

# Plug-and-Play Medical Dialogue System

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## Abstract

Medical dialogue systems aim to provide accurate answers to patients, necessitating specific domain knowledge. Recent advancements in Large Language Models (LLMs) have demonstrated their exceptional capabilities in the medical Q&A domain, indicating a rich understanding of common sense. However, LLMs are insufficient for direct diagnosis due to the absence of diagnostic strategies. The conventional approach to address this challenge involves expensive fine-tuning of LLMs. Alternatively, a more appealing solution is the development of a plugin that empowers LLMs to perform medical conversation tasks. Drawing inspiration from in-context learning, we propose PlugMed, a Plug-and-Play Medical Dialogue System that facilitates appropriate dialogue actions by LLMs through two modules: the prompt generation (PG) module and the response ranking (RR) module. The PG module is designed to capture dialogue information from both global and local perspectives. It selects suitable prompts by assessing their similarity to the entire dialogue history and recent utterances grouped by patient symptoms, respectively. Additionally, the RR module incorporates fine-tuned SLMs as response filters and selects appropriate responses generated by LLMs. Moreover, we devise a novel evaluation method based on intent and medical entities matching to assess the efficacy of dialogue strategies in medical conversations more effectively. Experimental evaluations conducted on three unlabeled medical dialogue datasets, including both automatic and manual assessments, demonstrate that our model surpasses the strong fine-tuning baselines.

## Introduction

Medical dialogue generation holds significant potential for reducing diagnostic costs and enhancing medical efficiency. As a specialized form of task-oriented dialogue (TOD), medical dialogue typically involves the completion of multiple tasks, including diagnosis and consultation (Valizadeh and Parde 2022). Prior studies (Li et al. 2021a; Varshney et al. 2023b,a) have emphasized the critical role of domain knowledge in medical conversation generation. Many of these studies have utilized knowledge injection modules to integrate general medical knowledge from knowledge bases into the models. However, with the growing size of models, the problem of knowledge scarcity is being mitigated.

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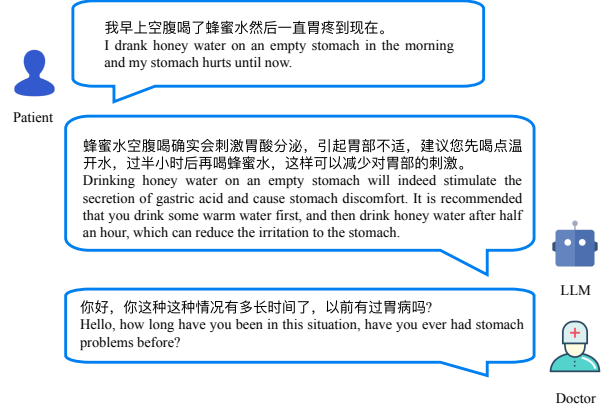


Figure 1: An example of a medical dialogue. For the same question, LLM and doctors adopted different response strategies.

This is evident in the performance of large language models (LLMs) such as Instruct GPT (Ouyang et al. 2022), which outperform small fine-tuning-based models on medical Q&A tasks without any training (Singhal et al. 2022). Based on this success, we believe that LLMs have significant potential for medical dialogue generation.

Despite the extensive domain knowledge possessed by LLMs, they still lack the ability to comprehend diagnostic logic, which can lead to potentially dangerous decisions (Howard, Hope, and Gerada 2023). For instance, as illustrated in Figure (1), when a patient claims to have a particular ailment and requests medication from a doctor, the doctor's priority is to first investigate the underlying disease rather than providing immediate medical advice. In contrast, LLMs tend to offer direct medical advice without gathering the necessary information. This places the burden on patients to possess a precise understanding of their symptoms and conditions, which is often impractical.

To tackle this challenge, the prevailing method involves fine-tuning LLMs using specialized datasets, despite the substantial costs associated with training and maintenance. However, a more enticing solution is to create a plugin that allows LLMs to participate in medical conversations without

requiring extensive training. This can be achieved through the implementation of in-context learning (ICL), which enables the model to learn and adapt dynamically during the dialogue process. Motivated by this concept, we present a Plug-and-Play Medical Dialogue System (PlugMed), which consists of two key components: a prompt generation module and a response ranking module.

In our approach, we have developed the prompt generation (PG) module to capture information from both a global and local perspective, enabling the model to achieve a comprehensive understanding of the dialogue. From a global viewpoint, we leverage the similarity of the entire dialogue history to select relevant examples. This ensures that the model possesses a holistic perspective on the entire dialogue process. On the other hand, from a local perspective, our design focuses on recent utterances to capture the most pertinent information for generating responses and maintaining conversation consistency. To accomplish this, we initially train a medical dialogue summary model that extracts patient symptoms. Subsequently, we construct an example retriever that utilizes a secondary index incorporating symptoms and recent conversation fragments. To further exploit the benefits of both global and local perspectives, we introduce a response ranking (RR) module. This module automatically selects the most suitable response for the ongoing dialogue. Notably, our experimental findings indicate that smaller language models (SLMs) that have fine-tuned on medical dialogue corpora exhibit greater accuracy in generating dialogue intentions than LLMs. Based on this observation, we employ a SLM to filter and identify the most suitable responses among the generated options, ensuring higher quality and relevance in the dialogue generation process.

In the construction of PlugMed, an important aspect is the proposal of appropriate automatic evaluation metrics. Many existing studies on unlabeled datasets have relied on open-domain dialogue evaluation methods, which have proven to be unreliable in task-oriented scenarios (Ji et al. 2023). To gain a better understanding of the system’s real-world performance, we conduct a comprehensive evaluation using two key aspects: intent accuracy and entity accuracy. Intent accuracy corresponds to the dialogue action in traditional task-based dialogue, reflecting whether the adopted strategy by the dialogue system is reasonable. To assess intent accuracy, we train a medical dialogue intent recognition model specifically for this purpose. Entity accuracy focuses on measuring whether the system’s responses contain the necessary medical information. In this regard, we follow and enhance the evaluation method proposed by Li et al. (2021a). However, we discovered that Li’s evaluation metric does not account for the similarity of medical entities, which results in unreasonable evaluations. To address this issue, we propose a new evaluation metric called “Top-n Match,” which is based on synonym similarity matching.

We evaluate our approach on the Meddg, MedDialogue and Kamed datasets. Both automated and manual evaluations show that our model can substantially outperform small models based on fine tuning. Our contributions can be summarized as follows:

- An ICL-based approach enables LLM to generate re-

sponses that conform to the diagnostic strategy.

- A comprehensive evaluation method for medical dialogue automation that can consider both intent accuracy and entity accuracy.
- An thorough experiment to demonstrate key elements of automatic medical diagnosis.

## Related Work

### Medical dialogue systems

Medical dialogue systems can be classified into pipeline and end-to-end systems based on their architecture (Valizadeh and Parde 2022). Pipeline systems typically involve four stages: natural language understanding, dialogue state tracking, dialogue action generation, and natural language generation. Researchers such as Wei et al. (2018); Xia et al. (2020) propose learning dialogue policies for automated diagnosis using reinforcement learning. However, their approaches heavily rely on user simulators, which only simulate a limited range of user actions, thus limiting the scope of application. In another study, Lin et al. (2019) construct a symptom graph to model associations between symptoms, aiming to enhance symptom diagnosis performance. However, these methods rely on comprehensive dialogue annotations. Recognizing the difficulty in collecting high-quality dialogue annotations, Li et al. (2021a) propose a different approach by using symptoms and diseases instead of dialogue states and actions. This allows medical dialogue systems to be trained on large-scale unlabeled datasets, reducing the reliance on dialogue annotations.

In recent years, end-to-end models, often adopting a sequence-to-sequence architecture (Sutskever, Vinyals, and Le 2014), have gained attention. Fine-tuning pre-trained models, such as GPT-2 (Radford et al. 2019), has proven effective in traditional task-based dialogue scenarios, as demonstrated by works such as Su et al. (2021); Yang, Li, and Quan (2020); Wang et al. (2021). Given the requirement for domain knowledge in medical tasks, approaches like BioBERT (Lee et al. 2019) and BioGPT (Luo et al. 2022) employ pre-training language models on medical corpora. Another solution proposed by Varshney et al. (2023b,a); Tang et al. (2022) involves using the Unified Medical Language System (UMLS) to explicitly incorporate knowledge during dialogue generation.

### ICL for dialogue

As large language models (LLMs) continue to advance, in-context learning (ICL) has emerged as a new paradigm in natural language processing. The exploration of ICL’s ability to evaluate and infer LLMs has become a prominent trend in the field (Dong et al. 2022). Recently, numerous studies have applied ICL to the subtask of dialogue generation. Roy et al. (2023) leveraged ICL for dialogue style transfer and introduced a two-stage style transfer framework. Meade et al. (2023) employed a retrieval-based framework to mitigate bias and toxicity in chatbot-generated responses, guiding the model towards safer and more responsible dialogue. Lee, Lim, and Choi (2022) proposed a similar approach to encourage LLMs to generate compassionate dia-

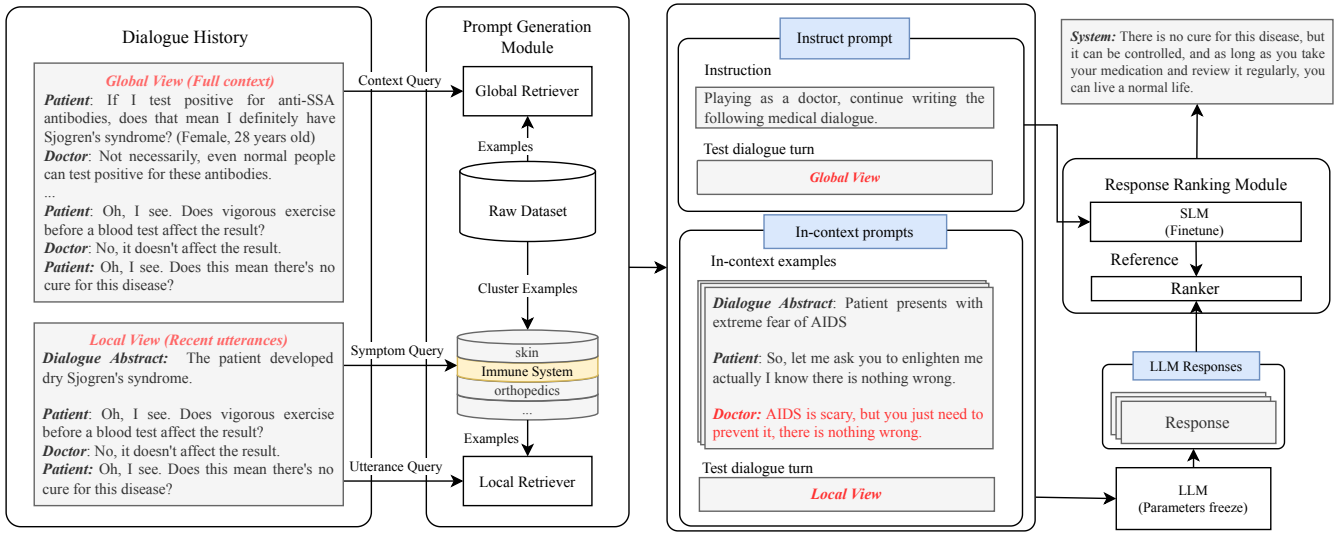


Figure 2: The overview of PlugMed. We divide PlugMed into a Prompt Generation module and a Response Ranking module.

logue. ICL has also demonstrated success in dialogue state tracking tasks. Hu et al. (2022); Chen, Qian, and Yu (2023) proposed methods for long dialogue compression, enabling each prompt to contain more examples and improving dialogue state tracking performance. Furthermore, ICL has been utilized for unsupervised generation of dialogue data in certain contexts (Li et al. 2022), expanding the potential applications of this approach. Overall, the adoption of ICL in dialogue generation has shown promising results across various aspects, including style transfer, reducing bias and toxicity, promoting compassionate dialogue, dialogue state tracking, and unsupervised generation of dialogue data.

## Methodology

### Overview

PlugMed comprises two main components: the Prompt Generation (PG) Module and the Response Ranking (RR) Module, illustrated in Figure (2). The PG Module accepts the dialog context as input and produces  $k$  in-context prompts, along with a single instruct prompt. Subsequently, these prompts are fed into the LLM, and the RR Module is employed to identify the optimal response.

### Prompt Generation Module

**Two Perspectives.** In generate prompts, it is necessary to retrieve relevant examples similar to the input dialogue sample. To leverage the dialogue information more effectively, a search is conducted from both global and local perspectives. As depicted in Figure (2, Dialogue History), the global perspective entails considering the entire history of the dialogue to retrieve similar dialogues from the original dataset. However, given that lengthy dialogues may contain substantial amounts of irrelevant information for the generation of the current dialogue, which could potentially impede the retrieval of pertinent examples. For this reason, we introduce the local perspective, focusing on recent rounds of dialogue.

**Example Retriever.** In the global view, we employ Sentence-Bert (Reimers and Gurevych 2019) to independently encode both the entire conversation history and examples. We then utilize cosine similarity to identify the closest  $k$  examples. However, the local perspective does not allow for a straightforward application of the same approach. This limitation arises from the fact that the last few rounds of dialogue provide insufficient information to unveil the patient’s symptoms and disease details, thereby presenting challenges for the retriever in finding similar cases.

To extract the maximum amount of relevant information from the early conversation history, we developed a medical dialogue summary model using the ICMS-MRG (Chen et al. 2022) dataset with Bart (Lewis et al. 2019) as the skeleton. Leveraging this model, we extracted the chief complaint/symptom information from the patient, effectively achieving the objective of compressing less informative conversations. To facilitate the retrieval of examples from a local perspective, we establish a two-level index retriever. Within this framework, the primary index encompasses the patient’s symptom information, which is extracted through the aforementioned dialogue summarization model. Employing the kNN algorithm, we cluster examples with similar symptoms together, designating the cluster center of symptoms as the primary index. Additionally, the secondary index incorporates the dialogue information from recent rounds, and we employ a similar methodology to the global retriever to retrieve comparable examples. Here, we limit the recent rounds dialogue to contain at most  $n$  tokens.

**Prompt Generation.** As depicted in Figure (2, Instruct prompt/In-context prompt), two distinct prompt types are generated. Regarding the in-context prompt, we encounter the need to compress examples in order to accommodate a greater number of demonstrations, given the input length constraint imposed by the LLM. Drawing inspiration from Hu et al. (2022), we utilize the patient’s chief complaint

as the conversation state, thereby replacing earlier conversations while retaining the last few rounds of dialogue. We enforce a restriction on the combined length of the dialogue and summary within each example (including the input sample) to be no greater than  $n' = n + m$ , where  $n$  represents the length of the aforementioned recent rounds of dialogue, and  $m$  denotes the maximum length of the summary. Consequently, if the input length of the LLM is confined to  $L$ , each in-context prompt can accommodate a maximum of  $\lfloor L/n \rfloor - 1$  examples. As the Instruct prompt does not require the inclusion of examples, it can encompass the entire dialogue history. This prompt is utilized to activate the zero-shot capability of the large model.

### Response Ranking Module

To leverage the strengths of both the global and local perspectives, it becomes essential to filter the responses generated by these two distinct strategies. Through rigorous experimentation, we have discovered that the Large Language Model (LLM) tends to produce a significant number of medical terms during dialogue generation, resulting in more comprehensive replies. However, the dialogue actions taken by the LLM are often incorrect, leading to an overall decrease in response quality. In contrast, a Small Language Model (SLM) fine-tuned on the dialogue corpus can employ more accurate dialogue actions but tends to include only a limited number of medical terms within its sentences. Recognizing the complementary nature of these two model classes, we propose the utilization of the SLM to evaluate responses generated by large language models. Specifically, we initiate the process by inputting the Instruct Prompt into the SLM to get the responses. Subsequently, we employ sentence-bert to encode both the response generated by the SLM and the responses produced by the LLM independently. By computing the similarity between these encoded representations, we determine the degree of resemblance. We posit that the response from the large model exhibiting a higher similarity to the response generated by the small model is indicative of more accurate actions. Consequently, we designate this response as the recommended output.

### Automatic Evaluation Metrics

Most unlabeled medical dialogue datasets employ the metrics utilized in open domain dialogue tasks. However, these metrics often fail to effectively measure system performance under task-oriented settings. In this regard, we propose two metrics that comprehensively evaluate system responses in terms of both intent (dialogue action) and medical entities.

#### Intent Evaluation

We employ intent accuracy (Int) to assess the conformity of the system’s response to the ground-truth response. To calculate Int, we train a medical dialogue intent classification model using the IMCS-IR dataset (Chen et al. 2022). In this process, Roberta serves as the skeleton to extract the primary intent of the responses for comparative analysis. The intentions considered are presented in Table (1), and the model achieves an accuracy of 0.86 on the validation set.

Action Type	Target
Request	Symptom
Request	Etiology
Request	Basic Information
Request	Existing Examination and Treatment
Inform	Drug Recommendation
Inform	Medical Advice
Inform	Precautions
Inform	Diagnose
Other	Other

Table 1: The intents of the doctor.

#### Entity Evaluation

It is noteworthy that several datasets, such as Meddg (Liu et al. 2020), have put forth analogous evaluation metrics. Typically, these datasets establish a predefined list of medical entities and subsequently train an entity extractor specifically for this list, utilizing manually annotated training data. During testing, the entity extractor identifies entities within the system responses and compares them against the ground-truth answers. In this study, we adopt a similar approach for entity matching evaluation; however, we have identified two issues with the existing dataset. Firstly, the proposed entities list tends to be relatively limited, as exemplified by the Meddg dataset which encompasses only 160 entities, resulting in sparse annotation (with an average of merely 0.56 entities per utterance in Meddg). Secondly, entity matching in these datasets does not take into consideration entity similarity, which is of utmost importance. For instance, when treating a disease, multiple drugs may be applicable, thus necessitating the consideration of drug effect similarity during system evaluation.

To tackle the aforementioned issue, we leveraged the Chinese medical high-frequency vocabulary obtained from THUOCL<sup>1</sup> as the entity list, encompassing 18,749 medical terms. Using this vocabulary as a foundation, we developed an entity extractor utilizing lexicon matching. When calculating the entity matching f1-score (micro), we introduced a novel approach called Top-n Match (TnM) instead of relying on exact matches. The definition of TnM is as follows.

**Definition 1 (TnM)** Let  $E = \{e_1, e_2, \dots, e_{|E|}\}$  be a set consisting of  $|E|$  entities, and let  $s$  be a similarity score function that satisfies  $0 \leq s(e_i, e_j) \leq 1$  for all  $e_i, e_j \in E$ . For a given entity  $e_i \in E$ , we define  $S_i^n(s, e_i) \subseteq E$  as the set of  $n$  entities that are closest to  $e_i$  based on the similarity function  $s$ . We say that entities  $e_i$  and  $e_j$  are considered a Top-N Match if and only if  $S_i^n(s, e_i) \cap S_j^n(s, e_j) \neq \emptyset$ .

By modifying the value of  $n$ , TnM enables the representation of matching scores for entities across varying levels of similarity. We present the f1-score results using T1M, T3M, and T5M configurations. For our implementation, the cosine similarity of the vector is denoted by  $s$ , and we generate the entity vectors through the utilization of the skip-gram algorithm. Further information regarding the implementation

<sup>1</sup><https://github.com/thunlp/THUOCL>

specifics of the entity extractor and skip-gram algorithm can be found in Appendix A.

## Experiment

This section delineates the evaluation setup and the results of the proposed approach in the context of medical dialogue generation, encompassing fluency, entity correctness, and intent correctness. Subsequently, we demonstrate the performance of our system through manual evaluation.

### Datasets and Evaluation metrics

We conducted experiments on three real-world datasets for our evaluation. 1) The **MedDG** dataset (Liu et al. 2020) was collected from *Doctor Chunyu*<sup>2</sup> and consists of 17,864 dialogue sessions. This dataset provides a limited number of entity annotations, with an entity list size of 160, and an average of 0.56 entities per utterance. 2) The **MedDialogue-CN** dataset (Zeng et al. 2020) was collected from *HaoDaifu*<sup>3</sup> and comprises 38,723 dialogues without any provided annotations. 3) The **KaMed** dataset (Li et al. 2021b) was also collected from *Doctor Chunyu*, but it is significantly larger, containing 63,754 dialogue sessions. Detailed statistics of the three datasets are presented in Table (2). To evaluate the quality of the generated text, we employed the BLEU-4 metric (Chen and Cherry 2014) to measure fluency. Furthermore, we utilized micro-precision, micro-recall, and micro-F1 scores for entity matching in T1M, T3M, and T5M settings to assess entity correctness based on the aforementioned definitions. Additionally, we employed the INT metric to measure the accuracy of the intended responses.

Dataset	Train / Valid / Test	Turn
MedDG	14,864 / 2,000 / 1,000	9.92
MedDialog	32,723 / 3,000 / 3,000	4.76
KaMed	57,754 / 3,000 / 3,000	11.62

Table 2: The details of datasets, where turn indicates the average number of rounds each dialogue session contains.

### Implementation Details

Our approach employs Bloom as the base model, and to ensure reproducibility, we avoid any form of sampling and instead utilize a greedy decoding strategy. In the case of a given sample, we produce a set of four prompts, consisting of an instruction prompt (referred to as "Vanilla") and three in-context prompts. These in-context prompts are generated using different perspectives. Specifically, one prompt is generated using the global perspective (+global), another is generated utilizing the local perspective with the primary index and random sampling (+local primary), and the third prompt is generated through the local perspective with both the primary and secondary indexes (+local secondary). Given the input length, the generated in-context prompt consists of

only 4 examples, while each dialogue history is limited to the last 120 tokens. During response ranking, Bart serves as the reference response generation model. We conducted our experiments using the PyTorch<sup>4</sup> and Huggingface Inference Api<sup>5</sup>, and we plan to release our code in the future.

### Baselines

**Fine-tuning Based Baselines** employ small language models (SML) as the backbone, trained on the aforementioned datasets for the medical dialogue generation task. These baselines encompass: 1) **Bart** (Lewis et al. 2019), a renowned Encoder-Decoder model renowned for its text generation capabilities. 2) **Mars** (Sun et al. 2022), the state-of-the-art model on the MultiWoZ dataset, adept at handling the TOD task. Please refer to Appendix B for further details on Mars.

**LLM Baselines** take the dialogue history as input and generate responses without any training. Our comparison targets consist of: 1) **Bloom** (Teven Le Scao 2022), a widely utilized open-access multilingual language model with 176B parameters. 2) **Bloomz** (Teven Le Scao 2022), the instruction-tuned variant of Bloom, specializing in zero-shot tasks.

**In-context Learning Baselines** utilize Bloom as the base model, and we compare different prompt generation strategies, including: 1) **Random**, where each prompt comprises a selection of randomly chosen examples. 2) **Sbert**, which leverages sentence bert (Reimers and Gurevych 2019) to encode the dialogue history and identify the closest examples to the sample, thereby generating the prompt. This prompt generation scheme corresponds to the global view scheme of our proposed method.

### Overall performance

Table (3) presents the automatic evaluation results on Meddg, MedDialog, and KaMed. Remarkably, PlugMed consistently attained top-ranking positions across a majority of the metrics. Particularly noteworthy is PlugMed’s exceptional performance in T1M@R, T3M@R, and T5M@F, outperforming even the strongest baselines. This remarkable achievement underscores PlugMed’s ability to generate highly accurate medical terminology. Notably, among all baselines leveraging the LLM, PlugMed not only generates responses with the most reasonable intent but also surpasses certain fine-tuning-based models, such as Mars, by a margin (+1.4%, +0.2%, and +0.3% respectively).

Moreover, our analysis unveils intriguing observations. Firstly, we discovered that fine-tuned SLM models tend to exhibit higher INT scores but lower BLEU and entity matching-related scores. This finding suggests that while such models excel in emulating the dialogue actions of doctors, they often struggle to generate appropriate medical terminology due to their lack of medical knowledge. Secondly, we observed that Bloomz performed worse than Bloom, indicating that the instruct-tuning process may compromise

<sup>2</sup><https://www.chunyuyisheng.com/>

<sup>3</sup><https://haodf.com>

<sup>4</sup><https://pytorch.org/>

<sup>5</sup><https://huggingface.co/docs/api-inference/index>

Dataset	Model	BLEU	T1M@P	T1M@R	T1M@F	T3M@P	T3M@R	T3M@F	T5M@P	T5M@R	T5M@F	INT
Meddg	Bart	5.9	<b>12.2</b>	4.6	6.7	<b>18.0</b>	6.8	9.9	<b>20.7</b>	7.9	11.4	32.0
	Mars	<b>6.3</b>	7.9	5.5	6.5	12.5	8.7	10.3	15.9	11.0	13.0	<u>39.9</u>
	Bloom	5.3	6.3	<b>6.9</b>	6.6	10.5	<b>11.4</b>	10.9	12.8	<b>13.9</b>	13.3	<u>26.3</u>
	Bloomz	4.2	5.6	4.8	5.2	9.2	7.9	8.5	11.2	9.5	10.3	24.8
	ICL Rand	5.2	6.2	6.2	6.2	10.9	10.3	10.6	13.4	<u>12.7</u>	13.0	29.6
	ICL Sbert	<u>6.2</u>	7.4	<u>6.3</u>	<u>6.8</u>	12.2	<u>10.5</u>	<u>11.3</u>	14.7	12.6	<u>13.5</u>	36.3
	PlugMed	<u>6.0</u>	<u>9.3</u>	<u>6.0</u>	<b>7.3*</b>	<u>15.4</u>	9.9	<b>12.1*</b>	<u>18.5</u>	11.9	<b>14.5*</b>	<b>41.3*</b>
MedDialogue	Bart	4.4	<b>18.3</b>	8.1	11.3	<b>26.0</b>	11.7	16.2	<b>31.0</b>	14.1	19.4	<b>42.0</b>
	Mars	4.8	13.7	8.9	10.8	21.2	13.9	16.8	26.3	17.3	20.9	37.7
	Bloom	5.1	11.9	9.3	10.4	18.5	14.4	16.2	22.8	17.7	19.9	33.0
	Bloomz	4.2	10.7	6.8	8.3	16.0	10.2	12.4	19.8	12.6	15.4	31.9
	ICL Rand	4.6	10.6	8.2	9.2	17.0	13.2	14.8	21.2	16.4	18.5	36.6
	ICL Sbert	<b>5.6</b>	12.5	<b>10.4</b>	<u>11.3</u>	19.5	<b>16.2</b>	<u>17.7</u>	24.1	<b>20.1</b>	<u>21.9</u>	37.3
	PlugMed	<u>5.4</u>	<u>14.6</u>	<u>10.2</u>	<b>12.0*</b>	<u>22.3</u>	<u>15.7</u>	<b>18.4*</b>	<u>27.2</u>	<u>19.2</u>	<b>22.5*</b>	<u>37.9</u>
KaMed	Bart	5.1	<b>17.0</b>	8.4	<u>11.3</u>	<b>23.4</b>	11.6	15.5	<b>27.3</b>	13.7	18.2	<b>45.0</b>
	Mars	5.6	11.5	9.7	10.5	17.9	15.1	16.4	22.2	18.7	20.3	41.4
	Bloom	5.0	10.5	12.0	11.2	15.8	<b>18.1</b>	<u>16.9</u>	19.3	<b>22.0</b>	<u>20.5</u>	34.1
	Bloomz	4.9	10.8	9.7	10.2	15.9	14.2	15.0	19.1	17.2	18.1	32.0
	ICL Rand	5.2	9.2	9.9	9.5	14.5	15.6	15.0	17.8	19.0	18.4	36.1
	ICL Sbert	<b>6.3</b>	10.9	<b>11.3</b>	11.1	16.6	<u>17.0</u>	16.8	20.1	<u>20.6</u>	20.4	37.9
	PlugMed	<u>6.1</u>	<u>13.8</u>	<u>11.2</u>	<b>12.4*</b>	<u>20.3</u>	16.4	<b>18.1*</b>	<u>24.3</u>	19.6	<b>21.7*</b>	<u>41.7</u>

Table 3: Automatic evaluation on the Meddg, MedDialogue and KaMed datasets. Boldface scores indicate best results, significant improvements over the best baseline are marked with \* (t-test,  $p < 0.05$ ). Underlining indicates the second best result.

the diagnostic capability of the model. We speculate that this discrepancy may stem from the prevalence of single-round Q&A tasks within the instruct-tuning dataset, which could potentially lead the model to prioritize generating direct responses to questions rather than actively gathering information from patients. Furthermore, our experiments demonstrated that incorporating ICL not only enhances the dialogue intent accuracy of the LLM regardless of the sampling strategy employed but also mitigates the decline in medical entity accuracy when providing similar examples.

### Ablation study

To investigate the influence of different prompt generation strategies on system responses and the efficacy of the RR module, we conducted ablation experiments. Our focus centered on exploring four strategies: 1) Vanilla: This strategy involves using the dialogue history directly as the prompt without incorporating any additional examples. 2) +Global View: This strategy includes finding examples based on the similarity of the conversation history and selecting the most similar examples to form the prompt. 3) +Local Primary: In this strategy, the patient’s symptoms are extracted from the conversation, and the closest example is selected based on symptom similarity. 4) +Local Secondary: Building upon the +Local Primary strategy, this approach additionally utilizes the similarity of the last few rounds of conversation to filter examples. The experimental results, as depicted in Table (4), indicate that both the global view and local view strategies effectively enhance the quality of the LLM output. Notably, the global view strategy outperforms the local view strategy, likely attributed to its capability to consider more diverse information beyond solely focusing on patient symptoms. When comparing the local primary and local secondary strategies, we observe that the impact of recent chat history on the LLM appears relatively minimal compared to

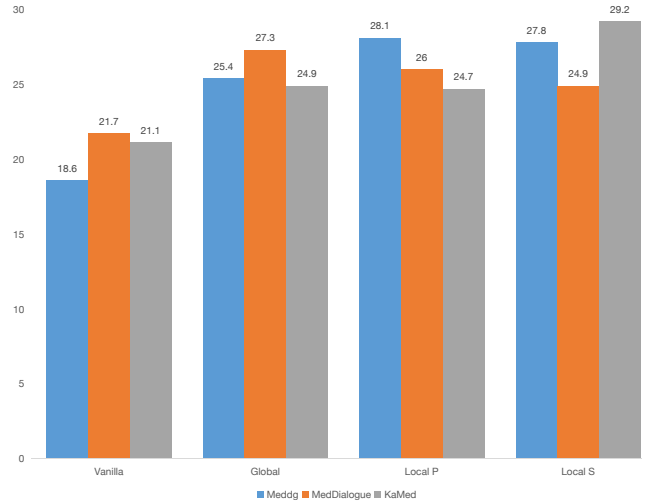


Figure 3: The evaluation results of the RR module for the four strategies. The vertical axis represents the proportion of the policy that generated the best response on the corresponding dataset.

the influence of the patient’s symptoms.

Moreover, we have observed a substantial enhancement in the quality of system responses due to the integration of the RR module. This observation not only underscores the efficacy of the fine-tuned SLM in effectively evaluating the LLM’s output but also highlights the complementary nature of the four strategies. In order to delve deeper into the contributions of these strategies to the outcomes, we utilize the RR module to rank the responses corresponding to each strategy, documenting the percentage of times each strategy achieves the top rank. The results are illustrated in Figure (3). Based



Dataset	Model	BLEU	T1M@P	T1M@R	T1M@F	T3M@P	T3M@R	T3M@F	T5M@P	T5M@R	T5M@F	INT
Meddg	Vanilla	5.3	6.3	6.9	6.6	10.5	11.4	10.9	12.8	13.9	13.3	26.3
	+global view	6.2	7.4	6.3	6.8	12.2	10.5	11.3	14.7	12.6	13.5	36.3
	+local primary	4.8	8.2	5.5	6.5	13.3	8.9	10.7	16.4	10.9	13.1	34.6
	+local secondary	5.2	7.2	5.6	6.3	12.8	9.9	11.2	15.6	12.1	13.6	34.9
	+ranking (Ours)	6.0	9.3	6.0	7.3	15.4	9.9	12.1	18.5	11.9	14.5	41.3
MedDialogue	Vanilla	5.1	11.9	9.3	10.4	18.5	14.4	16.2	22.8	17.7	19.9	33.0
	+global view	5.6	12.5	10.4	11.3	19.5	16.2	17.7	24.1	20.1	21.9	37.3
	+local primary	4.1	13.5	8.1	10.1	20.7	12.4	15.5	25.8	15.5	19.4	36.6
	+local secondary	4.9	12.5	9.1	10.5	19.8	14.4	16.7	24.3	17.8	20.6	36.1
	+ranking (Ours)	5.4	14.6	10.2	12.0	22.3	15.7	18.4	27.2	19.2	22.5	37.9
KaMed	Vanilla	5.0	10.5	12	11.2	15.8	18.1	16.9	19.3	22.0	20.5	34.1
	+global view	6.3	10.9	11.3	11.1	16.6	17.0	16.8	20.1	20.6	20.4	37.9
	+local primary	5.4	12.2	10.4	11.2	18.6	15.9	17.1	22.2	19.0	20.5	39.4
	+local secondary	6.1	11.4	11.7	11.6	17.5	18.0	17.7	21.2	21.7	21.4	36.7
	+ranking (Ours)	6.1	13.8	11.2	12.4	20.3	16.4	18.1	24.3	19.6	21.7	41.7

Table 4: Ablation study the Meddg, MedDialogue and KaMed datasets. Vanilla, +global, +local primary and +local secondary represent the four prompt generation strategies, respectively, and +ranking represents the result of the selection based on these four strategies using the RR module.

on the findings depicted in the figure, we can infer that the responses generated by the Vanilla strategy exhibit significantly inferior quality compared to those produced by the other three strategies. Furthermore, the probability of being selected by the remaining three strategies is approximately equal, indicating their complementary nature.

## Case Study

We selected a representative sample from the Kamed dataset to facilitate an interpretable comparison of different schemes. The corresponding results are presented in Table (5). In the scenario depicted within this sample, the patient’s mother provided limited information to the doctor, which proved insufficient to support an accurate diagnosis. Consequently, the doctor made the decision to gather the necessary symptom information. Our observations revealed that the Bart model exhibited an awareness of the information gap; however, it inquired about a known symptom, indicating that the SLM lacks certain medical common sense required to discern which information to collect. As for the Mars model, it placed greater emphasis on generating pertinent medical entities. In situations where other information was lacking, Mars opted to reiterate the patient’s utterances, aiming to increase the likelihood of aligning with relevant medical entities. Unfortunately, this approach resulted in the generation of responses of lower quality. The LLM produced lengthier responses, while ICL-Random and ICL-Sbert attempted to provide a diagnosis directly. On the other hand, Bloom and Bloomz generated false and biased utterances, respectively, indicating a dearth of diagnostic strategies within these larger models. In contrast, PlugMed generated responses similar to the ground-turth, thus suggesting the effectiveness of our proposed scheme.

## Conclusion

In this study, we demonstrate the utilization of In-context learning to develop a versatile medical dialogue model. To accomplish this objective, we introduce a Prompt Generation module capable of generating LLM input from both

global and local perspectives. Additionally, we construct a Response Ranking module using a supervised trained small model to filter the LLM output. Experimental results indicate that the responses generated by PlugMed exhibit a greater inclusion of comprehensive medical terms compared to those generated by the small model alone. Furthermore, when compared to direct employment of a large model for prediction, PlugMed yields more accurate dialogue intents.

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History	U: The baby has a cold for the sixth day, bronchitis, phlegm, cough, and runny nose. U: I went to the hospital of traditional Chinese medicine and prescribed Chinese medicine without decoc-tion. U: After taking it for three days, it didn't seem to work. What should I do (male, 13 months)
Golden	Hello! Does your baby have other symptoms? Such as fever?
Bart	Hello, is your baby coughing badly?
Mars	The baby is bronchial sinusitis, bronchitis, cough, runny nose.
Bloom	Your baby needs timely medical treatment. The child's current symptoms are obviously suppurative tonsil-litis. In addition to taking anti-inflammatory treatment for this disease, it is recommended to perform tonsil removal surgery at the same time.
Bloomz	The baby is still young, so it is recommended to take western medicine. Chinese medicine has too many side effects on the baby, and the effect is not good.
ICL-Random	If your child coughs and has phlegm, you can take some phlegm-reducing medicines, such as Mucosolvan and keep warm to avoid catching cold.
ICL-Sbert	The baby is now coughing and has phlegm. It is considered to be bronchitis. You can continue to take traditional Chinese medicine, or you can take cephalosporins, combined with atomization treatment.
PlugMed	Hello, does your baby have a fever now?

Table 5: One case extracted from KaMed. Note that these dialogues are originally in Chinese, the English version may not get the same dialogues.

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