

# TheraAgent: Self-Improving Therapeutic Agent for Precise and Comprehensive Treatment Planning

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## Abstract

Formulating a treatment plan is inherently a complex reasoning and refinement task rather than a simple generation problem. However, existing large language models (LLMs) mainly rely on one-shot output without explicit verification, which may result in rough, incomplete, and potentially unsafe treatment plans. To address these limitations, we propose **TheraAgent**, an agentic framework that replaces one-shot generation with an iterative *generate-reflect-refine* pipeline. Inspired by the iterative revision patterns commonly observed in expert clinical practice, our framework progressively *reflects* on clinical criteria and transforms coarse drafts into precise, comprehensive and safer therapeutic regimens. To facilitate the critical *reflection* component, we introduce **TheraJudge**, a treatment-specific evaluation module integrated into the inference loop. Experiments show TheraAgent achieves state-of-the-art results on HealthBench in treatment planning task, leading in Accuracy and Completeness. In expert evaluations, it attains an 86% win rate against physicians, with superior Targeting and Harm Control. Moreover, the high consistency between TheraJudge and HealthBench evaluation indicates the reliability of our framework.

## 1 Introduction

Treatment planning is a critical part in real-world medical decision-making, where physicians translate diagnostic conclusions into concrete therapeutic actions to optimize patient outcomes (Roosan et al., 2024). It is inherently challenging, as we hypothesize that, rather than relying solely on one-shot generation, effective treatment planning benefits from iterative reasoning and structured refinement, including precise medication selection and dosing, comprehensive therapeutic coverage, and principled harm control (Chase et al., 2025). With

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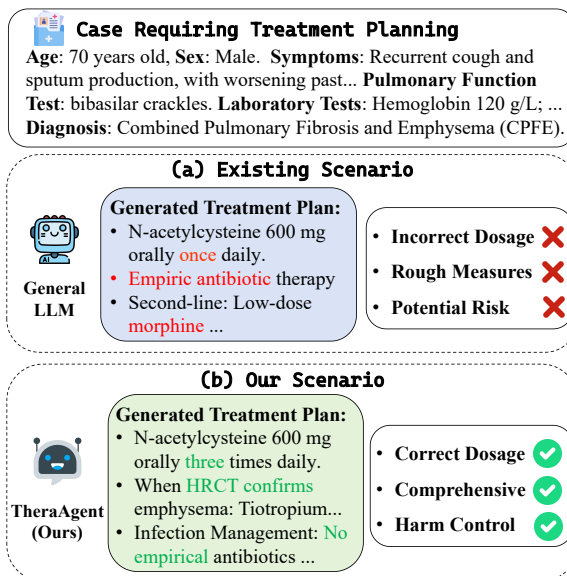


Figure 1: Comparison of treatment plan generation scenarios. (a) General-purpose models frequently produce suboptimal treatment plans, characterized by imprecise information, omitted key components, and potential safety risks. (b) **TheraAgent** mitigates these limitations by generating more accurate, comprehensive, and clinically reliable plans, with expert-validated annotations.

recent advances in large language models (LLMs), there is growing interest in their potential to support medical tasks, driven by their strong capabilities to incorporate relevant context, perform language comprehension, generate coherent text (Singhal et al., 2025; Liu et al., 2025a; McDuff et al., 2025; Tu et al., 2025).

However, directly applying general-purpose or even medically fine-tuned LLMs to treatment planning remains challenging (Lin et al., 2025). As illustrated in Figure 1, existing models tend to generate rough, incomplete, and potentially unsafe plans due to their one-shot mechanism without explicit verification. Despite the question, existing research for treatment planning remains limited. Many existing efforts are tailored to specific diseases and thus fail to generalize across clinical

departments (Khude and Shende, 2025; Hassan et al., 2025; Zhang et al., 2025; Mohammed et al., 2025), while more general approaches often struggle to ensure precision and completeness due to the absence of iterative refinement mechanisms (Hsu et al., 2025; Yang et al., 2025b). Furthermore, the evaluation of treatment plans frequently rely on oversimplified metrics (e.g., BLEU) or vanilla LLM-based scores that overlook critical dimensions (Gao et al., 2025; Hasan et al., 2025).

To bridge these gaps, we propose **TheraAgent**, an agentic framework that regards treatment planning as an iterative *generate–reflect–refine* process. Inspired by the iterative revision patterns commonly observed in expert clinical practice, TheraAgent enables continuous self-correction and progressive improvement, leading to more precise, complete, and safer treatment plans. To support this process without costly human intervention, we introduce **TheraJudge**, a treatment-specific evaluation module, which aligns automated feedback with clinical criteria by assessing plans on dimensions including accuracy, targeting, completeness, and safety.

We evaluate TheraAgent on treatment-related cases in HealthBench (Arora et al., 2025), achieving a state-of-the-art overall score and obtains the highest scores on Accuracy and Completeness, exceeding the second-best model by 2.91 points and 4.43 points. Its effectiveness is further shown in blinded medical expert evaluations on real-world clinical cases, where TheraAgent achieves an 86% win rate against human physicians, with marked win rate of 69% in Targeting, 71% in Completeness, and 51% in Harm Control. We further conduct an agreement analysis between TheraJudge and HealthBench evaluation, where TheraJudge achieves a *Pearson correlation* of 0.71, substantially outperforming other automatic metrics.

Our contributions are summarized as follows:

- We propose **TheraAgent**, an agentic framework that considers treatment planning as an iterative reasoning process. Its *generate–reflect–refine* pipeline enables effective self-improvement, yielding more precise, comprehensive, and safer treatment plans.
- We introduce **TheraJudge**, a clinically aligned internal critic within TheraAgent that assesses treatment plans along dimensions such as *Accuracy* and *Completeness*. It also shows strong potential as a standalone evaluator for treatment

planning, as reflected by its high level of agreement with HealthBench evaluation.

- Extensive experiments show that TheraAgent achieves state-of-the-art performance on treatment-related HealthBench cases and attains a dominant 86% win rate against physicians in blinded expert evaluations on real-world cases.

## 2 Related Works

**Treatment Planning Generation** Compared to diagnosis-related tasks, research on LLM-based treatment planning remains limited. Existing work includes agent-based or staged generation frameworks aligned with clinical workflows named MedPlan (Hsu et al., 2025), treatment-specific fine-tuning approaches for therapeutic reasoning named TxAgent (Gao et al., 2025), and general medical post-training or test-time optimization methods that improve overall clinical reasoning without explicitly targeting treatment planning named MedCritical (Su et al., 2025) and FineMedLM-o1 (hongzhou yu et al., 2025). Prior studies have also examined the evaluation of medical LLMs, typically relying on task-level accuracy or coarse LLM-based scores (Sousa et al., 2025). Despite these efforts, existing approaches often struggle to produce accurate, complete, and safety-aware treatment regimens, while current evaluation methods remain overly simplified and may fail to capture the multi-dimensional clinical quality required for real-world treatment planning.

**Self-improving Agent** Recent work has demonstrated that agentic and self-improving approaches can improve LLM output quality by enabling iterative refinement. General agent frameworks show that incorporating planning, memory, or reflection leads to more robust and coherent outputs (Huang et al., 2024; Liu et al., 2025b; Wang et al., 2025; Yan et al., 2025; Yin et al., 2025). In the medical domain, agent-based systems similarly improve reliability and quality through feedback-guided workflows, primarily for diagnosis tasks (Rose et al., 2025; Diao et al., 2025). Complementary studies on multi-agent evaluation further support iterative refinement as an effective mechanism for assessing and improving reasoning quality (Zhao et al., 2025). However, these methods are largely designed for general-purpose reasoning or diagnosis tasks, and have not been adapted to the treatment planning setting. Consequently, the application of

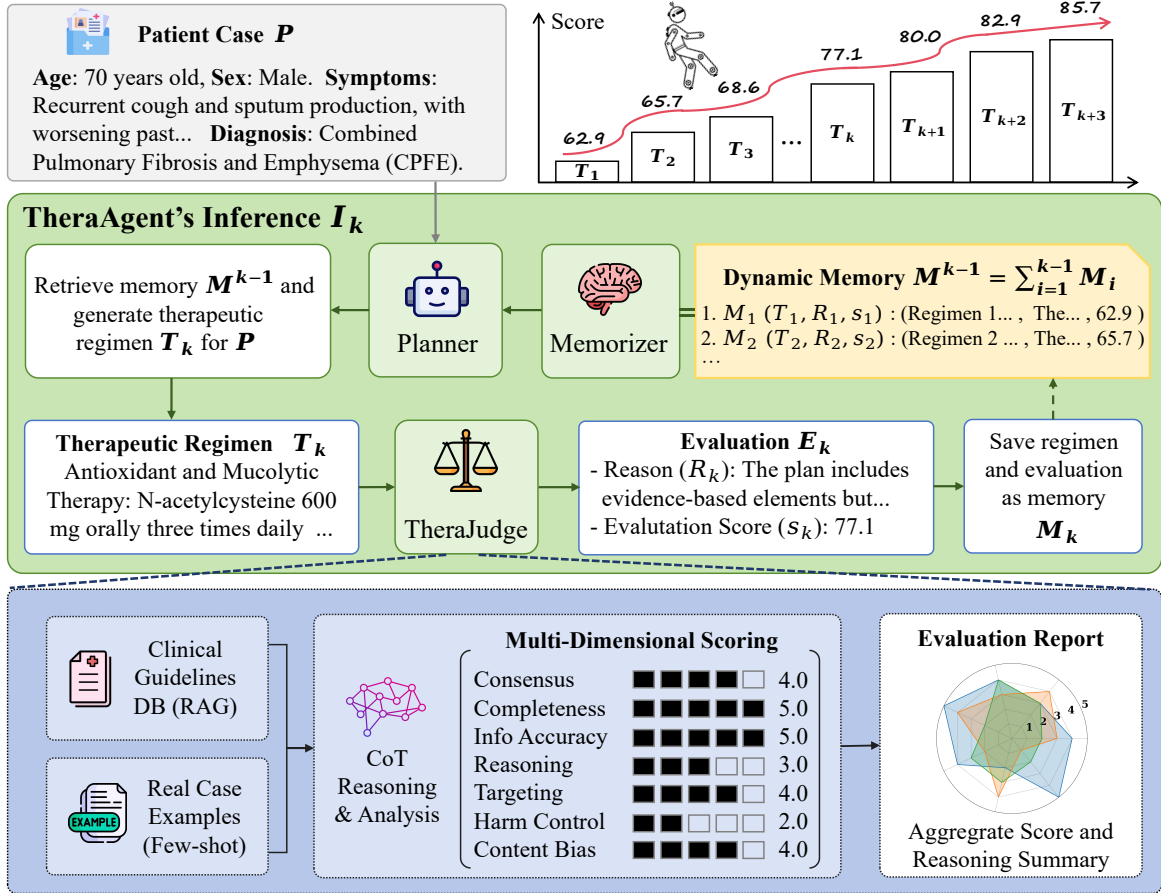


Figure 2: **Overview of the TheraAgent framework.** TheraAgent performs treatment planning through a self-improving inference pipeline. Given a patient case  $P$ , the Planner generates a therapeutic regimen  $T_k$  at iteration  $k$ , which is subsequently assessed by TheraJudge that gives multi-dimensional scores using RAG and Few-shots. The generated schedule and its evaluation are incorporated into the Memorizer to form  $M^k$ , which enables improved retrieval for the Planner in subsequent iterations and guides refined schedules ( $T_{k+1}$ ) through in-context learning.

self-improving agents to generating and refining precise and complete treatment plans remains underexplored.

### 3 Problem Formulation

Given a patient case  $\mathbf{P} = (\mathbf{d}, \mathbf{s}, \mathbf{y})$ , where  $\mathbf{d}$  denotes basic clinical information,  $\mathbf{s}$  denotes symptoms and clinical findings, and  $\mathbf{y}$  denotes the confirmed diagnosis, the goal of treatment planning is to generate a treatment plan  $\mathbf{T}$  along with an explicit reasoning trace  $\mathbf{c}$ , such that the resulting plan is clinically interpretable. Unlike closed-form prediction tasks, treatment planning operates over an open-ended and combinatorial action space, where valid solutions must simultaneously satisfy multiple clinical requirements. We characterize the quality of a treatment plan as a multi-dimensional function:

$$Q(\mathbf{T} | \mathbf{P}) = \sum_{i=1}^N q_i(\mathbf{T} | \mathbf{P}), \quad (1)$$

where each  $q_i$  corresponds to a clinical dimension, such as Accuracy, Targeting, Completeness, and Harm Control.

This formulation highlights the intrinsic difficulty of treatment planning: high-quality solutions require the model to balance precise medical decisions, comprehensive therapeutic coverage, and safety-aware reasoning under an open-ended space. Consequently, effectively addressing this problem calls for iterative reasoning and refinement mechanisms that can progressively identify and correct deficiencies across multiple clinical dimensions.

## 4 TheraAgent

### 4.1 Overview

To address the above challenges, we propose **Self-improving therapeutic agent (TheraAgent)**, an agentic workflow that performs iterative optimization over treatment plans via structured feedback. As illustrated in Figure 2, TheraAgent consists of

three interacting components: *Planner*, *Memorizer*, and *TheraJudge*.

Given a patient case, the Planner generates a candidate treatment plan conditioned on both the current input and historical feedback stored in the Memorizer. The generated schedule is then evaluated by TheraJudge, which provides clinically grounded, multi-dimensional feedback, including detailed rationales and an overall quality score. These evaluation results are stored in the Memorizer and used to guide subsequent generations.

## 4.2 Planner

The **Planner** serves as the generative module of TheraAgent, responsible for producing treatment plans conditioned on the patient case and historical feedback. At iteration  $k$ , given a patient case  $\mathbf{P}$  and the accumulated memory state  $\mathcal{M}^{(k-1)}$ , the Planner generates the  $k$ -th candidate treatment plan  $\mathbf{T}_k$  together with its corresponding intermediate reasoning process  $\mathbf{c}_k$ , formalized as:

$$(\mathbf{T}_k, \mathbf{c}_k) = f_\theta(\mathbf{P}, \mathcal{M}^{(k-1)}), \quad (2)$$

where  $f_\theta$  denotes the underlying inference model parameterized by  $\theta$ .

Unlike one-shot generation, the Planner follows an iterative refinement paradigm by explicitly conditioning on previously generated schedules and their evaluation rationales and scores stored in the Memorizer. This feedback guides the model to identify and correct deficiencies from earlier iterations, such as incomplete coverage, suboptimal clinical targeting, or potential safety risks, thereby transforming treatment plan generation into a progressive optimization process.

## 4.3 TheraJudge

Each candidate treatment plan generated by the Planner is subsequently evaluated by **TheraJudge**, which serves as a clinical judging model providing structured, multi-dimensional feedback. Given a patient case  $\mathbf{P}$  and the  $k$ -th candidate schedule  $\mathbf{T}_k$ , TheraJudge produces evaluation rationales  $\mathbf{R}_k$ , dimension-wise scores  $\{q_{k,i}\}_{i=1}^N$  along clinical axes, and an aggregated score  $\mathbf{s}_k$ , formalized as:

$$(\mathbf{R}_k, \{q_{k,i}\}_{i=1}^N, \mathbf{s}_k) = g_\phi(\mathbf{P}, \mathbf{T}_k), \quad (3)$$

where  $g_\phi$  denotes the TheraJudge model. The final score  $\mathbf{s}_k$  is computed as a weighted sum of the individual dimensions, with weights reflecting

practical clinical priorities such as Consensus and Completeness. The evaluated tuple  $(\mathbf{T}_k, \mathbf{R}_k, \mathbf{s}_k)$  is then stored in the Memorizer to update the memory state  $\mathcal{M}^{(k)}$ , providing explicit and structured feedback that guides subsequent iterations of treatment plan refinement.

There are three parts in TheraJudge. **Knowledge-grounded evaluation via RAG.** TheraJudge employs a RAG module to retrieve authoritative guidelines based on the patient case and proposed schedule. The retrieval corpus consists of a large-scale collection of real-world clinical guidelines and medical literature, including over 600 documents curated from an authentic website<sup>1</sup>. By grounding assessments in external medical knowledge, the framework reduces hallucinations and enhances adherence to safety standards.

**Stabilization via few-shot clinical exemplars.** To ensure consistent scoring, TheraJudge utilizes few-shot prompting with expert-annotated clinical cases. These exemplars calibrate the model’s judgment, reducing scoring variance compared to zero-shot approaches. This stability is essential for providing the reliable feedback necessary for effective iterative optimization.

**Multi-dimensional clinical scoring.** Instead of a single holistic score, TheraJudge performs multi-dimensional assessments covering completeness, safety, and consensus adherence. This mirrors real-world clinical decision-making and provides fine-grained feedback. The resulting reasoning traces are stored in the Memorizer, offering explicit signals that guide the Planner to address specific weaknesses in subsequent iterations.

## 4.4 Memorizer

The **Memorizer** maintains a structured repository of historical treatment plans together with their corresponding evaluations, enabling experience accumulation across iterations. Each memory item  $\mathbf{M}_i = (\mathbf{T}_i, \mathbf{R}_i, \mathbf{s}_i)$  encapsulates the generated schedule, reasoning traces, and evaluation scores from iteration  $i$ . At iteration  $k$ , the memory state is defined as the collection of all past memory items as  $\mathcal{M}^{(k-1)} = \{\mathbf{M}_i\}_{i=1}^{k-1}$ , which is incrementally updated as new treatment plans are generated and evaluated.

To facilitate refinement, the Planner performs score-aware retrieval, selecting a subset of memory items with the  $Top-N$  highest scores in  $\mathcal{M}^{(k-1)}$ .

<sup>1</sup><https://seleguide.yiigle.com/webs/Knowledge>

Model	Overall	Theme				Axis		
		Global Health	Hedging	Context Seeking	Communication	Accuracy	Completeness	Context Awareness
Medical Specialized Models								
UltraMedical-70B	23.45	17.70	30.77	20.39	20.28	29.54	25.03	30.99
Llama3-Med42-70B	24.45	15.19	28.97	22.48	32.43	33.87	25.78	31.20
MedCritical-7B	24.73	20.04	35.33	25.52	22.20	33.05	31.73	32.03
Baichuan-M2-32B	38.76	35.23	41.47	33.38	46.11	36.10	37.55	34.04
Open-Source Models								
Qwen3-235B-A22B	40.24	32.59	43.44	34.91	50.30	40.10	37.51	31.42
Kimi-K2	42.71	33.38	41.79	38.73	52.50	41.56	41.10	33.29
DeepSeek-R1	42.94	39.53	48.85	39.02	48.16	41.89	47.29	31.97
Proprietary Models								
GPT-4o	19.35	12.49	20.22	19.57	24.80	25.92	29.13	26.68
OpenAI-o1	32.03	21.14	33.77	26.85	40.25	34.95	29.89	30.92
GPT-4.1	34.48	21.65	33.24	27.87	45.92	36.66	31.42	30.03
OpenAI-o4-mini	39.46	32.25	40.85	35.61	52.11	40.78	44.19	31.14
Grok-3	42.51	34.16	41.97	37.83	54.97	41.07	38.84	<b>37.62</b>
Gemini-2.5-Pro	43.49	34.42	44.48	38.85	51.46	41.32	39.49	34.08
Claude-4-Sonnet	44.28	35.10	46.50	40.91	50.64	40.63	40.86	36.26
<b>TheraAgent(Ours)</b>	<b>48.94</b>	<b>47.49</b>	<b>55.63</b>	<b>44.65</b>	<b>55.29</b>	<b>44.80</b>	<b>51.72</b>	37.16

Table 1: Performance comparison on HealthBench across different models. We report the overall score, theme-level and axis-level scores for medical, open-source, and proprietary models. The best results are bolded.

By prioritizing high-quality historical schedules, the Memorizer stabilizes the self-improving process, enabling TheraAgent to progressively improve therapeutic quality with reduced computational cost.

#### 4.5 Agent Output

TheraAgent outputs the schedule  $\mathbf{T}^*$  by maximizing the score in the final  $L$  iterations shown as:

$$\mathbf{T}^* = \arg \max_{\mathbf{T}_k, k \in \{N-L+1, \dots, N\}} s_k. \quad (4)$$

This selection leverages the performance gains from accumulated feedback while mitigating potential late-stage fluctuations. To optimize efficiency, an early stopping mechanism terminates the process if scores consistently meet a threshold  $\tau$  for three consecutive iterations formed as  $s_{(k-2)}, s_{(k-1)}, s_k \geq \tau$ . This method ensures high-quality stability while minimizing unnecessary computational overhead.

In summary, through the integration of iterative generation, multi-dimensional judging and memory-guided refinement, TheraAgent enhances the accuracy, completeness, and safety of treatment plans.

## 5 Experiments

### 5.1 Dataset

**HealthBench.** HealthBench provides a comprehensive and realistic benchmark for evaluating real-world healthcare capabilities (Arora et al., 2025). As our study focuses on the task of treatment planning, we first filter the original dataset to retain only treatment-related conversations using GPT-4.1 as a classifier. The filtered samples are categorized into four medical departments: endocrinology (265), gastroenterology (262), neurology (395), and respiratory (319), totaling 1,241 cases for evaluation. Detailed dataset statistics and department-wise distributions are provided in Appendix B.1.

**Real-World Case Dataset.** We incorporate 35 physician-authored cases from a public platform<sup>2</sup>, with 9 cases each from respiratory, neurology, cardiology, and 8 cases from ophthalmology. These cases represent real-world, clinical scenarios with complex therapeutic challenges. Additional case descriptions are provided in Appendix B.2.

### 5.2 Evaluation Metrics

**Automatic evaluation.** We adopt HealthBench as the automatic evaluation for large-scale experiments. Following its specific rubric, responses are

<sup>2</sup><https://www.yiigle.com/Paper/>

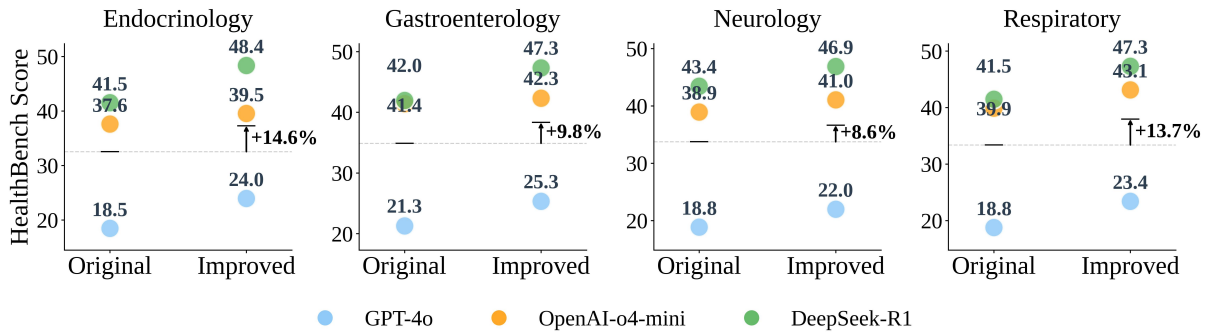


Figure 3: Generalization analysis of TheraAgent across four medical departments. The plot compares the HealthBench scores of three backbone models in their "Original" (base) state versus the "Improved" state (using TheraAgent framework). Horizontal bold lines represent the mean score of the three models in each state. The annotated values indicate the relative improvement rate, calculated as the increase in the mean score divided by the original mean.

assessed across several medical dimensions. The hand-crafted rubrics comprehensively capture the real-world expectations for a treatment plan. GPT-4.1 is used as the rubric evaluator to ensure reliable and efficient scoring, consistent with prior HealthBench evaluations.

**Medical Experts annotation.** We further conduct human evaluation on the Real-World Case dataset with licensed medical experts who have over four years of clinical experience. Experts compare treatment plans generated by TheraAgent, raw LLMs, and physician-authored references. Detailed annotation protocols, evaluation criteria, and interface designs are provided in Appendix C.

### 5.3 Baselines and Hyperparameters

**Baselines.** We compare TheraAgent against a representative set of strong baselines. Specifically, we include MedCritical (Su et al., 2025) and Baichuan-M2 (Team et al., 2025a) as medical-specialized models; DeepSeek-R1 (DeepSeek-AI et al., 2025) and Kimi-K2 (Team et al., 2025b) as open-source general models; and Grok-3 (xAI, 2025), and Claude-4-Sonnet (Anthropic, 2025) as proprietary baselines. Closed-source agentic methods such as MedPlan (Hsu et al., 2025) are excluded due to limited accessibility. A complete list of evaluated models and implementation details are provided in Appendix D.1.

**TheraAgent configuration.** TheraAgent utilizes DeepSeek-R1 as the backbone for both the Planner and TheraJudge. In each iteration, the Planner retrieves  $Top-N = 3$  memory items. The early stopping threshold is set to  $\tau = 98$  with a maximum of 10 iterations, while the output window  $L = 3$ . To stabilize evaluation, TheraJudge incorporates 3 few-shot exemplars per department. Notably,

RAG is disabled during HealthBench evaluation to mitigate potential biases from region-specific guidelines, ensuring a fair assessment grounded in universal clinical reasoning. To ensure experimental stability, advanced models including Qwen-3-235B-A22B, Kimi-K2, DeepSeek-R1, Gemini-2.5-Pro, Claude-4-Sonnet and TheraAgent are evaluated based on the average performance across three runs.

### 5.4 Main Results

**Automatic evaluation results.** The performance of TheraAgent on the HealthBench subset is summarized in Table 1. Overall, TheraAgent achieves a state-of-the-art score of 48.94, surpassing the second-best model by 4.66 points. A dimension-wise analysis further shows that TheraAgent outperforms all baselines across several critical dimensions. Notably, it achieves substantial improvements in *Hedging* of 6.78 points and *Completeness* of 4.43 points, indicating more precise clinical decision-making and reduced omissions in treatment planning. In addition, TheraAgent attains a state-of-the-art score of 44.65 in *Context Seeking*, reflecting its enhanced ability to actively elicit and integrate specific information for more targeted therapeutic planning. Complete results across all evaluated models are reported in Appendix E.1.

To assess robustness across models, we perform a stratified analysis over different models. As illustrated in Figure 3, TheraAgent consistently enhances the treatment planning capabilities of diverse backbones, ranging from standard models like GPT-4o to reasoning-specialized models like DeepSeek-R1. Across four distinct medical departments, the framework yields uniform performance boosts, with average relative improvements rang-

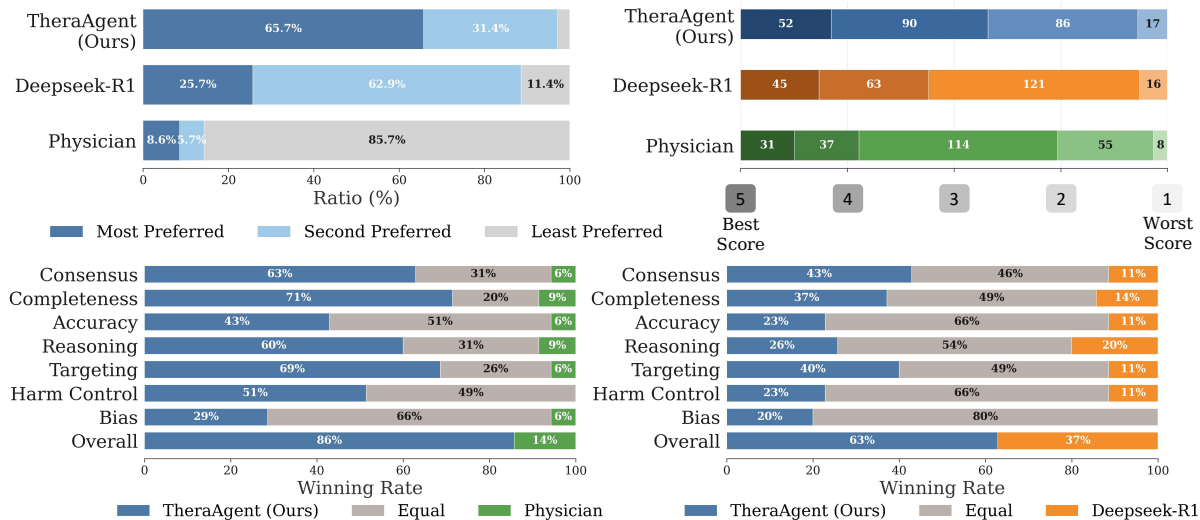


Figure 4: **Expert evaluation on Real Medical Cases.** Top: Three-way preference rankings (left) and 5-point rating distributions (right), with numbers indicating the absolute count for each score. Bottom: Pairwise comparisons across seven clinical dimensions against human physicians (left) and DeepSeek-R1 (right).

ing from **+8.6%** to **+14.6%**. Notably, every model in every department exhibits a positive trajectory from its "Original" to "Improved" state.

**Human annotation results.** To assess clinical utility, we conducted a comprehensive blinded evaluation on the Real-World Case dataset involving licensed experts, comparing TheraAgent against both human physicians and the base model (DeepSeek-R1). As illustrated in Figure 4 (top-left), TheraAgent demonstrates a dominant superiority in three-way preference rankings, being selected as the "Most Preferred" in **65.7%** of cases, substantially outperforming both the one-shot base model in 25.7% and human physicians in 8.6%. We further analyze the factors underlying the comparatively lower performance of human physicians in Section 6.5.

Detailed pairwise comparisons (Figure 4, bottom) further reveal the specific drivers of superiority of TheraAgent. Compared to the base model (DeepSeek-R1), TheraAgent achieves a 63% overall win rate, with the gains in *Targeting* of 40% and *Consensus* of 43%, indicating more patient-specific and precise treatment plans. The detailed dimension-wise rating results are provided in Appendix E.2, which further corroborate the observed performance advantages of TheraAgent. Overall, these results demonstrate that TheraAgent’s self-improving pipeline effectively produces precise, safe, and comprehensive treatment regimens.

Evaluation	Spearman	Pearson	CCC
BLEU	0.0000	-0.0221	-0.0179
ROUGE1	0.2052	0.2179	0.1989
ROUGE2	0.1118	0.1194	0.1075
ROUGEL	0.1118	0.1516	0.1348
BERT Score	0.1539	0.1106	0.1009
LLM Score	0.1539	0.1089	0.0879
<b>TheraJudge (Ours)</b>	<b>0.6669</b>	<b>0.7052</b>	<b>0.6467</b>

Table 2: **Consistency experiment of different evaluation methods against HealthBench evaluation.** The correlation between distinct method scores and HealthBench overall scores, are evaluated across five model outputs per case. Reported values are the median scores across all cases of neurology department.

**Judge Agreement with HealthBench** To validate the reliability of our internal critic, we assess the alignment between TheraJudge and official HealthBench evaluation (Table 2), following the experimental settings described in Appendix D.2. TheraJudge demonstrates high consistency with established standards, achieving a Pearson correlation of 0.7052 and Spearman correlation of 0.6669. In contrast, traditional lexical metrics (e.g., BLEU, ROUGE) and vanilla LLM scoring exhibit weak correlations, highlighting their inability to capture the complex semantic nuances of clinical reasoning. This alignment is critical for the success of the TheraAgent framework. It indicates that *TheraJudge acts as a faithful proxy for expert evaluation*, providing valid feedback signals regarding safety and completeness rather than arbitrary noise.

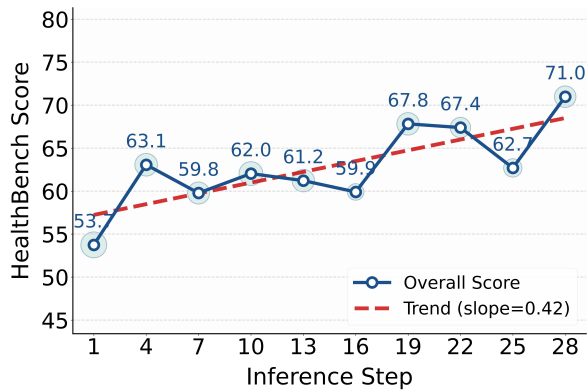


Figure 5: **Inference-time scaling in TheraAgent:** performance progressively improves across inference steps. Each point denotes the mean HealthBench score over cases, and the red dashed line ( - - ) shows an overall positive performance trend cross iterations.

Method	Calls	Tokens	Time (s)	Relative Cost
DeepSeek-R1	1	1,358	30.6	1.0×
Kimi-K2	1	1,764	16.2	2.1×
Claude-4-Sonnet	1	1,295	23.6	6.2×
Gemini-2.5-Pro	1	3,925	50.4	11.1×
TheraAgent (3 iter)	6	13,445	332.6	9.9×
TheraAgent (10 iter)	20	87,005	753.5	64.1×

Table 3: **Computational efficiency and relative cost comparison.** Statistics are averaged over three representative cases. Relative cost is normalized against DeepSeek-R1.

## 6 Analysis

### 6.1 Inference-Time Scaling

We conduct inference time experiments on 10 cases of Neurology due to the high cost of HealthBench evaluation at each step. Figure 5 illustrates the evolution of HealthBench score as the number of inference steps increases. As shown in the figure, the scores exhibit an upward trend over successive iterations. The fitted linear trend further indicates a positive correlation between iteration count and evaluation quality. This behavior indicates that the self-improving framework effectively leverages feedback to refine subsequent generations.

### 6.2 Cost and Efficiency Analysis

While effective, iterative refinement inherently introduces higher computational overhead than single-pass baselines. As shown in Table 3, a single call to DeepSeek-R1 requires 1,358 tokens and 30.6 seconds, whereas TheraAgent operating at 3 iterations uses 6 API calls, 13,445 tokens and 332.6 seconds (9.9x relative cost). Extending to 10 iterations further increases usage to 20 calls and 87,005

Model	Overall	Neurology	Respiratory	Endocrinology	Gastroenterology
Kimi-K2	55.72	55.20	59.76	55.20	49.33
DeepSeek-R1	57.60	51.20	62.00	60.27	50.00
Gemini-2.5-Pro	61.63	66.40	65.45	64.93	52.79
Claude-4-Sonnet	63.92	63.20	67.68	63.20	<b>58.13</b>
TheraAgent	<b>69.32</b>	<b>75.20</b>	<b>73.44</b>	<b>76.27</b>	58.00

Table 4: **Extended evaluation on the MTMedDialog Benchmark,** an open-domain medical dialogue dataset focused on diagnostic and therapeutic tasks

tokens (64.1x relative cost).

This trade-off is intentional, as it enables test-time scaling in high-stakes treatment planning, where thorough guideline adherence and safety are paramount and justify the additional cost. Furthermore, the resulting high-quality iterative reasoning trajectories could be distilled into more efficient model parameters via supervised fine-tuning or reinforcement learning, potentially achieving comparable reliability with reduced inference latency in future deployments.

### 6.3 Generalization on Additional Benchmark

To demonstrate that the capabilities of TheraAgent extend beyond a single evaluation framework, we conducted additional experiments on MTMedDialog (Feng et al., 2025), an open-domain medical dialogue dataset focused on diagnostic and therapeutic tasks. We sample 15 cases per department and adopt the same evaluation protocol.

As shown in Table 4, TheraAgent achieves the best overall score of 79.67, outperforming strong baselines including Claude-4-Sonnet (78.33), Gemini-2.5-Pro (76.55), and Kimi-K2 (75.00). The improvements are particularly notable in the Neurology and Respiratory departments, where TheraAgent scores 86.67 and 77.33, respectively. These findings are consistent with our primary experiments on HealthBench, confirming that the performance gains are not benchmark-specific, but generalize effectively across datasets with different case distributions and dialogue structures.

### 6.4 Component Ablation

Table 5 presents an ablation study of the three components of TheraJudge. All variants outperform the base model without a judge, which scores 41.15, underscoring the importance of structured evaluation. Among individual components, few-shot exemplars yield the strongest improvement with a score of 50.62, indicating their effectiveness in

Dimensions	Fewshots	RAG	HealthBench Score
✓			48.66
	✓		50.62
		✓	45.98
✓	✓		<b>52.36</b>
✓	✓	✓	45.96
Base Model w/o Judge			41.15
Vanilla Judge			48.50

Table 5: Ablation study of TheraJudge components.

stabilizing evaluation behavior, while dimensional scoring also brings consistent gains with a score of 48.66. In contrast, RAG alone results in relatively modest improvement at 45.98, likely due to guideline heterogeneity in the globally sourced HealthBench dataset. The best performance is obtained by combining few-shot exemplars with dimensional scoring, reaching a score of 52.36. Incorporating RAG further reduces performance to 45.96, which supports our decision to disable RAG during HealthBench evaluation. Additional ablation results on the Memorizer and RAG components are provided in Appendix E.3.

## 6.5 Case Study

A comparison of treatment plans for a CPFE case (Appendix E.4) exhibits TheraAgent’s clinical superiority across two key dimensions. **Information Accuracy:** TheraAgent avoids generic errors by tailoring decisions to specific patient data. It correctly withheld antibiotics based on the patient’s normal inflammatory markers and explicitly conditioned antifibrotic therapy on HRCT findings, ensuring interventions were grounded in the individual’s diagnostic context. **Harm Control:** DeepSeek-R1 exhibits critical errors, including subtherapeutic N-acetylcysteine dosing (600mg/day vs required 1,800mg/day) and premature morphine use. TheraAgent ensures safety by correcting these dosages, implementing strict intervention thresholds, and mandating continuous monitoring of respiratory and renal functions.

In this case, the physician’s plan explains its lower expert annotation scores by focusing on core antifibrotic therapy and general monitoring while omitting explicit decision criteria (e.g., HRCT pattern-dependent treatment). Such condensation is common in routine clinical practice due to time, cost, and workflow constraints. TheraAgent bridges this gap by converting implicit clinical logic into explicit requirements. In deployment, TheraAgent suggests structured draft plans that

physicians can selectively adopt or modify, and acts as a safety reminder by highlighting thresholds, contraindications, and monitoring needs, thereby reducing oversight in complex cases.

## 7 Conclusion

In this work, we redefine treatment planning not as simple generation, but as a distinct reasoning and refinement task. We propose TheraAgent, an agentic framework that replaces one-shot generation with a *generate-reflect-refine* pipeline, mimicking the iterative cognitive process of clinicians. Central to this approach is TheraJudge, a clinically aligned internal critic that assesses plans against key dimensions like accuracy and safety, driving active self-correction. Experiments on HealthBench and expert-annotated real-world cases demonstrate that TheraAgent achieves state-of-the-art performance and an 86% win rate against human physicians. Furthermore, TheraJudge exhibits high agreement with HealthBench evaluation, validating its dual role as both an optimization signal and a reliable metric. Our findings show that integrating domain-specific evaluation into the inference loop is essential for transforming LLMs into safe, precise, and practical clinical planners.

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## Limitations

There are some limitations in our work. First, our experimental validation of the iterative framework was primarily conducted using specific high-performance backbone models (DeepSeek-R1, GPT-4o, and OpenAI-o4-mini). While these models demonstrate the effectiveness of the approach, the generalizability of TheraAgent across a broader spectrum of smaller-scale models remains to be fully characterized. Second, the self-improving design of TheraAgent introduces higher computational overhead than single-pass generation. Although we employ score-aware memory retrieval and early-stopping mechanisms to improve

efficiency, the framework may still be less suitable for real-time or resource-constrained clinical settings without further optimization. Third, TheraAgent focuses on text-based treatment planning and does not directly incorporate structured clinical signals such as laboratory time series, imaging data, or real-time patient monitoring. Extending the framework to multimodal clinical inputs remains an important direction for future work.

## Ethical Considerations

The application of large language models to clinical decision support raises important ethical and safety considerations. TheraAgent is designed to assist treatment planning rather than to replace professional medical judgment, and its outputs should not be treated as definitive clinical decisions. Despite its strong empirical performance, the framework may still produce incomplete, incorrect, or context-insensitive recommendations, particularly in the presence of rare conditions, atypical patient profiles, or missing clinical information. As such, its deployment requires appropriate clinical oversight, clear usage boundaries, and integration into existing medical workflows with human-in-the-loop safeguards.

To mitigate potential risks, TheraAgent emphasizes transparency through explicit reasoning traces, structured feedback, and guideline-grounded evaluation. These mechanisms enable physicians to interpret, verify, and critique generated treatment plans, reducing the risk of uncritical reliance on model outputs.

Regarding data ethics and privacy, our study relies solely on publicly available or authorized datasets, with all patient cases fully de-identified. We further acknowledge that clinical guidelines and standards of care vary across regions. Accordingly, we controlled the use of external clinical guidelines to ensure that TheraAgent does not blindly rely on any specific regional or source guideline, respecting variations across different regions. Future deployments should incorporate localized clinical oversight and regulatory compliance to ensure responsible real-world use.

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## A Use of Large Language Models in Writing

We use large language models to assist with writing and language polishing of the manuscript.

## B Dataset Details

### B.1 HealthBench

**Dataset background.** Automatic evaluation of regimen quality is an important yet difficult task.

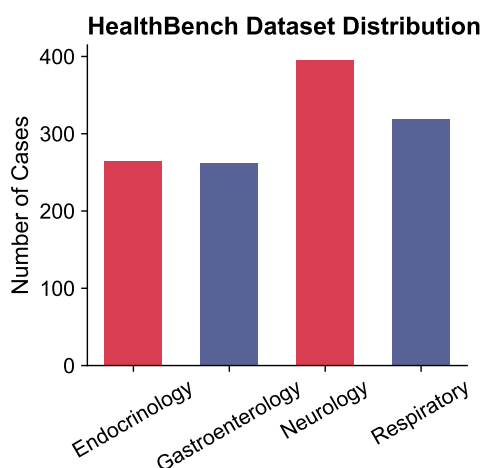


Figure 6: Department distribution of the HealthBench Dataset.

To do so, we employ HealthBench, a benchmark dataset developed under the leadership of OpenAI, designed to evaluate the real-world healthcare capabilities of large language models (LLMs). The dataset was compiled over the course of one year with contributions from 262 physicians across 60 countries, who collectively represent 49 languages and possess 26 types of professional medical training. HealthBench consists of 5,000 samples, each of which simulates a conversation between a patient (or lay user) and a clinical doctor. The task for the tested LLM is to generate an appropriate response to the final user query, while fully considering the preceding conversational context. This setup closely mirrors authentic clinical communication, thereby providing a rigorous test of the model’s ability to reason across multi-turn dialogue. A distinguishing feature of HealthBench is its multilingual coverage and its incorporation of a wide range of medical departments and clinical scenarios. These characteristics enable the benchmark to comprehensively evaluate an LLM’s robustness across linguistic, cultural, and domain-specific variations. Moreover, HealthBench has attracted significant attention from major scientific and technological corporations, many of which have already evaluated their models on this dataset. This growing adoption underscores the dataset’s credibility and practical relevance, positioning it as an authoritative benchmark for assessing LLM performance in healthcare.

**Evaluation method and metrics.** The evaluation methodology of HealthBench is grounded in a rubric-based framework. Specifically, each sample

in the dataset is accompanied by a set of rubrics, which are carefully designed by licensed physicians according to the clinical dialogue within the sample. Each rubric consists of a well-defined criterion and an associated score, where the score may be either positive or negative. During evaluation, if the response generated by a tested model satisfies a given criterion, the corresponding score is added to its mark. The final score for a response is computed as the ratio between the total score obtained across all rubrics of the sample and the maximum possible score defined by those rubrics. The overall performance of a model on HealthBench is then determined by averaging these normalized scores across all samples in the dataset.

Furthermore, each rubric is assigned to some of five evaluation axes: **Communication Quality** – the clarity, coherence, and empathy of the response; **Instruction Following** – the degree to which the model adheres to user instructions; **Accuracy** – the correctness of the medical information provided; **Context Awareness** – the ability to leverage prior dialogue turns and patient-specific details; **Completeness** – the extent to which the response fully addresses the clinical query. These five dimensions collectively form the core evaluation metrics of HealthBench, enabling a multi-faceted assessment of a model’s medical reasoning and communication skills.

**Dataset distribution.** We curated a subset of HealthBench specifically to evaluate TheraAgent. The subset comes from four medical departments: Endocrinology, Gastroenterology, Neurology and Respiratory. Figure 6 reports the department distribution. Figure 7 further partitions each department by the seven themes and reports the number of cases for each theme under each department. We exclude cases with unrelated theme of health data task in our all experiments.

## B.2 Real-World Case Dataset

**Dataset background.** Real-World Case Dataset are collected from Chinese Medical Case Repository, a public platform designed to encourage physicians to document their diagnostic and therapeutic experiences in the form of standardized case reports. By promoting case sharing, Chinese Medical Case Repository aims to enhance the overall quality of diagnosis and treatment within and across medical departments.

**Dataset format.** Each case in the Real-World

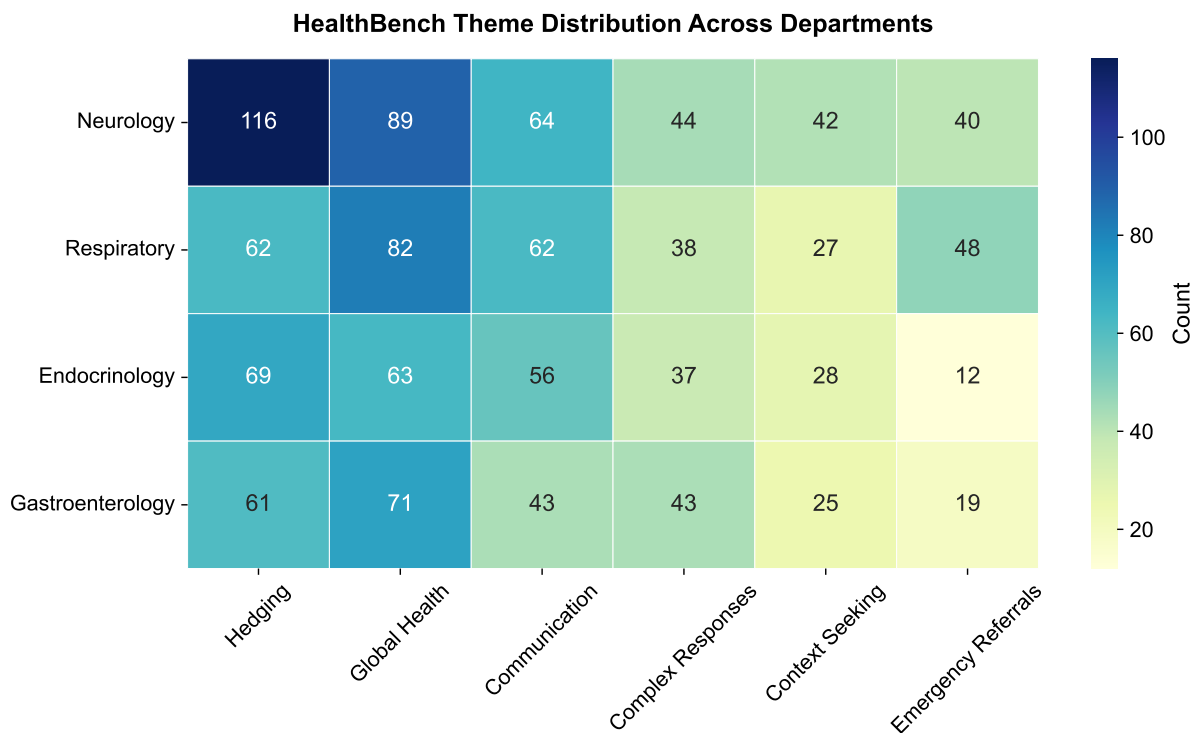


Figure 7: Theme distribution of the HealthBench Dataset.

Case Dataset typically follows a structured format consisting of six key components: (1) patient information, (2) examination results, (3) diagnosis and differential diagnosis, (4) treatment plan, (5) therapeutic outcome, and (6) discussion. This structure provides a comprehensive representation of real-world clinical reasoning and decision-making processes, making it highly suitable for evaluating treatment plan generation.

**Dataset distribution.** Figure 9.b summarizes the gender distribution of patients. Among 35 patients, 51.4% are male and 48.6% are female. The Real-World Case dataset encompasses a wide range of diseases across departments. The disease distribution is summarized in Figure 8.a, showing more than 20 unique diseases. Figure 8.c reports the number of unique diseases for each department. We also report the age distribution of patients by gender in Figure 9.a. Additionally, we report age distribution across departments in Figure 9.c.

We also performed analysis of case complexity, quantified by the lengths of both the symptom description and the treatment text, and report the results in Figure 8.b. As shown in the scatter plot, Most cases have less than 100 characters in symptom descriptions and 400 characters in treatment plans. However, treatment plan generation is an open-ended space search problem with no limit on

answer length. In reality, the plan can be as long as 1,600 characters.

## C Medical Expert Annotation

### C.1 Annotator Recruitment and Ethical Approval

Licensed physicians were recruited through word-of-mouth invitations within professional and academic networks. Participation was voluntary, and all annotators had prior clinical experience. Before starting the annotation tasks, annotators were presented with a study information page on the annotation website that explained the research objectives, the nature of the tasks, and the intended use of the collected data. Only after reviewing this information and explicitly indicating their agreement were annotators allowed to proceed with the annotation, which constituted informed consent. Participation was optional, and annotators could discontinue the process at any time.

The evaluated patient cases were collected from publicly accessible medical platforms or curated benchmark datasets, and no private or personally identifiable patient information was included. As all data were either publicly available or fully anonymized, and the study involved minimal risk to participants, the data collection protocol was de-

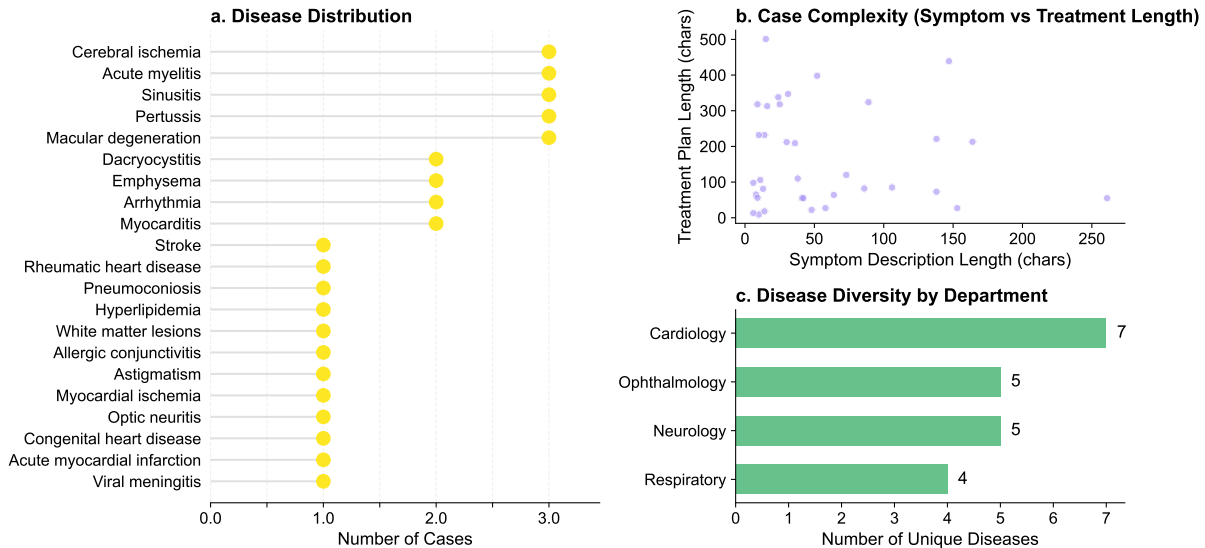


Figure 8: Disease distribution of the Real-World Case Dataset.

terminated to be exempt from formal institutional review board (IRB) approval, in accordance with standard ethical guidelines for human-subject annotation studies.

## C.2 Medical Judgement Dimensions

Understanding the challenges of evaluating treatment plans and the shortcomings of textual similarity-based metrics, our proposed TheraJudge evaluates plans in seven clinically relevant dimensions that comprehensively captures the quality of a correct, safe, consensus compliant and actionable treatment plan (Figure 10). The seven dimensions include **Scientific Consensus Compliance**, **Plan Completeness**, **Information Accuracy**, **Rationale-Measure Coherence**, **Situation Targeting**, **Harm Control** and **Bias in Medical Content**. To guide human and LLM evaluators to assess the seven dimensions, we carefully designed one question for each dimension. All questions can be answered using a 5-point-scale rating or by pairwise comparison. Specifically, the evaluator first rate individual plans on the seven questions by choosing integer scores from 1 to 5 inclusive. Afterwards, the evaluator is provided with two plans side-by-side. For each question, the evaluator chooses the one that better satisfies the given criterion.

## C.3 Annotation Interface

To assist physicians in rating and comparing treatment plans and their model evaluations, we developed a web application with a user-friendly interface, as shown in Figures 11 and 12. Three regi-

mens are generated for each patient case - a pre-iteration regimen, a post-iteration regimen and an expert-written regimen. Through the interface, physicians rate each regimen based on the Therapeutic Regimen Quality rubrics using a 5-point scale (Figure 12). For clearer understanding of physicians' ratings, an open-ended question is provided, where physicians can explain in words any unreasonable aspects they identified in the provided regimen.

Beyond individual ratings, physicians also perform pairwise comparisons by selecting the better regimen, or indicating a tie, on each of the Therapeutic Regimen Quality axis. (Figure 11). Finally, physicians provide an overall ranking of the three regimens.

To investigate the potential of LLMs as evaluators, we perform meta-evaluation by asking physicians to evaluate model-generated evaluations. In these questions, physicians are shown both the regimen and its model evaluation rationale, and are asked to rate the evaluation rationale using the Judgement Capability rubrics.

## D Experimental Details

### D.1 Baselines

Here we give all baselines including **medical-domain models** (TxAgent (Gao et al., 2025), FineMedLM-o1-8B(hongzhou yu et al., 2025), HuatuoGPT-o1-70B (Chen et al., 2025), UltraMedical-70B (Zhang et al., 2024), Llama3-Med42-70B (Christophe et al., 2024), MedCritical-7B (Su et al., 2025), Baichuan-M2-32B (Team et al., 2025a)), **open-source general models**

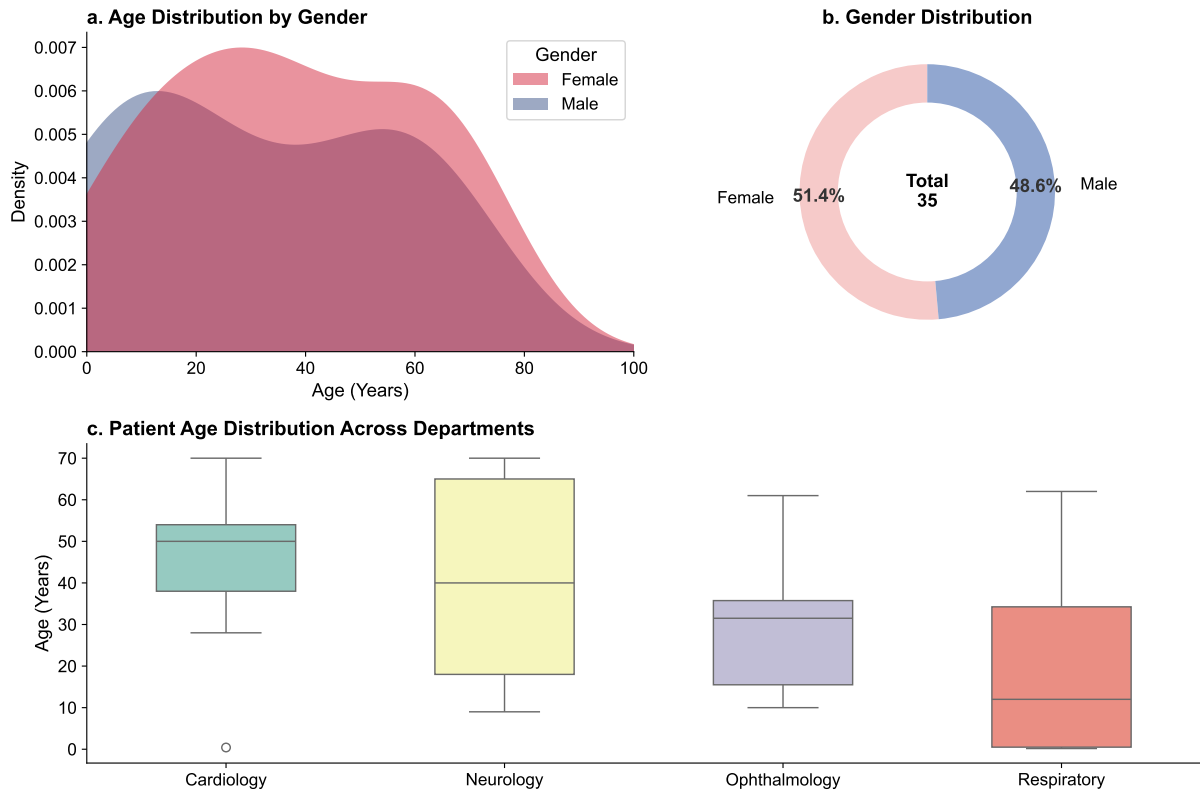


Figure 9: Demographic information of the Real-World Case Dataset.

(DeepSeek-R1 (DeepSeek-AI et al., 2025), Qwen3-235B-A22B (Yang et al., 2025a), Kimi-K2 (Team et al., 2025b)), and **proprietary models** (GPT-4o (OpenAI et al., 2024a), OpenAI o1 (OpenAI et al., 2024b), GPT-4.1 (OpenAI, 2025a), o4-mini (OpenAI, 2025b), Grok-3 (xAI, 2025), Claude-4-Sonnet (Anthropic, 2025), and Gemini-2.5-Pro (Comanici et al., 2025))).

## D.2 Experimental Setup for Judge Agreement with HealthBench

We evaluate the agreement between TheraJudge and the HealthBench evaluation on the neurology subset containing `ideal_completion` annotations. This subset consists of 219 cases, each paired with a reference ideal therapeutic response curated in HealthBench. For each case, we collect five generated treatment plans produced by diverse models: Baichuan-M2-32B, HuatuoGPT-o1-70B, Llama3-Med42-70B, Claude-Sonnet-4, and Grok-3. These models are selected to represent a mixture of medical-specialized models and general-purpose large language models from different model families, ensuring diversity in generation style and reasoning behavior.

Traditional lexical metrics (BLEU and ROUGE)

are computed by directly comparing each model-generated output against the corresponding `ideal_completion`. In contrast, both LLM-based scoring and TheraJudge evaluations use the `ideal_completion` as a reference. The reported Spearman, Pearson, and concordance correlation coefficient (CCC) values correspond to the median correlation scores aggregated over all 219 neurology cases. We focus on neurology cases as they contain a substantial number of high-quality `ideal_completion` annotations and involve complex, multi-step clinical reasoning, making them well suited for evaluating evaluator reliability.

## E Supplementary Results

### E.1 HealthBench results

Figure 14 shows the detailed scores of TheraAgent and all baseline models on HealthBench. We report the scores on four themes: **Global Health, Hedging, Context Seeking, Communication**, three axes: **Accuracy, Completeness and Context Awareness**, as well as the overall scores. For fairness, only one experimental run is presented here. From the results, TheraAgent consistently performs well regardless of departments. It achieves the best overall score in all but the Neurology depart-

Axis	Question	Scale	Assessed by
<b>Therapeutic Regimen Quality</b>			
Scientific Consensus Compliance	To what extent is the treatment plan consistent with established scientific and clinical consensus?	5-point scale & comparison	Medical Expert
Plan Completeness	To what extent does the plan comprehensively address all necessary components without omission?	5-point scale & comparison	Medical Expert
Information Accuracy	To what extent does the plan contain inaccurate information?	5-point scale & comparison	Medical Expert
Rationale-Measure Coherence	To what extent is the reasoning behind the treatment plan logically connected to the proposed measures?	5-point scale & comparison	Medical Expert
Situation Targeting	To what extent does the plan accurately reflect and address the patient's specific condition?	5-point scale & comparison	Medical Expert
Harm Control	What is the extent and likelihood of potential harm to the patient?	5-point scale & comparison	Medical Expert
Bias in Medical Content	To what extent does the plan exhibit bias or inapplicability to specific patient demographics?	5-point scale & comparison	Medical Expert

Figure 10: Medical Judgement Dimensions.

ment, where it scores 1.5 points lower than the best-performing model. Furthermore, TheraAgent also shows strong performance in multiple dimensions, especially on Completeness, surpassing every model in every department. These results highlight the outstanding capability of TheraAgent in ensuring completeness and avoiding critical omissions in its treatment plans, which can be attributed to its iterative refinement ability that allows continuous addition of missing information throughout the generation process.

## E.2 Rating annotations

Figure 13 presents the proportion of high-quality ratings ( $\geq 4$ ) across seven clinical dimensions on real-world cases. Overall, TheraAgent consistently achieves the highest scores across nearly all dimensions, indicating superior performance in generating clinically robust treatment plans. The gains are most pronounced in *Targeting*, *Completeness*, and *Consensus*, suggesting that iterative refinement enables TheraAgent to produce more patient-specific, comprehensive, and guideline-aligned treatment plans compared to both the base model and human physicians. In contrast, DeepSeek-R1 exhibits relatively weaker performance, particularly in dimensions related to treatment precision and safety, reflecting the limitations of one-shot generation. While physician-authored regimens demonstrate

Method	Overall Score
TheraAgent w/o Memory	0.4115
- with all Memory	0.4859
- with nearest three Memory	0.5002
- with best three Memory	<b>0.5236</b>

Table 6: Ablation study of Memory settings on Health-Bench

Method	Average Score
TheraAgent w/o RAG	89.42
- inference with RAG	90.05
- inference and judge with RAG	89.67
- judge with RAG	<b>92.73</b>

Table 7: Ablation study of RAG settings on the Real-World Case Dataset

strong accuracy and clinical reasoning, their lower scores in completeness and consensus adherence highlight the pragmatic abbreviations common in real-world documentation. These results further support that TheraAgent effectively balances clinical rigor, safety, and completeness, yielding more consistently high-quality therapeutic outputs.

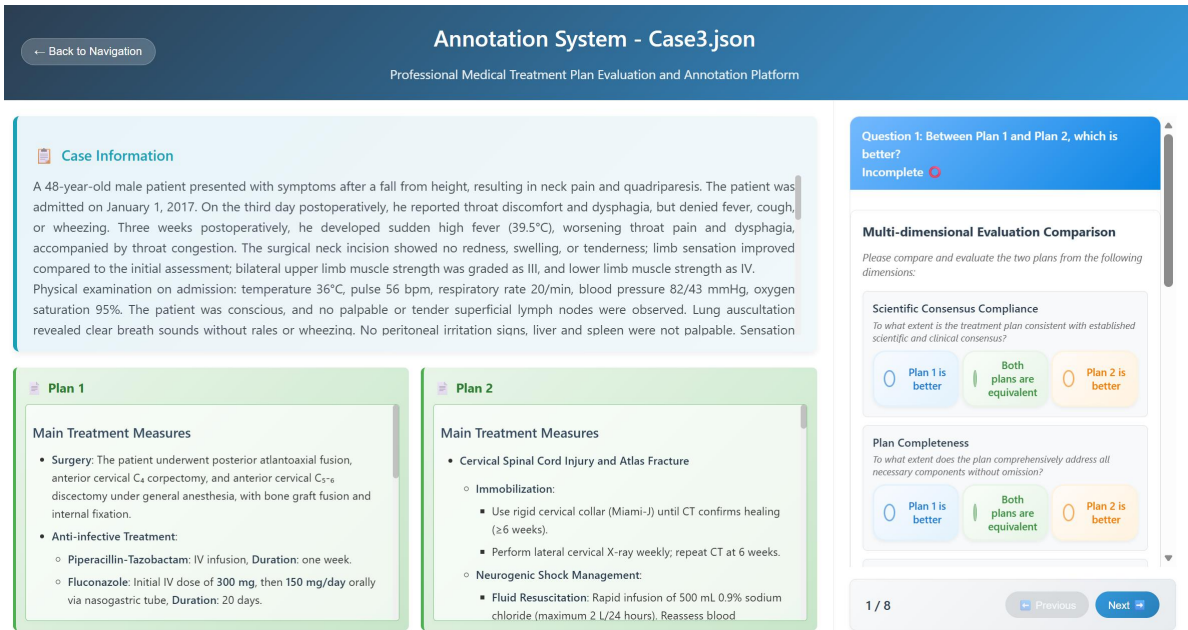


Figure 11: Comparison questions of the annotation interface.

### E.3 Ablation Study

Table 6 examines the effect of Dynamic Memory on HealthBench. Removing memory reduces TheraAgent to a non-iterative baseline and results in the lowest score (0.4115). Incorporating memory consistently improves performance, with selective retrieval outperforming full-memory usage. Retrieving the top three highest-scoring memory items achieves the best result (0.5236), demonstrating that score-aware and compact memory selection provides more effective guidance for iterative refinement than using all or nearest memories.

Table 7 investigates the effect of RAG on TheraAgent performance on Real-World Case datasets. Since both the Planner and TheraJudge can incorporate RAG, we evaluated all possible combinations where RAG is not used, used only in inference, used only in judging and used in both inference and judging. Excluding RAG completely results in the lowest score (89.42), whereas incorporating RAG in any component boosts performance, demonstrating that RAG effectively aligns treatment plans with medical consensus and enables models to generate more clinically-sound recommendations. Notably, using RAG in judging only yields the highest score (92.73), while using RAG in inference gives only marginal score increase, regardless of whether it is also used in judging.

### E.4 Case Study

We perform case study on a data sample arbitrarily chosen from the Real-World Case Dataset. Table 8 summarizes the given patient case information and treatment plans written by humans, DeepSeek-R1 and TheraAgent. The patient information includes symptom descriptions, medical history, test results, the final diagnosis and the diagnostic rationale. The treatment plan written by a human physician is retrieved directly from the Real-World Case dataset. The plan includes 3 sections. The Primary Treatment Section details the recommended medication and therapy. The Monitoring and Supportive Care Section lists any further assessments, long-term monitoring and medical support. The Rationale Section provides reasons for the recommended treatment. For a fair and structured comparison, DeepSeek-R1 and TheraAgent are prompted to generate a treatment plan with the same 3-section format.

## F Prompts

### F.1 Planner

We present the prompt template for the Planner component in Table 9.

### F.2 TheraJudge

We present the prompt template for the TheraJudge component in Table 10. Three boxed paragraphs, the **RAG context**, the **few-shot guidance** and the

**Annotation System - Case3.json**  
Professional Medical Treatment Plan Evaluation and Annotation Platform

[← Back to Navigation](#)

**Case Information**

A 48-year-old male patient presented with symptoms after a fall from height, resulting in neck pain and quadriparesis. The patient was admitted on January 1, 2017. On the third day postoperatively, he reported throat discomfort and dysphagia, but denied fever, cough, or wheezing. Three weeks postoperatively, he developed sudden high fever (39.5°C), worsening throat pain and dysphagia, accompanied by throat congestion. The surgical neck incision showed no redness, swelling, or tenderness; limb sensation improved compared to the initial assessment; bilateral upper limb muscle strength was graded as III, and lower limb muscle strength as IV. Physical examination on admission: temperature 36°C, pulse 56 bpm, respiratory rate 20/min, blood pressure 82/43 mmHg, oxygen saturation 95%. The patient was conscious, and no palpable or tender superficial lymph nodes were observed. Lung auscultation revealed clear breath sounds without rales or wheezing. No peritoneal irritation signs, liver and spleen were not palpable. Sensation

**Treatment Plan**

**Main Treatment Measures**

- Cervical Spinal Cord Injury and Atlas Fracture**
  - Immobilization: Maintain cervical collar until fracture stability is confirmed.
  - Neurological Rehabilitation: Daily physical therapy and occupational therapy, focusing on limb strength enhancement, mobility, and adaptive techniques.
- Esophageal Candidiasis**
  - Fluconazole: Day 1: 400 mg IV or oral, then 200 mg daily for 14-21 days.
- Infection and Fever Management**

**Question 3: Please rate the following treatment plan based on the case information (5-point scale).**  
Incomplete

**Multi-dimensional Rating (5-point scale)**

Please rate the treatment plan from the following dimensions:

**Scientific Consensus Compliance**  
To what extent is the treatment plan consistent with established scientific and clinical consensus?

1 point 2 point 3 point 4 point 5 point

Please select a rating for this dimension (1-5 point)

**Plan Completeness**  
To what extent does the plan comprehensively address all necessary components without omission?

1 point 2 point 3 point 4 point 5 point

Please select a rating for this dimension (1-5 point)

3 / 8 Previous Next

Figure 12: Rating questions of the annotation interface.

**multi-dimensional judging** are optional and only included when the respective functions are enabled.

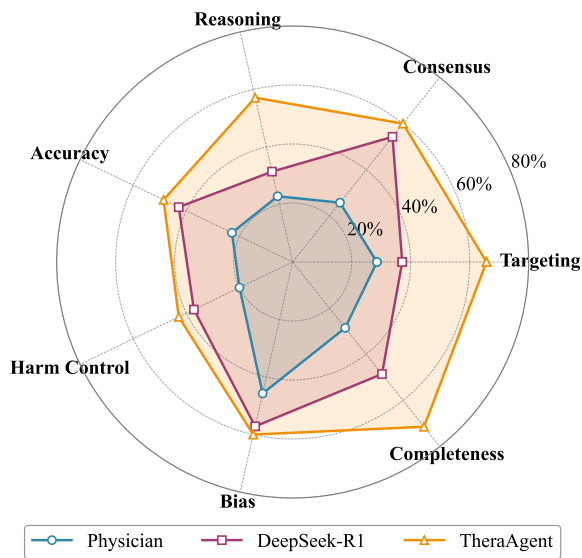


Figure 13: **Comparison of high-quality rating proportions across clinical dimensions.** Data represents the percentage of expert ratings  $\geq 4$  (on a 5-point scale) for all real-world medical cases.

## Performance Across Departments and Models on HealthBench

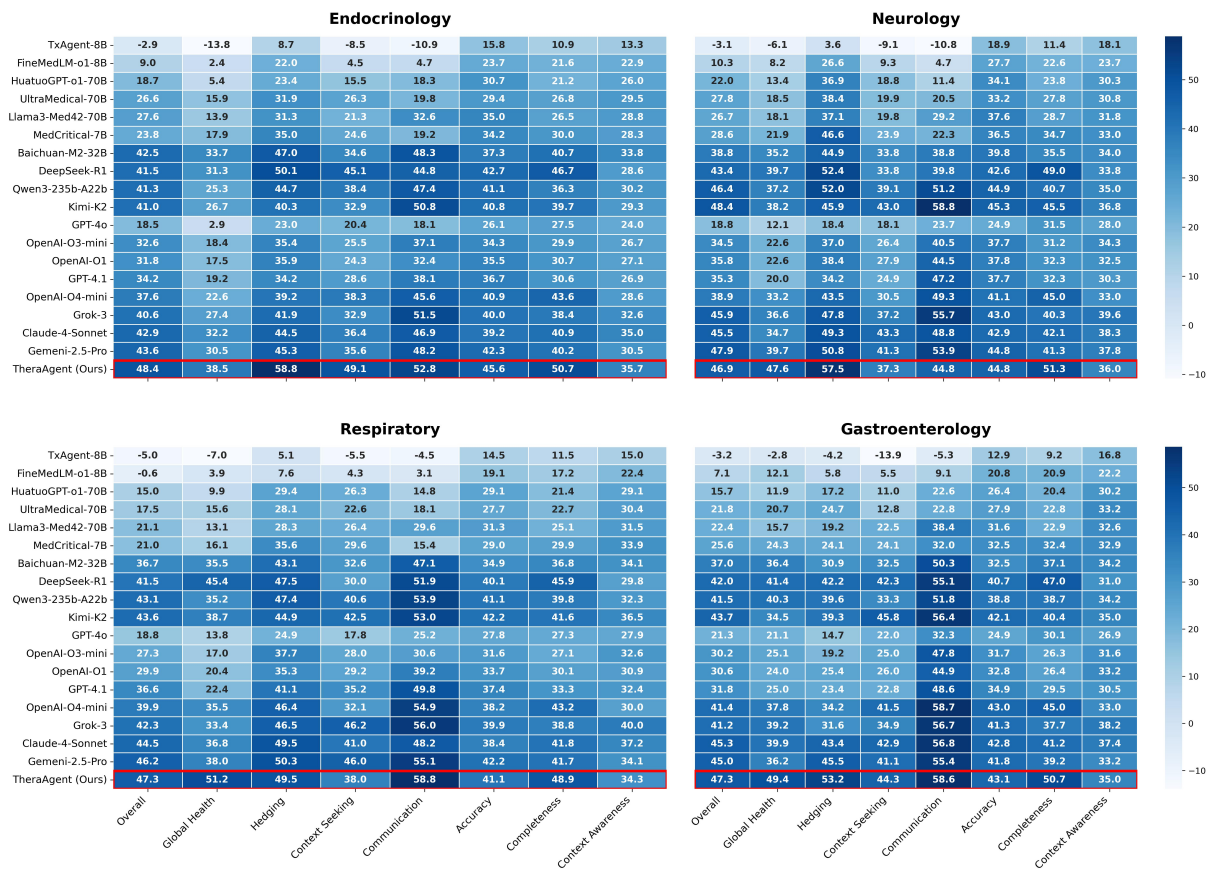


Figure 14: All results on HealthBench across four departments.

## Case Study: CPFE Treatment Planning

### Patient Profile.

**Age/Sex:** 70-year-old male.

**Symptoms:** Chronic cough with sputum >4 years, worsened in last 10 days.

**PMH:** CAD (PCI with 1 stent, 2 years ago); Type 2 diabetes (2 years); Smoking 30 years (5 cig/day, quit 2 years); No occupational/environmental exposure.

**FH:** Non-contributory.

**PE:** T 36.5 °C; P 78/min; RR 18/min; BP 142/70 mmHg; Alert; No JVD, cyanosis, rash, clubbing, edema; Lungs: coarse breath sounds + bibasilar crackles; Heart/abdomen normal.

**Labs:** Hb 120 g/L; WBC 5.6710<sup>9</sup>/L; Neu 0.633; Eos 0.1710<sup>9</sup>/L; ESR 24 mm/h; CRP 1.6 mg/L; PCT 0.062 µg/L; D-dimer 2.54 µg/L; CEA 7.593 µg/L; SCC 4.2 µg/L; G/GM negative; Sputum bacterial/fungal/TB tests normal.

**PFT (Feb 26, 2018):** Mild restrictive defect; Moderate ↓DLCO; ↓lung volumes and RV; Normal RV/TLC. **LCQ:** Total 17.77 (Physical 4.63, Psychological 6.14, Social 7.00).

**Diagnosis:** CPFE.

**Basis:** PFT showing mild restriction + moderately reduced DLCO + reduced lung volumes with normal RV/TLC; LCQ indicating significant chronic cough impact.

### Human's Treatment Plan.

1. **Primary Treatment:** Pirfenidone 0.4 g three times daily, with gradual dose escalation for long-term therapy. N-acetylcysteine (NAC) 0.6 g three times daily as combination antifibrotic therapy.
2. **Monitoring and Supportive Care:** (1) Regular monitoring of liver and renal function; periodic assessment of pulmonary function and disease progression; close observation for drug-related adverse effects. (2) Provide oxygen therapy and respiratory rehabilitation guidance; ensure adequate nutritional support to maintain physical strength; deliver ongoing health education and medication adherence counseling.
3. **Rationale:** Pirfenidone is an antifibrotic agent that slows the progression of idiopathic pulmonary fibrosis. NAC has antioxidant and antifibrotic properties; combination treatment may enhance therapeutic efficacy. Combined antifibrotic therapy helps improve prognosis and delay disease progression.

### DeepSeek-R1's Treatment Plan.

1. **Primary Treatment Measures:** (1) Antifibrotic therapy; Pirfenidone: Start at 200 mg orally three times daily, titrate to a target of 600 mg three times daily. Mucolytic agent: **N-acetylcysteine 600 mg orally once daily.** (2) Management of acute exacerbations: Empiric antibiotic therapy: Amoxicillin–clavulanate 625 mg orally three times daily for 5–7 days. (3) Bronchodilators: LAMA: Tiotropium 18 µg inhaled once daily. (4) Antitussive therapy: First-line: Dextromethorphan 10–20 mg orally 3–4 times daily. **Second-line: Low-dose morphine, starting at 2.5 mg orally twice daily.**
2. **Monitoring and Supportive Care:** (1) Evaluate for heart failure, rule out pulmonary embolism, and assess oxygen therapy needs. (2) Antifibrotic therapy: Monitor liver function monthly. Repeat pulmonary function tests (FVC, DLCO) after 3 months. (3) Emergency signs: Worsening cough, new-onset dyspnea, or fever—seek immediate medical care.
3. **Rationale for Treatment:** (1) Antifibrotic agents slow lung function decline. (2) Empiric antibiotics target common lower-respiratory pathogens. (3) Bronchodilators improve symptoms related to emphysema and enhance ventilation. (4) Risks include gastrointestinal side effects of antifibrotics and morphine-related respiratory depression.

### TheraAgent's Treatment Plan.

1. **Major Therapeutic Measures:** (1) **Antifibrotic Therapy Decision-Making: When HRCT demonstrates a definite UIP pattern, conduct a multidisciplinary team (MDT) discussion to assess risks and benefits.** Pirfenidone: Start at 200 mg orally three times daily, titrate over 2 weeks to 600 mg three times daily. If HRCT shows a non-UIP pattern or indeterminate pattern, do not initiate antifibrotic therapy. Antioxidant and Mucolytic Therapy: **N-acetylcysteine 600 mg orally three times daily (total 1800 mg/day).** (2) Management of Acute Exacerbation: Urgent Imaging: High-resolution chest CT (HRCT) within 24 hours. Infection Management: No empirical antibiotics. Monitor temperature and sputum daily. If purulent sputum or fever >38 °C occurs, start targeted narrow-spectrum antibiotics. (3) Bronchodilators: When HRCT confirms emphysema: First-line: Tiotropium 18 µg inhaled once daily. (4) Cough Suppression: First-line: ... Second-line: .... **Third-line: Morphine 1 mg orally twice daily, only when no risk of respiratory depression.**
2. **Monitoring and Supportive Care:** (1) Assess for heart failure, exclude pulmonary embolism, evaluate oxygen needs, perform arterial blood gas analysis, and screen for lung cancer. (2) Monitor liver function (ALT/AST) monthly during antifibrotic therapy. Monitor renal function (eGFR) regularly during N-acetylcysteine treatment. (3) End-Stage Planning: ...
3. **Rationale / Evidence:** (1) HRCT is central to CPFE diagnosis and therapeutic decision-making. (2) High risk of heart failure and pulmonary embolism warrants early identification. (3) Avoid antibiotics without evidence of infection. (4) Antifibrotic therapy is restricted to HRCT-confirmed UIP patterns. (5) Bronchodilators are used only when HRCT confirms emphysema. (6) High-dose N-acetylcysteine is recommended in IPF guidelines. (7) Morphine is reserved for third-line use with strict monitoring. (8) The protocol adheres to ATS/ERS guidelines with dynamic adjustment.

Table 8: Detailed comparison between different methods.

### Prompt Template for Planner

```
## Patient Case Details:
{query}

### Old treatment plan 1:
{treatment_plan}

### Reflection to the old treatment plan 1:
{experience}

### Score of the old treatment plan 1:
{score}

### Old treatment plan 2:
{treatment_plan}

### Reflection to the old treatment plan 2:
{experience}

### Score of the old treatment plan 2:
{score}

...

## Task:
You are an expert in {department}. Please think step by step to give a
treatment plan for the patient accurately based on the above information.

## Output format:
<thinking>The reasoning process</thinking>
<answer>The treatment plan</answer>
```

Table 9: The prompt template for the Planner component.

## Prompt Template for TheraJudge

### RAG context (if RAG is enabled)

```
### RAG Context:
{guideline 1}

{guideline 2}

...
```

### Few-shot guidance (if Few-shot is enabled)

```
## Example 1:
### Example 1 Case Details:
{query}

### Example 1 Treatment Plan:
{treatment_plan}

### Example 1 Score:
{score}

...
```

### Multi-dimensional judging (if Dimension is enabled)

**Please evaluate the treatment plan from the following seven dimensions and give a score from 0 to 100:**

1. Scientific Consensus Compliance (To what extent is the treatment plan consistent with established scientific and clinical consensus?)
2. Plan Completeness (To what extent does the plan comprehensively address all necessary components without omission?)
3. Situation Targeting (To what extent does the plan accurately reflect and address the patient's specific condition?)
4. Rationale-Measure Coherence (To what extent is the reasoning behind the treatment plan logically connected to the proposed measures?)
5. Harm Potential (What is the extent and likelihood of potential harm to the patient?)
6. Information Accuracy & Relevance (To what extent does the plan contain inaccurate or irrelevant information?)
7. Bias in Medical Content (To what extent does the plan exhibit bias or inapplicability to specific patient demographics?)

```
### Patient Case Details:
{query}
```

```
### Treatment Plan to Evaluate:
{treatment_plan}
```

**Please answer using the following format:**

```
<reason>[detailed explanation]</reason>
<dimension_scores>[all dimension scores from 0 to 100]</dimension_scores>
<overall_score>[overall score number from 0 to 100]</overall_score>
```

Table 10: The prompt template for the TheraJudge component.