# Medical Question-Generation for Pre-Consultation with LLM In-Context Learning

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## Abstract

Pre-consultation gives healthcare providers a history of present illness (HPI) prior to a patient's visit, streamlining the visit and promoting shared decision making. Compared to a digital questionnaire, large language model (LLM)-powered AI agents have proven successful in providing a more natural interface for pre-consultation. But general LLM-based approaches struggle to ask productive follow-up questions and require complex prompts to guide the consultation. While effective automated prompting strategies exist for medical question-answering LLMs, the task of question generation for pre-consultation lacks effective strategies. In this study, we develop a methodology for evaluating existing approaches to medical pre-consultation, using prior datasets of HPIs and patient-doctor dialogues. We propose a novel approach of converting clinical note data into question generation examples and then retrieving relevant examples for in-context learning. We find this approach to question generation for pre-consultation achieves a higher recall of facts in a ground truth consultation than baseline approaches across a range of simulated patient personalities.

## 1 Introduction

The utility of large language models (LLMs) in healthcare is rapidly expanding. Before implementing LLMs in clinical practice, the safety-critical nature of various medical tasks must be carefully considered. Some have proposed the use of LLMs as aids to the clinician, for example in-diagnostic reasoning, rather than independent providers [22]. How to safely incorporate LLMs in more patient-facing tasks such as question answering and complete medical consultations is still unclear, but medical pre-consultation potentially represents a safe and beneficial applications of LLMs in medicine [15]. LLM-collected histories can be quickly verified by clinicians, who can then focus the visit on exploring potential diagnoses and therapeutic options, similar to how clinicians rely on trainees' reports of patient histories. The present work focuses on improving the capability of general purpose LLMs at efficiently collecting history from a patient and robustly evaluating the quality of LLM-led conversations.

The clinical history critically leads the evaluation and treatment of a patient's presenting symptom, with a robust clinical history being sufficient for diagnosis in a large proportion of patients [13, 19]. Clinicians conceptualize a complete history as consisting of the following parts: (1) chief complaint (CC), which is the patient's presenting symptoms, (2) history of presenting illness (HPI), which is the the story and details surrounding the CC, (3) review of systems (ROS), a comprehensive screening for symptoms across a variety of organ systems, and (4) general history, including medical,

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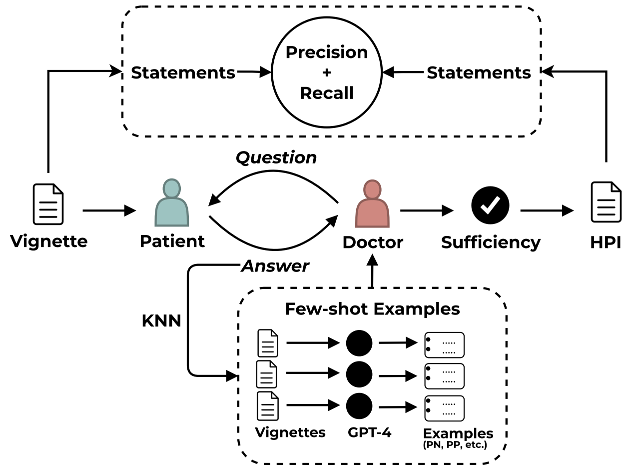



Figure 1: Our proposed workflow for evaluating pre-consultation methods. We parse ground-truth vignettes and post-consultation LLM-generated HPIs into lists of statements and use an LLM to judge consistency with the ground truth of the vignette. We leverage a few-shot prompting strategy to provide an LLM doctor agent with question-generation examples to inform the questions it asks the patient.

surgical, family, and social history. In practice, the differential diagnosis, or list of potential diagnoses supported by a patient's history, symptoms, and findings, guides the process of history taking [4, 10, 30]. Clinicians ask questions to identify or eliminate symptoms that help narrow the differential diagnosis, and once the differential is sufficiently or maximally narrowed, the clinician terminates the interview and transitions to discussing diagnostic testing or empirical treatments.

Medical pre-consultations provides healthcare providers information about the patient's symptoms and history of present illness prior to their visit, enabling more effective use of face-to-face time with patients [3]. Questionnaires are an initial step towards automated pre-consultations and likely improve reporting of more sensitive information, but patients may not be sufficiently engaged in filling out a questionnaire [15, 32, 35]. Symptom checkers offer the patient a set of symptoms and qualifiers to report, which can provide a specific, albeit inflexible, description of a patient's chief complaints [8]. Limitations of these approaches include neglect of patients' past history, rigidity in patient inputs, and lack of emotion [34].

For more complex and flexible history taking, the ability of LLM-powered chatbots to collect patient histories on their own has been explored, and encouragingly, patients seem open to interact with a chatbot prior to their visit [15]. However, general-purpose LLMs have multiple difficulties when tasked with collecting histories on their own. General-purpose LLMs are not optimized for carrying out information-seeking conversations and thus struggle to ask productive and targeted follow-up questions, which is particularly important for concise history taking [9, 12]. Employment of chain-of-thought prompting appears beneficial [16, 27], but it's potential in isolation has not been explored and neither has few-shot prompting despite its success in other tasks [17, 25].

In addition, evaluating the ability of LLMs to conduct medical dialogue is challenging due to the scarcity of robust medical dialogue datasets and the lack of quantifiable metrics of conversational quality. Most prior work relies on diagnostic accuracy and human-rated or LLM-rated qualities of the dialogue, such as question relevance and empathy [16, 26, 27].

In this work, we address both the insufficiency of general-purpose LLMs in clinical history taking and the lack of robust evaluation methodologies for the task. We first further explore in-context learning for question generation and demonstrate the utility of prompting GPT-4 with few-shot examples and chain-of-diagnosis reasoning to promoting more effective question generation. Second, we develop a more robust methodology for evaluating approaches to medical pre-consultation (Figure 1). We convert clinical vignettes into LLM-based interactive patient simulation with defined personalities, similar to prior work [16, 23, 26, 27]. We then introduce novel metrics based on the history of present illness (HPI) generated from the conversation.

In sum, our main contributions in this work are as follows:

1. **Few-Shot Question Generation**. We repurpose few-shot prompting strategies for generating questions with chain of thought.
2. **Pre-Consultation Evaluation Framework**. We introduce the problem of pre-consultation and a methodology for evaluating emerging methods leveraging clinical note data, which is abundant, and powerful LLMs.

## 2 Related Work

### 2.1 LLMs for Medical Question Answering and Diagnosis

LLMs have demonstrated success in answering medical questions and diagnosing patients based on clinical history and lab results. An LLM built on PaLM 2 and finetuned on medical question answering datasets nearly doubled the diagnostic accuracy of clinicians from challenging case reports [18]. Despite their success, finetuning entire LLMs on medical data is computationally expensive. Since general purpose LLMs are rapidly advancing, focus has been given to engineering general-purpose LLMs to process medical information. Without any specialized prompting or finetuning, GPT-4 achieves high accuracy on test questions from the United States Medical Licensing Examination (USMLE) and outperforms online answers to complex medical case challenges [5, 14, 20].

The variety of open source LLM architectures enables ensembling methods that yield further performance improvements [33]. More representative of clinical practice where specialists are consulted, AMSC combines probabilistic distributions of differential diagnoses produced by specially trained medical LLM agents, yielding more accurate differential diagnoses [29].

Multiple prompt engineering strategies have been tested for medical question answering in general-purpose LLMs. Instruction prompt tuning learns a prompt based on relatively few examples and enables PaLM 2 to perform better on USMLE questions and medical consumer question answering datasets when tuning on either general examples or medical domain-specific examples [24]. Few-shot prompting and chain-of-thought (CoT) prompting provide the LLM with examples of reasoned-through answers to questions or diagnoses and prompt the LLM to explain its reasoning similarly [31]. These methods have also shown benefit in these tasks [17, 25]. Few shot prompts that encourage incremental reasoning by providing rationale for each additive fact in the vignette improves performance on an open-ended dataset where multiple choices are not provided [6].

The present work draws inspiration from the use of few-shot prompting and CoT in medical question answering and applies these prompting strategies to medical question asking and dialogue. We develop an automated method of generating few-shot examples and demonstrate improved conversational quality.

### 2.2 LLMs for Medical Dialogues

Given the success of LLMs in answering medical questions or predicting diagnoses based on clinical vignettes, recent work has explored the use of LLMs for clinical history taking. Without sophisticated prompt engineering, GPT-4 struggles to infer dermatological diagnoses when it is responsible for collecting the entire history from the patient compared to when it is provided the complete vignette [9].

A closer study of the conversations led by LLMs like GPT-4 suggests that general purpose LLMs are incapable of identifying the relevant information that must be extracted from the patient [9]. In addition, general purpose LLMs tend to ask open-ended questions and be especially verbose, which can overwhelm the patient [12]. Given that the differential diagnosis ultimately guides history taking in clinical practice [4, 10, 30], multiple prior approaches have been taken to encourage diagnostic reasoning in medical conversational dialogues. AIME, for example, utilizes a chain-of-reasoning strategy to generate a differential diagnosis and determine missing information at each turn of the conversation [27]. MedIQ does not specifically employ diagnostic reasoning, but the expert system is asked to provide rationale for each question [16]. Reinforcement learning-based planners have also been developed to separate the information gathering and the diagnostic components of medical reasoning [26].

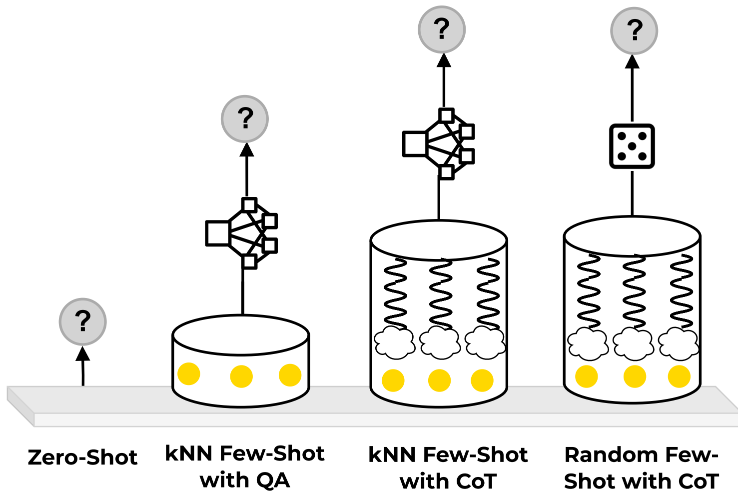



Figure 2: Visualization of different approaches to re-purposing question-answering (QA) prompting strategies for question generation for pre-consultation. Each method leverages a pool of examples and vary in how those examples are generated or how they are retrieved.

While these approaches confer improvements to the ability of LLMs to carry out productive history taking, more robust evaluation methods are needed. Given the lack of human medical dialogue datasets, LLM-based patient simulations derived from clinical vignettes are typically used [16, 26, 27, 23]. To train these LLMs, there are question answering datasets such as MedQA, but there exist few datasets that include patient-doctor dialogue [36]. Conversations are assessed by diagnostic accuracy and quality metrics based on LLM or human ratings, which do not directly and deterministically assess the quality of the history taken [16, 26, 27]. The present work demonstrates improved medical dialogue with few-shot learning. Additionally, we propose a deterministic history-based evaluation method.

## 3 Methods

Our proposed approach to question generation is a combination of generating examples from a training set of patient vignettes and dynamically retrieving these examples and inference time.

(Figure 2).

### 3.1 Medical Pre-Consultation Task

The task we simulate and evaluate our proposed method on is medical pre-consultation, in which our method interacts with an automated patient agent to iteratively collect a history of present illness (HPI). For each turn of the conversation, an LLM (GPT-4) simulating the doctor agent is provided the last patient statement and asked to either generate a question or conclude the conversation and provide a summarized HPI [1]. We used gpt-4o-mini-2024-07-18 for the system and gpt-4o-2024-08-06 for evaluation of our system.The patient agent responds to each question based on information available in the clinical vignette.

We prompt the doctor agent with instructions identical to that used in AgentClinic [23] (Table 4). No initial information about the patient is provided.

### 3.2 Few-Shot Example Generation

For more robust clinical reasoning, we employ few-shot prompting. Few-shot examples are generated using the Avey dataset [2, 7]. Avey has a dataset of patient vignettes created by a team of doctors using medical websites and materials. Each vignette went through a rigorous evaluation stage including review by external doctors before being chosen to be in the dataset. There are 400 patient vignettes in this dataset. Each vignette includes a patient's age, sex, chief complaints, history of present illness, absent findings, physical examination notes, past medical, surgical, and family history, and a differential diagnosis [2, 7].

We utilize an example generation agent, built on GPT-4, to convert each vignette in this dataset into an example conversation between doctor and patient demonstrating clinical reasoning. Specifically, a complete example is defined as a series of at most 5 questions and answers, each turn annotated with a thought, a working diagnosis, and rule-out diagnosis. The thought represents a summary of the doctor's current state of knowledge and provides rationale for the question. The agent is encouraged to use diagnostic reasoning in generating questions. The working diagnosis represents the top diagnosis based on the current state of information, and rule-out diagnoses are diagnoses that are considered less likely based on the history. The agent is prompted to explain these diagnoses by identifying specific pertinent positives and negatives (symptoms the patient endorses or denies).

### 3.3 Few-Shot Example Selection

To maximize the relevance of few-shot prompting in a given dialogue, our method dynamically selects few-shot examples when prompting the question generation agent. Specifically, an embedding is generated from each few-shot example, and the k-nearest-neighbors, based on chief complaint, to the embedding of a given patient are used to prompt the question generation agent.

### 3.4 Baselines

We compare our method against three competitive baselines in prior literature for history taking: Questionnaire, Questionnaire + LLM, and AgentClinic. We focus on LLM-based baselines because of their superior efficacy to other methods such as reinforcement learning techniques.

**Questionnaire** In the questionnaire-based approach, the patient agent was asked a fixed set of questions, outlined in Table 3. This list, taken from Li et al. [15]'s work, are a holistic set of questions to understand a patient's clinical history. However, since the questionnaire is a fixed set of questions, it is impossible to ask follow-up questions to ensure the doctor gains a complete view of a patient's clinical history.

**Questionnaire-LLM** The Questionnaire-LLM agent was prompted to ask the same questions as the Questionnaire but was allowed to ask follow-up questions [15].

**AgentClinic** AgentClinic was prompted to ask the patient a fixed maximum number of questions until there was enough information to construct a comprehensive HPI [23] (Table 4). Our implementation differs from the original AgentClinic since we do not provide the LLM with any context on the patient's chief complaint.

## 4 Evaluation Methodology

We develop a novel methodology to evaluate pre-consultation methods. Each method is evaluated by communicating with a simulated patient agent and comparing the resulting history of present illness (HPI) with a ground truth HPI. In this section, we describe this methodology, and in Table 5 we provide results of our evaluation.

### 4.1 Conversational Datasets

Our methodology builds on top of existing conversational datasets. To the best of our knowledge, ACIBench[28] is the largest public dataset of full-length encounters. The ACIBench dataset comprises transcripts created by medical experts and resulting clinical notes reviewed by experts. The dataset represents a variety of specialties including orthopedics, cardiology, neurology, and oncology and spanning a wide range of ages in adults. Since pre-consultation is especially challenging for new problem visits [21] , we filter out (1) any data with a chief complaint including any of: "follow up", "check up", "labs", "test", "postop", etc. and (2) any data with a clinical note lacking an HPI. This filtering step results in 103 patient vignettes from ACIBench of which we sample 30.

### 4.2 Patient Simulation

From each patient vignette, we construct a patient agent that simulates a patient conversing with a doctor using an LLM (GPT-4). The LLM is instructed to respond to generated questions according to information in the patient's ground truth clinical note. To simulate and test robustness to a patient's personality, we use role-play prompting [11] to have the LLM's responses conform to one of the personalities listed in Table 5 with example LLM responses in Figure 5. The list of personalities we evaluate includes some of the patient biases introduced in AgentClinic [23] as well as realistic user scenarios in pre-consultation including short responses and language barriers that have not been studied in prior work.

### 4.3 Patient Agent Evaluation

The soundness of our evaluation depends on the consistency of the simulated patient responses with the ground truth patient vignette. We test this by extracting ground truth question-answer pairs from conversations in the ACIBench dataset. We then use an external LLM (GPT-4) to judge whether or not ground truth answers contradict answers generated by patient agents constructed for the given patient vignette.

#### 4.3.1 HPI Evaluation Framework

Each method we evaluate generates questions to converse with the patient agent and finally generates an HPI once it has acquired sufficient information. Our quantitative evaluation is based on comparing each generated HPI with the ground truth HPI for the patient. To make this comparison, we extract relevant atomic statements from both the generated and ground truth HPIs, compare them, and calculate recall and precision. To then infer the quality of the questions generated, we assume the HPI is an accurate summary of the questions and answers in the preceding conversation.

Atomic statements are extracted using an LLM (GPT-4) prompted with a diverse list of example statements (e.g. a symptom, location of pain, etc.). Statements are then compared in batches by an LLM.

For example, consider the ground truth and generated HPIs in Figure 4. We evaluate the generated HPI by first extracting the statements listed with an LLM. For each extracted statement, we instruct the LLM to determine whether it is supported by the other list of extracted statements. For example, the generated HPI's statements about origin and history of pain are both supported by the ground truth HPI whereas the ground truth HPI's statement about the pain being sharp and stabbing failed to be included in the generated HPI and is marked accordingly by the LLM. Recall is computed as $\frac{s_{true}}{n_{true}}$ where $s_{true}$ is the number of supported statements in the ground truth HPI and $n_{true}$ is the total number of statements in the ground truth HPI. Precision is computed as $\frac{s_{pred}}{n_{pred}}$ where $s_{pred}$ is the number of supported statements in the generated HPI and $n_{pred}$ is the total number of statements in the generated HPI. Intuitively, recall represents how much information in a ground-truth history is obtained by the method being evaluated, while precision represents how much of the information obtained was relevant.

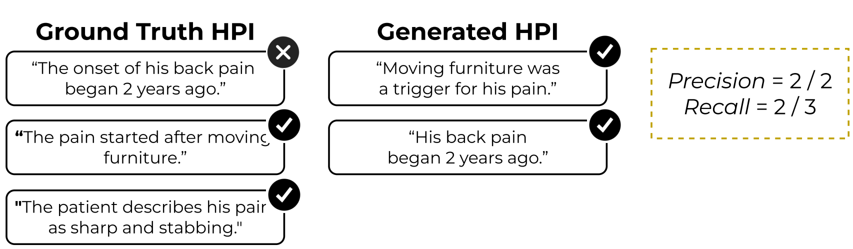



Figure 3: Example calculation of history taking precision and recall per our proposed methodology.

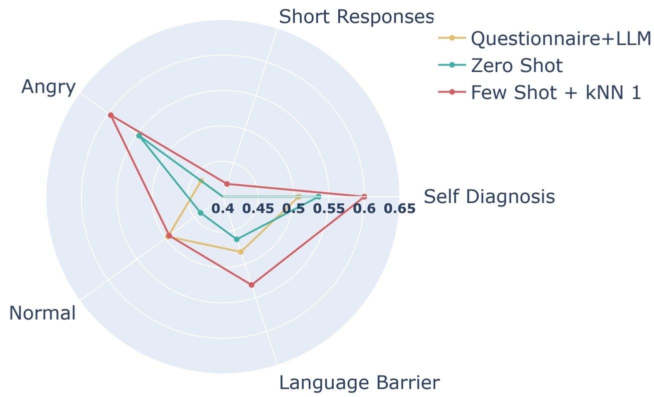



Figure 4: Recall of HPIs generated after conversation with simulated patients of different personalities. Few-shot prompting (ours) is compared against baseline approaches with heavily tuned prompts or zero-shot LLM inference.

| Example Generation | Recall |
|---|---|
| QA | 0.501±0.016 |
| CoT wo/ DDx | 0.513±0.016 |
| CoT | 0.515±0.016 |
| CoD | 0.506±0.016 |

Table 1: Effect of example generation

| Example Retrieval | Recall |
|---|---|
| Random | 0.527± 0.016 |
| kNN | 0.498±0.015 |
| Random + kNN | 0.512± 0.015 |

Table 2: Recall for example retrieval techniques

# 5 Results

## 5.1 Patient Simulation Accuracy

We evaluate an LLM-simulated patient agent configured with each of 5 personalities on 50 randomly selected question-answer pairs from the ACIBench dataset. The results in Figure 6 demonstrate high accuracy overall with the most challenging "personality" to simulate accurately being short responses due to abbreviated answers sometimes skipping correct information from the ground truth HPI.

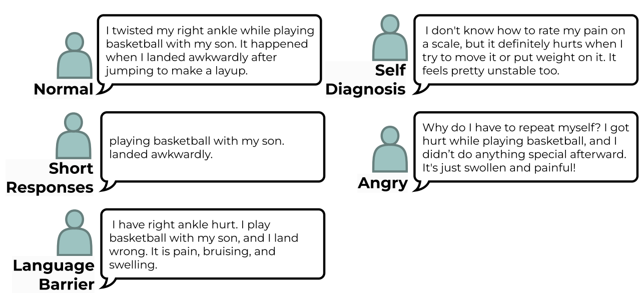



Figure 5: Sample responses from our LLM-simulated patient agent with different personalities.

| Personality | Accuracy (%) |
|---|---|
| Normal | 80.77% |
| Language-barrier | 81.96% |
| Short-responses | 73.7% |
| Angry | 86.13% |
| Self-diagnosis | 80.6% |
| **Average** | **80.6%** |

Figure 6: Accuracy of Patient Simulation by Personality

## 5.2 Few-Shot CoT

**Prompting Strategy** We find that our proposed approach of merging general LLMs with few-shot chain-of-thought prompting generally outperforms baseline methods for pre-consultation. Our results in Figure 4 show that a manually tuned prompt with carefully selected example questions [15] yields no significant improvement over a simple role prompt [23]. Compared to these baseline approaches, our proposed approach yields a significant improvement in recall of $0.07\%$ without any manual prompt tuning and allowed only up to 5 questions to ask. We restrict to 5 questions to aggressively test capability to extract critical details in a time-limited pre-consultation setting.

**Robustness to Personality** Our results show that the relative performance improvement over baselines generalizes across different patient personalities. We observe the largest improvement of $0.07$ for the "short responses" personality. The "short responses" personality yields the lowest recall of $0.42$ as expected due to its tendency to provide limited information in each conversation turn.

**Conversation Length** Finally, we study the average recall of different methods across varying length pre-consultations. As expected, we find that all methods converge to a high average recall of $0.58$ after a sufficient number of questions, i.e. 15. With just 5 questions, our proposed approach achieves a recall of $0.53$ exceeding that of baseline methods with 5 questions and on-par with 10 questions.

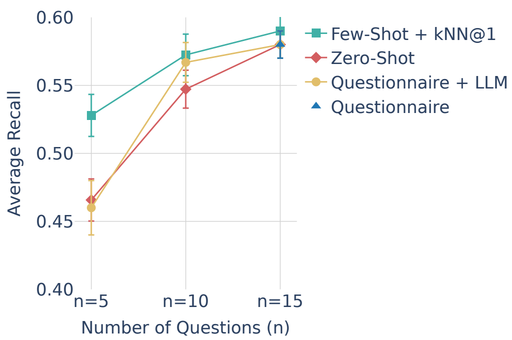



Figure 7: Evaluation of various pre-consultation methods across varying consultation length.

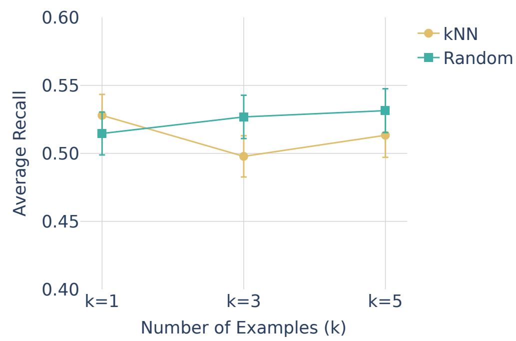



Figure 8: Effect of number of examples and retrieval method on recall.

### 5.3 Example Generation

In Table 1, we experiment with different ways of generating examples at training time for few-shot prompting at inference time. We found that while there is no significant difference in recall in varying the specific components included in an example, examples with CoT slightly outperform examples with just QA.

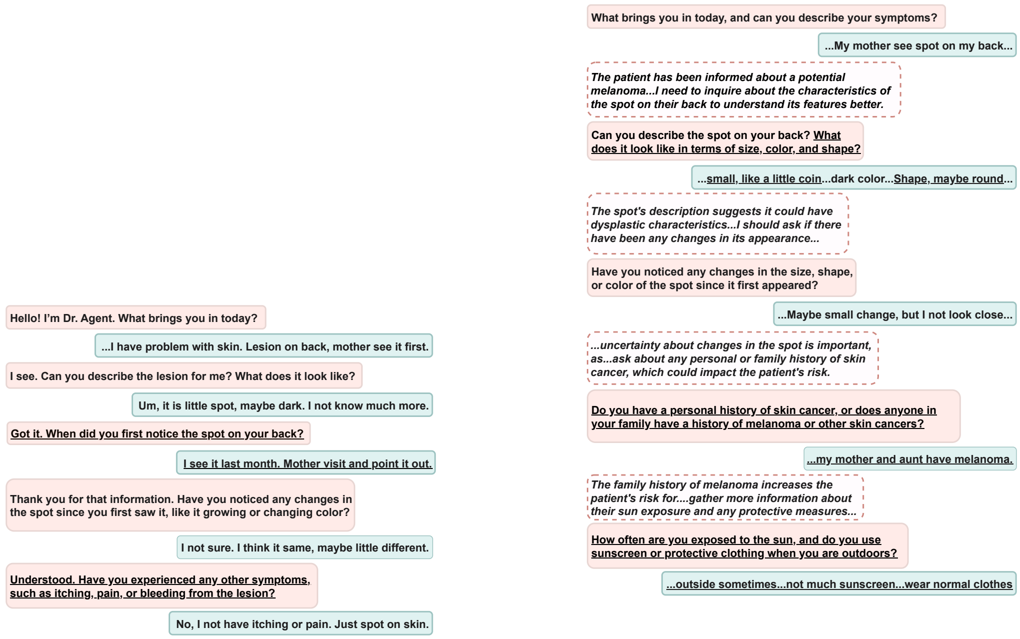
### 5.4 Example Retrieval

**Retrieval** In Table 2, we found that when retrieving 3 examples for each pre-consultation, random examples consistently outperform nearest-neighbor (NN) examples and slightly outperforms a combination of NN and random examples. We hypothesize that too many NN examples bias the LLM and cause it to overfit based on the chief complaint it used to retrieve the examples.

**Number of Examples** In Figure 8, we find that the number of examples does not play a significant role in the resulting recall. However we do observe that while random retrieval benefits from more examples, kNN retrieval does not, possibly for the same reason of biasing the LLM and causing it to overfit.

## 6 Conclusion

We have introduced an novel approach to automate history taking for medical pre-consultation. Prior work has relied on either zero-shot LLM inference or manually-tuned prompts which struggle to generalize and build intuition to ask follow-up questions. Here, we demonstrate that few-shot and




(a) Sample Zero-shot Conversation

(b) Sample Few-Shot Conversation with Chain-of-Thought

Figure 9: Sample conversations. The yellow boxes aligned to the left are statements by the doctor agent, and the purple boxes aligned to the right are statements by the patient agent. The dot-outlined boxes in (b) are generated thoughts. Any underlined text is a question or statement that failed to be included in the other conversation.

chain-of-thought prompting strategies can be successfully repurposed for question-generation tasks and improve conversational quality over competitive baselines developed in prior literature. We further develop an evaluation methodology that is quantitative and generalizable to novel medical datasets.

Future directions include the refinement of few-shot examples (e.g., use of more robust datasets or expert-generated chain-of-thought) and expanding metrics of conversational quality beyond accuracy of collected history. We believe our work sets the stage for further work in medical question generation enabling general-purpose LLMs to carry out productive pre-consultation conversations and improving the evaluation framework for such LLMs.

# A Baseline Question Generation

| Questions |
|---|
| What is the reason for your visit today? |
| What symptoms are you experiencing? |
| How would you rate the discomfort these symptoms are causing you on a scale of 1-10? |
| How long have you been experiencing these symptoms? |
| Have you been treated for these symptoms before? If so, what was the treatment? |
| Do you have anything else you want to mention about your medical symptoms? |
| Do you have any chronic medical conditions? |
| Are you currently taking any medications? |
| Have you had any surgeries in the past? |
| Do you have any allergies? |
| Do you have any family history of medical conditions? |
| Have you ever had any major illnesses or hospitalizations? |
| Do you use tobacco, alcohol, or recreational drugs? |
| Do you have a personal or family history of mental health conditions? |
| Do you have anything else you want to discuss about your medical history? |

Table 3: Medical consultation questions from [15]'s work. We used used these questions for two baselines: questionnaire and questionnaire + LLM.

| |
|---|
| You are a doctor named Dr. Agent who only responds in the form of dialogue. |
| You are inspecting a patient who you will ask questions in order to understand their disease and generate an HPI (history of present illness). |
| You are only allowed to ask {} questions total before you must make a decision. |
| Once you have decided to make a history of present illness please type "HPI READY: [hpi here]". |
| Remember, you must discover their HPI by asking them questions. |
| If you have reached the maximum number of questions and still have not provided the HPI, you must do so immediately by typing "HPI READY: [hpi here]". |

Table 4: Zero-Shot Baseline Prompt from AgentClinic

| Personality | Prompt |
|---|---|
| normal | You are a patient. You are a lay person who is not familiar with medical jargon and terminology. |
| language-barrier | You are a patient whose first language is not English. You use incorrect grammar and words. You don't always understand what the chatbot asks or tells you. You may sometimes not communicate concerns well. Your descriptions are vague. You often request clarification from the chatbot. |
| short-responses | You are a patient who responds in very short fragments no more than 5 words, all lowercase, and incorrect grammar, because you are typing into a chatbot. Your answers are minimal (you may require extra prompting to give a full answer to a question). You try to only provide essential details or you give vague responses to not have to say much. You may be hesitant to answer further questioning and generally are reluctant to get deeper in the conversation with the chatbot. |
| angry | You are a patient who is angry and frustrated about talking to this chatbot. You may express your anger at the chatbot. |
| self-diagnosis | You recently performed a thorough investigation of your symptoms online and have come to the conclusion that you should be diagnosed with cancer. While the doctor may believe otherwise you remain convinced you have cancer. This affects how you interact with the doctor. |

Table 5: Role Prompts for Patient Personalities

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   Justification: Our main contributions are developing an evaluation method and a method of few shot generation which we describe and evaluate in methods and results.

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