.61	68.44	72.78	70.10
	RSS	0.439	0.500	0.530	0.529

Table 5: Backbone robustness analysis comparing KAMAC-3 and SAMAC-3 with GPT-4.1-mini and DeepSeek (DS) across different datasets and metrics.

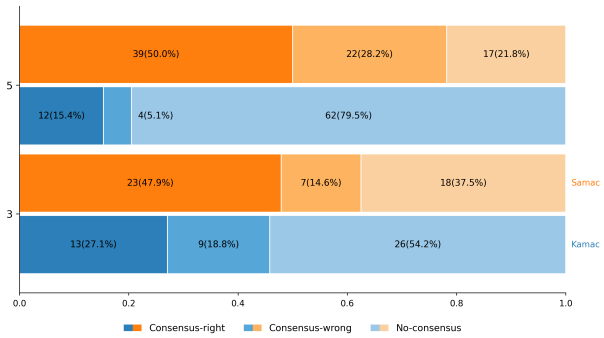

Figure 3: Consensus analysis under initial disagreement. The results are computed on cases where the initially recruited agents produce conflicting opinions. For a fair comparison, SAMAC and KAMAC start from the same set of initial agent opinions and then execute their complete reasoning pipelines. The bars show the final consensus status after the full process, including correct consensus, incorrect consensus, and no consensus, under different initial agent numbers.

incorrect consensus in this setting, KAMAC mainly avoids errors by failing to make a decision in most cases. Overall, these results show that structured and strategy-aware collaboration helps agents reach more decisive and accurate collective decisions under initial disagreement.

5 Conclusion

We propose SAMAC, a structured framework for adaptive MDT-style medical reasoning. By explicitly detecting disagreement and adaptively applying Self-refinement and Counter-questioning, SAMAC transforms disagreement into constructive collaborative correction rather than passive aggregation. Experiments on three medical benchmarks show that SAMAC improves average predictive performance and collaboration-aware correction metrics over competitive multi-agent baselines. The results suggest that controlling the deliberation process can benefit MDT-style reasoning workflows.

6 Limitations

Although SAMAC shows consistent improvements across three medical benchmark datasets, several aspects remain to be further explored. First, SAMAC uses agent-reported opinions and confidence signals to decide when structured discussion should be triggered. This provides an explicit and interpretable mechanism for identifying disagreement or insufficient confidence. However, confidence estimation in LLMs remains an active research problem. More calibrated confidence modeling or external verification modules may further improve the reliability of discussion triggering and strategy selection. Second, our experiments are conducted on three oncology-related datasets, including survival prediction and recurrence prediction tasks. These datasets provide representative multimodal clinical scenarios, but medical decision-making covers a broader range of tasks, such as differential diagnosis, treatment recommendation, and longitudinal patient management. Exploring its broader applicability to additional clinical workflows remains an interesting direction for future work. Finally, SAMAC is intended to support structured MDT-style reasoning rather than replace clinician judgment. In high-stakes clinical settings, more decisive consensus is not always preferable to abstention, especially when agents converge to an incorrect conclusion. Therefore, practical deployment would require clinician-in-the-loop review, external evidence verification, confidence calibration, and explicit abstention criteria for high-disagreement or low-confidence cases.

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