FaithMed: Training LLMs for Faithful Evidence-Based Medical Reasoning

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Abstract

Faithful reasoning is essential in medicine, where clinical decisions require transparent justification grounded in reliable evidence. Current medical LLMs either lack active access to evidence or use retrieved evidence without supervising how it should be appraised and applied during reasoning. To address this, we formalize evidence-based medicine principles as process-level criteria and introduce FaithMed, a framework that combines clinician-designed, automatically refined rubrics with reinforcement learning using step-level process reward assignment and advantage grouping. Across seven medical benchmarks, FaithMed improves over agentic-search baselines (+9% on average) and outcome-only RL (+5.8%), while raising average evidence-based medicine rubric scores over agentic-search Qwen3 baselines (+15.5%). This work demonstrates that explicit step-level supervision can improve both task success and the faithfulness of the reasoning process. Code is available at https://github.com/cxcscmu/FaithMed.

1 Introduction

In medicine, reliable clinical decision-making depends on reasoning that connects patient-specific information with trustworthy evidence and makes its justification transparent (Schwartz and Elstein, 2008). Evidence-based medical reasoning operationalizes this goal, requiring physicians to synthesize patient history, clinical findings, and medical guidelines to support accurate diagnoses and treatment planning (Sackett et al., 1996). In real-world healthcare settings, this reasoning process is often complex, time-consuming, and vulnerable to incomplete documentation, noisy observations, and inconsistent evidence across longitudinal patient records (Gruppen, 2017; Temsah et al., 2023).

Recent advances in large language models (LLMs) have demonstrated strong capabilities in medical question answering (QA) and clinical reasoning, motivating the development of automated systems that can assist clinicians in interpreting medical evidence and supporting healthcare decisions (Jin et al., 2019; Singhal et al., 2023b; Sun et al., 2024). However, ensuring that these systems produce faithful and evidence-grounded reasoning remains critical for improving reliability, transparency, and patient safety in high-stakes clinical environments (Singhal et al., 2023a; Saab et al., 2024).

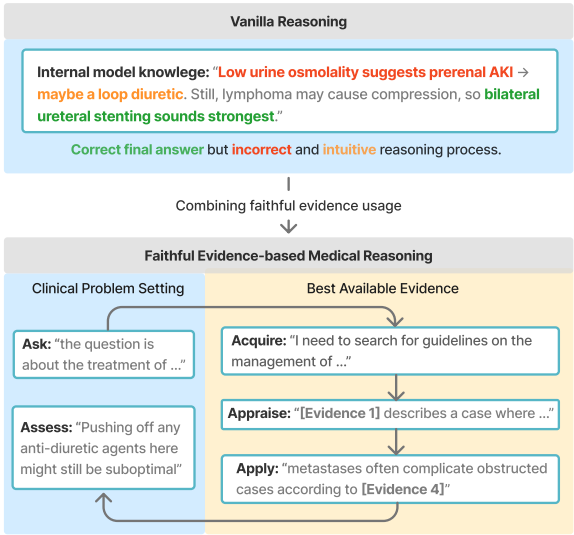

Figure 1: Comparing unfaithful reasoning with evidence-based medical reasoning.

To improve factual grounding and attribution, prior work has explored retrieval-augmented generation (RAG), which combines LLMs with external trustworthy medical knowledge sources to generate verifiable responses with supporting citations (Wang et al., 2025; Xiong et al., 2024; Gao et al., 2023). While these approaches can improve answer correctness and attribution, the reasoning process itself may still be unfaithful to the supporting evidence. In particular, models may generate

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plausible rationales that drift from the patient context, cite irrelevant evidence, or make claims that are not fully supported by the retrieved information, as illustrated in Figure 1. Although the final answer is correct, the underlying reasoning process can still be flawed and unreliable.

To address this limitation, we introduce FaithMed, a framework for faithful evidence-based medical reasoning that trains LLMs to generate evidence-supported reasoning through rubric-guided reinforcement learning. Inspired by real-world evidence-based medicine workflows—*ask*, *acquire*, *appraise*, *apply*, and *assess*—we collaborate with clinicians to design initial rubrics that evaluate reasoning quality across these five dimensions, then automatically refine them to reduce redundancy and improve discriminativeness. We then integrate these refined rubrics into a step-level reinforcement learning framework with rubric-guided rewards. Instead of producing unconstrained rationales, FaithMed encourages the model to follow clinically meaningful reasoning by grounding intermediate reasoning steps in supporting evidence and generating accurate answers consistent with the evidence-based reasoning process.

Across seven medical benchmarks, FaithMed improves answer accuracy by 9% over agentic-search methods and by 10.8% over outcome-only RL baselines, while achieving a 15.5% gain in evidence-based medicine rubric scores. These gains suggest that faithful process supervision improves not only the reasoning trace but also final task performance. We further investigate different faithful reasoning injection strategies by comparing episode-level and step-level process rewards in reinforcement learning, and show that fine-grained step-level rewards derived from individual rubrics achieve superior performance. Moreover, our analysis reveals that episode-level process rewards can incorrectly assign credit across step groups, leading to suboptimal optimization. Finally, clinician-annotated case studies demonstrate that the reasoning produced by our method aligns more closely with the corresponding evidence-based medicine dimensions than strong baselines with agentic search.

Our main contributions can be summarized as follows:

- We propose a framework for faithful evidence-based medical reasoning that enables LLMs to generate clinically grounded responses with evidence-supported reasoning processes.
- We develop clinician-designed and automatically refined rubrics for faithful reasoning evaluation, and use them for reinforcement learning with step-level process reward assignment and advantage grouping.
- We demonstrate that our method improves not only answer accuracy but also reasoning faithfulness, outperforming existing baselines across multiple medical QA benchmarks.

2 Related Work

Medical RAG. Large language models have demonstrated promising performance on medical question answering benchmarks, as shown by systems such as Med-PaLM (Singhal et al., 2023a), Meditron (Chen et al., 2023), and Med-Gemini (Saab et al., 2024). However, these models remain prone to hallucination, motivating the adoption of retrieval-augmented generation (RAG) to ground responses in retrieved medical documents and improve factuality (Lewis et al., 2021; Xiong et al., 2024; Yang et al., 2024; Sun et al., 2025). Recent work such as MedCite (Wang et al., 2025) further emphasizes response verifiability by adapting citation generation and retrieval strategies (Gao et al., 2023; Huo et al., 2023; Ye et al., 2024) to the medical domain with specialized evaluation protocols, improving attribution to external medical knowledge sources. Nevertheless, existing approaches primarily focus on the factuality of final responses, while largely overlooking the faithfulness of the intermediate reasoning process, which may still lead to unreliable clinical conclusions.

Medical Reasoning. Clinical decision-making often requires complex multi-step reasoning over patient evidence during diagnosis and treatment planning. Prior work such as MedPrompt (Nori et al., 2023) leverages Chain-of-Thought (CoT) prompting (Wei et al., 2023) to improve medical reasoning capabilities of general-purpose LLMs during inference. Similarly, Huatuo-o1 (Chen et al., 2024) iteratively improves multi-step reasoning trajectories through verifier-guided feedback.

More recently, agentic medical systems have begun integrating reinforcement learning with RAG and process reward modeling using LLM-as-a-judge frameworks to improve reasoning quality (Jin et al., 2025; Yun et al., 2025; Jiang et al., 2025). Different from prior work, our method incorporates realistic evidence-based medicine workflows

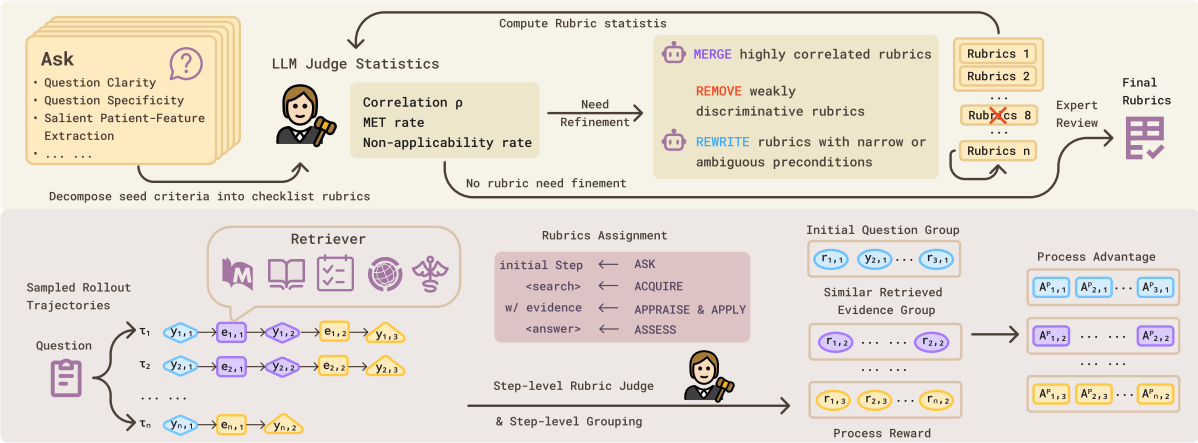


Figure 2: Method overview. We first design and refine rubrics for evaluating the reasoning process across five evidence-based medicine dimensions. We then use these rubrics to construct step-level process rewards, which are integrated with outcome rewards for policy optimization.

into a reinforcement learning framework with fine-grained step-level rewards. Guided by clinician-curated rubrics, our framework explicitly promotes faithful and trustworthy reasoning processes that remain grounded in supporting medical evidence throughout the path toward the final clinical conclusion.

3 Preliminaries

Reasoning Environment. We formulate evidence-based medical reasoning as an agent–environment interaction. Given a clinical question x, the initial state s_1 is conditioned on x. At each turn k, the model observes s_k and generates $y_k = (t_k, a_k)$, where t_k denotes the reasoning trace and $a_k \in \{\texttt{search}, \texttt{answer}\}$ is the action (Jin et al., 2025). A `search` action retrieves external evidence $e_k = \{e_{k,j}\}_j$, transitioning to the next state s_{k+1} and yielding reward r_k. The episode terminates when the model selects the `answer` action, producing a T-turn trajectory $\tau = \{(s_k, t_k, a_k, r_k)\}_{k=1}^{T}$. To enable citation grounding, each retrieved document $e_{k,j}$ is serialized within an `<information>` block and assigned the identifier $[Tk\text{-}Ej]$, which the model is prompted to reference in subsequent reasoning.

Outcome-Reward RL. The outcome reward for a trajectory τ is defined as $R^O(\tau) = \sum_{k=1}^{T} r_k^O$. In the standard GRPO setting, reward is assigned only at the end of the episode (Shao et al., 2024): $r_k^O = 0$ for $k < T$, while r_T^O is a binary signal indicating the correctness of the final answer. For each question, GRPO samples N candidate episodes $\{\tau_i\}_{i=1}^{N}$ from the policy $\pi_\theta(y_k \mid s_k, x)$ and computes group-normalized episode rewards:

$$A_i^O = \frac{R^O(\tau_i) - \text{mean}\big(\{R^O(\tau_j)\}_{j=1}^{N}\big)}{\text{std}\big(\{R^O(\tau_j)\}_{j=1}^{N}\big)}. \quad (1)$$

This yields an episode-level outcome advantage shared across the entire trajectory.

4 FaithMed: Towards Fine-Grained Process Reward in Medical Reasoning

We present FaithMed, which trains LLMs with rubric-guided step-level process rewards for evidence-based medical reasoning. We first describe how the evaluation criteria are designed and refined in Section 4.1. We then define the step-level process reward in Section 4.2 and show how it is incorporated into policy optimization in Section 4.3.

4.1 Rubrics Design and Refinement

We first define the process-reward dimensions following the principles of evidence-based medicine (Sackett et al., 1996; Dusin et al., 2023): *Ask*, *Acquire*, *Appraise*, *Apply*, and *Assess*. Specifically, (1) *Ask* evaluates whether the information need is formulated as a clear clinical question; (2) *Acquire* measures whether the model retrieves relevant external evidence; (3) *Appraise* evaluates whether the retrieved evidence is critically assessed for relevance and support; (4) *Apply* measures whether the evidence is integrated with the clinical context; and (5) *Assess* evaluates whether the overall reasoning process and final decision are reviewed. For each dimension, we first design

seed criteria and then decompose them into binary checklist-style rubrics following CheckEval (Lee et al., 2025).

To reduce redundancy and eliminate uninformative criteria, we use teacher-generated medical QA reasoning trajectories to iteratively refine the curated rubric set until convergence. Specifically, we adopt a metric-driven recursive rubric-refinement procedure. In each iteration, an LLM judge scores all trajectory–rubric pairs, after which we compute rubric-level statistics, including non-applicability rate, MET rate, and pairwise Pearson correlation between rubrics.

These rubric-level statistics are then used to determine the refinement action: (1) MERGE rubrics with high pairwise correlation, as they capture overlapping reasoning behaviors; (2) REMOVE weakly discriminative rubrics with nearly constant labels, including rubrics that are almost always MET or UNMET; and (3) REWRITE rubrics with high non-applicability rates, which typically reflect overly narrow or ambiguous preconditions. The refinement process terminates when no active rubric satisfies any refinement criterion. MERGE and REWRITE operations are automatically performed by an LLM editor. Finally, a medical expert reviews the refined rubric set and performs final edits, yielding the rubrics used for process evaluation; the final rubric set is provided in Appendix A.2.

4.2 Step-level Process Reward

Outcome rewards only indicate whether the final answer is correct, but provide limited guidance on whether intermediate reasoning decisions are faithful to the available evidence. We therefore construct a process reward for each generated step $y_k = (t_k, a_k)$ by judging the step against the rubric dimensions that are relevant to its local context. Let $e_0 = \emptyset$. For a step k, we assign a dimension set D_k as follows: the initial step includes *Ask*; a `search` action includes *Acquire*; if the model has observed non-empty retrieved information e_{k-1}, the step includes *Appraise* and *Apply*; and an `answer` action includes *Assess*. These assignments are additive, so a step can be evaluated by multiple dimensions.

Then, we construct the applicable rubric set and evaluate the corresponding reasoning step:

$$\mathcal{R}_k = \bigcup_{d \in D_k} \mathcal{R}_d, \tag{2}$$

$$J_k = J(y_k, e_{k-1}, \mathcal{R}_k) \in \{0,1\}^{|\mathcal{R}_k|}, \tag{3}$$

where $\mathcal{R}_d$ denotes the refined rubrics for dimension d, and J_k denotes the binary rubric scores returned by the judge for step k. For trajectory i, we aggregate the applicable rubric scores into a scalar step-level process reward $r^P_{i,k} = \mathrm{Agg}(J_{i,k})$, where $\mathrm{Agg}(\cdot)$ denotes mean-centered rubric aggregation.

To obtain comparable process rewards, we group reasoning steps with similar observation contexts and retrieved evidence as anchor-state, following the strategy of GiGPO (Feng et al., 2025). The process advantage is computed using group-normalized step-level rewards:

$$A^P_{i,k} = \frac{r^P_{i,k} - \mathrm{mean}(\mathcal{G}(\tilde{s}_{i,k}))}{\mathrm{std}(\mathcal{G}(\tilde{s}_{i,k})) + \epsilon}, \tag{4}$$

where $\mathcal{G}(\tilde{s}_{i,k})$ denotes the multiset of process rewards in the anchor group associated with anchor state $\tilde{s}_{i,k}$. This yields fine-grained comparative process feedback, where a search or answer step is rewarded when it better satisfies the relevant rubrics than alternative steps under a similar observation context.

4.3 FaithMed Policy Optimization

Outcome-only RL assigns the same episode-level signal to every step in a trajectory. In FaithMed, the final-answer reward r^O and rubric-guided process reward r^P are treated as separate supervision signals: r^O defines the episode-level outcome advantage A^O_i in Eq. 1, while r^P defines the step-level process advantage $A^P_{i,k}$ in Eq. 4. The advantage for step k in trajectory i is computed as

$$A_{i,k} = A^O_i + \lambda A^P_{i,k}, \tag{5}$$

where λ controls the contribution of rubric-guided process feedback. The first term encourages trajectories that reach the correct final answer, while the second term provides additional credit to intermediate reasoning steps that better satisfy the process rubrics under a similar evidence context. We then optimize $A_{i,k}$ using the standard GRPO clipped objective over the generated tokens in step $y_{i,k}$, together with the standard reference-policy KL penalty. This enables FaithMed to jointly optimize final-answer correctness and intermediate evidence-based medicine behaviors.

5 Experiments Setup

Datasets. We evaluate on a diverse suite of medical benchmarks that cover complementary

Table 1: Main benchmark results. FaithMed here uses the no-SFT recipe. GRPO uses outcome rewards only. § denotes reference LLM values reported by Medmarks-Verifiable (Warner et al., 2026). † denotes in-domain datasets and * denotes out-of-domain datasets.

Method		MedQA†	MedMCQA†	HeadQA†	MedCalc-Bench†	MedBullets*	MMLU-Pro-Health*	MedXpert QA*	Overall Acc.
Reference LLMs									
Llama 3.1 8B Instruct		61.8	57.3	67.6	21.4	52.2	56.0	11.8	46.9
Gemma 3 12B§		69.0	59.0	73.0	27.0	51.0	59.0	16.4	50.6
Qwen3 8B		79.4	66.3	83.4	44.9	61.8	69.7	19.2	60.7
MedGemma 27B§		83.0	73.0	84.0	49.0	75.0	72.0	19.0	65.0
Claude Sonnet 4.5§		93.0	80.0	91.0	76.0	80.0	84.0	39.4	77.6
DeepSeek-R1		94.2	72.8	93.4	72.7	73.2	74.2	42.9	74.8
FaithMed									
Qwen3 1.7B	Base	48.9	48.0	66.2	16.9	35.7	43.4	9.3	38.3
	MedRAG	51.4	51.3	67.5	8.4	**40.8**	48.5	14.2	40.3
	Agentic Search	49.2	46.8	65.5	15.3	36.0	46.4	11.1	38.6
	Agentic Search + GRPO	50.9	50.1	68.5	27.1	31.0	48.1	11.5	41.0
	FaithMed	**61.4**	**56.9**	**75.6**	**33.2**	38.5	**52.0**	**17.1**	**47.8**
Qwen3 4B	Base	69.3	59.7	81.3	13.7	46.3	63.0	16.0	49.9
	MedRAG	70.2	59.8	83.9	10.3	52.1	55.5	19.0	50.1
	Agentic Search	70.6	63.4	81.5	29.6	47.3	55.4	19.6	52.5
	Agentic Search + GRPO	71.3	63.2	84.4	39.0	49.8	**66.1**	22.0	56.5
	FaithMed	**74.8**	**64.1**	**85.7**	**56.5**	**55.6**	63.5	**28.2**	**61.2**

Table 2: Process scores across five dimensions. + Ep. PR uses episode-level process reward, while FaithMed uses step-level process reward.

Backbone	Method	Ask	Acquire	Appraise	Apply	Assess
DeepSeek-R1		94.7	52.7	48.5	46.2	14.6
Qwen3 1.7B	Base	82.3	27.1	23.5	20.6	6.6
	+ Ep. PR	84.6	38.6	34.3	31.6	10.9
	FaithMed	**85.8**	**50.1**	**44.9**	**38.8**	**17.5**
Qwen3 4B	Base	87.0	30.2	26.1	23.3	9.0
	+ Ep. PR	86.7	41.4	36.4	34.0	12.5
	FaithMed	**90.4**	**53.9**	**48.5**	**41.4**	**19.1**

types of medical tasks: (1) knowledge-intensive question answering, including HeadQA (Vilares and Gómez-Rodríguez, 2019), MedMCQA (Pal et al., 2022), and MMLU-Pro-Health (Wang et al., 2024); (2) expert-level medical reasoning, represented by MedXpertQA (Zuo et al., 2025); (3) quantitative medical calculation, represented by MedCalc-Bench (Khandekar et al., 2024); and (4) clinical application question answering, including MedQA (Jin et al., 2021) and MedBullets^{5op} (Chen et al., 2025). We use HeadQA, MedMCQA, MedCalc-Bench, and MedQA for training and in-distribution evaluation, and reserve MMLU-Pro-Health, MedXpertQA, and MedBullets^{5op} for out-of-distribution evaluation. To reduce near-duplicate leakage, we apply 16-gram decontamination against the held-out evaluation sets.

Baselines. We compare FaithMed against three categories of baselines: (1) reference LLMs, including general-purpose, and medical models; (2) evidence-utilization strategies, including MedRAG-style pre-retrieval (Xiong et al., 2024) and agentic search prompting; and (3) training variants, including GRPO with episode-level outcome rewards and alternative process-reward formulations.

Rubrics Refinement. We use 300 medical QA reasoning trajectories generated by the teacher model to refine the rubric set. The refinement criteria are instantiated as follows: MERGE is applied when any pair of rubrics has an absolute Pearson correlation above 0.70, REWRITE when the non-applicability rate exceeds 0.80, and REMOVE when the MET rate is above 0.95 or below 0.05. Starting from 26 seed rubrics, the refinement procedure converges after three iterations, yielding 15 rubrics.

Training Recipes. (1) *SFT training.* We construct supervised trajectories using DeepSeek-R1 with agentic search prompting on 2,650 questions from MedQA, MedMCQA, HeadQA, and MedCalc-Bench. For each question, we retain 6 trajectories with correct answers and valid formats; questions with fewer than 6 valid trajectories within 20 attempts are filtered out. We fine-tune Qwen3 backbones for one epoch using a learning rate of 5×10^{-5}, cosine decay, and a 1% linear warmup ratio. (2) *RL training.* We perform RL training for 300 steps with a batch size of 32 and

Table 3: Training-recipe ablation. OR denotes outcome reward, PR denotes process reward, and Ep. and Step indicate episode-level and step-level PR, respectively.

Backbone	SFT	RL Rewards		MedQA†	MedMCQA†	HeadQA†	MedCalc-Bench†	MedBullets*	MMLU-Pro-Health*	MedXpertQA*	Overall Acc.
		OR	PR								
FaithMed 1.7B	×	×	None	49.2	46.8	65.5	15.3	36.0	46.4	11.1	38.6
	×	✓	None	50.9	50.1	68.5	27.1	31.0	48.1	11.5	41.0
	×	✓	Ep.	49.1	48.9	67.9	18.9	39.7	51.0	15.0	41.5
	×	✓	Step	**61.4**	**56.9**	**75.6**	33.2	38.5	**52.0**	**17.1**	**47.8**
	✓	×	None	48.6	46.4	64.4	40.9	33.6	41.8	11.4	41.0
	✓	✓	None	52.4	51.0	66.9	49.8	**41.3**	46.1	14.4	46.0
	✓	✓	Ep.	52.3	52.5	64.2	47.0	35.2	43.1	12.0	43.8
	✓	✓	Step	53.5	53.2	66.4	**56.2**	37.5	48.3	14.5	47.1
FaithMed 4B	×	×	None	70.6	63.4	81.5	29.6	47.3	55.4	19.6	52.5
	×	✓	None	71.3	63.2	84.4	39.0	49.8	66.1	22.0	56.5
	×	✓	Ep.	71.9	63.5	83.2	41.6	48.7	**66.3**	22.5	56.8
	×	✓	Step	**74.8**	**64.1**	**85.7**	56.5	**55.6**	63.5	**28.2**	**61.2**
	✓	×	None	69.5	56.1	78.2	57.8	47.4	54.5	16.0	54.2
	✓	✓	None	70.4	58.8	80.2	60.3	47.0	66.0	18.9	57.4
	✓	✓	Ep.	69.4	59.2	79.7	62.3	47.2	63.5	18.2	57.1
	✓	✓	Step	70.5	61.4	83.0	**65.2**	48.5	64.9	23.0	59.5

8 rollouts per prompt. We use Gemini-2.5-Flash-Lite as the process-reward judge, set $\lambda = 0.05$ for step-level process rewards, and use a maximum response length of 3072. For anchor-state grouping, we use a fuzzy string similarity threshold of 0.8. Additional implementation details are provided in the appendix A.3.

6 Results

In this section, we provide a comprehensive evaluation of FaithMed. We first report benchmark performance and evidence-based medicine reasoning scores in Section 6.1. We then present ablation studies over training recipes and rubric dimensions in Section 6.2, followed by diagnostics of process-reward granularity and advantage grouping in Section 6.3. Finally, we present case studies that illustrate evidence-based behaviors in Section 6.4.

6.1 Overall Results

Table 1 shows that FaithMed consistently improves benchmark answer accuracy across both backbones. The baseline comparisons indicate that external evidence is useful, but the best access strategy depends on model capacity: MedRAG improves the 1.7B model more than agentic search (40.3% vs. 38.6%), whereas agentic search is more effective for the 4B model (52.5% vs. 50.1%), suggesting that smaller models may struggle to execute agentic workflows while benefiting more from retrieved medical knowledge.

Beyond evidence access, outcome-only RL improves performance, but FaithMed yields larger gains, raising benchmark answer accuracy from 41.0% to 47.8% on 1.7B and from 56.5% to 61.2% on 4B. This shows that learning a faithful evidence-based reasoning process improves task success, not only reasoning quality; notably, FaithMed-4B surpasses the larger Qwen3 8B reference model (61.2% vs. 60.7%).

Table 4: Process reward dimension ablation results. Ablation rows report changes from the full model.

Training	Ask	Acquire	Appraise	Apply	Assess
FaithMed 1.7B	85.8	50.1	44.9	38.8	17.5
w/o. Ask	-3.17	-3.11	-4.35	-0.26	-4.79
w/o. Acquire	-0.46	-8.28	-5.92	-0.11	-4.17
w/o. Appraise	-0.06	-0.10	-9.35	-0.14	-2.48
w/o. Apply	+0.03	-1.04	-0.11	-8.51	-1.06
w/o. Assess	-0.01	+0.06	-2.92	-2.55	-8.44

Beyond answer accuracy, Table 2 shows that FaithMed substantially improves the evidence-based medicine reasoning process itself. Improvements are strongest on dimensions requiring active evidence use: for both backbones, FaithMed improves Acquire by roughly 23–24%, Appraise by roughly 21–22%, and Apply by roughly 18% over the base model. We also compare against an episode-level process-reward baseline, which provides episode-level process feedback without assigning it to specific reasoning steps. FaithMed consistently outperforms this baseline on both backbones, demonstrating the benefit of fine-grained faithful reasoning supervision. FaithMed-4B even matches the teacher model DeepSeek-R1 on 3 out of 5 dimensions.

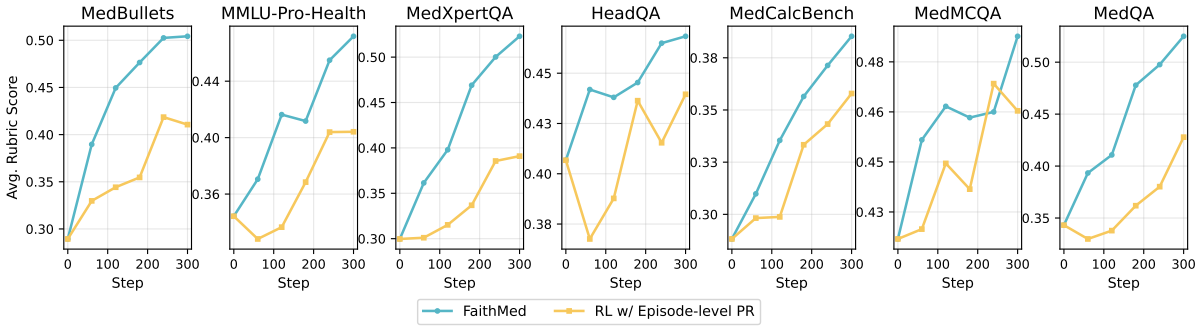


Figure 3: Rubric-score curves across seven medical benchmarks. Scores are averaged over the five rubric dimensions for Qwen3-1.7B trained with SFT + RL using episode-level or step-level process reward.

Table 5: Case studies of process-dimension behaviors. High-quality responses are selected from FaithMed-4B, while lower-quality responses are selected from Qwen3-4B with agentic search. Green and red highlights mark phrases most aligned or misaligned with the corresponding rubric dimension. Ellipses mark omissions made for space.

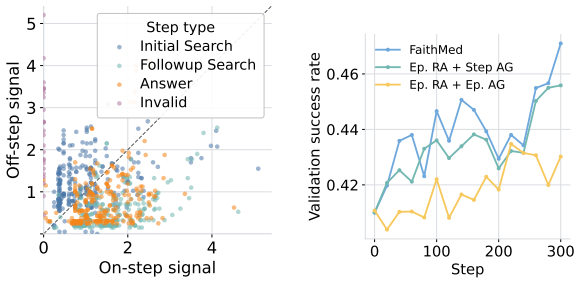
Dimension	FaithMed-4B response	Qwen3-4B agentic-search response
Ask	The clinical problem is to identify the metal accumulated in a patient with neuropsychiatric symptoms, dystonia, ataxia, and peripheral corneal rings. The **decisive clue** is the Kayser-Fleischer-type ring together with movement and psychiatric findings. This **narrows the answer** to Wilson disease and copper accumulation.	The patient has tremor and abnormal gait, so this is a **neurologic toxicity question**. Metals can cause neurologic symptoms, especially lead or mercury. I will **pick the metal most associated with tremor**.
Acquire	I need the **exact SIRS thresholds** before counting criteria because the answer changes if respiratory rate, PaCO2, temperature, or WBC cutoffs are different. The patient's admission values are . . . , so the search should target "SIRS criteria temperature heart rate respiratory rate WBC PaCO2 thresholds." `<search>SIRS criteria temperature heart rate respiratory rate WBC PaCO2 thresholds</search>`	This is about a hospitalized patient with a lung infection and abnormal labs. I should look up the **underlying disease first**: `<search> coccidioidomycosis symptoms treatment </search>`.
Appraise	The **strongest retrieved evidence is direct**: [T1-E1] says Kayser-Fleischer rings in Wilson disease are due to copper deposition, and [T1-E2] links excess copper deposition to neurologic and psychiatric manifestations. These passages directly answer the mechanism question, whereas passages listing broad differentials are less useful for deciding the accumulated metal.	[T1-E5] lists several differential diagnoses for Wilson disease, including tuberculosis meningoencephalitis and CNS lymphoma, so the tissue accumulation is **probably lead**. The citation supports **excluding copper** because Kayser-Fleischer rings can occur in other diseases.
Apply	Because the child has **4 anesthetic skin patches**, he falls on the **paucibacillary side** of the lesion-count split rather than the multibacillary branch, which starts at 6 or more lesions [T1-E4]. For paucibacillary disease, the regimen is rifampicin plus dapsone [T1-E1], so options that add clofazimine are not supported . . . . The dosing choice should therefore follow the PB child/adolescent regimen rather than defaulting to the adult MB-looking option.	The patient has hypopigmented patches and sensory loss, which **suggests multibacillary leprosy**. WHO MDT includes rifampicin, dapsone, and clofazimine, so option D matches best. The **adult multibacillary regimen** is used even though the patient is 12 and has only 4 lesions.
Assess	There is a **classification tradeoff**: treating as multibacillary adds clofazimine and broader coverage, but the stem's 4 lesions suggests paucibacillary disease where simpler rifampicin+dapsone therapy is standard. Because **unnecessary clofazimine increases treatment burden and adverse effects**, the regimen should follow lesion count and age-specific guidance rather than defaulting to adult MB therapy.	Leprosy is serious, so the **strongest three-drug regimen** is best. More antibiotics should cover more disease, and the **exact number of patches does not change** the treatment choice.

6.2 Ablation Study

Step-level process reward is the most reliable training recipe. We first examine which training recipe is responsible for the gains of FaithMed. Table 3 varies (1) supervised fine-tuning and RL rewards: (2) outcome reward and (3) episode- versus step-level process reward. Outcome-only RL improves over the untrained policy, but the largest gains come from adding step-level process reward. Without SFT, step-level process reward improves overall accuracy by 9.2 points for the 1.7B backbone and 8.7 points for the 4B backbone. The same pattern holds after SFT, where it adds 6.1 and 5.3 points over the SFT-only 1.7B and 4B models, respectively.

Combining outcome reward with episode-level process reward is less reliable: it improves some no-SFT settings but offers little or negative gain after SFT. This pattern supports a central design choice of FaithMed: process supervision should be assigned at finer granularity, so each reasoning step can be compared with similar step groups on the corresponding evidence-based behavior.

Rubric dimensions target distinct reasoning stages. Table 4 then ablates the reward dimen-



(a) Episode-level signal (b) RA and AG ablation

Figure 4: Diagnostics for reward assignment (RA) and advantage grouping (AG).

sions themselves. The largest drops occur on the ablated dimension: removing Acquire, Appraise, Apply, and Assess reduces the corresponding score by 8.28, 9.35, 8.51, and 8.44 points, respectively. This concentration of errors shows that the reward dimensions target distinct parts of the reasoning trace. At the same time, the effects are not fully isolated. Removing Ask or Acquire also lowers later stages such as Appraise and Assess, suggesting that evidence-based medical reasoning is sequential and interdependent: poor question formulation or evidence gathering can limit the quality of later evidence evaluation and clinical application.

6.3 Diagnosing Step-Level Process Reward

The ablations above show that step-level process reward is more reliable than episode-level process reward. Figure 3 confirms this trend across benchmarks: it provides more consistent reasoning-quality gains than the episode-level baseline. To understand why step-level process reward works better, we diagnose this advantage through two components of process-reward training: reward assignment (RA), which assigns rubric feedback to steps or episodes, and advantage grouping (AG), which normalizes advantages within anchor-state step groups or rollout groups.

Episode-level assignment creates off-step credit. Episode-level reward assignment can give a step feedback from rubrics that the step does not directly control. Figure 4a shows this credit-assignment mismatch by decomposing the rubric signal assigned to each step into on-step and off-step components. This mismatch is especially problematic for early search actions, which can be covered by only a small number of corresponding rubrics. Their updates can therefore be dominated by noisy off-step feedback from later evidence appraisal or answer quality, causing the model to learn unstable signals at the start of the reasoning process.

Grouping helps only with step-aligned rewards. To separate the role of grouping from reward assignment, we compare an intermediate setting that uses step-level advantage grouping but keeps episode-level reward assignment. In Figure 4b, this setting provides only limited improvement, whereas combining step-level reward assignment with step-level advantage grouping substantially improves performance. This suggests that the main gain comes from aligning both the reward signal and the comparison group with the reasoning step being optimized.

6.4 Case Study

Case studies reveal concrete reasoning differences. Beyond aggregate rubric scores, we examine representative trajectories to identify what the process improvements look like in model outputs. Table 5 shows that the FaithMed responses explicitly identify decisive clinical clues, formulate decision-directed searches, prioritize directly supporting evidence, and check whether retrieved guidance applies to the patient. In contrast, the agentic-search baseline often uses plausible but underspecified heuristics, generic search queries, or evidence that is not logically aligned with the clinical decision. These examples show how the rubric gains in Table 2 correspond to concrete improvements in the reasoning trace rather than only higher final-answer accuracy.

7 Conclusion

We introduced FaithMed, a rubric-guided training framework for faithful evidence-based medical reasoning. Instead of rewarding only final answers, FaithMed decomposes reasoning into evidence-based medicine dimensions and uses step-level process rewards to give credit to local actions that ask clinically precise questions, acquire relevant evidence, appraise retrieved passages, apply evidence to the patient context, and assess the final decision. Across seven medical benchmarks, FaithMed improves both 1.7B and 4B Qwen3 backbones and outperforms retrieval-only and agentic-search baselines. Our ablations show that step-level process rewards provide more consistent gains than episode-level process rewards, and rubric-level analyses confirm that these gains reflect improved evidence-use behaviors rather than only better answer se-

lection. These results suggest that faithful medical reasoning requires not only access to external knowledge, but also explicit training of how evidence should be sought, judged, and applied.

8 Limitations

Our study focuses on textual medical question answering benchmarks, which simplify the complexity of real clinical workflows involving longitudinal records, laboratory results, imaging, physical examinations, and institution-specific constraints. In addition, our process supervision depends on clinician-reviewed rubrics and LLM-based judges, which are useful but still imperfect proxies for faithful medical reasoning; models may learn to satisfy rubric criteria without fully eliminating unsupported claims. The current experiments are also limited to Qwen3 backbones, English medical QA settings, and a fixed retrieval pool, so broader evaluation across model families, languages, specialties, and evolving medical evidence sources remains future work.

9 Ethical Considerations

This work is intended as research on improving the faithfulness of medical reasoning in language models and should not be used as a substitute for professional diagnosis, treatment planning, or patient-specific medical advice. We evaluate on existing medical QA benchmarks and use publicly available medical corpora for retrieval; we do not collect new patient records or personal health information. However, models trained or evaluated in this setting can still produce incorrect answers, misleading explanations, or unsupported medical claims, and any real-world use would require rigorous clinical validation, privacy safeguards for user-provided health information, and oversight by qualified medical professionals. We also note that medical benchmarks and retrieval corpora may encode demographic, geographic, linguistic, or institutional biases, so improved benchmark performance does not guarantee equitable behavior across patient populations.

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A Appendix

A.1 Agentic Search Prompts

We use three compositional prompt templates to elicit multi-turn agentic search: the initial medical-QA template, a MedCalc-specific replacement, and an evidence-grounding addition used after retrieval. We present each template in a separate block.

Prompt A.1: Medical QA initial agentic search template

```
You are a medical expert AI assistant. You have access to an
external search tool to retrieve information. You can answer a
question with many turns of search and reasoning.

Based on your search history, you need to take the next action to
complete the task. You will be provided with:
1. Your history search attempts: query in format
   <search> query </search> and the search results returned by
   the external search tool.
2. The question to answer.

Valid actions (ONLY TAKE ONE of the following):
(1) <search> your query </search>: search to verify a specific
    medical fact, diagnosis, treatment, drug mechanism, or clinical
    guideline relevant to the question. Your turn ends here; do not
    fabricate search results -- the external search tool will return
    them in the next turn.
(2) <answer> your answer, with the final choice in \boxed{}
    </answer>: output the final answer once you have verified
    the key medical facts.

Strategy: Think step by step about what specific medical knowledge
is needed to answer this question, then search to verify it.

Note:
(1) DO NOT simulate or imagine search results in your reasoning. If
    you decide to search, you must output a <search> action.
(2) Output EXACTLY ONE action block (search or answer).

Question: {task_description}
```

Prompt A.2: MedCalc-Bench replacement

```
<search> your query </search>: search to verify a specific medical
formula,
reference value, drug dose, or clinical parameter needed to solve
this
calculation. Your turn ends here; do not fabricate search results
-- the
external search tool will return them in the next turn.
<answer> your answer, with the final value in \boxed{} </answer>:
output the
final answer once you have verified the formula or key values.
Think step by step about which formula or reference value is
required, then
search to confirm it.

Use one of the following final-value formats:
- Decimal Answer Format: 17.29
- Score-Based Answer Format: 5
- Estimated Date Answer Format: 5/21/2021
- Estimated Age Answer Format: (4 weeks, 3 days)
```

Prompt A.2 follows the Medmarks-Verifiable value formats for MedCalc-Bench (Warner et al., 2026). At the first turn, the model receives an empty history and no citation requirement. After the search tool returns at least one real `<information>` block, we append Prompt A.3; its citation rule grounds internal reasoning over retrieved results while preserving the one-action output constraint.

Prompt A.3: Evidence-grounding addition after retrieval

```
1. Your history search attempts: query in format
   <search> query </search> and the returned search results
   in <information> and </information>.

Citation rule (ONLY for internal thinking):
(1) Whenever you draw on a fact from prior search results
    (from <information> blocks), cite it inline using
    [T<turn>-R<result>] (example: [T2-R3]) in the thinking
    process.
(2) If no prior <information> block exists, or the retrieved
    information is irrelevant or noisy, do not output any
    citations.
(3) Do not invent citation ids.

For MedCalc-Bench calculation questions, cite retrieved facts,
formula inputs, or numeric assumptions in the same format.

Text between <information></information> is the search results
from the search engine after you perform a search action.
DO NOT include any information in <information></information>
in your output.

History Turns: {memory_context}
```

Format reminder. When a model emits an invalid action, we provide the lightweight repair prompt in Prompt A.4. This prompt does not introduce new task information; it only restates the required action schema so that the next turn can be parsed by the agent environment.

Prompt A.4: Format reminder

```
You generated an invalid action in your previous turn.
Output EXACTLY ONE action block:
(1) If taking a search action, please use format:
    <search> your query </search>. Do not fabricate search
    results; the external search tool will return them in the
    next turn.
(2) If taking an answer action, please use format:
    <answer> your answer, with the final choice in \boxed{}
    </answer>.
```

A.2 Rubric Details

We list our evidence-based medicine rubrics in Tables 6 and 7. Each rubric is binary-scored as MET or UNMET with examples from teacher-generated medical QA reasoning trajectories.

A.3 Implementation Details

Retriever Implementation. We build the retrieval pool from five medical corpora. Four corpora—PubMed, StatPearls, medical textbooks, and Wikipedia—are taken from the MedRAG benchmark (Xiong et al., 2024). We additionally include the clinical guideline corpus released with MediTron-70B (Chen et al., 2023). We segment all source documents into short snippets and encode them with MiniCPM-Embedding-Light using the Tevatron dense-retrieval pipeline (Gao et al., 2022). The resulting snippet embeddings are sharded and served with DiskANN indices for efficient vector search (Subramanya et al., 2019).

Table 6: Ask and Acquire rubrics used to evaluate evidence-based medical reasoning.

Name	Description	Binary condition
Ask		
Question clarity	Does the model contain an explicit sentence restating or paraphrasing the core clinical question, identifying the condition, mechanism, or scenario at issue?	**MET:** The <think> block contains a sentence such as "The key is to choose the correct sequence of management for this genital trauma case" or "For this stroke patient on heparin, the task is to determine the cause of the new respiratory decline." **UNMET:** No concrete restatement appears, or the model only says vague phrases like "the key point is the diagnosis" without naming the requested target.
Salient patient-feature extraction	Does the model identify the small set of stem features that drive the answer, rather than merely restating many details?	**MET**: The <think> block marks one or more features as decisive because they change the diagnosis, mechanism, calculation, management step, or option choice, e.g., "ptosis + miosis + normal extraocular movements are the key clues for Horner syndrome"; "catalase-positive, coagulase-positive organism is the decisive clue for Staphylococcus aureus and CGD"; "positive pregnancy test plus LLQ pain/hypotension makes ectopic pregnancy the key concern"; or "height 162.1 cm and weight 71.4 kg are the only values needed for BMI." **UNMET**: The model only paraphrases the stem, lists non-decisive details, or does not identify which features are answer-driving.
Question specificity	Is the clinical problem narrowed to a specific question before searching or answering, rather than left as a vague topic area?	**MET**: The <think> block contains a precise, answerable question before <search> that directly maps to the decision required, e.g., "I need to confirm whether diastolic RV collapse is specific to tamponade vs. constrictive pericarditis." **UNMET**: The model only states the broad task type without naming the decision boundary, such as "answer a thyroid nodule question" or "calculate creatinine clearance."
Acquire		
Search Motivation and Alignment	Does the model explicitly identify a clinically relevant knowledge gap, unresolved uncertainty, or claim that genuinely needs verification, and does its search directly target that gap?	**MET**: Immediately before <search>, the model names one specific unresolved decision-critical gap, such as a diagnostic discriminator, legal/ethical rule, dosing formula, threshold, or comparison between answer options, and the query explicitly contains the terms needed to resolve that exact gap. A high-level topic query is not enough: the query should encode the actual decision boundary named in <think>, not just the domain. **UNMET**: The model has already mostly committed to an answer and the search is only decorative confirmation, or it searches for information it already states with confidence and does not explain why verification is still necessary.
Gap-directed search progression	This rubric requires at least one prior retrieval to assess progress. Compared to information retrieved in prior turns, does the current search make progress toward resolving the outstanding evidence need, rather than repeating resolved topics or drifting to unrelated areas?	**MET**: The <think> block names what the previous results did not resolve and searches more specifically, e.g., "The first search returned general thyroid malignancy features, but I need the official ACR scoring categories" or "The results mention treatment but not renal-failure dosing, so I should search dosing in renal impairment." **UNMET**: No explicit gap-directed search progression pattern appears.
Query constraint preservation	Does the search query preserve the answer-critical constraints from the question stem, such as patient subgroup, timing, comparator, option term, disease subtype, formula variable, or requested source standard?	**MET**: The query includes the key constraint that would change the answer if omitted, e.g., "complications of meningococcal meningitis in children" or "tetanus prophylaxis in patients taking glucocorticoids." **UNMET**: No explicit query-constraint-preservation pattern appears.

RL Implementation. We denote the score for rubric $m \in \mathcal{R}_k$ as $J_m(y_k, e_{k-1}, \mathcal{R}_k)$. In our retrieval setting, the anchor state $\tilde{s}_{i,k}$ for step k in trajectory i is the observation-induced state used for grouping: $\tilde{s}_{i,1} = x$ for the initial step, and $\tilde{s}_{i,k} = e_{i,k-1}$ for later steps. For the N trajectories sampled for the same question x, the step-level group anchored at $\tilde{s}$ is

$$\mathcal{G}(\tilde{s}) = \{(i,k) : \mathrm{sim}(\tilde{s}_{i,k}, \tilde{s}) \geq \eta\}, \tag{6}$$

where $\mathrm{sim}(\cdot,\cdot)$ measures anchor-state similarity and η is the grouping threshold. Thus, all initial steps for the same question form one group, and later steps are compared with other steps that condition on similar retrieved evidence.

Before summing rubric scores, we center each rubric within the local group to remove rubric-specific baselines. Let $\mu_{i,k,m}$ denote the mean score of rubric m among group members for which m is applicable. The step-level process reward is then the sum of centered rubric scores:

$$r^P_{i,k} = \sum_{m \in \mathcal{R}_{i,k}} \left(J_m(y_{i,k}, e_{i,k-1}, \mathcal{R}_{i,k}) - \mu_{i,k,m}\right). \tag{7}$$

This rubric-level centering reduces sensitivity to rubric-specific positive rates before scores are accumulated into a step reward. We then compute the process advantage with a group-wise scale factor:

$$A^P_{i,k} = \frac{r^P_{i,k} - \mathrm{mean}(\{r^P_{j,l} : (j,l) \in \mathcal{G}(\tilde{s}_{i,k})\})}{\mathrm{std}(\{r^P_{j,l} : (j,l) \in \mathcal{G}(\tilde{s}_{i,k})\}) + \epsilon}. \tag{8}$$

This makes the process feedback comparative: a search, or answer step is rewarded when it better satisfies the relevant rubrics than alternative steps taken under a similar observation context.

Supervise Finetuning. We construct supervised trajectories using DeepSeek-R1 from 1k MedQA, 0.5k HeadQA, 1k MedMCQA, and 0.5k

Table 7: Appraise, Apply, and Assess rubrics used to evaluate evidence-based medical reasoning. Each rubric is binary-scored as MET or UNMET with examples from teacher-generated medical QA reasoning trajectories.

Name	Description	Binary condition
Appraise		
Evidence-faithful synthesis	Do the clinical claims attributed to specific [Tn-Rn] passages accurately reflect the content of those passages, with the correct logical direction and without inferential jumps not shown in <think>?	**MET**: Every claim that cites a [Tn-Rn] passage (a) can be verified by reading that passage, (b) preserves the direction of the cited relationship, such as causality, magnitude, or association, and (c) requires no unstated inferential step between the passage text and the attributed claim. **UNMET**: At least one [Tn-Rn] citation violates any of these conditions: the passage does not support the attributed claim, the direction of the cited relationship is reversed or distorted, or the attributed claim requires an inferential step not shown in <think>.
Evidence conflict recognition	When the model notices inconsistent or qualifying retrieved information, does it explicitly name the discrepancy?	**MET**: The <think> block contains a clear conflict-recognition pattern comparing retrieved passages, e.g., "[T1-R2] says two tetanus doses during pregnancy, while [T1-R3] says complete a three-dose primary series; the guidance differs." **UNMET**: The conflict is invisible in the reasoning.
Evidence sufficiency judgment	When the retrieved [Tn-Rn] passages do not directly address the clinical concept targeted by the preceding <search>, does <think> explicitly state this insufficiency before proceeding to draw conclusions?	**MET**: The <think> block contains a sentence such as "the retrieved passages do not directly confirm polonium's reactivity with HCl," "no passage specifically addressed dosing in renal failure" before reasoning forward from indirect evidence, or "The retrieved passages do not directly address renal dosing, so the answer remains tentative." **UNMET**: The <think> block does not contain any explicit statement acknowledging that the retrieved passages fail to directly address the search target.
Apply		
Setting applicability	Does the model explicitly assess whether at least one key [Tn-Rn] passage applies to the specific patient or scenario described in the question stem, by comparing the passage's population or context to the patient's features?	**MET**: The <think> or <answer> block contains an explicit applicability statement, e.g., "T2-R1 reports echocardiographic findings in ICU patients with effusion, which matches the ED presentation in this case," "T1-R3 is about neonates born to infected mothers, directly applicable here," or "The CGD evidence applies because the patient has recurrent catalase-positive infections." **UNMET**: No explicit applicability pattern appears.
Evidence-based exclusion of alternatives	Does the model ground its option exclusion reasoning in [Tn-Rn] citations in <think>, rather than dismissing options by parametric assertion alone?	**MET**: Option elimination in <think> is explicitly tied to a [Tn-Rn] citation, e.g., "[T1-R2] confirms pericardial thickening is the hallmark of constrictive pericarditis, ruling out option B in this patient whose echo shows no thickening" or "[T1-R6] lists margin, echogenicity, and shape as ACR features, leaving vascularity as the exception." **UNMET**: Option elimination in <think> relies on bare assertion with no [Tn-Rn] citation.
Evidence Substantiation and Prioritization	Does the model explicitly prioritize the most direct or authoritative retrieved evidence when supporting the answer?	**MET**: The reasoning uses retrieved evidence as the main basis for the answer and names why the chosen evidence is more direct, authoritative, or answer-relevant than alternatives, e.g., "The official ACR TI-RADS feature list is more directly relevant than a general malignancy-feature review, so I will use [T1-R6]"; "CDC guideline language should outweigh a broad background article for vaccination scheduling"; or "[T1-R1] and [T1-R5] directly address radiolucency of uric acid stones, while composition-only passages are less useful for this question." **UNMET**: No explicit evidence-prioritization or authority-evaluation pattern appears.
Assess		
Uncertainty calibration	Does the model explicitly acknowledge limitations in the retrieved information or express appropriate uncertainty before drawing a conclusion?	**MET**: At least one explicit hedge appears in <think> or <answer> whenever the evidentiary basis is weak, e.g., "the retrieved passages do not confirm X; based on clinical reasoning I tentatively conclude Y," or "limited data support this – evidence suggests..." in <answer> when the trajectory contained only peripheral [Tn-Rn] passages. **UNMET**: No explicit uncertainty/calibration pattern appears.
Premature closure self-check	Does the model avoid locking onto an early answer by explicitly checking and revising a plausible but wrong hypothesis before committing?	**MET**: The <think> block contains a visible self-correction pattern: it names an initial candidate or tempting interpretation, identifies the specific stem clue or retrieved evidence that weakens it, and shifts to the better-supported answer, e.g., "I initially thought this was tension pneumothorax because of tracheal deviation, but the percussion is dull rather than hyperresonant, so that hypothesis fails and hemothorax is the answer" or "I was leaning toward opioid intoxication, but opioid toxicity should cause miosis and respiratory depression, whereas this stem has dry mucous membranes, agitation, hypertension, and mydriasis, so I should switch to anticholinergic toxicity." **UNMET**: No explicit hypothesis-checking or self-correction pattern appears before the final answer.
Tradeoff communication	Does <think> or <answer> explicitly name at least one relevant tradeoff, such as benefit–harm, efficacy–tolerability, or convenience–monitoring burden?	**MET**: The <think> or <answer> block discusses at least one tradeoff relevant to the recommendation, e.g., "[T1-R4] reports ATA has higher sensitivity for thyroid nodule biopsy decisions, while [T1-R5] reports ACR TI-RADS has higher specificity and fewer unnecessary FNAs; this is a sensitivity-specificity tradeoff rather than a single uniform recommendation" or "[T1-R6] shows TXA is more effective than packing in antiplatelet users, but IV administration adds procedural burden compared to topical oxymetazoline." **UNMET**: No explicit tradeoff-communication pattern appears.

MedCalc-Bench training questions. We apply rejection sampling by retaining only trajectories with correct answers and valid output formats. For each question, we collect up to 6 valid trajectories; questions with fewer than 6 valid trajectories after 20 attempts are filtered as hard questions. In total, the SFT data generation process yields 2,650 questions, 15,900 trajectories, and 28,368 SFT training samples, where each reasoning step is treated as one training sample. We additionally collect 7,538 rejected trajectories and trajectories from hard questions.

Table 8: Complementary comparison with medical process-reward models on the same Qwen3 backbones and seven benchmarks. MedS^3 and Med-PRM use best-of-4 PRM reranking, whereas FaithMed directly optimizes an agentic policy with EBM-aligned process rewards.

Backbone	Method	MedQA	MedMCQA	HeadQA	MedCalc	MedBullets	MMLU-Pro	MedXpert	Avg.
Qwen3-1.7B	Base	48.9	48.0	66.2	16.9	35.7	43.4	9.3	38.3
	MedS^3	58.4	55.8	63.7	12.8	36.2	39.0	9.0	39.3
	Med-PRM	60.1	51.2	70.5	24.1	37.6	42.0	16.0	43.1
	FaithMed	**61.4**	**56.9**	**75.6**	**33.2**	**38.5**	**52.0**	**17.1**	**47.8**
Qwen3-4B	Base	69.3	59.7	81.3	13.7	46.3	63.0	16.0	49.9
	MedS^3	67.6	57.4	83.0	17.2	46.9	56.0	24.0	50.3
	Med-PRM	74.5	55.0	81.2	26.7	50.3	62.0	23.0	53.2
	FaithMed	**74.8**	**64.1**	**85.7**	**56.5**	**55.6**	**63.5**	**28.2**	**61.2**

Reinforcement Learning. We implement RL training using verl-agent, an agent-training extension of verl (Sheng et al., 2025; Feng et al., 2025). Training is performed for 300 steps with a batch size of 32 and 8 rollouts per prompt. For advantage grouping, we follow GiGPO (Feng et al., 2025). For process-reward scoring, we use Gemini-2.5-Flash-Lite as the LLM judge. Rubric evaluation is performed with a single batched judge call per reasoning step instead of scoring rubrics independently, improving training efficiency. Training takes approximately 32 hours on 4 H100 GPUs.

Process Reward Aggregation. We first mean-center each rubric score within its applicable subset, since some rubrics require specific preconditions such as search actions, citations, or evidence from multiple sources. This prevents the model from favoring trajectories that only satisfy easier or more frequently applicable rubrics. The process reward for each reasoning step is then computed as the mean of centered scores across all applicable rubrics.

A.4 Comparison with Medical PRMs

We further compare FaithMed with two medical process reward model (PRM) baselines, MedS^3 (Jiang et al., 2025) and Med-PRM (Yun et al., 2025), using the same Qwen3 backbones over the same seven benchmarks. Both baselines train a PRM to score the step-level factual or logical correctness of a reasoning trace: MedS^3 trains on MCTS-collected rollouts, while Med-PRM trains on guideline-grounded supervision. At inference time, both methods sample four candidate trajectories per question and use their PRM to select the best one post hoc.

Unlike these post-hoc PRM baselines, FaithMed integrates EBM-aligned evidence use directly into policy learning. Table 8 reports average accuracy across the seven benchmarks for each backbone: FaithMed attains the highest average accuracy in both settings, even though the PRM baselines benefit from best-of-four selection at inference time.

A.5 Sensitivity to the Process-Reward Weight

Table 9: Sensitivity of FaithMed with the Qwen3-1.7B backbone to the process-reward weight λ. All other training settings are held fixed.

Benchmark	$\lambda = 0$	$\lambda = 0.01$	$\lambda = 0.05$	$\lambda = 0.5$
MedQA	50.9	54.1	**61.4**	47.7
MedMCQA	50.1	54.4	**56.9**	52.6
HeadQA	68.5	69.7	**75.6**	64.9
MedCalc	27.1	28.7	**33.2**	20.8
MedBullets	31.0	35.8	**38.5**	33.5
MMLU-Pro	48.1	51.7	**52.0**	49.4
MedXpert	11.5	13.1	**17.1**	10.5
Average	41.0	43.8	**47.8**	39.9

We vary the process-reward weight λ for FaithMed with the Qwen3-1.7B backbone while holding the remaining training recipe fixed. As shown in Table 9, small-to-moderate process-reward weights improve the balance between outcome and process supervision. Relative to outcome-only RL ($\lambda = 0$), $\lambda = 0.01$ and $\lambda = 0.05$ improve average accuracy by 2.8 and 6.8 points, respectively. Increasing the weight to $\lambda = 0.5$ instead reduces average accuracy by 1.1 points. Performance peaks at $\lambda = 0.05$ on all seven benchmarks, indicating that process feedback is most effective when it complements rather than dominates the outcome reward.

A.6 LLM-judge Evaluation

Table 10: Meta-evaluation of LLM judges across five evidence-based medicine dimensions. Gemini 2.5 and Gemini 3 denote Gemini-2.5-Flash-Lite and Gemini-3-Flash, respectively. Agree. denotes inter-annotator agreement between the two judges.

Dimension	Gemini 2.5 Score	Gemini 3 Score	Agree.	Cohen's κ
Ask	0.90	0.89	0.93	0.62
Acquire	0.54	0.57	0.71	0.41
Appraise	0.48	0.44	0.79	0.58
Apply	0.41	0.42	0.77	0.54
Assess	0.19	0.21	0.82	0.45
Macro Avg.	0.50	0.51	0.80	0.52

Table 10 compares rubric scores from Gemini 2.5 and Gemini 3. The two judges produce nearly identical macro-average rubric scores (50% vs. 51%) with 80% average agreement, suggesting that the rubric labels are robust across judges. Agreement is highest for Ask (93%) and lower for Acquire and Apply, which require more subjective assessment of search and evidence use. The average Cohen's κ is 0.52, indicating moderate agreement beyond label imbalance and supporting the reliability of our process-quality analysis.