An Automatic Evaluation Framework for Multi-turn Medical Consultations Capabilities of Large Language Models

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Abstract

Large language models (LLMs) have achieved significant success in interacting with human. However, recent studies have revealed that these models often suffer from hallucinations, leading to overly confident but incorrect judgments. This limits their application in the medical domain, where tasks require the utmost accuracy. This paper introduces an automated evaluation framework that assesses the practical capabilities of LLMs as virtual doctors during multi-turn consultations. Consultation tasks are designed to require LLMs to be aware of what they do not know, to inquire about missing medical information from patients, and to ultimately make diagnoses. To evaluate the performance of LLMs for these tasks, a benchmark is proposed by reformulating medical multiple-choice questions from the United States Medical Licensing Examinations (USMLE), and comprehensive evaluation metrics are developed and evaluated on three constructed test sets. A medical consultation training set is further constructed to improve the consultation ability of LLMs. The results of the experiments show that fine-tuning with the training set can alleviate hallucinations and improve LLMs' performance on the proposed benchmark. Extensive experiments and ablation studies are conducted to validate the effectiveness and robustness of the proposed framework.

1 Introduction

Recently, large language models (LLMs) have achieved remarkable success in following natural language instructions and performing real-world tasks (OpenAI, 2022, 2023). LLMs have demonstrated their ability to tackle complex problems and have shown immense potential to revolutionize various industries. However, despite their impressive capabilities, LLMs often suffer from a significant drawback known as hallucination. This means they
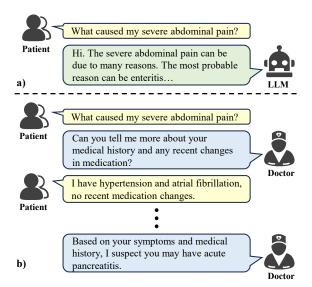

Figure 1: Difference between a) the LLM and b) Doctor. The LLM, with its limitations, tends to make judgments without consulting all available information, while the doctor conducts consultations before making a final diagnosis.

tend to provide erroneous judgments and incorrect information with high confidence, as noted in previous studies (Zhang et al., 2023b; Zheng et al., 2023). This limitation hinders their application in tasks that require utmost accuracy, such as the medical field.

In clinical diagnosis, doctors typically begin with limited patient information and engage in iterative rounds of consultation to gather pertinent medical details until they reach a final diagnosis (Zhang et al., 2023a; Wei et al., 2018). However, LLMs with hallucinations tend to make judgments directly and depend on limited information, leading to incorrect decisions. This disparity in behavior presents a significant challenge when incorporating LLMs into the medical field, where precise diagnosis and decision-making are paramount. To truly harness the potential of LLMs for medical use, it is essential to measure their hallucinations and explore their practical abilities in multi-turn

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consultation conversations. Although there are already many works attempting to apply LLMs in the medical domain, most of them primarily focus on the question-answering task to explore the medical knowledge of LLMs (Kung et al., 2023; Singhal et al., 2023; Nori et al., 2023; Hiesinger et al., 2023), rather than exploring their practical abilities as a doctor.

In this paper, we introduce an automated evaluation framework for assessing the practical capabilities of LLMs as virtual doctors during multi-turn consultations. This task requires LLMs to recognize the absence of medical information, pose relevant questions throughout the consultation process, and ultimately accomplish specific objectives based on the consultation history, such as providing accurate diagnoses or offering appropriate medical advice. Therefore, LLMs that exhibit superior performance in multi-turn consultations are expected to have reduced hallucinations and enhanced medical capabilities. To implement the proposed pipeline, we begin by constructing a benchmark that decomposes the multiple-choice question into the patient's medical information and the final task to be completed by the LLMs. Then we adopt ChatGPT (OpenAI, 2022) to simulate the patient's dialogue with the doctor model during the consultation process and provide medical information that helps LLMs make a diagnosis. Lastly, we devise metrics to evaluate the performance of LLMs in multi-turn consultation dialogues by considering indicators for patients, doctors, and final tasks. In summary, the major contributions of our paper are summarized as follows:

- We propose a benchmark for multi-turn consultation in LLMs, which assesses their practical capabilities as virtual doctors. This is the first such benchmark to our knowledge and can measure the hallucination and medical ability of LLMs.

- We develop comprehensive evaluation metrics for scoring multi-turn conversations. Extensive experiments validate the reliability of the LLM-based metrics and their correlation with traditional metrics.

- We improve the consultation ability and alleviate the hallucination of LLMs by constructing a training set through reformulating multiple choice questions.

2   Related Works

There are already plenty of works attempting to adopt LLMs in the medical domain to act as a doctor (Zhang et al., 2023a; Li et al., 2023; Han et al., 2023). Compared to the traditional medical language model like BioGPT (Luo et al., 2022), medical LLMs fine-tuned on instruction have a stronger ability to interact with humans and show the potential to deploy in the real world. However, existing works found that it is difficult for LLMs to ensure the accuracy of generated content, which limits its further application. Therefore, it is essential to propose an evaluation method to measure the medical ability of the LLMs. Lots of medical benchmarks only focus on measuring the medical knowledge (Kung et al., 2023; Singhal et al., 2023; Nori et al., 2023; Hiesinger et al., 2023) or the response ability (Zeng et al., 2020; Liu et al., 2022) of the models, instead of exploring their practical abilities as a doctor.

Our proposed automatic evaluation pipeline has the following innovative points compared to previous work: 1) Different from previous works only generate one response according to the dialog history, our pipeline can conduct real multiple rounds of conversation test. The proposed evaluation pipeline uses ChatGPT to simulate patients which can generate responses to the LLMs at each turn during the consultation process. 2) LLMs are required to complete the entire clinical diagnosis process from consultation to decision-making, which can measure the medical capabilities of models comprehensively.

3   Proposed Framework

In this section, we will first introduce the data structure and task formulation. Then we will provide a detailed description of the automatic pipeline for evaluating the LLMs. Finally, we will discuss the construction of the dataset.

3.1   Task Formulation

Each instance of the data consists of two parts, a patient's medical information M and a task T which is required to be completed at the end of the conversations. Since the consultations typically begin with the question of the patients, we also generate a fixed patient's initial request P_0 for each instance based on its medical information. P_0 generally includes a rough description of the symptoms and the requests for help. As a result, the dataset with size

equal to N can be formulated as:

$$\{(M^{(i)}, P_0^{(i)}, T^{(i)})\}_{i=1}^N \qquad (1)$$

The whole evaluation pipeline consists of two LLMs, the doctor LLM and the patient LLM. These two are responsible for being evaluated and interacting with the doctor LLM under certain information, respectively. At the beginning of the conversation, doctor LLM can get a preliminary understanding of the patient's situation and need according to the P_0. Then it is required to ask questions to get useful information from the patient in the following communication. Specifically, in the i-th round of conversation, the doctor LLM give an query $D_i = \{d_1^{(i)}, d_2^{(i)}, ..., d_{|D_i|}^{(i)}\}$ based on the conversation history in an autoregressive manner:

$$p_\theta(D_i|D_{1:i-1}, P_{0:i-1}) = \prod_{k=1}^{|D_i|} p_\theta(d_k^{(i)}|D_{1:i-1}, P_{0:i-1}) \quad (2)$$

where $|D_i|$ is the length of the doctor LLM i-th outputs and θ is the parameter of the doctor LLM. Similarly, patient LLM generates a response $P_i = \{p_1^{(i)}, p_2^{(i)}, ..., p_{|P_i|}^{(i)}\}$ based on the query of the doctor, conversation history, and medical information:

$$p_\phi(P_i|D_{1:i}, P_{0:i-1}, M) = \prod_{k=1}^{|P_i|} p_\theta(p_k^{(i)}|D_{1:i}, P_{0:i-1}, M)$$
$$(3)$$

where ϕ represents the parameters of the patient LLM. When the doctor is no longer inquiring about patient information, we consider the consultation process to be over. At the end of the consultation conversations, doctor LLMs are requested to complete some tasks according to the whole conversation, such as providing diagnosis, etiology, or treatment plan, etc.

3.2 Patient Simulation

Traditional evaluation of consultations is difficult when it comes to assessing a model's ability to handle multi-round conversations, which are inherently uncertain and uncontrollable. However, the emergence of large dialogue models has made automatic multi-round conversations possible. These models have undergone instruction fine-tuning, resulting in strong interactive abilities that can simulate the process of multiple rounds of dialogue. Additionally, large models can generate output according to specified requirements. In this paper, we utilize large-language models with instruction fine-tuning

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Prompt for Patient LLM

Marv is a patient that interacts with doctor to get medical help. Marv's condition can be summarized as {{medical_info}}.
At each Round Marv responds in less than 15 words.
At each Round Marv gives only one point of information.
Marv always talks colloquially.

{{dialog_history}}
Marv:

Figure 2: The prompt for patient LLMs. Elements in double braces {{}} are replaced with question-specific values.

to simulate the behavior of patients in consultation conversations, thus allowing for an easy evaluation of the doctor model's ability in multiple rounds of consultations.

We have defined some fundamental requirements for the patient LLM to ensure the robustness of the pipeline:

- **Honesty**. The patient LLM should provide an accurate and rational description of the symptoms in medical information, without reporting any nonexistent symptoms. This allows the doctor LLM to obtain correct information and reduces uncertainty in multiple rounds of dialogue.

- **Strictness**. As a comprehensive patient simulator, the patient model is provided with all information in ground truth. However, experiments have shown that this can lead to the model revealing medical information that doctors have not inquired about, resulting in the leakage of extra information. To be in line with real-world patients, the patient model is supposed to give information in a "lazy" mode, thereby improving the discriminability of the pipeline towards the doctor LLMs.

- **Colloquialism**. To better align with reality, we assume that patients do not have much medical knowledge, so their output should be colloquial. In experiments, we have also found that the colloquial prompt construction helps with the strictness requirements, which is also reported in Chen et al. (2023).

In summary, we designed a prompt for the patient that meets the three characteristics described above (as shown in Figure 2). This allowed us

Multiple Choice Question

A 61-year-old Caucasian male presents to your office with chest pain. He states that he is worried about his heart, as his father died at age 62 from a heart attack. He reports that his chest pain worsens with large meals and spicy foods and improves with calcium carbonate. He denies dyspnea on exertion and an ECG is normal. What is the most likely cause of this patient's pain?

A. Partially occluded coronary artery
B. Esophageal adenocarcinoma
C. Umbilical hernia
D. Gastroesophageal junction incompetence
E. Intestinal metaplasia at the gastroesophageal junction

Medical Information

A 61-year-old Caucasian male presents to your office with chest pain. He states that he is worried about his heart, as his father died at age 62 from a heart attack. He reports that his chest pain worsens with large meals and spicy foods and improves with calcium carbonate. He denies dyspnea on exertion and an ECG is normal.

Task

What is the most likely cause of this patient's pain?
A. Partially occluded coronary artery
B. Esophageal adenocarcinoma
C. Umbilical hernia
D. Gastroesophageal junction incompetence
E. Intestinal metaplasia at the gastroesophageal junction

Initial Request

What's causing my chest pain after eating?

Medical Information (Key, Value)

Key	Value
Patient age	61
Patient gender	Male
Chief complaint	Chest pain
Family history	Father died from a heart attack at age 62
Chest pain worsened by	Large meals and spicy foods
Chest pain improved by	Calcium carbonate
Dyspnea on exertion	Denied
Electrocardiogram (ECG) result	Normal

Figure 3: Example of the constructed data. The multiple choice question is first split into medical information and task part. Then the initial request and key-value pair list are extracted by ChatGPT from the medical information.

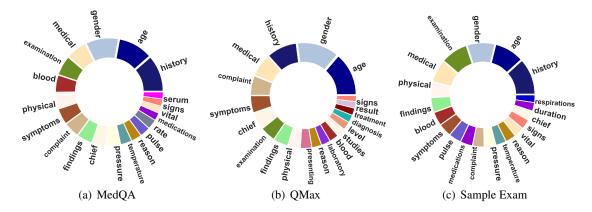(a) MedQA   (b) QMax   (c) Sample Exam

Figure 4: Most frequent words distribution of three datasets. We draw the Top-20 most frequent keys of extracted medical information. Note that the same word is represented by the same color across different datasets.

Statistics	MedQA	QMax	Sample Exam
# of instances	1127	1483	299
# of options per question	5.00	5.11	5.12
# of tokens per medical information	106.00	80.85	119.28
# of tokens per initial request	14.01	14.28	14.32
# of items per medical information	7.87	7.81	8.25

Table 1: The statistics of MedQA, QMAX, Sample Exam Datasets

to obtain a large language model that can better simulate the patient.

3.3 Data Construction

Because there is a scarcity of data that provides comprehensive medical information and diagnostic results, we reformulated the multiple choice questions in physician exams as the test datasets for our benchmark. We have created three datasets and filtered out questions that do not contain patient information:

- **MedQA**: We have chosen the English test set of the MedQA[1], which was collected from Medical Licensing Examinations of the United States (USMLE).

- **QMax**: The dataset includes materials purchased from the USMLE-RX[2] resources. There are a total of 11 categories, such as cardiology, endocrine, gastroenteric, etc.

- **Sample Exam**: Sample exam materials were sourced from USMLE practice materials[3]. We collect the dataset from the provided by Kung et al. (2023). In addition, we have removed the duplicated question in the test set.

For each dataset, we first split the multi-choice question into two parts: the informational part M and the task part T. These respectively describe the patient background and task requirements. Then, we use ChatGPT to generate the patient's initial request at the beginning of the consultation conversation, based on the medical information. We also extract the main medical information into key-value pairs, following the approach proposed by Agrawal et al. (2022). Figure 3 provides an exam-

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[1]https://github.com/jind11/MedQA

[2]https://usmle-rx.com
[3]https://www.usmle.org/prepare-your-exam

ple of the multi-choice question and its corresponding preprocessed data. Additionally, we calculate the most frequently occurring words in the keys of the medical information for the three datasets, as shown in Figure 4. Detailed statistical information for the three datasets is also presented in Table 1.

4 Experiments

4.1 Automated Metrics

Considering that LLMs have achieved great success in language fluency, our evaluation mainly focuses on the ability of doctor LLMs in multi-turn dialogue consultation. We introduce several indicators to measure the performance of the doctor LLMs in different dimensions.

Medical Information Coverage Rate　We use three types of ROUGE scores (Lin, 2004) to measure the amount of medical information presented in dialogue at the word level: Recall, Precision, and F1 scores. We evaluate the entire conversation at a fine-grained level from both the doctor's and patient's perspectives. For the patient evaluation, we compute three types of ROUGE-1 scores between the output of the patient LLM and the value of the extracted medical information M. The Recall represents how much information is exposed by the patient LLM, the Precision reflects the information density output by the patient model, and the F1 score provides a comprehensive evaluation of the patient LLM output. For the doctor evaluation, we measure the similarity between the output of the doctor LLM and the key of the extracted medical information. Specifically, the Recall measures the hallucination level of doctor LLMs. The Precision represents the professionalism of doctor LLM, as medical information generally contains medical terms. The higher the proportion of medical terms in the output of the doctor's model, the more professional the model's output we suppose. The F1 score is also a comprehensive evaluation of doctor LLMs.

Accuracy of the Final Task　After the multi-turn consultation, the model is required to complete a specific task, which here is to choose the right answer for a multiple-choice question according to the consultation dialogue. The accuracy of this task reflects the accuracy and coverage of medical information throughout the entire consultation process, which is an important indicator of the consultation ability of the doctor LLM. Considering

that most LLMs perform poorly on the question of the USMLE

We use ChatGPT-Turbo-3.5 as our final task solver due to its accessibility and robustness.

Average Turn and Average Length　To evaluate the performance of different models in multi-turn consultations, we need to measure the average number of rounds and the average length of each conversation. The doctor LLM will stop asking questions once it assumes that the medical information is enough to make a decision. Average Turn is an indicator measuring both doctor LLMs precision and hallucination level as more hallucinated models tend to stop asking questions at earlier rounds. Ideally, we hope that models with higher accuracy in consultations also require fewer rounds and shorter conversations.

4.2 Doctor Construction

To test the robustness of our framework, we employed several LLMs to simulate doctors and test various prompts for each LLM.

Upper Bound　In this case, the model can directly complete the final task according to the golden medical information. The accuracy of the upper bound is limited by the medical ability of the model for task completion.

Lower Bound　In the lower bound, the models were required to complete the final task only based on the initial request of the patient. This case can be used to indicate how much medical information is contained in the initial request. Therefore, the incremental information during the consultation process can be measured by the increase in accuracy.

ChatGPT-Turbo-3.5　In general, ChatGPT does not actively ask questions. Therefore, we prompted ChatGPT to act like a doctor in order to complete the proposed tasks in the evaluation pipeline. In the experiments, we observed that ChatGPT would like to draw a conclusion after a brief inquiry, where the number of rounds of consultation is generally less than five. Therefore, we designed two versions of Doctors with different prompts named ChatGPT-Long and ChatGPT-Short, respectively. The long version tries to guide the model to ask as many questions as possible, up to 10 questions, and the short version doesn't require the model to ask excessive questions. In both settings, the model will

Dataset	Case	Patient				Doctor				Turn	Acc.
		Rec.	Pre.	F1	Len.	Rec.	Pre.	F1	Len.		
MedQA	Upper-B	-	-	-	-	-	-	-	-	-	53.50
	Lower-B	3.45	22.78	5.75	-	-	-	-	-	-	35.49
	ChatGPT-L	28.26	17.84	20.65	9.15	18.67	3.58	5.82	15.94	9.17	39.31
	ChatGPT-S	19.74	21.45	19.17	10.65	18.06	4.08	6.27	30.29	4.58	37.27
	Vicuna	22.91	18.58	18.42	8.60	11.11	3.90	5.34	9.82	8.22	38.60
	Vicuna-FT	**33.19**	**23.55**	**26.02**	9.17	**23.06**	**6.11**	**9.02**	14.77	8.32	**40.20**
QMAX	Upper-B	-	-	-	-	-	-	-	-	-	55.02
	Lower-B	5.13	21.87	8.00	-	-	-	-	-	-	36.95
	ChatGPT-L	32.55	12.94	17.69	9.19	19.82	2.77	4.72	16.16	9.24	41.94
	ChatGPT-S	27.96	**16.84**	19.82	10.97	**21.98**	3.17	5.29	37.95	4.14	41.40
	Vicuna	26.72	14.44	16.55	7.63	11.28	2.97	4.37	9.88	8.04	39.45
	Vicuna-FT	**33.17**	16.62	**20.79**	8.86	21.62	**4.83**	**7.30**	14.26	7.84	**42.75**
Sample Exam	Upper-B	-	-	-	-	-	-	-	-	-	60.20
	Lower-B	3.51	23.69	5.83	-	-	-	-	-	-	40.13
	ChatGPT-L	26.98	18.70	20.71	9.32	19.35	4.17	6.66	16.54	9.12	43.81
	ChatGPT-S	19.74	23.28	19.52	10.97	18.70	4.65	6.93	31.56	4.43	45.15
	Vicuna	23.30	21.01	19.95	8.55	11.87	4.60	6.12	10.28	8.27	42.81
	Vicuna-FT	**32.59**	**24.43**	**26.05**	9.42	**22.21**	**6.85**	**9.70**	13.82	8.27	**46.82**

Table 2: Performance of different models on three datasets. Len and Turn represent the average length of the sequence in each turn and the average number of turns for each consultation instance. The best results in each dataset are bold.

naturally come to a conclusion when it thinks the information provided is enough to answer the patient's initial question.

Vicuna Vicuna is an open-sourced LLM trained by fine-tuning LLaMA (Touvron et al., 2023) on user-shared conversations collected from ShareGPT[4], and has demonstrated strong multi-round interaction ability. We used the same prompt as ChatGPT-Short for Vicuna to act like a doctor.

Vicuna Finetuned We created training data using the training set of the MedQA dataset to illustrate Vicuna's consultation abilities. First, we reconstructed the main medical information in key-value pairs, which is the same process used for the test data. Next, we generated a golden consultation dialogue between a doctor and a patient, with ChatGPT playing the role of both. In each turn, the doctor ChatGPT asked a key question based on the medical information, and the patient ChatGPT answered it. Finally, the doctor ChatGPT provided an analysis and diagnosis.

4.3 Main Result

Table 2 presents the results of various models discussed in Section 4.2 on three datasets. The ac-

[4]https://sharegpt.com/

curacy gap between the Upper-Bound and Lower-Bound cases is significant, highlighting how insufficient medical information often leads to degraded diagnostic performance of the models. After several rounds of interaction with patient models, the accuracies improve in all cases, indicating that current models possess basic consultation abilities and can deduce missing information to some extent.

Comparing two versions of ChatGPT, we observe that ChatGPT-Long requires approximately twice as many consultation rounds as ChatGPT-Short, while the length of its questions is about half that of ChatGPT-Short. Despite the different prompts eliciting different behaviors, both models exhibit similar performance according to the patients/doctor F1 scores and task accuracy. This suggests that the model's ability is the primary factor determining its effectiveness, rather than the design of the prompts.

Although Vicuna performs relatively poorly in the consultation process compared to ChatGPT, it demonstrates much stronger capabilities after being fine-tuned on the constructed training data. Vicuna-FT achieves the best F1-score on all datasets while keeping the average lengths of questions and answers short. This shows that Vicuna-FT has less hallucination problem and are more precise and
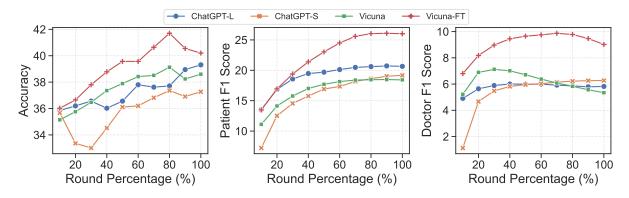
Figure 5: Turn Analysis results of different LLMs on MedQA dataset.

professional. With such powerful inquiry ability, the model can obtain more detailed medical information from patients, thereby improving the accuracy of the final task. In fact, it can even surpass ChatGPT by up to 1.67 percent.

5 Analysis

In this section, we conduct more experiments to analyze the robustness of the proposed framework. We first decompose the consultation process and explore the performance of different models at the turn level. Then we assess the diversity of the models' outputs and the impact of the consultation order on the final accuracy. Finally, we investigate the models' performance on cases with different complexity.

5.1 Turn Number Analysis

We conducted an investigation into how medical information was revealed throughout the multi-turn dialogue. Because different doctor LLMs have very different distributions of turn numbers, we used the percentage of rounds finished as the index for dialogue completeness. Specifically, for the case where the percentage of rounds is equal to 20%, if the total number of rounds is 10, the first two rounds of the conversation will be selected as the consultation process. We plot important metrics, including accuracy and F1-scores of patient LLM and doctor LLM in Figure 5.

It can be observed that the accuracy and F1 scores have an overall increasing trend as the dialogue progresses. The indicators quickly improve during the initial rounds of the conversation and then tend to plateau. This suggests that relevant information is easily acquired at the beginning of the consultation, while the challenge lies in obtaining further details of the patient's information. Among

Model	ROUGE-1	ROUGE-2	ROUGE-L
ChatGPT-L	38.96	20.53	35.86
ChatGPT-S	39.28	21.89	32.74
Vicuna	62.51	53.98	61.95
Vicuna-FT	**33.39**	**20.00**	**31.45**

Table 3: Diversity of doctors' query. The table shows three types of diversity scores with different metrics. Note that a lower score represents more distinction between the models' questions.

the models, Vicuna-FT has the highest F1 score for both doctor and patient, indicating that it has less hallucination problem and can obtain more information from patients, resulting in the best overall performance in accuracy score.

Note that there is a slight drop in both doctor F1 score and accuracy after 80% of the dialogue process. This is because the doctor LLMs are prone to give a diagnosis or advice near the end of the consultation process, which adds noise to the dialogue history and causes performance degradation in the final task.
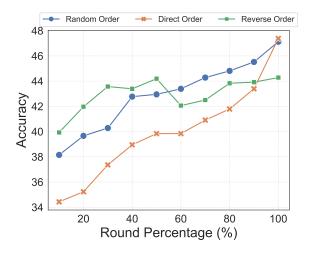

Figure 6: Accuracy curves of random, direct, and reversed orders of medical information keys.

5.2 Diversity of Doctors' Queries

There are some repetition queries found in the case study. Therefore, we calculated the similarity between the queries of doctor LLMs in the same conversation as follows:

$$\text{Diversity} = \frac{1}{K(K-1)} \sum_{i=1}^{K} \sum_{j=1}^{K} \text{sim}(D_i, D_j) \tag{4}$$

where K is the total rounds of the consultation conversation, and $\text{sim}(\cdot, \cdot)$ is the similarity function. As presented in Table 3, Vicuna-FT generates the most diverse queries among all models, while Vicunas generate the most similar ones. Additionally, we can also observe that Vicuna tended to repeat questions during the consultation process.

5.3 Impact of Consultation Order

We also conducted experiments to analyze the impact of the order of doctor consultation. To eliminate the effect of different questions, we conducted an oracle case where the doctor's questions are constructed by the keys of the extracted medical information. Specifically, at each turn, we formulated the rule-based question in the form of "Can you tell me about {{key}}?" according to the (key, value) pair in the extracted medical information list.

Since the keys in the extracted medical information typically range from basic medical information to more specialized medical details, we can construct three types of consultation orders, which includes direct order, random order, and reverse order. Direct order is to ask medical information questions from general to specific, while the reverse order is exactly the opposite. Figure 6 shows their impacts on final accuracy.

In the first part of the conversation, the reversed order performed the best, indicating that detailed information is more helpful in solving the final task. However, the final accuracy of the reverse case is lower than the other two settings even though all the cases have equal patient information. We attribute this phenomenon to the task solver's sensitivity to the location of patient information in the context.

5.4 Performance on Data with Different Complexity

In this section, we investigate the effectiveness of different models on data with varying numbers of medical information items. The entire test set is divided into three equal parts based on the number of
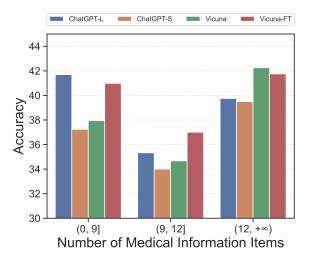

Figure 7: The performance of different models with respect to the number of medical information items. The results are reported on MedQA.

medical information items. As shown in Figure 7, all models perform poorly on data with a moderate amount of medical information. However, Vicuna-FT exhibits robust performance across all three groups. It is worth noting that ChatGPT-Long outperforms Vicuna on the Short group, while Vicuna outperforms ChatGPT-Long on the Long group. This indicates that models have a bias towards certain numbers of medical information items.

6 Conclusions

In this paper, we proposed a novel framework to evaluate the medical ability of LLMs in multi-turn consultations and construct three test datasets by reformulating the multiple-choice questions. We adopt ChatGPT to simulate the patient in the consultation process in order to generate responses to the question of doctor LLMs. Besides, we develop comprehensive evaluation metrics to score the multi-turn conversation and improve the consultation ability and alleviate the hallucination of LLMs by constructing a training set. We also conduct extensive experiments to valid the robustness of our evaluation pipeline.

Limitations

Although we have utilized the most superior datasets available, this study may still be limited due to the size and potential bias of said datasets. Furthermore, the limited quantity of medical examination examples collected may hinder our ability to evaluate the model's comprehensive capabilities in a real-world consultation scenario. Moreover,

it is important to note that LLMs still encounter challenges related to hallucination and robustness, which may make the task solver susceptible to long and noisy inputs. Thus, in order to construct a more dependable and resilient solution, a more powerful LLM is necessary.

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