

# MedReason: Eliciting Factual Medical Reasoning Steps in LLMs via Knowledge Graphs

Juncheng Wu<sup>1,\*</sup>, Wenlong Deng<sup>2,8,\*</sup>, Xingxuan Li<sup>3</sup>, Sheng Liu<sup>4</sup>, Taomian Mi<sup>2</sup>, Yifan Peng<sup>5</sup>, Ziyang Xu<sup>6</sup>, Yi Liu<sup>5</sup>, Hyunjin Cho<sup>7</sup>, Chang-In Choi<sup>9</sup>, Yihan Cao<sup>10</sup>, Hui Ren<sup>10</sup>, Xiang Li<sup>10</sup>, Xiaoxiao Li<sup>2,8,†</sup>, Yuyin Zhou<sup>1,†</sup>

<sup>1</sup>UC Santa Cruz; <sup>2</sup>University of British Columbia; <sup>3</sup>Nanyang Technological University;

<sup>4</sup>Stanford University; <sup>5</sup>Weill Cornell Medicine; <sup>6</sup>NYU Langone Health;

<sup>7</sup>Chungnam National University Sejong Hospital; <sup>8</sup>Vector Institute;

<sup>9</sup>Pusan National University Hospital; <sup>10</sup>Massachusetts General Hospital;

\*Equal Contribution, †Corresponding author

<https://github.com/UCSC-VLAA/MedReason>

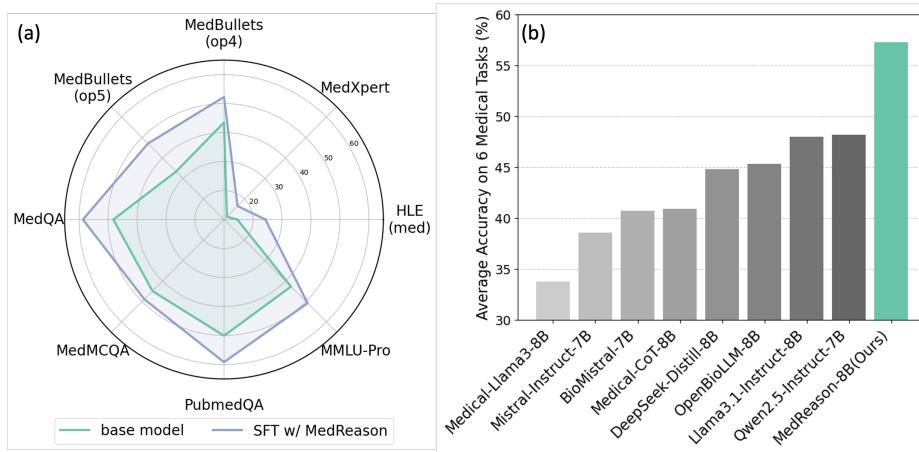


Figure 1: **MedReason-8B significantly enhances medical reasoning capability in LLMs.** (a) SFT with MedReason consistently improves base LLMs across multiple datasets. (b) Our fine-tuned model achieves state-of-the-art performance among 7-8B LLMs.

## Abstract

Medical tasks such as diagnosis and treatment planning require precise and complex reasoning, particularly in life-critical domains. Unlike mathematical reasoning, medical reasoning demands meticulous, verifiable thought processes to ensure reliability and accuracy. However, there is a notable lack of datasets that provide transparent, step-by-step reasoning to validate and enhance the medical reasoning ability of AI models. To bridge this gap, we introduce **MedReason**, a large-scale high-quality medical reasoning dataset designed to enable faithful and explainable medical problem-solving in large language models (LLMs). We utilize a structured medical knowledge graph (KG) to convert clinical QA pairs into logical chains of reasoning, or “thinking paths”, which trace connections from question elements to answers via relevant KG entities. Each path is validated for consistency with clinical logic and evidence-based medicine. Our pipeline generates detailed reasoning for various medical questions from 7 medical datasets, resulting in a dataset of 32,682 question-answer pairs, each with detailed, step-by-step explanations. Experiments demonstrate that fine-tuning with our dataset consistently boosts medical problem-solving capabilities, achieving significant gains of up to 7.7% for DeepSeek-Ditill-8B. Our top-performing model, MedReason-8B, outperforms the Huatuo-o1-8B, a state-of-the-art medical reasoning model, by up to 4.2% on the clinical benchmark MedBullets. We also engage medical professionals from diverse specialties to assess our dataset’s quality, ensuring MedReason offers accurate and coherent medical reasoning.

**Question:** Identify a treatment commonly associated with acute respiratory distress syndrome (ARDS) that has not been proven effective according to evidence-based research.

**Ground-truth Answer:** Inhaled nitric oxide

**GPT-4o Generated Reasoning:** ... taking all this into account, **early steroid administration** seems to be a common yet not strongly effective treatment for ARDS based on the evidence.

**Ours Generated Reasoning:** ... **Inhaled nitric oxide** can temporarily improve oxygenation in ARDS patients by addressing hypoxemia. However, evidence-based research indicates that it does not improve survival rates or long-term outcomes.

Figure 2: An Example from Huatuo’s CoT Data, highlighting the factual error in the reasoning process generated by GPT-4o. In comparison, our generated reasoning leads to correct answer with accurate knowledge.

## 1 Introduction

Recent advancements in Reasoning Large Language Models (Xie et al., 2024b; Zhong et al., 2024; Wang et al., 2024a) highlight the remarkable effectiveness of utilizing *Chain-of-Thought* (*CoT*) reasoning (Huang & Chang, 2022; Miao et al., 2024) prior to the final answers. Although general-purpose reasoning models achieve parity with human performance in mathematical and coding tasks (Guo et al., 2025; Team et al., 2025; Jaech et al., 2024), their applications in the medical domain have not been fully explored. One of the key challenges is the scarcity of high-quality *CoT* data, which is essential for developing medical reasoning models. Studies like s1 (Muennighoff et al., 2025) and LIMO (Ye et al., 2025) have illustrated the crucial role of high-quality data in improving the LLMs’ reasoning capability. The limited scalability of this high-quality medical data has hindered the development of more powerful medical intelligence.

One straightforward way to tackle this challenge is by distilling *CoT* data from open-source reasoning models (Madhusudhan et al., 2025; Huang et al., 2024; Min et al., 2024; Huang et al., 2025). However, these methods often omit **quality filtering** (i.e. verifying whether the generated *CoT* data logically leads to the correct answer). Pang et al. (2025) introduces BOLT, which integrates LLMs within a multi-agent framework to produce extensive *CoT* data while employing an outcome reward model to filter out low-quality reasoning traces. Nevertheless, the proportion of medical-specific reasoning data remains limited, compromising the resulted model’s clinical applicability. Efforts like HuatuoGPT-01 (Chen et al., 2024b) aim to bridge this gap by generating medical *CoT* data using GPT-4o (Hurst et al., 2024). However, it is inevitable that general-purpose LLMs will generate responses that include factual errors. As shown in Fig. 2, GPT-4o erroneously concludes that early administering steroids is not a highly effective treatment for ARDS, contradicting established findings (Qadir et al., 2024).

In the medical domain, it is vital for the model to guarantee both the quality and rigorous factual guidance throughout every reasoning step, upholding medical reliability and clinical validity. In this paper, we argue that knowledge graph (KG) integration can provide **factual guidance** during *CoT* data generation, ensuring (1) logical coherence across all reasoning steps, and (2) clinical validity grounded in established medical knowledge. To achieve this, we propose a novel data generation pipeline that actively constrains the reasoning process to align with medical facts from KG, enhancing direct clinical utility. Specifically, our approach expands medical question-answering pairs into high-quality *CoT* data by searching reasoning paths from a high-quality medical KG (Chandak et al., 2023), which serves as reliable medical knowledge sources. We initially compile question-answering pairs from 7 medical datasets, encompassing general knowledge QA datasets as well as clinically challenging datasets which require complex reasoning. As shown in Fig. 3, for each question-answering pair, we firstly prompt an LLM to extract entities from the question and answer components, then map these entities to corresponding nodes in our medical knowledge graph through either exact matching or LLM-based similarity selection (Sec. 3.1.1). We subsequently identify all reasoning paths connecting the question and answer entities within the knowledge graph, and instruct the LLM to prune reasoning paths that do not pertain to the current question (Sec. 3.1.2). Finally, the remaining reasoning paths serve as structural

Data Source	Quality Filtering	Medical Specific	Factual Guidance	Expert Checking
Distillation	✗	✗	✗	✗
BOLT	✓	✗	✗	✗
Huatuo-o1 CoT	✓	✓	✗	✗
MedReason(ours)	✓	✓	✓	✓

Table 1: **Comparison between Chain-of-Thought data sources.** MedReason provides high-quality medical CoT with factual guidance. Medical experts from seven departments assess the generated CoT data sampled from MedReason, further ensuring the quality of our data.

scaffolds to guide the LLM in generating medically grounded CoT explanations, enhancing interpretability and reasoning quality (Sec. 3.2).

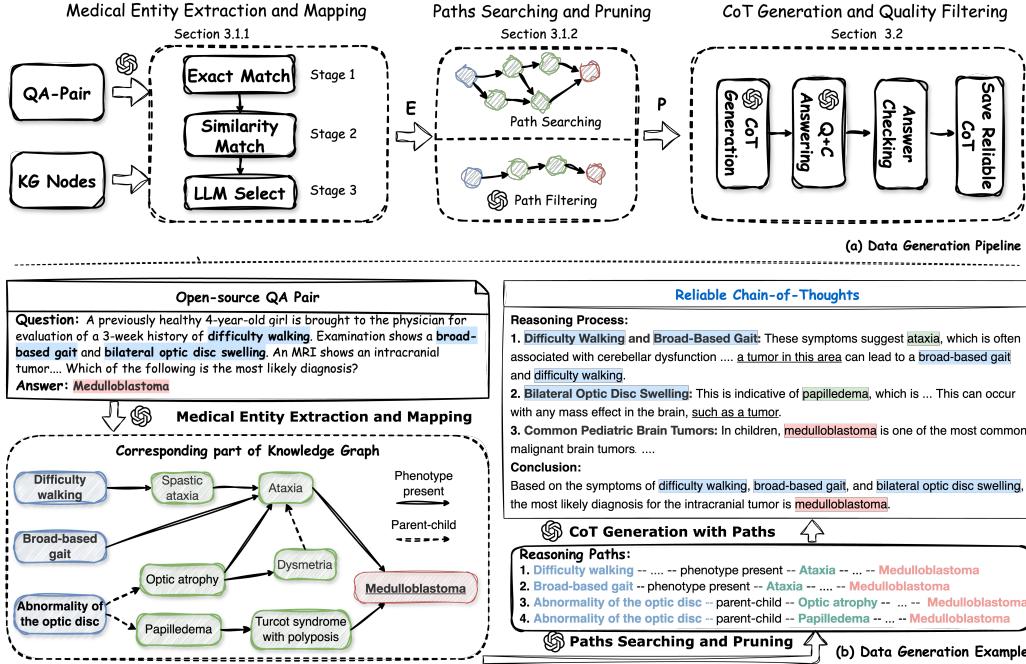
To ensure the quality of the generated CoT data, we implement a verification step where an LLM answers each question using the generated reasoning path. We systematically eliminate any CoT samples that fail to produce correct answers, ensuring only logically sound and clinically valid reasoning paths are retained (Sec. 3.2). As shown in Tab. 1, our proposed generation pipeline yields 32,682 high-quality CoT samples with consistently improved reasoning quality across all evaluation metrics.

We assess the effectiveness of MedReason through supervised fine-tuning (SFT) on 1) instruction fine-tuned models (LLaMA 3.1-Instruct-8B (Grattafiori et al., 2024), Mistral-Instruct-7B (Jiang et al., 2023)) and 2) medical reasoning specialists (Medical-CoT-8B (Karataş, 2025), DeepSeek-Distill-8B (Guo et al., 2025)). Our extensive experimental evaluation on 7 QA benchmarks, encompassing 4 common medical benchmarks (MedQA (Jin et al., 2021), MedMCQA (Pal et al., 2022), MMLU-Pro (Wang et al., 2024b), and PubMedQA (Jin et al., 2019)), and 3 challenging clinical benchmarks (MedBullets (Chen et al., 2024a), MedXpert (Zuo et al., 2025), and Humanity’s Last Exam (HLE) (Phan et al., 2025)) demonstrate the following key benefits of our generated CoT data: First, supervised fine-tuning (SFT) with our data yields consistent performance improvements across diverse base models and benchmarks. Notably, it enhances both instruction-tuned LLMs (Tab. 2) and specialized medical reasoning models (Tab. 3), with our best model achieving state-of-the-art performance among 7-8B parameter LLMs on challenging clinical benchmarks (Tab. 4 and Fig. 1). Second, MedReason produces higher-quality medical reasoning through knowledge-graph grounded generation, outperforming existing datasets (Chen et al., 2024b) in both automated metrics (Tab. 2) and expert evaluations conducted by physicians across seven clinical specialties (Fig. 5). Third, our approach enables superior clinical utility, as evidenced by side-by-side comparisons showing our model generates more factually precise and clinically supportive reasoning chains than competing approaches (Fig. 2 and Fig. 4).

## 2 Related Works

**Reasoning with knowledge in LLMs.** Recent reasoning large language models (LLMs) have demonstrated impressive performance in the math and coding domains (Guo et al., 2025; Team et al., 2025; Jaech et al., 2024; Li et al., 2025), prompting the need for analogous development in the medical domain (Goh et al., 2024; Lucas et al., 2024). However, training these models typically requires vast amounts of high-quality data that include intermediate reasoning steps (Shao et al., 2024; Guo et al., 2025). Since manually annotating such data is not scalable, they are often distilled from more powerful LLMs. This distillation process introduces unique challenges for tasks that demand factual knowledge, as LLMs can prone to generating hallucinations (Huang et al., 2023). This issue is even more pronounced in the medical domain, where even state-of-the-art LLMs struggle to provide high-quality and accurate reasoning (Griot et al., 2025; Chen et al., 2024c; Patel et al., 2005). To address these challenges, this work introduces MedReason, a medical reasoning dataset with high-quality CoT data designed to elicit factual-based and interpretable medical reasoning within LLMs.

**LLM-Distilled Medical Datasets.** Pre-training and fine-tuning medical LLMs demand extensive and high-quality datasets. Earlier research has primarily focused on gathering instruction-tuning data to imbue general domain LLMs with medical expertise (Xie et al., 2024a; Li et al., 2023). Recently, to improve the medical reasoning capability of LLMs, Chen et al. (2024b) introduced a medical CoT dataset by leveraging GPT-4o (Hurst et al., 2024) for



**Figure 3: Overview of Our Data Generation Pipeline.** We first extract and map entities within each medical Q&A pair, (see Sec. 3.1.1). Next, we search and prune the reasoning paths between Q&A entities in the KG (see Sec. 3.1.2), which are utilized as factual guidance to construct the CoT data(see Sec. 3.2). Finally, we discard any generated CoT that can not lead to reach the correct answer to ensure the quality of our data (see Sec. 3.2).

strategy-based retrieval, which yielded 20K question-answer pairs with complex CoT data. However, directly employing general domain LLMs to generate CoT data poses challenges in maintaining the integrity of medical knowledge at every reasoning step. Inspired by Xie et al. (2024c), which obtains dependable information to assist in producing multigranular captions for medical images, our work employs a medical knowledge graph Chandak et al. (2023) to provide factual guidance during the generation of medical CoT data.

### 3 Method

#### 3.1 Retrieving Reasoning Paths from Knowledge Graph

In this section, we detail the process of retrieving reasoning paths from the knowledge graph (KG). In the data generation process, we define the Language Model as  $LLM$  and the knowledge graph as  $G$ . We utilize OpenAI GPT-4o (Hurst et al., 2024) as  $LLM$  and employ PrimeKG (Chandak et al., 2023) as our knowledge base.

##### 3.1.1 Medical Entity Extraction and Mapping

As shown in Fig. 3 (b), given a question  $Q$  and its corresponding answer  $A$ , we first utilize the Language Model  $LLM$  to identify the medical entities present in  $Q$  and  $A$ . This results in the extracted entity sets  $\{e_i^Q\}_{i \in [n]}$  and  $\{e_j^A\}_{j \in [m]}$ , where  $n$  and  $m$  denote the number of entities in  $Q$  and  $A$ , respectively. These entities are then mapped to the corresponding nodes in the knowledge graph  $G$  through a three-step mapping process, as shown in Fig 3 (a). First, a text embedding model is used to encode each entity  $e \in E$  and compute its similarity with the node embeddings in the  $G$ . This generates a ranked list of candidate matches, from which we then extract the Top- $K$  most similar entities to form a candidate set  $S$ . Thirdly, we select the final entity from the Top- $K$  entities, following the three matching stages:

**Stage 1 (Exact Match):** The algorithm iterates over  $S$  and checks for an exact match with  $e$ . If an exact match is found  $e \in S$ , the corresponding node is selected.

**Stage 2 (Similarity Match):** If an exact match is not found and the top similarity score exceeds a predefined threshold  $\tau$  (set to 0.85 in our case), the most similar entity from  $S$  is selected.

$$\hat{e} = \arg \max_{s_k \in S} \cos(e, s_k), \text{ if } \cos(e, s_k) > \tau \quad (1)$$

**Stage 3 (LLM-based Selection):** If no suitable candidate is found in the above two stages, we instruct the LLM to analyze the question-answer context and the entity name to determine the most relevant node from  $S$ . The selection prompt  $I_{\text{select}}$  is demonstrated in Fig. 7 in the Appendix.

$$\hat{e} = LLM(S, Q, A | I_{\text{select}}), \quad (2)$$

Finally, we derive mapped entity sets from the graph, denoted as  $\{\hat{e}_i^Q\}_{i \in [n]}$  and  $\{\hat{e}_j^A\}_{j \in [m]}$ , respectively. We detail the algorithm in Appendix Algorithm 1. As illustrated in Fig. 3(b), besides the entities *difficulty walking* and *broad-based gait* which exactly match graph nodes, the entity *bilateral optic disc swelling* is mapped to a similar concept, *Abnormality of the optic disc*, in the knowledge graph.

### 3.1.2 Paths Searching and Pruning

Given the mapped entities  $\{\hat{e}_i^Q\}_{i \in [n]}$  from the question and  $\{\hat{e}_j^A\}_{j \in [m]}$  from the answer, our goal is to identify reasoning paths that logically connect the question to its corresponding answer. These paths will later serve as guidance for CoT generation (Sec. 3.2), ensuring that every reasoning step (1) originates from authoritative medical knowledge, and (2) maintains factual consistency with the KG. Specifically, we determine the shortest paths to avoid overthinking (Luo et al., 2025; Chen et al., 2024d) and maintain concise reasoning for each pair of question-answer entities  $\{\hat{e}_i^Q, \hat{e}_j^A\}$ , which identify the most immediate correlations.

This set of shortest paths for the node pair is represented as  $\tilde{P}_{i,j}$ . We demonstrate examples of paths in Fig. 3 (b), where the entities in question (blue nodes) are connected to the answer entity (red node). However, there may be a significant number of paths of the same length linking  $\hat{e}_i^Q$  to  $\hat{e}_j^A$  within the KG  $G$ . To ensure that we can retrieve the reasoning paths that are correlated to our question, we employ the LLM to prune the irrelevant paths as shown in Fig. 3 (a). In particular, we provide the shortest paths set  $\tilde{P}_{i,j}$  and the question  $Q$  to the LLM, which is prompted to select  $K$  paths that are most correlated to the question. In summary, for the node pair  $\{\hat{e}_i^Q, \hat{e}_j^A\}$ , the reasoning paths searching and filtering process is denoted as:

$$\begin{aligned} \{\tilde{P}_{i,j}^k\}_{k \in [K]} &= \text{shortest\_paths}(\hat{e}_i^Q, \hat{e}_j^A, G), \\ P_{i,j}^k &= LLM(\tilde{P}_{i,j}^k, Q | I_{\text{prune}}), \quad k \in [K] \end{aligned} \quad (3)$$

where  $I_{\text{prune}}$  is the path pruning prompt, and we set  $K = 3$  during data generation. More details can be found in Appendix Fig. 8. Finally, we aggregate all identified reasoning paths across the question-answer pairs, forming the complete set  $\mathcal{P} = \{P_{i,j}^k\}_{i \in [n], j \in [m], k \in [K]}$ , for CoT generation. As illustrated in Fig. 3 (b), we explore various reasoning paths that connect question and answer entities within the corresponding subgraph of the KG. After filtering out the irrelevant paths, the pruned paths effectively identify the link between symptoms like ‘Difficulty walking’ and the diagnosis ‘Medulloblastoma’, uncovering the critical intermediary disease ‘Ataxia’.

## 3.2 CoT Generation and Quality Filtering

**CoT Generation with Reasoning Paths** Utilizing step-by-step reasoning paths in  $\mathcal{P}$  as guidance, we are able to distill the reliable knowledge from the off-the-shelf KG into our CoT data. To achieve this, we prompt the LLM to analyze the given reasoning paths and elaborate on the relevant ones to formulate medically grounded CoT explanations of the response, represented as:

$$C = LLM(Q, A, \mathcal{P} | I_{\text{gen}}), \quad (4)$$

where  $I_{\text{gen}}$  represents our carefully designed generation prompt (see Appendix Fig. 9). As illustrated in Fig. 3b, our approach produces clinically grounded reasoning chains - for instance, beginning with symptom analysis, progressing through pathological deduction (e.g., tumor identification), and ultimately concluding the final diagnosis. Each step maintains direct alignment with the KG-derived evidence in  $\mathcal{P}$ , ensuring both factual accuracy and clinical relevance.

**Quality Filtering** Lastly, to ensure the quality of the generated data, we design a simple quality filtering strategy to filter out low-quality CoT data. Specifically, for each generated CoT  $C$ , we prompt the LLM to produce an answer  $\hat{A}$  using *only* the information contained in  $C$  (see details in Appendix Fig. 10). The answer generation process can be denoted as:

$$\hat{A} = \text{LLM}(Q, C | I_{\text{eval}}), \quad (5)$$

where  $I_{\text{eval}}$  denotes the prompt for generation. Subsequently, as illustrated in Fig. 3 (a), we compare  $\hat{A}$  with the original ground-truth answer  $A$ . We apply this quality filtering strategy to all 45K generated samples, retaining only those CoT instances (32K) that yield correct answers, to ensure both logical validity and factual accuracy in our final dataset.

## 4 Experiment

### 4.1 Experimental Setup

**Data Collection and Preprocessing.** Our data pipeline generates CoT reasoning for Question-Answering (QA) pairs. To curate medical QA pairs, we gather datasets such as MedQA (Jin et al., 2021), MedMCQA (Pal et al., 2022), PubmedQA (Jin et al., 2019), MMLU (Hendrycks et al., 2020), HuatuoGPT-o1 (Chen et al., 2024b), MedXpert (Zuo et al., 2025), and Humanity’s Last Exam (HLE) (Phan et al., 2025). To prevent data leakage, we exclusively use the training set from each dataset for CoT data generation, culminating in a total of 55K QA pairs. We exclude the QA pairs that cannot produce CoT data using our pipeline due to the absence of entities in either the question or answer, such as when the answer is merely a number, ultimately leading to 45K QA pairs for CoT data generation. Additional statistics for the generated and quality-filtered datasets are provided in Table 6 in the Appendix.

**Baseline Models.** To evaluate the effectiveness of our dataset across various base models, we select multiple 7-8B models as baselines and conduct supervised fine-tuning (SFT) on MedReason. Specifically, we fine-tune two representative instruction-tuned models: LLaMA 3.1-Instruct-8B (Grattafiori et al., 2024) and Mistral-Instruct-7B (Jiang et al., 2023). Following (Chen et al., 2024b), we train these models for three epochs using a learning rate of 5e-6 and a batch size of 128, employing DeepSpeed-ZeRO stage 3 (Rajbhandari et al., 2020). To further assess the impact of our dataset on reasoning models, we also fine-tune Medical-CoT-8B (Karataş, 2025), DeepSeek-Distill-8B Guo et al. (2025), and Huatuo-o1-RL-8B (Chen et al., 2024b) using the same hyperparameter settings.

Finally, in Tab. 4, we benchmark our model against three categories of models: (1) General LLMs, including LLaMA 3.1-Instruct-8B (Grattafiori et al., 2024), Mistral-Instruct-7B (Jiang et al., 2023), and Qwen-Instruct-7B (Yang et al., 2024); (2) Medical-Specific LLMs, such as Medical-Llama (Qiu et al., 2024), OpenBiLLM (Ankit Pal, 2024), Huatuo-o1-SFT (Huang et al., 2024), and BioMistral Labrak et al. (2024); and (3) Medical Reasoning Models, including Medical-CoT (Karataş, 2025) and Huatuo-o1-RL (Huang et al., 2024).

**Benchmarks.** We evaluate on standard medical benchmarks: MedQA (USMLE test set) (Jin et al., 2021), MedMCQA (validation set) (Pal et al., 2022), health and biology tracks of MMLU-Pro (Wang et al., 2024b), and PubMedQA (test set) (Jin et al., 2019). Additionally, we evaluated the medical sections of some challenging LLM benchmarks, including the clinical expertise benchmark MedBullets (Chen et al., 2024a), expert-level medical knowledge and advanced reasoning MedXpert (Zuo et al., 2025), and the most recent medical questions in Humanity’s Last Exam (HLE) (Phan et al., 2025).

### 4.2 Results

**MedReason on Instruction Fine-tuned Model.** In this section, we showcase the enhancement of Instruction Finetuned Models using MedReason. Tab. 2 displays the accuracy (%) of Llama3.1-Instruct-8B and Mistral-Instruct-7B across various medical benchmarks. The

Benchmarks	Llama3.1-Instruct-8B			Mistral-Instruct-7B		
	original	w/ huatuo CoT	w/ ours	original	w/ huatuo CoT	w/ ours
MedQA	58.7	<b>70.2 (+11.5)</b>	68.4 ( <b>+9.7</b> )	48.2	<b>59.9 (+11.7)</b>	58.7 ( <b>+10.5</b> )
MedMCQA	56.0	<b>58.2 (+2.2)</b>	57.5 ( <b>+1.5</b> )	44.9	46.9 ( <b>+2.0</b> )	<b>48.9 (+4.0)</b>
PubmedQA	75.2	76.1 ( <b>+0.9</b> )	<b>77.6 (+2.4)</b>	50.1	57.5 ( <b>+7.4</b> )	<b>59.2 (+9.1)</b>
MMLU-Pro	58.2	59.9 ( <b>+1.7</b> )	<b>63.1 (+4.9)</b>	42.7	47.6 ( <b>+4.9</b> )	<b>50.8 (+8.1)</b>
MedBullets(op4)	48.7	53.3 ( <b>+4.6</b> )	<b>57.5 (+8.8)</b>	43.5	50.0 ( <b>+6.5</b> )	<b>52.3 (+8.8)</b>
MedBullets(op5)	42.5	49.7 ( <b>+7.2</b> )	<b>52.3 (+9.8)</b>	33.4	46.1 ( <b>+12.7</b> )	<b>47.1 (+13.7)</b>
MedXpert	13.2	<b>17.3 (+4.1)</b>	16.4 ( <b>+3.2</b> )	11.4	14.4 ( <b>+3.0</b> )	<b>16.6 (+5.2)</b>
HLE (med)	13.6	14.6 ( <b>+1.0</b> )	<b>16.5 (+2.9)</b>	14.6	14.6 ( <b>+0.0</b> )	<b>24.3 (+9.7)</b>
Avg	45.8	49.9 ( <b>+4.1</b> )	<b>51.2 (+5.4)</b>	36.1	42.1 ( <b>+6.0</b> )	<b>44.7 (+8.6)</b>

Table 2: **Results of instruction-tuned LLMs fine-tuned with Huatuo complex CoT and MedReason (Ours).** Integrating our high-quality reasoning data into supervised fine-tuning significantly improves model performance across various benchmarks and model types.

Base Model	Data	Clinical Challenging Datasets				
		MedBullets(op4)	MedBullets(op5)	MedXpert	HLE (med)	Avg
Medical-CoT-8B	original	39.3	34.1	12.6	15.5	25.4
	w/ ours	<b>49.0 (+9.7)</b>	<b>41.9 (+7.8)</b>	<b>14.2 (+1.6)</b>	<b>17.5 (+2.0)</b>	<b>30.6 (+5.3)</b>
DeepSeek-Distill-8B	original	41.9	35.1	13.5	11.7	25.5
	w/ ours	<b>53.6 (+11.7)</b>	<b>49.0 (+14.0)</b>	<b>15.9 (+2.4)</b>	<b>14.6 (+2.9)</b>	<b>33.3 (+7.7)</b>
Base Model	Data	Common MedicalQA Datasets				
		MedQA	MedMCQA	PubmedQA	MMLU-Pro	Avg
Medical-CoT-8B	original	49.0	42.6	68.0	48.7	52.1
	w/ ours	<b>58.0 (+9.0)</b>	<b>46.6 (+4.0)</b>	<b>74.6 (+6.6)</b>	<b>50.4 (+1.7)</b>	<b>57.4 (+5.3)</b>
DeepSeek-Distill-8B	original	55.4	49.0	73.9	53.8	58.0
	w/ ours	<b>63.7 (+8.3)</b>	<b>51.8 (+2.8)</b>	<b>73.0 (-0.9)</b>	<b>57.5 (+3.8)</b>	<b>61.5 (+3.5)</b>

Table 3: **Fine-tuning with our data further enhances reasoning LLMs.** We perform supervised fine-tuning on reasoning models in both general and medical domains, with our data consistently improving performance by providing high-quality medical knowledge.

model finetuned on MedReason (**w/ ours**) consistently outperforms both the base models and the Huatuo CoT data (Chen et al., 2024b) finetuned model.

For Llama3.1-Instruct-8B, finetuning using MedReason improves the average accuracy from **45.8%** to **51.2% (+5.4%)**, surpassing the **+4.1%** gain achieved with Huatuo CoT data. In the case of Mistral-Instruct-7B, the improvement is even more substantial, rising from **36.1%** to **44.7% (+8.6%)**, exceeding Huatuo CoT data’s **+6.0%** gain. Our method demonstrates consistent and substantial improvements, particularly in complex reasoning tasks (HLE) and specialized clinical benchmarks (MedBullets, MedXpert).

**MedReason on Reasoning Models.** We then showcase the improvements in reasoning models achieved through fine-tuning with our MedReason dataset. As shown in Tab. 3, fine-tuning with our dataset (**w/ ours**) significantly enhances performance across both clinical and general medical question-answering tasks compared to the original model without fine-tuning. On challenging clinical datasets, Medical-CoT-8B achieves an average gain of 5.3%, while DeepSeek-Distill-8B demonstrates an even greater improvement of 7.7%. Similarly, for general medical QA datasets, Medical-CoT-8B improves by 5.3% on average, and DeepSeek-Distill-8B gains 3.5%. These results highlight the effectiveness of our KG-driven dataset MedReason in enhancing reasoning LLMs by integrating factual guided medical knowledge.

**MedReason achieves state-of-the-art on 7B-8B LLMs.** Finally, we obtain the state-of-the-art model by fine-tuning Huatuo-o1-RL-8B with MedReason, denoting it as MedReason-8B. The results in Tab. 4 show that MedReason-8B, fine-tuned using MedReason, outperforms all other models across five evaluation datasets, achieving the highest average score of **57.3%**. It surpasses its base model, Huatuo-o1-RL-8B, by 1.4%, demonstrating the effectiveness of

Model	MedBullets (op4)	MedBullets (op5)	MedXpert	MedQA	MedMCQA	PubmedQA	Avg
Llama3.1-Instruct-8B	43.2	40.9	14.3	58.7	56.0	75.2	48.0
Qwen2.5-Instruct-7B	50.0	41.6	12.6	57.0	55.6	72.7	48.2
Mistral-Instruct-7B	43.5	33.4	11.4	48.2	44.9	50.1	38.6
Medical-Llama3-8B	33.4	25.3	9.0	40.3	46.8	48.0	33.8
OpenBioLLM-8B	39.2	35.7	10.7	57.7	54.1	74.1	45.3
BioMistral-7B	46.4	33.1	12.4	45.0	40.2	66.9	40.7
Medical-CoT-8B	39.3	34.1	12.6	49.0	42.6	68.0	40.9
DeepSeek-Distill-8B	41.9	35.1	13.5	55.4	49.0	73.9	44.8
Huatuo-o1-SFT-8B	53.3	49.7	17.3	70.2	58.2	76.1	54.1
Huatuo-o1-RL-8B	55.2	51.3	16.7	72.6	60.4	79.2	55.9
MedReason-8B (ours)	<b>57.5</b>	<b>55.5</b>	<b>19.0</b>	71.8	<b>60.7</b>	<b>79.4</b>	<b>57.3</b>

Table 4: **Comparison across various medical benchmarks.** Our best model achieves state-of-the-art performance comparing with 7B-8B LLMs.

Quality Filtering	MedQA	MedMCQA	PubmedQA	MedBullets (op4)	MedBullets (op5)	MedXpert	Avg
w/o	0.669	0.569	0.737	0.571	0.510	<b>0.178</b>	0.539
w/	<b>0.684</b>	<b>0.575</b>	<b>0.776</b>	<b>0.575</b>	<b>0.523</b>	0.164	<b>0.550</b>

Table 5: **The ablation study on quality filtering.** The results demonstrate that maintaining high-quality (correct) generated CoT consistently enhanced overall performance.

MedReason fine-tuning. Notably, it demonstrates even greater improvements on challenging reasoning tasks, outperforming Huatuo-o1-RL-8B by 4.2% on MedBullets (op5) and 2.3% on MedXpert. Compared to other strong baselines, such as OpenBioLLM-8B and DeepSeek-Distill-8B, MedReason-8B demonstrates substantial performance gains of approximately 12%. These results confirm that our KG-guided CoT data enhances reasoning capabilities, establishing a new state-of-the-art for medical QA tasks.

### 4.3 Ablation Study and Expert Verification

**Effect of Quality Filtering.** As outlined in Section 3.2, we implement quality filtering to ensure the generated CoT data effectively guides a LLM to produce correct answers. To evaluate its impact, we perform an ablation study using the LLama3.1-Instruct-8B model. Table 5 illustrates that quality filtering enhances performance across the majority of medical datasets, enhancing the average score by 1.1%. This further underscores the crucial role of CoT data quality in enhancing the reasoning capabilities of LLMs in medical applications.

**CoT Case study.** To showcase the effectiveness of our dataset, we analyze a challenging medical case from MedBullets, comparing its performance against two other reasoning models—DeepSeek-distilled and HuatuoGPT-o1—in Fig. 4. Our dataset accurately diagnosed Cri-du-Chat syndrome, linking the patient’s symptoms to a chromosome 5p deletion, consistent with the ground-truth answer, thus validating its reasoning precision. In contrast, DeepSeek-distilled model frequently responded with *I’m not sure*, as indicated by the yellow shadow in Fig. 4, reflecting uncertainty and a lack of clarity, which makes it unsuitable for assisting doctors. While HuatuoGPT-o1 provided a more confident response, it relied on incorrect knowledge, as indicated by the red shadow, leading to an inaccurate diagnosis.

**Expert Verification.** To further evaluate the medical accuracy and clarity of CoT data within MedReason, we engaged domain experts from seven different medical specialties. Each expert was given two anonymized CoT data—one produced by MedReason and the other by HuatuoGPT-o1—and asked to choose which explanation, if any, was more accurate and easier to understand. Experts could also skip if they found both CoT data to be equally good or equally inadequate. For each specialty, we evaluated responses to over 25 randomly sampled questions.

Fig. 5 presents the results, illustrating the proportion of high-quality CoT data sources verified by licensed clinicians. As shown, specialists across all departments preferred MedReason,

**Clinical Scenario:** A newborn boy is evaluated in the hospital nursery 2 hours after birth... The patient's mother received routine prenatal care and the pregnancy was uncomplicated. The patient's birth weight is 2.6 kg (5 lb 11 oz), which is at the 5th percentile. His height and head circumference are in the 15th and 3rd percentile, respectively. His temperature is 97.1°F (36.2°C), blood pressure is 57/42 mmHg, pulse is 140/min, and respirations are 38/min. On physical exam, the patient has a wide nasal bridge, down slanting palpebral fissures, and widely spaced eyes. He has good respiratory effort with a high-pitched cry. This patient is most likely to have experienced a deletion on which of the following chromosomes?

**Options:** (A) 4p; (B) 5p; (C) 5q; (D) 7q; (E) 15q.

**Ground-truth Answer:** 5p

Sample from [Medbullets]

DeepSeek-distilled Qwen	HuatuoGPT-o1	Our Model
Uncertain Reasoning	Inaccurate Knowledge	Accurate Reasoning
Okay, so I have this medical case to solve... He has good respiratory effort with a high-pitched cry. The cry can sometimes be a clue, but I'm not sure. High-pitched cry is sometimes associated with conditions like croup or maybe something else, but I'm not sure how that ties into the genetic aspect. ... Or maybe 7q, which can cause a wide deletion on chromosome 7. So, that's a big bridge of the nose. Alternatively, 5p deletions can cause a phenotype with a triangular face, short stature, and maybe some heart issues. But I'm not sure about the facial features. ... In summary, the facial features point towards 7q deletion.	Alright, let's think this through. We've got a newborn boy here, and he's showing some distinct physical features. He's got a wide nasal bridge, down-slanting eyes, and widely spaced eyes. ... Oh right, Williams syndrome! That's the one. People with Williams syndrome often have these facial features, and it's usually linked to a deletion on chromosome 7. So, that's a big clue ... And chromosome 5p is associated with Cri-du-chat syndrome, which has a unique cat-like cry, but this baby's cry is described as high-pitched, not like a cat. So that's not it either. ... I'm pretty confident that the answer is chromosome 7q.	<b>Finding Reasoning Paths:</b> 1. ... 2. ... 3. Dysmorphic features are characteristic of certain chromosomal deletions, such as 5p deletion syndrome (cri-du-chat syndrome). 4. High-pitched cry is a hallmark of cri-du-chat syndrome, which is associated with a deletion on chromosome 5p. <b>Reasoning Process:</b> ... <b>Exclusion of Other Syndromes:</b> - Prader-Willi syndrome and Angelman syndrome are associated with deletions on chromosome 15q11-q13, but they do not present with a high-pitched cry, or the specific dysmorphic features seen in this patient. <b>Conclusion:</b> The most likely diagnosis for this patient is Cri-du-chat syndrome, which is associated with a deletion on chromosome 5p.

Figure 4: Case Study on Medbullets Benchmark. Some part of reasoning is omitted due to the space limitation. Our model generates accurate reasoning with reliable knowledge.

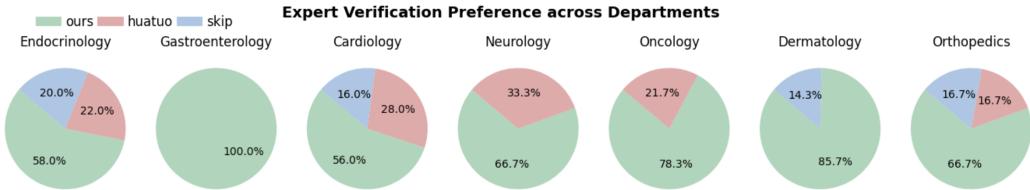


Figure 5: **Expert verification on CoT data quality** across seven medical specialties. Doctors were shown CoT data from both our dataset (green) and Huatuo-Complex CoT (red) and asked to pick the higher-quality explanation or skip (blue) if neither was clearly superior. Each pie indicates the proportion of doctors in that specialty who selected our data, Huatuo-Complex CoT, or skipped. Our CoT data was consistently favored across all the specialties.

with Gastroenterology experts unanimously selecting MedReason (100%), and Dermatology and Oncology also demonstrated a strong preference (over 80%). These findings suggest that MedReason consistently provides more medically precise and coherent reasoning across multiple specialties, underscoring its potential for real-world clinical applications.

## 5 Conclusion

This paper presents a scalable, knowledge-guided pipeline for automatically generating high-quality medical Chain-of-Thought (CoT) data. By leveraging structured knowledge graphs to anchor the reasoning process, our method produces medically grounded and interpretable explanations that enhance the clinical validity of LLM-generated reasoning. Experiments on instruction-tuned and reasoning-specialized LLMs demonstrate consistent improvements across medical benchmarks, particularly in complex clinical scenarios, while expert evaluations confirm superior reasoning quality over prior methods. We hope our work can encourage future exploration on clinically valid reasoning to advance trustworthy medical AI.

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## A Appendix

### A.1 OpenAI API Usage

In this work, we employ GPT-4o from Azure in our data generation pipeline. The version for GPT-4o is 'gpt-4o-0806-nofilter-global', and the API version is '2024-12-01-preview'. Total API usage is about \$3,600.

### A.2 Data Statistics

The following table demonstrates the specification of the data distribution of MedReason across various source datasets. In the case of Humanity's Last Exam (HLE) (Phan et al., 2025) and MedXpert (Zuo et al., 2025), we allocated 57 and 666 data samples, respectively, for training and reserved the rest for testing. For other datasets, we strictly use only the training data for data generation to avoid any potential data leakage.

Datasets	MedQA	MedMCQA	PubmedQA	MMLU	MedXpert	Huatuo	HLE	Total
Raw	9595	9131	24826	1089	1000	9271	159	55071
Generated	8528	7598	20613	893	951	7010	132	45725
Quality Filtered	8016	6197	10444	827	666	6475	57	32682

Table 6: **Statistics of the collected QA dataset (Raw), Generated dataset, and final Quality-Filtered dataset.**

### A.3 Prompts

The prompts used in our data generation pipeline are shown in the following figures. We provide details about prompts for (a) identifying entities in the question and answer (Fig. 6), (b) selecting the most relevant nodes for extracted entities (Fig. 7), (c) pruning irrelevant paths (Fig. 8), (d) CoT data generation with paths (Fig. 9), and (e) generating the answer based on provided CoT data for quality filtering (Fig. 10).

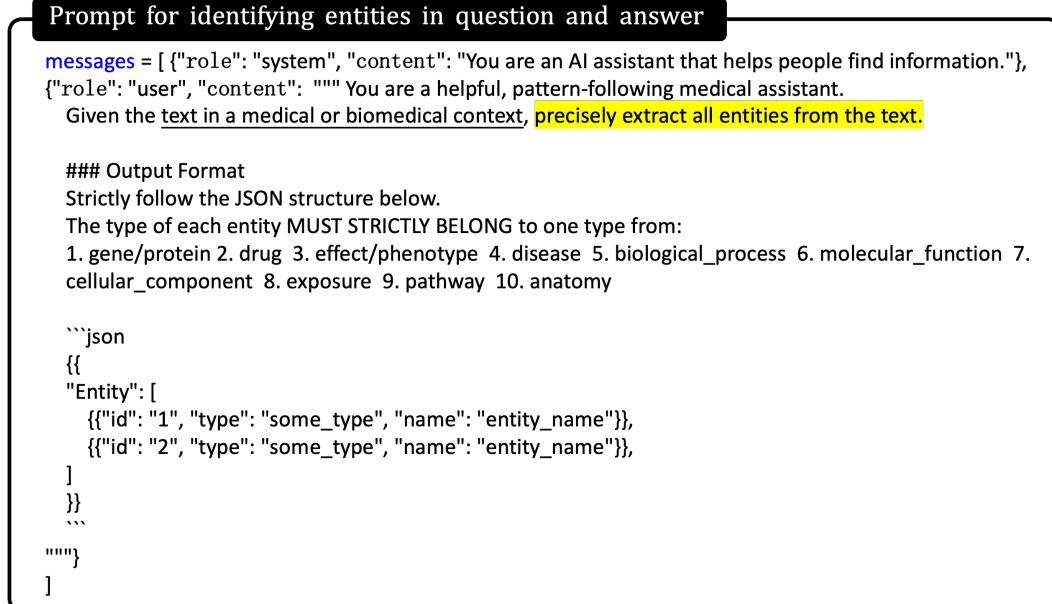


Figure 6: Prompt for identifying entities in the question and answer.

**Prompt for finding most related node entity**

```

messages = [ {"role": "system", "content": "You are an AI assistant that helps people find information."}, {"role": "user", "content": "You are a helpful, pattern-following medical assistant."}
Given a medical question and corresponding answer, an query entity which is extracted from the question, and a list of similar entities.
Select ONE most correlated entity from the list of similar entities based on the question and query entity.
SELECTED ENTITY MUST BE IN THE SIMILAR ENTITIES.
If there is not suitable entity in the similar entities, directly return the NONE.

### Output Format
Strictly follow the JSON structure below:
```json
{
  "selected_entity": {
    "name": "selected_entity_name",
    "id": "a int number, the index of the selected entity in the similar entities list, from 0 to N-1",
    "reason": "reason for choosing this entity"
  }
}
```
]

```

Figure 7: Prompt for selecting the most relevant nodes for extracted entities.

**Prompt for pruning irrelevant paths**

```

messages = [ {"role": "system", "content": "You are an AI assistant that helps people find information."}, {"role": "user", "content": "You are a helpful, pattern-following medical assistant."}
Given a medical question and possible relation paths that link to the answer.
Select up to {topK} most correlated entity from the relation paths list based on the question and the answer.
If total number of paths is less than {topK}, select all of them.

### Output Format
Strictly follow the JSON structure below.
```json
{
  "Paths": [
    {"ranking": "1", "path": "sample_path_1", "reason": "reason for choosing this path"},
    ....
  ]
}
```
]

```

Figure 8: Prompt for pruning irrelevant paths.

#### A.4 Detailed Algorithm

In algorithm 1, we present our detailed algorithm for entity extraction and mapping, as outlined in Sec. 3.1.1. First, a text embedding model is used to encode each entity  $e \in E$  and compute its similarity with the node embeddings in the  $G$ . This generates a ranked list of candidate matches, from which we then extract the Top- $K$  most similar entities to form

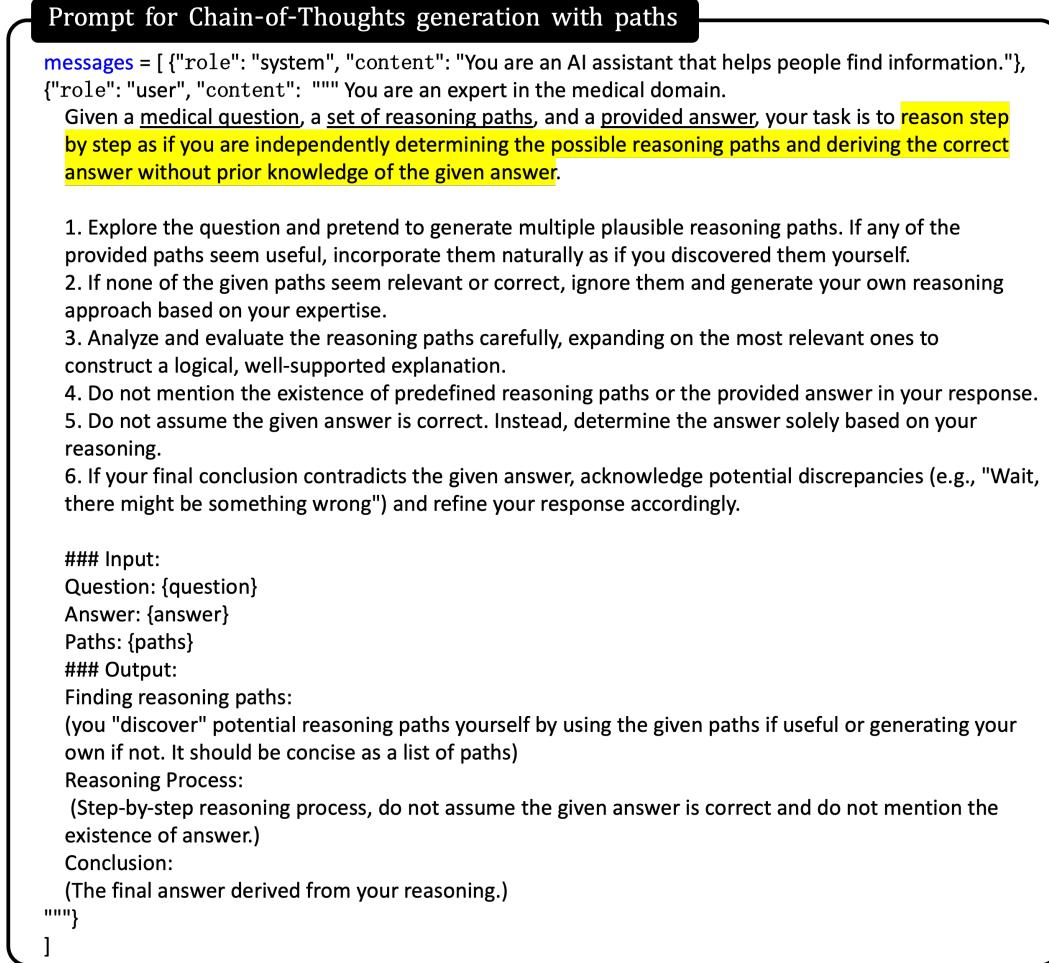


Figure 9: Prompt for Chain-of-Thoughts generation with paths.

a candidate set  $S$ . Thirdly, we select the final entity from the Top- $K$  entities, following the three matching stages:

**Stage 1 (Exact Match):** The algorithm iterates over  $S$  and checks for an exact match with  $e$ . If an exact match is found  $e \in S$ , the corresponding node is selected.

**Stage 2 (Similarity Match):** If an exact match is not found and the top similarity score exceeds a predefined threshold  $\tau$  (set to 0.85 in our case), the most similar entity from  $S$  is selected.

$$\hat{e} = \arg \max_{s_k \in S} \cos(e, s_k), \text{ if } \cos(e, s_k) > \tau \quad (6)$$

**Stage 3 (LLM-based Selection):** If no suitable candidate is found in the above two stages, we instruct the LLM to analyze the question-answer context and the entity name to determine the most relevant node from  $S$ . The selection prompt  $I_{\text{select}}$  is demonstrated in Fig. 7 in the Appendix.

$$\hat{e} = LLM(S, Q, A \mid I_{\text{select}}), \quad (7)$$

Finally, we derive mapped entity sets from the graph, denoted as  $\{\hat{e}_i^Q\}_{i \in [n]}$  and  $\{\hat{e}_j^A\}_{j \in [m]}$ , respectively. As illustrated in Fig. 3, besides the entities *difficulty walking* and *broad-based gait* which exactly match graph nodes, the entity *bilateral optic disc swelling* is mapped to a similar concept, *Abnormality of the optic disc*, in the knowledge graph.

Prompt for generating answer with Chain-of-Thoughts reasoning

```

messages = [{"role": "system", "content": "You are an AI assistant that helps people find information."}, {"role": "user", "content": "You are an expert in the medical domain. You need to answer the following question based on the provided reasoning."}
YOU MUST USE THE PROVIDED REASONING TO ANSWER THE QUESTION.
If the answer choices are provided, please choose ONE answer from the answer choices, ensuring your response concludes with the correct option in the format: 'The answer is A.'\n{question}\n{option_str}
Question:
{question}
{options}
Reasoning:
{reasoning}
"""}]

```

Figure 10: Prompt for generating the answer based on provided CoT data.

**Algorithm 1** Mapping Extracted Entities to Knowledge Graph Nodes

**Require:** Extracted entity set  $\mathcal{E}$  from  $Q$  or  $A$ , Knowledge Graph  $G$ , text embedding model  $f_T$ , similarity threshold  $\tau$ , lower case operation  $\text{lower}$ , prompt instruction  $\mathcal{I}_s$  and LLM function  $f_L$ .

**Ensure:** Mapped knowledge graph nodes for each entity in  $\mathcal{E}$

```

1: for each entity  $e$  in  $E$  do
2:    $S \leftarrow \text{get\_similar\_entities}(e, G, f_T)$ 
3:    $s_{\text{top}} \leftarrow \text{top\_similarity}(S)$ 
4:   selected  $\leftarrow \text{None}$ 
5:   for each candidate  $c$  in  $S$  do                                 $\triangleright$  Stage 1: Exact Match
6:     if  $\text{lower}(e) = \text{lower}(c)$  then
7:       selected  $\leftarrow c$ 
8:       break
9:     end if
10:   end for
11:   if selected = None and  $s_{\text{top}} > \tau$  then           $\triangleright$  Stage 2: Similarity Match
12:     selected  $\leftarrow S[0]$ 
13:   end if
14:   if selected = None then                             $\triangleright$  Stage 3: LLM-based Selection
15:     selected  $\leftarrow f_L(Q, A, e, S | \mathcal{I}_s)$ 
16:   end if
17:   Map  $e$  to node selected  $\hat{e}$ 
18: end for

```

**A.5 Detailed comparison between MedReason-8B and Huatuo-o1-RL-8B.**

In Fig. 11, we present a comprehensive comparison of MedReason-8B and Huatuo-o1-RL-8B in tackling complex clinical issues. Huatuo-o1-RL-8B delivered an incorrect answer due to overlooking the link between vomiting and hyperglycemia, whereas our MedReason-8B accurately identified the correct answer, grounded in factual reasoning.

**Clinical Scenario:** A 32-year-old female with obesity, hypertension, and type 2 diabetes seeks treatment for ongoing hyperglycemia. Her glycated hemoglobin is 7.9% (normal: 4.3–5.6%), and she shows consistent elevated post-meal blood glucose levels without any hypoglycemic episodes. Her current medications include metformin 1000 mg twice daily and lisinopril 5 mg daily, a regimen she has maintained for several years.  
She has developed diabetes-related retinopathy and neuropathy, but her kidney function remains intact. Her symptoms include early fullness after eating, post-meal nausea, and frequent vomiting of undigested food consumed hours earlier. To manage these symptoms, she has adopted a pattern of eating small, frequent meals. She also experiences tingling sensations in both legs.  
Which of the following medication modifications would be most appropriate to improve her blood glucose control?

**Options:** (A) Add acarbose; (B) Add dapagliflozin; (C) Switch to dulaglutide; (D) Add semaglutide;  
(E) Add pioglitazone; (F) Replace metformin with glipizide; (G) Add sitagliptin.

**Ground-truth Answer:** Add dapagliflozin

Sample from [MedXpert]

**HuatuoGPT-o1** Inaccurate Knowledge

## Thinking  
Alright, let's think about this. We've got a 32-year-old woman dealing with obesity, hypertension, and type 2 diabetes. She's been on metformin and lisinopril for a while, but her blood sugar levels are still high, especially after meals. She's also experiencing some unpleasant symptoms like feeling full quickly, nausea, and vomiting after eating, which makes sense because those are classic signs of gastroparesis. Oh, and she's got tingling in her legs, which could be related to her diabetes.  
Now, what do we do about her blood sugar? We need something that works well with her current meds and helps with her symptoms. Metformin is doing its job, but it's not enough on its own. We need to add something that targets post-meal spikes and helps with her symptoms. Hmm, what about acarbose? It's known for slowing down the digestion of carbs, which should help with the nausea and vomiting by giving her stomach more time to process food. Plus, it's designed to tackle those pesky post-meal glucose spikes.  
Let's think about the other options. Dapagliflozin and empagliflozin are SGLT2 inhibitors, which are great for lowering blood sugar but don't really address the nausea and vomiting. Dulaglutide, semaglutide, and liraglutide are GLP-1 receptor agonists, which can help with blood sugar and weight, but they might make nausea worse. Pioglitazone is more for improving insulin sensitivity, not really for nausea. And then there's glimepiride and sitagliptin, which are sulfonylureas and DPP-4 inhibitors, respectively. They work on increasing insulin but don't help with gastroparesis symptoms.  
So, acarbose seems like the best fit here. It's designed for situations just like hers, where you've got high blood sugar and symptoms of gastroparesis. It's a good match because it can help manage her symptoms and improve her blood sugar control without making her feel worse. Yeah, adding acarbose makes the most sense.  
## Final Response  
**The answer is A.**

**Our Model** Accurate Reasoning

**Finding Reasoning Paths:** ### Finding Reasoning Paths:  
1. \*\*Hyperglycemia and Type 2 Diabetes\*\*: The patient has chronic hyperglycemia and type 2 diabetes, managed with metformin and lisinopril. Additional glucose control measures are needed.  
2. \*\*Retinopathy and Neuropathy\*\*: These are complications of diabetes, which are not directly related to blood glucose control but may necessitate a more aggressive glucose management strategy.  
3. \*\*Frequent Symptoms of Hyperglycemia\*\*: Post-meal nausea, vomiting, and early fullness suggest poor glucose control, possibly due to inadequate insulin or medications.  
4. \*\*Lipid Profile\*\*: A high LDL cholesterol and low HDL cholesterol indicate metabolic derangement, which may require additional medications to improve lipid control.  
5. \*\*Tingling in Legs\*\*: This could be due to neuropathy or other complications, but it is not directly linked to blood glucose management.  
6. \*\*Medication Options\*\*: The patient is already on metformin and lisinopril. Additional medications targeting glucose metabolism or insulin secretion may be considered.  
## Reasoning Process:  
1. \*\*Current Glucose Control\*\*: The patient's glycated hemoglobin is 7.9%, which is significantly elevated. Metformin and lisinopril are her current medications. Metformin is effective for hyperglycemia but may not be sufficient in cases of advanced diabetes or when combined with other complications like retinopathy and neuropathy.  
2. \*\*Symptoms of Hyperglycemia\*\*: The symptoms of post-meal nausea, vomiting, and early fullness are classic for poorly controlled hyperglycemia. These symptoms suggest that her blood glucose levels are not being tightly controlled, possibly due to inadequate insulin or medications.  
3. \*\*Treatments for Hyperglycemia\*\*: To improve blood glucose control, medications targeting insulin secretion, glucose uptake, or insulin resistance may be considered. Examples include sulfonylureas, DPP-4 inhibitors, GLP-1 receptor agonists, and GLP-1 receptor antagonists.  
4. \*\*DPP-4 Inhibitors (e.g., dapagliflozin)\*\*: These medications improve insulin secretion and glucose uptake, which can help control hyperglycemia. They are often used in diabetic patients with retinopathy and neuropathy.  
5. \*\*GLP-1 Receptor Antagonists (e.g., semaglutide)\*\*: These medications inhibit GLP-1 secretion, promoting insulin secretion and glucose uptake. They are particularly effective in patients with advanced diabetes and retinopathy.  
6. \*\*GLP-1 Receptor Agonists (e.g., sitagliptin)\*\*: These medications stimulate GLP-1 secretion, which can help lower blood glucose levels but are less commonly used in advanced diabetes.  
7. \*\*Sulfonylureas (e.g., glimepiride, glipizide)\*\*: These medications stimulate insulin secretion and are often used in diabetic patients. However, they are generally considered less effective in advanced diabetes compared to DPP-4 inhibitors or GLP-1 receptor antagonists.  
## Conclusion:  
The most appropriate medication modification to improve her blood glucose control is \*\*to add dapagliflozin\*\*. This treatment targets insulin secretion and glucose uptake, addressing the symptoms of poorly controlled hyperglycemia and supporting her overall glucose management.  
## Final Answer  
**(B) Add dapagliflozin**

Figure 11: Full comparison between MedReason-8B and Huatuo-o1-RL-8B.