CURE-MED: Curriculum-Informed Reinforcement Learning for Multilingual Medical Reasoning

Anonymous ACL submission

Abstract

While large language models (LLMs) have shown to perform well on monolingual mathematical and commonsense reasoning, they remain unreliable for multilingual medical reasoning applications, hindering their deployment in multilingual healthcare settings. We address this by first introducing CUREMED-BENCH, a high-quality multilingual medical reasoning dataset with open-ended reasoning queries with a single verifiable answer, spanning thirteen languages, including underrepresented languages such as Amharic, Yoruba, and Swahili. Building on this dataset, we propose CURE-MED, a curriculum-informed reinforcement learning framework that integrates code-switching-aware supervised fine-tuning and Group Relative Policy Optimization to jointly improve logical correctness and language stability. Across thirteen languages, our approach consistently outperforms strong baselines and scales effectively, achieving 85.21% language consistency and 54.35% logical correctness at 7B parameters, and 94.96% language consistency and 70.04% logical correctness at 32B parameters. These results support reliable and equitable multilingual medical reasoning in LLMs. The code and dataset will be made publicly available upon acceptance.

1 Introduction

Recent progress in large language models (LLMs) and reasoning-oriented systems has produced strong performance in mathematical reasoning and code generation (Li et al., 2022; Liu et al., 2024a; Wei et al., 2022; Huang and Chang, 2022). While these advances suggest LLMs can learn structured solution strategies beyond pattern completion, medical reasoning remains challenging (Magrabi et al., 2019; Stead, 2018) because it requires domain knowledge, careful use of context, and reasoning that clinicians can inspect (Patel et al., 2005; Arocha et al., 2005).

Prior work shows promising medical QA results, yet reliable medical reasoning still depends on reasoning-centric data and evaluations that test reasoning behavior rather than answer plausibility (Liévin et al., 2024; Singhal et al., 2025; Nori et al., 2023). Without such resources, models may generate fluent, credible-sounding outputs without dependable reasoning. The problem is amplified in multilingual settings: progress remains English-centered, leaving mid- and low-resource languages underrepresented and reliability uneven across communities. Despite cross-lingual transfer, open-ended medical reasoning often exhibits two recurring failures: *reduced logical accuracy* and *unstable language behavior* (Cahyawijaya et al., 2024; Nguyen et al., 2023). For clinical use, these failures erode interpretability and trust, since clinicians and patients must understand not only what a system concludes, but how it arrives there (Amann et al., 2020).

While recent efforts attempt to strengthen medical capability through domain-specific supervision (Liu et al., 2024b; Shengyu et al., 2023), benchmarks primarily remain monolingual and rely on closed-form settings, providing limited visibility into multilingual reasoning quality and language fidelity (Qiu et al., 2024). As LLMs increasingly support clinical education and decision-making, systematic evaluation of multilingual reasoning and language consistency becomes essential for fairness, reliability, and generalization (Liévin et al., 2024; Cahyawijaya et al., 2024).

In this work, We study multilingual medical reasoning across 13 high-, mid-, and low-resource languages. We introduce CUREMED-BENCH, an open-ended benchmark where each query has a single verifiable answer, enabling independent evaluation of logical accuracy and language consistency and analysis of cross-lingual generalization under clinically grounded constraints.Next, we propose CUREMED, a two-stage training framework

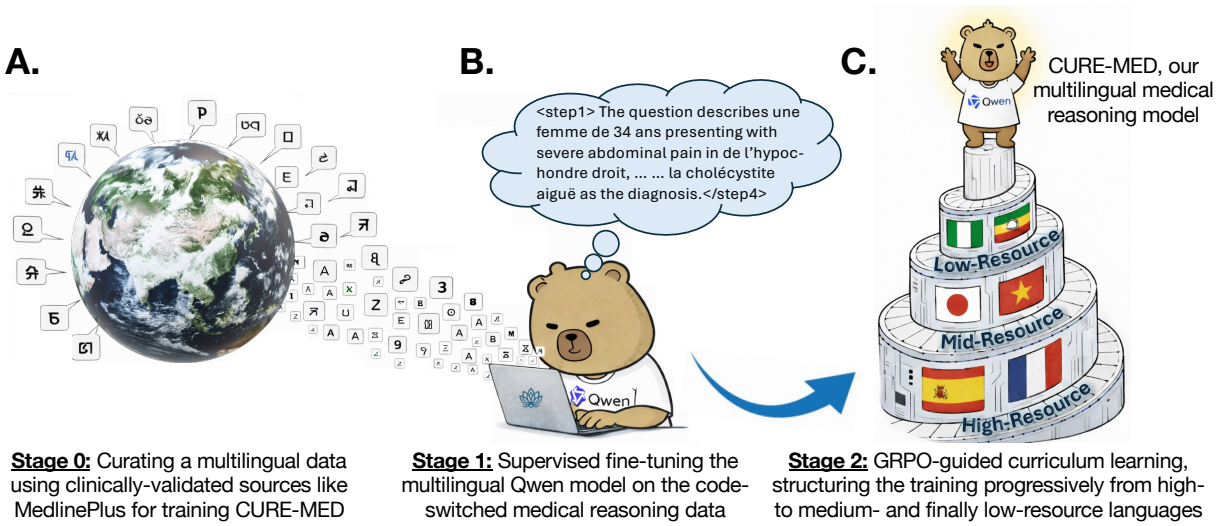

Figure 1: **The CURE-MED pipeline for multilingual medical reasoning.** The framework progresses through three stages: (A) curation of clinically validated multilingual data from sources like MedlinePlus to enable cross-lingual reasoning; (B) supervised fine-tuning of the Qwen2.5-Instruct backbone on code-switched reasoning traces; and (C) GRPO-guided curriculum reinforcement learning, progressively training from high- to mid- and low-resource languages to enhance logical correctness and language consistency.

(see Figure 1) for multilingual medical reasoning. We apply code-switching-aware supervised fine-tuning (SFT) to stabilize language usage during intermediate reasoning steps and perform curriculum-informed GRPO to improve logical correctness and language fidelity. Our contributions are: **1)** We present a systematic evaluation of multilingual medical reasoning of LLMs using verifiable medical queries, enabling reliable measurement of logical accuracy and language consistency across languages; **2)** We introduce CUREMED-BENCH, a large-scale multilingual medical reasoning dataset spanning 13 languages across high-, mid-, and low-resource settings; **3)** We propose CURE-MED, a two-stage training framework for multilingual medical reasoning that combines code-switching-aware SFT with curriculum-informed reinforcement learning (RL) to jointly optimize logical correctness and linguistic fidelity; and **4)** Through extensive automatic and human evaluations, we show that CURE-MED achieve state-of-the-art performance on CUREMED-BENCH and demonstrate improved out-of-distribution generalization, including improved robustness in low-resource languages and stronger performance on unseen medical questions and languages.

2 Related Work

This work lies at the intersection of medical reasoning with LLMs and multilingual reasoning. We summarize key gaps in prior work and position CURE-MED as a unified response.

Large Medical Reasoning Models. LLMs have been widely studied for medical QA, clinical retrieval, and diagnostic tasks (Guo et al., 2022; Singhal et al., 2025; Liu et al., 2024b). Domain-specific pretraining and instruction tuning can improve factuality, yet benchmark gains often do not translate to reliable medical reasoning (Nori et al., 2023; Chen et al., 2025), with models producing fluent but clinically unsound explanations (Amann et al., 2020). A core issue is evaluation: many medical benchmarks are closed-form (e.g., multiple-choice), which hides intermediate reasoning and limits verification of logical validity (Chen et al., 2025; Qiu et al., 2024). Recent open-ended evaluations exist, but are largely monolingual or limited to a few high-resource languages, leaving multilingual medical reasoning underexplored (Qiu et al., 2024; Schmidgall et al., 2024).

We address these gaps by introducing open-ended medical queries with single verifiable answers across 13 diverse languages, enabling independent assessment of reasoning correctness.

Multilingual Reasoning and Language Fidelity. Prior work shows CoT prompting can enable cross-lingual inference transfer (Wei et al., 2022; Shi et al., 2022; Kojima et al., 2022), but evaluations mostly target general-domain math/symbolic tasks and skew toward high-resource languages (Huang

and Chang, 2022; Chen et al., 2023a; She et al., 2024; Nguyen et al., 2023; Cahyawijaya et al., 2024). In medical settings, models often exhibit degraded accuracy, language drift, and weak cross-lingual generalization (Qiu et al., 2024; Schmidgall et al., 2024). Methods such as language mixing and supervised reasoning distillation can improve fluency, but are typically studied in limited bilingual settings or overfit high-resource languages (Hämmerl et al., 2022; Yoo et al., 2024; Ge et al., 2023; Huang et al., 2024; Ye et al., 2025). RL has also been used to promote structured reasoning, but remains largely English-centric and general-domain (Ouyang et al., 2022; Achiam et al., 2023; Jaech et al., 2024; Guo et al., 2025; Luong et al., 2024).

CURE-MED *differs from prior work by optimizing language fidelity and reasoning correctness jointly. We evaluate across high-, mid-, and low-resource languages, and integrate code-switching-aware supervision with curriculum-informed RL for robust multilingual medical reasoning.*

3 Methodology

Here, we describe the construction of CUREMED-BENCH (Sec. 3.1), including dataset collection and human verification. Next, we present CURE-MED: cold-start initialization (Sec. 3.2), reward design (Sec. 3.3), and GRPO-guided curriculum reinforcement learning (Sec. 3.4).

3.1 Dataset Collection

We construct CUREMED-BENCH, a multilingual medical reasoning dataset of 15,774 open-ended QA instances across 13 languages spanning Africa, Asia, and Europe, enabling evaluation under diverse linguistic conditions (including African languages such as Hausa, Yoruba, and Swahili). A breakdown by language and language family is provided in Appendix C.

Source Material and Question Generation. CUREMED-BENCH is grounded in *MedlinePlus*, a clinically validated medical resource curated by U.S. federal health agencies. Following tool-assisted synthetic data generation (Parisi et al., 2022; Taori et al., 2023; Zhou et al., 2023; Wang et al., 2022; Schick et al., 2023; Ghosh et al., 2025), we use GPT-4o to retrieve MedlinePlus content and draft closed-ended multiple-choice questions in each target language. Each item is anchored to the source, includes four options with exactly one correct answer, and provides clinically grounded supervision prior to conversion to open-ended prompts.

Filtering for Reasoning Difficulty. Following Chen et al. (2024), we apply multi-stage filtering to retain questions requiring substantive medical reasoning. We remove trivial items by discarding questions answered correctly by all three compact LLMs: Qwen2.5-3B/7B (Xu et al., 2025) and LLaMA-3.1-8B (Grattafiori et al., 2024). We further exclude under-specified or ambiguous questions, retaining samples with a single, unambiguous correct answer and consistent cross-lingual interpretation; GPT-4o is used to identify cases with multiple valid answers or cross-lingual inconsistency.

Conversion to Open-Ended Problems. We convert each remaining item into an open-ended prompt x using GPT-4o, and generate an explicit reasoning chain r with a free-form ground-truth answer y^*. This removes multiple-choice cues and yields open-ended instances with supervised reasoning, enabling direct evaluation of reasoning quality and answer correctness. We define the dataset as $\mathcal{D} = \{(x, r, y^*)\}$, where each instance has a single clinically grounded solution supported by an explicit reasoning trace. As summarized in Table 1, CUREMED-BENCH contains 15,774 instances across 13 languages, including low-resource languages, extending prior benchmarks that are largely multiple-choice and/or linguistically limited.

Human Verification and Ethical Review. All samples are verified by native speakers and medical experts (physicians, advanced medical students, and nursing PhD candidates). Reviewers assess clinical correctness, linguistic fidelity, and cultural appropriateness, revising culture-specific terminology and removing translation artifacts or medically inappropriate content. Across 13 languages, user studies report an average rating of **4.89/5**, supporting clinical validity (Appendix Table 5). All procedures were approved by an Institutional Review Board for social and behavioral sciences and followed established ethical research standards. Additional details are provided in Appendix D.

3.2 Cold-Start Initialization via Supervised Fine-Tuning (SFT)

We initialize multilingual reasoning with a cold-start SFT stage on *code-switched long CoT* trajectories. This stage stabilizes multi-step reasoning in the base model before we introduce stricter language-consistency constraints in later training.

Dataset	Lang.	Size	Open-ended?	Reasoning Supervision	Low-resource?
MMedBench	6	8.5k	✗	✓	✗
MedQA	3	13k	✗	✗	✗
MedExpQA	4	2,488	✗	✓	✗
PubMedQA	1	211k	✗	✓	✗
MedQAUSMLE	1	11.4k	✗	✗	✗
MedMCQA	1	193k	✗	✓	✗
OphthaLingua	7	1,184	✗	✗	✓
MCMLE	1	270k	✗	✗	✗
XMedBench	4	8,280	✗	✗	✗
WorldMedQA	4	568	✗	✗	✗
HealthSearchQA	1	3,173	✓	✓	✗
CURE-MED-Bench	**13**	**15,774**	✓	✓	✓

Table 1: Comparison of medical domain benchmarks.

Given an input query x in the target language ℓ, we construct a multi-step reasoning trajectory that allows controlled code-switching in intermediate steps (see Figure 2 for a French subset example). Each trajectory contains reasoning steps $\mathbf{r} = \{r_1, \ldots, r_T\}$, where step r_t may be written in language $\ell_t \in \mathcal{L}$, followed by a final answer y^* written in the target language ℓ.

We fine-tune the model by maximizing the likelihood of the reasoning trajectory and final answer conditioned on the input: $\mathcal{L}_{\text{SFT}} = -\log p_\theta(\mathbf{r}, y^* \mid x)$, training the model to produce multi-step reasoning before generating the final response. Code-switching in $\mathbf{r}$ allows the LLM use the most effective language for intermediate inference while keeping the final answer in ℓ. The resulting language-adaptive reasoning behavior provides a strong initialization for RL stages that enforce language consistency without degrading logical accuracy.

3.3 Reward Design

We train CURE-MED with a weighted reward that promotes clinical correctness, language fidelity, and adherence to a structured output format. We use a closed-source multilingual reward model that performs competitively on RewardBench (Lambert et al., 2025). To mitigate same-model judge bias, we use a separate model for LLM-as-a-judge verification (Verga et al., 2024; Bansal et al., 2023).

Correctness Reward. Following Zheng et al. (2023), we use GPT-4.1 as a verifier to score semantic and clinical equivalence between the model output (y), and reference answer (y^*). The verifier returns a continuous score in $[0, 1]$:

$$R_{\text{acc}}(y \mid x, y^*) = v_{\text{acc}}(x, y, y^*) \in [0, 1]. \quad (1)$$

We use exact-match scoring for closed-ended questions. For open-ended questions, the verifier assigns partial credit when the response reaches the correct conclusion via clinically valid reasoning, even under paraphrase (Su et al., 2025), providing smoother learning signals.

Language Consistency Reward. We enforce strict output-language fidelity by scoring whether y is written entirely in the query language ℓ:

$$R_{\text{lang}}(y \mid \ell) = \begin{cases} 1 & \text{if the language of } y \text{ matches } \ell \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

Format Reward. A parser checks compliance with the required structure (`<thinking>`, numbered `<step n>`, and `<answer>` tags):

$$R_{\text{fmt}}(y) = \begin{cases} 1 & \text{if the required format is followed} \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

The final composite reward is defined as:

$$R(y \mid x, y^*, \ell) = \lambda_{\text{acc}} R_{\text{acc}}(y \mid x, y^*) + \lambda_{\text{lang}} R_{\text{lang}}(y \mid \ell) + \lambda_{\text{fmt}} R_{\text{fmt}}(y) \quad (4)$$

3.4 GRPO-guided curriculum reinforcement learning

After SFT, we fine-tune the model with curriculum-guided GRPO (Shao et al., 2024; Guo et al., 2025) for optimizing the reasoning policy under the multilingual verifier-driven reward described in Sec. 3.3.

Curriculum Design. We design the curriculum around language resource availability rather than problem complexity. This is motivated by the observation that models achieve higher reasoning accuracy in high-resource languages, providing more stable reward signals early in reinforcement learning. We therefore treat languages as tasks of increasing difficulty and progress from high→medium→low-resource tiers. Based on baseline performance, we define three tiers: high- (French, Japanese, Spanish, Vietnamese), medium- (Korean, Thai, Turkish, Bengali), and low-resource (Amharic, Yoruba, Hausa, Hindi, Swahili). We start GRPO on the high-resource and progressively expand training to lower-resource tiers. To reduce catastrophic forgetting, we retain a fixed fraction of samples from the previous phase when introducing a new tier. Formally, curriculum phase C_i draws samples from languages in tier $L_i \in \{\text{high}, \text{medium}, \text{low}\}$.

Training Procedure. While following prior works (Shao et al., 2024; Guo et al., 2025; Hwang et al.,

Example: Cold-Start Code-Switched Reasoning (French)

Question. Une femme de 34 ans se présente aux urgences avec des douleurs abdominales sévères localisées dans l'hypochondre droit, associées à des nausées et des vomissements. Étant donné ses antécédents de calculs biliaires, quel est le diagnostic le plus probable pour son état?

Reasoning (code-switched CoT). <thinking> <step1> The question describes une femme de 34 ans presenting with severe abdominal pain in the région de l'hypochondre droit, along with des nausées et des vomissements. These are classic upper abdominal symptoms. </step1> <step2> Ses symptômes suggèrent une atteinte possible de la vésicule biliaire, especially given her history of calculs biliaires. This could indicate a gallbladder-related condition. </step2> <step3> The presence of fièvre à 38,5°C and tenderness upon palpation of the quadrant supérieur droit indicates an inflammatory process — likely une infection. </step3> <step4> In this context, on peut fortement envisager la cholécystite aiguë (acute cholecystitis) as the most probable diagnosis given the presentation and risk factors. </step4> </thinking>

Answer. <answer> Le diagnostic le plus probable est la cholécystite aiguë </answer>

Language: French **Type:** Cold-start code-switched CoT sample

Figure 2: An example from the cold-start multilingual dataset showing CoT reasoning in French. The reasoning combines English-based clinical terms and local-language expressions, reflecting code-switching in medical contexts.

Example: Baseline vs. CURE-Med (Spanish)

Question. *Un paciente presenta congestión nasal y tos leve desde hace dos días. No tiene fiebre ni dificultad para respirar. ¿Cuál es la causa más probable?*

Baseline model (incorrect)

Reasoning (flawed). El cuadro parece un resfriado común, pero la ausencia de fiebre podría indicar que no es viral y la tos podría ser señal de algo más serio como una infección pulmonar temprana. La congestión nasal podría ser un síntoma inicial de una patología más grave.

Answer. Podría tratarse de una infección pulmonar temprana. ✗

CURE-Med (correct)

Reasoning (code-switched CoT). <step1> The symptoms are mild, lo que coincide con un resfriado leve. </step1> <step2> No fever, lo que reduce la probabilidad de neumonía. </step2> <step3> Lo más probable es un resfriado viral leve. </step3>

Answer. Lo más probable es un resfriado viral leve. ✓

Figure 3: Qualitative Spanish medical-reasoning example comparing a baseline Qwen2.5-7B-Instruct model and CURE-MED-7B. The baseline model produces fluent but clinically flawed reasoning (red) and an incorrect diagnosis, whereas CURE-MED generates a structured, code-switched CoT (blue) and arrives at the correct diagnosis (green).

2025), we apply GRPO without modifying the optimization rule, the training was designed in curriculum phases. When reward improvements plateau within a tier, we expand sampling to include the next tier while mixing in data from the previous phase to preserve earlier capabilities. At phase i, we sample batches from: $\mathcal{D}_i = \alpha\,\mathcal{D}_{i-1} + (1-\alpha)\,\mathcal{D}_{L_i}$, where $\mathcal{D}_{L_i}$ denotes data from tier L_i, $\mathcal{D}_{i-1}$ is the retained data from phase $i-1$, and α=0.85 controls the retention ratio. This retention-aware curriculum supports incremental transfer to low-resource languages while maintaining performance.

4 Experiments

Next, we outline the experimental setup, baseline models, training and evaluation procedures used to address key research questions: **RQ1)** Does CURE-MED improve multilingual medical reasoning over instruction-tuned baselines and their vanilla variants? **RQ2)** What is the performance trade-off between language fidelity and medical reasoning accuracy? **RQ3)** How does curriculum-guided learning affect performance across model scales? **RQ4)** Does CURE-MED generalize to unseen medical questions and languages under out-of-distribution evaluation?

4.1 Experimental Setup

Dataset and Splits. All experiments are conducted on CUREMED-BENCH, where the dataset is partitioned into 80% train and 20% held-out test set. The train set is further divided into 80% for supervised fine-tuning and 20% for reinforcement fine-tuning. Dataset construction and filtering procedures are described in Sec. 3.

Baselines. We benchmark CURE-MED against 28 baseline models comprising i) general-purpose, including Qwen 2.5-Instruct (Yang et al., 2024), LLaMA (Dubey et al., 2024), Gemma (Team et al., 2024), Mistral (Jiang et al., 2023), Apollo2 (Zheng et al., 2024), and Ministral (Team, 2024); and ii) medical-specific, including MedAlpaca (Han et al., 2025), Meditron (Chen et al., 2023b), UltraMedical (Zhang et al., 2024), HuatuoGPT (Zhang et al.), OpenBioLLM (Labs, 2024), BioMistral (Labrak et al., 2024), and MMed-LLaMA (Qiu et al., 2024). All models are evaluated in a zero-shot setting across three independent runs.

Model Training and Evaluation. We use Qwen-2.5-{1.5B,3B,7B,14B,32B} instruction-tuned models as backbones. Training is performed on eight NVIDIA A100 GPUs in two stages: i) SFT on the multi-step cold-switched dataset for three epochs and ii) language-resource-aware curriculum fine-tuning with GRPO. Reinforcement progresses from

Model	Consistency (↑)	Accuracy (↑)
Small Models (≤ 3B)		
LLaMA-3.2-3B	23.69±0.36	10.41±0.38
Qwen2.5-Instruct-1.5B	3.84±0.25	6.20±0.24
Qwen2.5-Instruct-3B	8.39±0.42	10.83±0.60
CURE-MED-Qwen2.5-1.5B	57.60±0.65	28.32±0.35
CURE-MED-Qwen2.5-3B	**74.28**±0.60	**42.93**±0.60
Medium Models (7–9B)		
BioMistral-7B	7.10±0.90	4.80±0.95
Gemma-7B	0.37±0.25	1.23±0.80
MedAlpaca-7B	3.50±0.90	2.47±0.95
Meditron-7B	0.43±0.40	2.50±1.10
Mistral-7B	18.70±1.30	15.23±1.20
Apollo2-7B	25.63±1.35	15.93±1.35
Qwen2.5-Instruct-7B	25.44±0.36	29.56±0.42
LLaMA-3.1-Instruct-8B	36.56±0.31	18.91±0.18
HuatuoGPT-o1-8B	67.30±0.14	46.86±0.09
OpenBioLLM-Llama3-8B	1.47±0.45	36.62±0.72
MMed-Llama-3-8B	21.38±0.56	28.09±0.62
UltraMedical LLaMA-3-8B	47.03±1.03	35.29±1.10
Ministral-8B	46.93±0.45	42.87±0.21
LLaMA-3-8B	31.58±0.12	28.93±0.42
Gemma-9B	23.22±1.14	36.97±1.03
CURE-MED-Qwen2.5-7B	**85.21**±0.63	**54.35**±0.50
Large Models (≥ 14B)		
MedAlpaca-13B	0.10±0.17	0.07±0.12
Qwen2.5-Instruct-14B	35.57±0.38	41.79±0.39
Qwen2.5-Instruct-32B	41.51±0.38	49.69±0.40
Qwen2.5-Instruct-72B	70.73±1.10	58.80±1.20
LLaMA-3.1-70B	75.68±1.01	54.65±0.31
LLaMA-3.3-Instruct-70B	79.66±0.32	60.80±0.72
HuatuoGPT-o1-70B	86.79±0.44	66.67±0.24
OpenBioLLM-Llama3-70B	70.30±0.43	51.22±0.41
Meditron-70B	0.21±0.55	4.54±0.59
MMed-LLaMA-3.1-70B	26.49±0.36	37.85±0.76
CURE-MED-Qwen2.5-14B	90.27±0.31	63.74±0.43
CURE-MED-Qwen2.5-32B	**94.96**±0.40	**70.04**±0.04

Table 2: Mean results across 13 languages on 28 baseline models and CURE-MED. We observe that CURE-MED models outperform models in each parameter scale. **Consistency** denotes language consistency and **Accuracy** denotes logical accuracy. Best overall results are **bold**, best baselines are underlined.

high- to low-resource languages, retaining 85% of data from earlier stages to mitigate catastrophic forgetting. See Appendix C.1 for additional details on our high-/low-resource language definition and the criteria used to assign languages to each group.

Following Chen et al. (2024), we evaluate on the held-out test set using an LLM-as-a-judge framework, with GPT-4o used to match each model output to the known ground-truth answer. We assess *logical accuracy* (LA), defined as the clinical accuracy of the final answer, and *language consistency* (LC), defined as whether the final answer is produced in the question's corresponding target language. Figure 3 provides a representative Spanish example, illustrating how curriculum-guided reinforcement improves accuracy while maintaining language consistency compared to a fluent but incorrect baseline. See Appendix B for Additional implementation details.

5 Results

Here, we report results that answer RQ1–RQ4 from Sec. 4. We compare CURE-MED to instruction-tuned baselines and analyze language-reasoning trade-offs, scaling under curriculum-guided reinforcement, and out-of-distribution generalization.

RQ1) CURE-MED outperforms baselines. Table 2 compares CURE-MED to three baseline families: general-purpose instruction-tuned LLMs, medical-domain instruction-tuned models, and medical-specialized LLMs. Across scales, CURE-MED improves both logical accuracy and target-language consistency. At ≤3B, baselines show low correctness and frequent language violations, while CURE-MED reaches 42.93% logical correctness and 74.28% consistency (3B). At 7–9B, CURE-MED improves over the best baseline in logical correctness (54.35% vs. 46.86%) while maintaining 85.21% consistency. At ≥14B, CURE-MED remains best, reaching 70.04% logical correctness and 94.96% consistency. Notably, our 32B model is competitive with closed-source systems and outperforms several proprietary models on CUREMED-BENCH (See Appendix E.3, E.4; Tables 8, 9, 10).

RQ2) CURE-MED achieves better language and reasoning trade-offs. Figure. 4 shows that while baselines exhibit a weak trade-off between language consistency and logical correctness, CURE-MED shifts this in the upper-right corner, highlighting that CURE-MED improves medical reasoning without sacrificing target-language fidelity, addressing a key failure mode of prior multilingual medical systems. We observe that CURE-MED-1.5B outperform several baselines ranging from 7B to 70B and our CURE-MED-32B model outperform all 28 baseline models.

RQ3) Scaling Trends of CURE-MED. Fig. 5 shows that CURE-MED smoothly scale language consistency (57.6%@1.5B → 95.0%@32B) and logical correctness (28.3%→70.0%). By comparison, instruction-tuned baselines exhibit only modest gains in language consistency as scale increases, remaining unreliable even at larger scale. Tables 6-7 in App. E report per-language results, showing that CURE-MED consistently improves performance across languages and scales effectively. These trends indicate that curriculum-guided reinforcement fundamentally alters scaling behavior by cou-

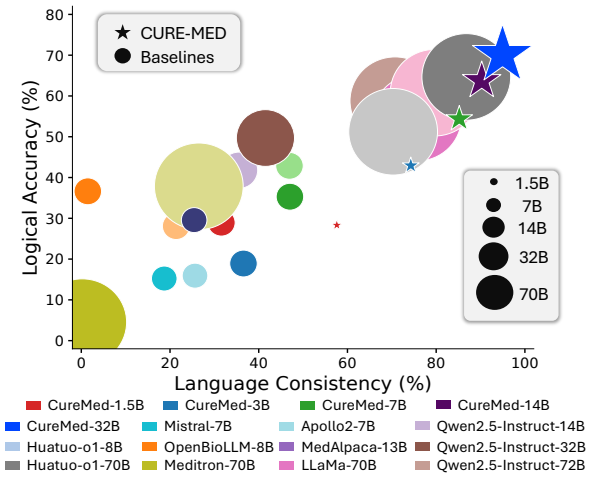

Figure 4: Trade-off performance between logical of multilingual medical reasoning models, where each point represents a model instance with bubble size reflecting model scale. Baseline and CURE-MED models are shown as ● and ★, respectively. CURE-MED shifts performance toward the upper-right, indicating consistent gains in language consistency and logical accuracy.

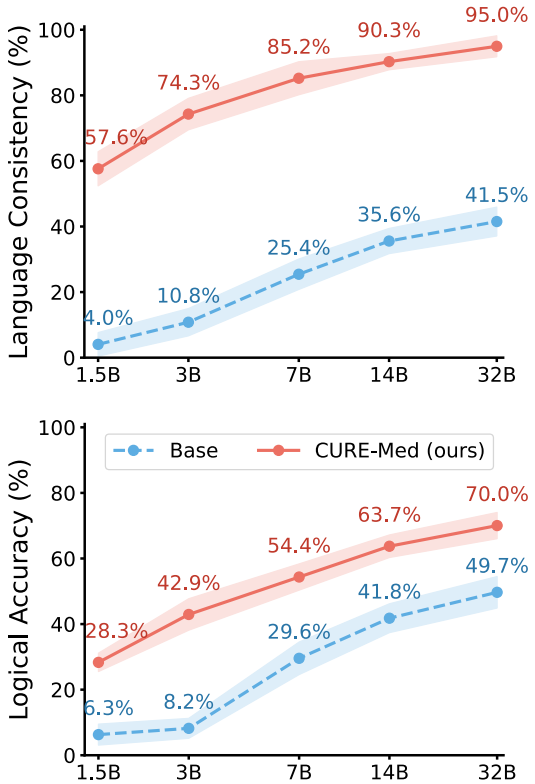

Figure 5: Scaling performance of CURE-MED vs. base across Qwen2.5-Instruct variants on language consistency **(top)** and logical accuracy **(bottom)**. Our method (solid red line) consistently outperforms the base model (dashed blue line), with performance gaps widening at larger model scales, highlighting the effectiveness of CURE-MED for multilingual medical reasoning.

pling reasoning optimization with language fidelity.

RQ4) Out-of-distribution cross-lingual generalization. We evaluate transfer to held-out medical benchmarks: MMedBench (Qiu et al., 2024), MedExpQA (Alonso et al., 2024), and MedQA (Jin et al., 2021). Across all three benchmarks, CURE-MED improves accuracy over the Qwen2.5 backbones in the majority of language–scale settings, with the clearest gains for smaller models. On MMedBench (Table 4), the 1.5B backbone increases from 6.00→24.00 and from 20.00→57.50 on representative languages, demonstrating strong transfer under limited capacity. MedExpQA (Table 11) shows a similar large jump at 1.5B, rising from 1.40→44.80, while MedQA (Table 12) improves from 21.00→59.50 at 1.5B on Chinese variants. These gains remain at larger scales, indicating that curriculum-guided RL transfers beyond in-domain training to unseen questions and language variants.

6 Ablation Study

Here, we ablate CURE-MED's key components and measure their impact on logical accuracy. We also assess robustness by evaluating CURE-MED across multiple multilingual medical QA benchmarks and strong medical-domain LLM baselines.

Effect of Codeswitched Supervised Fine-Tuning. We isolate the effect of code-switched supervision during SFT by contrasting the base model, naïve SFT trained on multilingual long-CoT data, and CURE-MED SFT without reinforcement learning. Naïve SFT yields small and sometimes unstable improvements: language consistency rises from 8.39%→13.07% at 3B, yet logic accuracy decreases from 10.83%→9.50%, indicating that multilingual instruction tuning does not consistently strengthen medical reasoning as shown in Table 3. In contrast, code-switched SFT in CURE-MED produces large, consistent gains across model scales. At 1.5B, language consistency increases from 3.84%→53.67% and logic accuracy from 6.20%→22.97%. These improvements persist as scale increases, reaching 90.29% language consistency and 66.34% logic accuracy at 32B. In summary, the results show that structured code-switching during SFT drives the strongest gains, while naïve multilingual SFT remains insufficient for reliable multilingual medical reasoning.

Effect of GRPO-guided curriculum reinforcement learning. We assess whether RL adds value beyond SFT by comparing naïve single stage GRPO based RFT against the curriculum and

Model size	Base	Naïve SFT	CURE-MED (w/o RL)	Naïve RFT	CURE-MED (w/ RL)
Qwen2.5-Instruct — Language consistency (↑)					
1.5B	3.84±0.25	8.60±1.23	53.67±0.38 (**+45.07**)	8.81±0.34	57.60±0.65 (**+48.79**)
3B	8.39±0.42	13.07±0.33	72.68±0.38 (**+59.61**)	13.28±0.57	74.28±0.60 (**+61.00**)
7B	25.44±0.36	37.11±0.44	83.46±0.36 (**+46.35**)	38.99±0.68	85.21±0.63 (**+46.22**)
14B	35.57±0.38	37.20±0.33	84.28±0.35 (**+47.08**)	39.10±1.05	90.27±0.31 (**+51.17**)
32B	35.57±0.38	43.00±0.27	90.29±0.21 (**+47.29**)	45.10±1.12	94.96±0.40 (**+49.86**)
Qwen2.5-Instruct — Logic accuracy (↑)					
1.5B	6.20±0.24	4.61±0.36	22.97±0.57 (**+18.36**)	8.80±0.47	28.32±0.35 (**+19.52**)
3B	10.83±0.60	9.50±0.38	39.13±0.53 (**+29.63**)	10.06±0.45	42.93±0.60 (**+32.87**)
7B	29.56±0.42	30.05±1.10	50.03±0.48 (**+19.98**)	38.50±0.38	54.35±0.50 (**+15.85**)
14B	41.79±0.39	43.10±0.13	61.91±0.45 (**+18.81**)	45.20±0.55	63.74±0.43 (**+18.54**)
32B	49.69±0.40	51.21±0.15	66.34±0.43 (**+15.13**)	53.40±0.49	70.04±0.04 (**+16.64**)

Table 3: Ablation study of CURE-MED. Results are averaged over three runs and reported as mean ± standard deviation and green columns denote CURE-MED variants.

Model	French	Japanese	Russian	Spanish
Qwen2.5-1.5B	6.00	11.06	20.00	20.00
↪ CURE-MED	**24.00**	**35.18**	**57.50**	**44.50**
Qwen2.5-3B	6.50	24.62	22.50	23.00
↪ CURE-MED	**42.00**	**37.69**	**60.50**	**56.00**
Qwen2.5-7B	42.00	**51.76**	53.50	63.00
↪ CURE-MED	**50.00**	46.73	**66.00**	**64.00**
Qwen2.5-14B	61.00	57.29	63.00	71.50
↪ CURE-MED	**64.00**	**65.83**	**75.50**	**78.00**
Qwen2.5-32B	69.50	67.84	72.00	29.50
↪ CURE-MED	**78.50**	**77.29**	**80.00**	**82.50**

Table 4: OOD accuracy on MMedBench. CURE-MED improves reasoning performance across all model sizes, showing strong cross-lingual generalization to unseen medical questions and languages. See Tables 11-12 for results on MedExpQA and MedQA datasets.

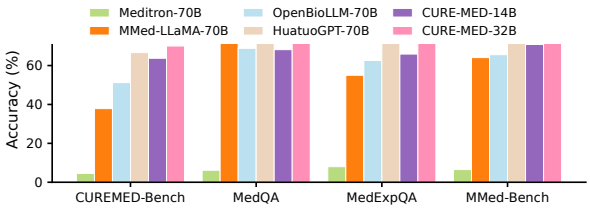

Figure 6: CURE-MED vs. medical LLM baselines across four multilingual medical QA benchmarks. Results show logi cal accuracy, highlighting CURE-MED's consistent across diverse evaluation settings.

language resource-aware RL used in CURE-MED, with results summarized in Table 3. Naïve RFT yields limited and uneven gains, especially at smaller scales, suggesting that uniform reinforcement signals do not consistently shape multilingual behavior. In contrast, CURE-MED applies RL after code switched SFT and delivers reliable improvements in both language consistency and logical accuracy across all model sizes. These results show that curriculum and resource-aware RL stabilizes optimization and strengthens multilingual medical reasoning beyond naïve GRPO.

CURE-MED vs. Medical LLM baselines across Benchmarks. We evaluate CURE-MED against strong medical-domain LLM baselines across four multilingual medical benchmarks (see Fig. 6). CURE-MED remains consistent, with CURE-MED-32B achieving the best performance on CUREMED-BENCH (70.04%) and MMed-Bench (79.57%), and remains competitive on MedQA and MedExpQA, where HuatuoGPT-70B leads narrowly. CURE-MED-14B also provides strong results across all benchmarks, while other medical baselines lag behind more substantially, highlighting CURE-MED's robustness across diverse evaluation settings.

7 Conclusion

We introduce CUREMED-BENCH, a multilingual medical reasoning benchmark of open-ended questions with explicit reasoning traces and a single verifiable answer across 13 languages, including low-resource settings. Using CUREMED-BENCH, we propose CURE-MED, which combines cold-start code-switched initialization, structured supervised fine-tuning, and language-resource-aware curriculum-RL to improve reasoning while preserving target-language fidelity. Across languages, datasets, and model scales, CURE-MED improves logical correctness and language consistency over strong baselines; ablations show supervised and RL stages provide complementary gains for stable multilingual reasoning.

8 Limitations

CureMed-Bench is constrained by the availability of clinically reliable source material across languages, which limits coverage and can create uneven difficulty between high- and low-resource settings. Our benchmark targets open-ended questions with a single verifiable answer and thus does not capture longitudinal care trajectories, multi-visit decision-making, or multimodal clinical evidence. In addition, parts of our pipeline rely on API-based models (e.g., for generation and/or verification), which can be costly and may hinder reproducibility for some researchers; a practical direction is to replace these components with smaller open-source models trained for the same roles and to release prompts, code, and verifier alternatives to reduce dependence on paid APIs. Future work will expand language coverage, broaden clinical settings and modalities, and further reduce reliance on proprietary APIs.

9 Ethical Considerations

This work supports the evaluation and training of multilingual medical reasoning systems by measuring reasoning correctness and target-language fidelity across diverse languages. CureMed-Bench is derived from publicly available, clinically curated sources and contains no patient records or personally identifiable information. Native speakers and medical experts reviewed all samples for clinical correctness, linguistic fidelity, and cultural appropriateness under IRB-approved procedures, and we report per-language results to surface reliability differences across resource levels.

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A LLM-as-a-Judge Verification Protocol

Inspired by (Chen et al., 2024), We employ an LLM-as-a-judge framework to automatically evaluate the correctness of model-generated responses. In this setup, GPT-4o acts as a verifier that compares a model's prediction against a reference answer and determines whether the response is logically correct and linguistically valid. The verifier outputs a binary decision, returning `True` when the response aligns with the reference and `False` otherwise. Fig. 7 shows the exact prompt used for verification.

Prompt for the LLM-as-a-Judge Evaluator

```
<Model Response>
{Model Response}
</Model Response>

<Reference Answer>
{Ground-truth Answer}
</Reference Answer>
```

You are given a model-generated response and a reference answer. Determine whether the model response is correct with respect to the reference. Output "`True`" if the response is correct and "`False`" otherwise.

Figure 7: Prompt used for LLM-as-a-judge verification.

B Training and Verification Protocols

This section documents the prompts, reward verification procedures, and training hyperparameters used for supervised and reinforcement fine-tuning. Together, these components define the optimization signals and structured supervision underlying the proposed framework.

B.1 Reward Verification and Weighting

We design a composite reward that jointly enforces clinical correctness, language fidelity, and output format compliance. The final reward is defined as

$$R = 0.65 \times R_{\text{accuracy}} + 0.30 \times R_{\text{language}} + 0.05 \times R_{\text{format}}.$$

This weighting prioritizes medical correctness while explicitly penalizing language drift and format violations.

B.2 Verifier Models and Prompts

Both correctness and language rewards are scored using **gpt-4.1** with `temperature=0.0` and `max_tokens=10`. For each prompt, we generate 16 candidate responses to estimate stable reward signals.

B.3 Accuracy Verifier.

You are an expert multilingual medical evaluator. Score the generated response for correctness and medical validity on a continuous scale from 0.0 to 1.0. Give 1.0 if the reasoning is clinically sound and semantically correct, even if phrased differently from the reference. Focus on factual and clinical accuracy rather than wording.
Question: {question}
Ground truth answer: {ground_truth}
Generated response: {generated}
Output only a float between 0.0 and 1.0.

B.3.1 Language Consistency Verifier Prompt

You are an expert multilingual medical evaluator. Determine whether the model response is written entirely in the same language as the question.
Question language: {language}
Generated response: {generated}
Output 1.0 if the language matches exactly; otherwise output 0.0.

B.3.2 Format Reward

We apply a deterministic rule-based check requiring exactly one `<thinking>` block and one `<answer>` block, implemented using regular expressions with `re.DOTALL`. This constraint ensures consistent structure during reinforcement learning.

B.4 Training Hyperparameters

B.4.1 Supervised Fine-Tuning.

- Optimizer: AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.999$)
- Learning rate: 1×10^{-5} (cosine scheduler, 10% warmup)
- Epochs: 3
- Effective batch size: 32
- Max sequence length: 4096
- Precision: bf16
- Optimization: DeepSpeed ZeRO-3 with gradient checkpointing

B.4.2 Reinforcement Fine-Tuning.

- Algorithm: GRPO
- Learning rate: 1×10^{-6} (cosine scheduler, warmup ratio 0.1)
- Weight decay: 0.1
- Effective batch size: 16
- Generations per prompt: 16
- Max training steps: 500
- Max prompt / completion length: 1024 / 1024

C Dataset Details

This appendix characterizes the linguistic composition of CUREMED-BENCH. Figure 8 shows the per-language instance distribution, with French contributing the largest share (13.5%) and Bengali the smallest (2.9%), and most languages occupying a mid-range band of roughly 7–10% of the data. The figure also groups the 13 languages into eight language families, spanning Afroasiatic and Niger–Congo as well as Indo–European, Turkic, Austroasiatic, Tai–Kadai, Japonic, and Koreanic. Together, these statistics highlight both the dataset's uneven language coverage and its broad typological diversity.

C.1 Language-based Curriculum Tiers

We construct our curriculum by defining difficulty along the linguistic axis rather than by question complexity. To operationalize this design, we use Qwen2.5-14B-Instruct as a reference model and estimate baseline reasoning accuracy separately for each language. The model performs best on high-resource languages and degrades as linguistic resources and model familiarity decrease, so we treat high-resource languages as easier tasks and progressively introduce more challenging languages during training. This curriculum aims to transfer reasoning competence learned in high-resource settings to underrepresented languages while maintaining language fidelity.

Based on the baseline accuracy ranking, we partition languages into three tiers. The high-resource tier includes French, Japanese, Spanish, and Vietnamese. The medium-resource tier includes Korean, Thai, Turkish, and Bengali. The low-resource tier includes Amharic, Yoruba, Hausa, Hindi, and Swahili. This tiering reflects the reference model's initial proficiency distribution and provides a structured progression from easier to harder multilingual reasoning conditions.

D Data Curation

The following prompt was used to generate the initial pool of medically grounded multiple-choice questions across 13 languages. Inspired by the approach of Hwang et al. (2025) and Zhang et al., we adapted their template and instructed GPT-4o to query MedlinePlus directly and independently construct questions in each target language rather than translating from a shared source. This ensures linguistic naturalness, cultural appropriateness, and strong domain grounding across all languages.

D.1 Human Verification Protocol and Rater Instructions

This section documents the human verification procedures used to validate the quality of our synthetic data. We provide the exact instructions used by medical professionals who assessed the clinical correctness of question-answer pairs and by native speakers who evaluated the language's correctness and fidelity in the target language, as shown in Figures 10 and 11. These materials specify the task setup, scoring rubric, and optional comment guidelines used throughout our verification pipeline.

D.2 Human Verification Scores by Language

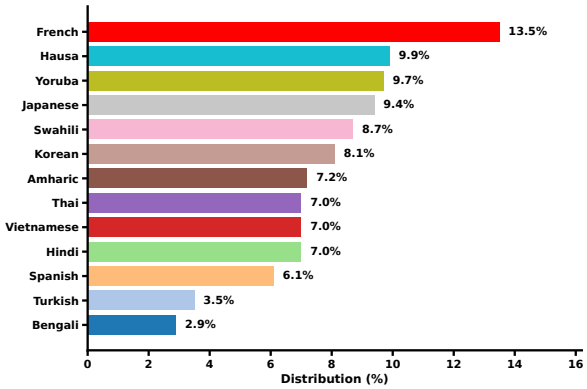
We report per-language human verification scores from two rater groups. Medical professionals score clinical correctness of each question–answer pair, while native speakers score target-language quality and fidelity. Table 5 summarizes both scores on a 1–5 scale, where higher values indicate better quality.

Language	Medical correctness	Language quality
Amharic	4.45	4.45
Bengali	4.92	4.96
French	5.00	5.00
Hausa	4.96	5.00
Hindi	5.00	4.92
Japanese	4.96	4.96
Korean	5.00	5.00
Spanish	5.00	5.00
Swahili	5.00	4.96
Thai	4.70	4.70
Turkish	4.60	4.60
Vietnamese	4.95	4.95
Yoruba	5.00	5.00

Table 5: Per-language human verification scores (1–5) from medical professionals (clinical correctness) and native speakers (language quality). Higher is better.

E Per-Language Model Performance

This section provides a fine-grained analysis of multilingual medical reasoning performance broken down by language. We compare CURE-MED with instruction-tuned baselines across all 13 languages in CUREMED-BENCH, enabling a detailed examination of logical correctness and language consistency under diverse linguistic and resource conditions. This per-language view complements aggregate results by revealing where gains are most pronounced and where challenges remain.



Language Family	Languages
Afroasiatic	Amharic (Am), Hausa (Ha)
Niger–Congo	Swahili (Sw), Yoruba (Yo)
Indo-European	Bengali (Bn), Hindi (Hi), French (Fr), Spanish (Es)
Turkic	Turkish (Tr)
Austroasiatic	Vietnamese (Vi)
Tai–Kadai	Thai (Th)
Japonic	Japanese (Ja)
Koreanic	Korean (Ko)

Figure 8: **Language and family composition of CureMed-Bench. Left:** Number of dataset instances per language across the 13 languages. **Right:** Assignment of languages to eight language families with standard abbreviations.

E.1 Per-Language Results for Qwen2.5-7B

Table 6 reports per-language performance for the Qwen2.5-7B-Instruct baseline and its Cure-Med variant. Across all 13 languages, Cure-Med substantially improves both logical accuracy and language consistency. Gains are especially large in low-resource languages such as Amharic, Hausa, Swahili, and Yoruba, where the baseline frequently fails to produce correct or language-faithful responses. In higher-resource languages such as French, Japanese, and Spanish, Cure-Med yields more moderate but consistent improvements, indicating that GRPO-guided curriculum RL enhances reasoning robustness without degrading performance in well-resourced settings. Overall, these results show that Cure-Med improves multilingual medical reasoning uniformly while significantly narrowing performance disparities across languages.

E.2 Per-Language Results for Qwen2.5-3B

Table 7 shows that Cure-Med consistently improves the 3B model across all evaluated languages in both logical correctness and language accuracy. The baseline 3B model exhibits extremely low performance for several languages, including Amharic, Hausa, Swahili, and Turkish, whereas the Cure-Med variant achieves large absolute gains, often exceeding 40–80 percentage points. Even in languages where the base model is already relatively stronger, such as French, Japanese, Spanish, and Vietnamese, Cure-Med delivers clear and reliable improvements. These results demonstrate that curriculum-guided reinforcement is particularly effective for small models, enabling robust multilingual medical reasoning despite limited model capacity.

E.3 Proprietary Model Performance on CureMed-Bench

Table 8 summarizes inference-only performance of frontier models on CureMed-Bench, reporting language consistency and logical accuracy averaged over 13 languages. While some models maintain strong target-language adherence (*e.g.,* Claude 3 Haiku), results reveal substantial brittleness: GPT-5-nano exhibits notably weaker language consistency, and the Gemini 2.5 family degrades sharply in both language control and reasoning quality (with Gemini 2.5 Pro nearly collapsing). These averages also conceal larger failures in low-resource languages, where models more frequently drift from the target language and show steeper drops in logical accuracy (see Appendix E.4). Overall, CureMed-Bench exposes a reliability gap for proprietary LLMs: strong performance in some settings does not ensure robust multilingual reasoning or consistent target-language adherence.

E.4 Per-language Performance of Closed-source Models

We analyze proprietary models on CureMed-Bench at the per-language level using logical accuracy (Table 9) and language consistency (Table 10). Even among the five evaluated systems (GPT-5-nano, GPT-5-mini, Gemini 2.5 Flash/Pro, and Claude 3 Haiku), strong aggregate scores mask substantial cross-lingual brittleness.

Across higher-resource languages, performance is comparatively stable: French and Spanish achieve high logical accuracy (often $\geq$90%) and strong language adherence, and we observe

Prompt for Generating Multilingual Medical Multiple-Choice Questions

Task: You are an expert medical content generator. Generate {num_questions} high-quality, medically accurate multiple-choice questions (MCQs) based strictly on content from MedlinePlus by searching and curating from the website.

You must independently compose each question in **ALL** of the following languages: Amharic, Bengali, French, Hausa, Hindi, Japanese, Korean, Spanish, Swahili, Thai, Turkish, Vietnamese, Yoruba.

Requirements:

1. **Medical Grounding:** All information must be sourced from MedlinePlus, covering symptoms, causes, risk factors, diagnostics, treatments, or prevention strategies.
2. **Independent Composition:** Each language version must be originally written (not translated) using natural phrasing and medically appropriate terminology for that language.
3. **Clinical Reasoning Depth:** Questions must require genuine clinical reasoning beyond trivial fact recall. Each question should have exactly one unambiguous correct answer.
4. **Format:** 4-option MCQ (A/B/C/D) with one correct answer.

Output Format: Return valid JSON array:

```
[
\{"question_id": "<id>", "source_concept": "<MedlinePlus_topic>",
"mcq_items": [\{"language_code": "<lang>", "question": "<text>",
"option_A": "<text>", "option_B": "<text>", "option_C": "<text>", "option_D": "<text>",
"correct_answer": "<A|B|C|D>"\}, ...]\}
]
```

IMPORTANT: Return ONLY valid JSON without explanations, formatting, or additional text. Ensure all special characters are properly escaped.

Figure 9: Prompt for Stage 1 multilingual MCQ generation. Here, `{num_questions}` specifies the number of questions to generate, and GPT-4o queries MedlinePlus directly to construct clinically grounded questions independently in each of the 13 target languages.

Participant Instructions: Verification Task

Task Overview
You will review synthetically generated medical question–answer pairs based on public sources such as MedlinePlus. These pairs are generated synthetically and do not involve real patient data. Your role is to assess medical correctness and accuracy.

What You Will Do
For each question–answer pair:

- Read the question and the provided answer.
- Check for medical correctness: ensure the information is accurate, logically sound, and aligned with standard medical knowledge.
- Assign a score from 1 to 5:
  - **1**: Completely inaccurate or misleading.
  - **2**: Mostly inaccurate with major errors.
  - **3**: Partially accurate but with notable issues.
  - **4**: Mostly accurate with minor issues.
  - **5**: Fully accurate and reliable.
- (Optional) Provide a brief comment if necessary (e.g., explain errors, suggest corrections, or note cultural/language specifics). Comments are optional but helpful.

You will receive batches of 50–100 pairs via an online survey. The task takes approximately 1–2 hours and can be completed remotely at your convenience. You may skip any pair or stop at any time.

Figure 10: Instructions provided to medical professional annotators for verifying clinical correctness of synthetic question–answer pairs.

similarly consistent behavior in Japanese, Korean, Thai, Turkish, and Vietnamese, where language consistency typically remains high alongside solid reasoning performance. In contrast, low-resource languages expose clear failure modes. Amharic exhibits severe target-language breakdown for several models (*e.g.,* GPT-5-nano and Gemini 2.5 Flash/Pro), where language consistency collapses

Participant Instructions: Language Verification Task

Task Overview
You will review synthetically generated medical question–answer pairs written in one of the following target languages: Amharic, Bengali, French, Hausa, Hindi, Japanese, Korean, Spanish, Swahili, Thai, Turkish, Vietnamese, and Yoruba. These pairs are generated synthetically and do not include real patient data. Your role is to verify whether the question and answer are written correctly and naturally in the target language.

What You Will Do
For each question–answer pair:

- Read the question and the provided answer.
- Verify language correctness and fidelity:
  - The text is in the requested target language (no switching to another language).
  - The wording is grammatical and understandable for a native speaker.
  - The phrasing is natural and appropriate for medical communication.
  - Medical terms are expressed in an acceptable way for the target language (including common loanwords, when appropriate).
- Assign a score from 1 to 5:
  - **1**: Not in the target language or largely unintelligible.
  - **2**: Major language errors; difficult to understand.
  - **3**: Understandable but with noticeable errors or unnatural phrasing.
  - **4**: Mostly correct and natural with minor issues.
  - **5**: Fully correct, natural, and clearly in the target language.
- (Optional) Provide a brief comment to note issues (e.g., incorrect language, grammar problems, unnatural phrasing, or better word choices).

You will receive batches of 50–100 pairs via an online survey. The task takes approximately 1–2 hours and can be completed remotely at your convenience. You may skip any pair or stop at any time.

Figure 11: Instructions provided to native-speaker annotators for verifying language correctness and target-language fidelity of synthetic question–answer pairs.

despite non-trivial logical accuracy for some settings; Claude 3 Haiku is more robust, maintaining high language adherence and stronger accuracy. Hausa shows a different dissociation: multiple models drift from the target language even when logical accuracy remains moderate to high, indicating that medical reasoning does not imply reliable language control under inference-only prompting. Yoruba is the most challenging overall: language adherence is often low (notably for GPT-5 and Gemini 2.5 variants), and logical accuracy drops sharply across models, revealing compounding failures in both reasoning and language control. Overall, these results underscore a persistent reliability gap in proprietary LLMs and motivate evaluating multilingual medical reasoning with joint measures of correctness and target-language fidelity.

Language	Logic (Base)	Logic (CURE-MED)	Δ	Lang. (Base)	Lang. (CURE-MED)	Δ
Amharic	0.95	17.14	**+16.19**	0.00	64.76	**+64.76**
Bengali	10.00	60.00	**+50.00**	2.14	91.43	**+89.29**
French	67.86	77.86	**+10.00**	71.43	96.43	**+25.00**
Hausa	5.06	43.04	**+37.98**	0.00	77.22	**+77.22**
Hindi	4.48	48.51	**+44.03**	5.97	90.30	**+84.33**
Japanese	68.57	77.14	**+8.57**	60.00	94.29	**+34.29**
Korean	41.33	52.00	**+10.67**	26.67	84.00	**+57.33**
Spanish	62.86	72.38	**+9.52**	60.95	96.19	**+35.24**
Swahili	0.00	35.71	**+35.71**	0.00	67.14	**+67.14**
Thai	51.02	59.18	**+8.16**	37.76	86.73	**+48.97**
Turkish	12.50	43.75	**+31.25**	3.57	75.89	**+72.32**
Vietnamese	66.67	70.48	**+3.81**	61.90	94.29	**+32.39**
Yoruba	0.00	40.86	**+40.86**	0.00	77.42	**+77.42**

Table 6: Per-language performance of Qwen2.5-7B-Instruct (Base) and the CURE-MED 7B variant on CUREMED-BENCH. We report logical correctness and language accuracy, along with absolute gains Δ (CURE-MED −Base).

Language	Logic (Base)	Logic (CURE-MED)	Δ	Lang. (Base)	Lang. (CURE-MED)	Δ
Amharic	0.95	14.29	**+13.34**	0.00	40.95	**+40.95**
Bengali	2.86	55.71	**+52.85**	0.00	85.00	**+85.00**
French	12.14	70.71	**+58.57**	22.14	95.71	**+73.57**
Hausa	2.53	27.85	**+25.32**	0.00	64.56	**+64.56**
Hindi	5.97	28.36	**+22.39**	0.00	83.58	**+83.58**
Japanese	23.81	62.86	**+39.05**	26.67	89.52	**+62.85**
Korean	8.00	36.00	**+28.00**	2.67	76.00	**+73.33**
Spanish	17.14	62.86	**+45.72**	23.81	94.29	**+70.48**
Swahili	0.00	17.86	**+17.86**	0.00	51.43	**+51.43**
Thai	10.20	58.16	**+47.96**	0.00	73.47	**+73.47**
Turkish	1.79	28.57	**+26.78**	0.00	53.57	**+53.57**
Vietnamese	44.76	69.52	**+24.76**	79.05	80.00	**+0.95**
Yoruba	6.45	17.20	**+10.75**	0.00	69.89	**+69.89**

Table 7: Per-language performance of the 3B Base model and its CURE-MED variant on CUREMED-BENCH. We report logical correctness and language accuracy, along with absolute gains Δ (CURE-MED −Base).

Model	**Lang. Consistency** (↑)	**Logical Acc.** (↑)
GPT-5-nano	69.11	73.24
GPT-5-mini	75.33	80.57
Gemini 2.5 Flash	48.01	54.79
Gemini 2.5 Pro	4.33	10.62
Claude 3 Haiku	93.43	73.31

Table 8: Inference-only performance of proprietary models on CUREMED-BENCH (averaged across 13 languages).

Language	GPT-5-nano	GPT-5-mini	Gemini 2.5 Flash	Gemini 2.5 Pro	Claude 3 Haiku
Amharic	5.71	41.90	24.76	0.95	70.48
Bengali	65.00	73.57	38.57	9.29	62.86
French	89.29	93.57	75.71	23.57	90.71
Hausa	78.48	89.87	43.04	3.80	55.70
Hindi	78.36	78.36	62.69	14.93	76.12
Japanese	84.76	84.76	69.52	13.33	87.62
Korean	78.67	80.00	62.67	6.67	73.33
Spanish	89.52	94.29	74.29	18.10	88.57
Swahili	84.29	86.43	48.57	7.14	77.14
Thai	85.71	90.82	64.29	6.12	75.51
Turkish	79.46	84.82	53.57	6.25	70.54
Vietnamese	88.57	88.57	63.81	18.10	84.76
Yoruba	35.48	56.99	25.81	2.15	25.81

Table 9: Logical accuracy (%) of proprietary models on CUREMED-BENCH across 13 languages under inference-only prompting. We report accuracy against the single ground-truth answer.

Language	GPT-5-nano	GPT-5-mini	Gemini 2.5 Flash	Gemini 2.5 Pro	Claude 3 Haiku
Amharic	1.90	24.76	12.38	1.90	92.38
Bengali	39.29	65.71	34.29	1.43	95.71
French	92.86	98.57	67.86	5.00	98.57
Hausa	56.96	43.04	35.44	1.27	73.42
Hindi	53.73	73.88	58.96	8.21	97.76
Japanese	80.00	88.57	56.19	5.71	96.19
Korean	92.00	88.00	56.00	4.00	97.33
Spanish	97.14	98.10	71.43	5.71	91.43
Swahili	82.86	77.86	32.86	2.86	98.57
Thai	94.90	88.78	59.18	9.18	97.96
Turkish	90.18	93.75	52.68	7.14	96.43
Vietnamese	89.52	91.43	60.00	0.95	99.05
Yoruba	27.96	32.26	23.66	2.15	67.74

Table 10: Language consistency (%) of proprietary models on CUREMED-BENCH across 13 languages under inference-only prompting. We report the fraction of outputs that adhere to the requested target language.

Model	English	French	Italian	Spanish
Qwen2.5-1.5B	1.40	6.40	4.80	6.80
↪ CURE-MED	**44.80**	**47.20**	**24.00**	**32.80**
Qwen2.5-3B	24.8	12.00	13.60	13.60
↪ CURE-MED	**48.00**	**50.60**	**36.80**	**48.80**
Qwen2.5-7B	**54.40**	44.00	34.40	48.00
↪ CURE-MED	53.60	**56.80**	**47.20**	**57.60**
Qwen2.5-14B	61.60	54.40	46.40	60.00
↪ CURE-MED	**66.40**	**64.40**	**64.80**	**68.00**
Qwen2.5-32B	**72.80**	**73.60**	64.80	70.40
↪ CURE-MED	72.20	73.00	**72.60**	**76.20**

Table 11: OOD accuracy on MedExpQA across four languages. CURE-MED improves reasoning performance across model sizes, showing cross-lingual generalization to unseen medical questions and languages.

Model	English	Simplified Chinese	Traditional Chinese
Qwen2.5-1.5B	18.50	21.00	16.00
↪ CURE-MED	**37.80**	**59.50**	**47.50**
Qwen2.5-3B	32.50	55.00	36.00
↪ CURE-MED	**41.00**	**68.00**	**54.00**
Qwen2.5-7B	50.50	**73.00**	**60.00**
↪ CURE-MED	**51.50**	70.00	57.00
Qwen2.5-14B	56.00	**80.50**	69.50
↪ CURE-MED	**59.50**	75.00	**70.00**
Qwen2.5-32B	63.00	**84.00**	71.00
↪ CURE-MED	**64.00**	81.00	**76.00**

Table 12: OOD accuracy on MedQA across English and Chinese. CURE-MED improves reasoning performance across model sizes, demonstrating robustness across unseen languages.