

Benchmarking Large Language Models on CMExam - A Comprehensive Chinese Medical Exam Dataset

Junling Liu^{1†*} Peilin Zhou^{2†} Yining Hua^{3,4†} Dading Chong⁵
 Zhongyu Tian⁶ Andrew Liu⁵ Helin Wang⁷ Chenyu You⁸
 Zhenhua Guo⁹ Lei Zhu¹⁰ Michael Lingzhi Li^{4,11}

¹Alibaba Group ²Hong Kong University of Science and Technology (Guangzhou)

³Harvard Medical School ⁴Boston Children’s Hospital ⁵Peking University

⁶Second Affiliated Hospital of Zhejiang University School of Medicine ⁷Johns Hopkins University

⁸Yale University ⁹Tianyi Traffic Technology ¹⁰Ant Group ¹¹Harvard Business School

{william.liuj, zhoupalin, andrew.promed, cszguo, zhulei0305}@gmail.com
 1601213984@pku.edu.cn, zhongyutian@zju.edu.cn, hwang258@jhu.edu
 yining_hua@hms.harvard.edu, chenyu.you@yale.edu, mili@hbs.edu

Abstract

Recent advancements in large language models (LLMs) have transformed the field of question answering (QA). However, evaluating LLMs in the medical field is challenging due to the lack of standardized and comprehensive datasets. To address this gap, we introduce **CMExam**, sourced from the Chinese National Medical Licensing Examination. CMExam consists of 60K+ multiple-choice questions for standardized and objective evaluations, as well as solution explanations for model reasoning evaluation in an open-ended manner. For in-depth analyses of LLMs, we invited medical professionals to label five additional question-wise annotations, including *disease groups*, *clinical departments*, *medical disciplines*, *areas of competency*, and *question difficulty levels*. Alongside the dataset, we further conducted thorough experiments with representative LLMs and QA algorithms on CMExam. The results show that GPT-4 had the best accuracy of 61.6% and a weighted F1 score of 0.617. These results highlight a great disparity when compared to human accuracy, which stood at 71.6%. For explanation tasks, while LLMs could generate relevant reasoning and demonstrate improved performance after finetuning, they fall short of a desired standard, indicating ample room for improvement. To the best of our knowledge, CMExam is the first Chinese medical exam dataset to provide comprehensive medical annotations. The experiments and findings of LLM evaluation also provide valuable insights into the challenges and potential solutions in developing Chinese medical QA systems and LLM evaluation pipelines.¹

1 Introduction

Recent advancements brought by large language models (LLMs) such as T5 (Raffel et al., 2020) and GPT-4 (OpenAI, 2023) have revolutionized natural language processing (NLP). However, evaluating LLMs in the medical field poses significant challenges due to the paucity of standardized and comprehensive datasets compiled from reliable and unbiased sources (Li et al., 2023). Most existing medical datasets (Hendrycks et al., 2020; Abacha et al., 2019b; Li et al., 2023) for language model evaluation have limitations that hinder comprehensive assessment of LLM performance. Many

*Corresponding Author. †Co-first authors

¹The dataset and relevant code are available at <https://github.com/williamliuj1/CMExam>

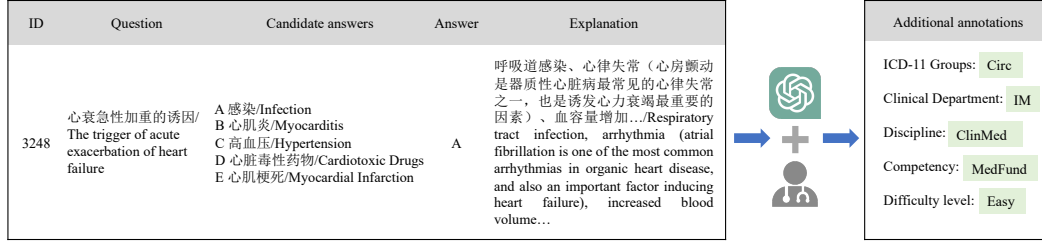


Figure 1: An example question of CMExam. Abbreviations: Circulatory System Diseases (Circ), Internal Medicine (IM), Clinical Medicine (ClinMed), Medical Fundamentals (MedFund).

datasets are insufficient in terms of size and diversity, preventing a thorough evaluation of LLM capabilities. Furthermore, most datasets primarily focus on text generation tasks rather than utilizing clear choice evaluations, impeding objective and quantitative measurement of LLM performance. Additionally, a majority of these datasets (Li et al., 2023; Pal et al., 2022; Zhu et al., 2020) are sourced from online forums and consumer feedback, which could suffer from significant bias and error. These challenges are particularly amplified in non-English languages, such as Chinese, due to the pervasive inequality in language resources that exists in the NLP field (Bird, 2020; Zeng et al., 2022). Overall, due to the lack of qualified evaluation datasets, the strengths and weaknesses of LLMs in the medical field have not been fully studied.

In response, we present a novel dataset called CMExam to overcome these challenges and benchmark LLM performance. CMExam is sourced from authentic medical licensing exams. It contains more than 60K questions and utilizes the multiple-choice question format to allow standardized and objective evaluations. Questions in CMExam have corresponding solution explanations that can be used to test LLM’s reasoning ability in an open-ended manner. To offer diverse perspectives for measuring LLM performance in the medical field, we created five additional question-wise annotation dimensions based on authenticated resources and objective metrics. To reduce the substantial time and labor costs associated with annotating large-scale datasets, we propose an innovative strategy called GPT-Assisted Annotation. This approach harnessed the power of GPT-4 to automate the initial annotation process. Subsequently, the annotated data underwent a meticulous review and manual verification conducted by two medical professionals. Figure 1 shows an example question from CMExam and the annotation process.

Furthermore, we benchmark the performance of general domain LLMs and medical domain LLMs on answer prediction (multiple-choice) and answer reasoning (open-ended) tasks of CMExam. This comprehensive assessment aims to highlight the strengths and weaknesses of various approaches in Chinese medical QA, with a focus on LLMs. The main findings of this benchmark are as follows:

- GPT-4 (OpenAI, 2023) demonstrates impressive zero-shot performance on the answer prediction task compared to other models, though still significantly lagging behind human performance.
- GPT-3.5 (Brown et al., 2020) and GPT-4 generated reasonable answers on the answer reasoning task despite low BLUE and ROUGE scores. This is because they tended to generate short answers with reasonable quality.
- Existing medical domain LLMs, such as Huatuo (Li et al., 2023) and DoctorGLM (Xiong et al., 2023), exhibit poor zero-shot performance on both tasks, indicating their limited coverage of medical knowledge and substantial room for improvement.
- Lightweight LLMs (e.g., ChatGLM (Du et al., 2022)) fine-tuned on CMExam with supervision achieve performance close to GPT-3.5 on the answer prediction task. They also significantly outperform GPT-3.5 and GPT-4 on the reasoning task while having only 3% of the parameters of GPT-3.5.

In summary, this study provides valuable insights into the performance of LLMs in medical contexts from multiple perspectives, benefiting both the artificial intelligence research community and the medical research community. Our findings contribute to a deeper understanding of the capabilities and limitations of LLMs in the medical domain. Additionally, the CMExam dataset and benchmark introduced in this study serve as valuable resources to inspire researchers in exploring more effective ways of integrating medical knowledge into LLMs, ultimately enhancing their performance in medical applications.

Table 1: A review of medical QA datasets. * indicates availability of additional annotations, † indicates availability of benchmarks, and ‡ indicates datasets with more than 50K questions

Language	Data Source Type	Question Type	
		Multiple Choice	Open-ended
English	Consumer Questions	MedMCQA (Pal et al., 2022)	LiveQA-Med (Abacha et al., 2017)
			CliCR [†] (Šuster and Daelemans, 2018)
			HealthQA (Zhu et al., 2019)
			MEDIQA (Abacha et al., 2019b)
English	Research, Books, or Exams	MEDQA [‡] (Jin et al., 2021) MMLU ^{†‡} (Hendrycks et al., 2020) MedMCQA (Pal et al., 2022) MultiMedQA ^{*†} (Singhal et al., 2022)	emrQA [‡] (Pampari et al., 2018)
			MedQuaD (Ben Abacha and Demner-Fushman, 2019)
			MedicationQA [*] (Abacha et al., 2019a)
			MEDIQA-AnS (Savery et al., 2020)
Chinese	Consumer Questions	-	MASH-QA (Zhu et al., 2020)
			BioASQ (Krithara et al., 2023)
			MultiMedQA ^{*†} (Singhal et al., 2022)
Chinese	Research, Books, or Exams	MLEC-QA [‡] (Li et al., 2021) CMExam ^{*†‡} (ours)	webMedQA ^{*‡} (He et al., 2019)
			cMedQA-v1.0 [‡] (Zhang et al., 2017)
			cMedQA-v2.0 [‡] (Zhang et al., 2018)
			ChiMed (Tian et al., 2019)
Chinese	Research, Books, or Exams	MLEC-QA [‡] (Li et al., 2021) CMExam ^{*†‡} (ours)	Huatuo-26M ^{†‡} (Li et al., 2023)
			MLEC-QA [‡] (Li et al., 2021)
			CMExam ^{*†‡} (ours)

2 Related Work

Medical Question-Answering Datasets Table 1 presents a summary of medical QA datasets published after 2017. In particular, we focus on categorizing the data source and question types of the different datasets. Most existing medical QA datasets adopt an open-ended format, primarily because they were constructed directly from consumer questions and answers from doctors. However, multiple-choice and fill-in-the-blank questions provide a more standardized and objective evaluation, and only a small portion of medical QA datasets have adopted these formats. Notable examples include CliCR (Šuster and Daelemans, 2018), MEDQA (Jin et al., 2021), MMLU (Hendrycks et al., 2020), MLEC-QA (Li et al., 2021), and MedMCQA (Pal et al., 2022). Note that the multiple-choice questions in MultiMedQA (Singhal et al., 2022) come from MEDQA, MedMCQA, and MMLU.

Data source types generally determine the reliability of a dataset. Consumer questions collected from web sources require human review to ensure the correctness of the answers. As datasets grow in size, quality control becomes increasingly challenging (Li et al., 2023). In contrast, datasets built from case reports (e.g., CliCR), research literature (e.g., BioAsq (Krithara et al., 2023)), medical books, exams, and related practices (e.g., MMLU and MedMCQA) are often more reliable.

From Table 1, we observe that there are few datasets based on multiple-choice questions from authoritative sources. In particular, the most related dataset is the MLEC-QA dataset, which is also derived from the Chinese National Medical Licensing Examination. Despite a shared data source, our CMExam dataset stands out due to more extensive and well-designed analysis dimensions, making it highly suitable for evaluating the medical capabilities of LLMs. We have curated a comprehensive range of disease groups, clinical departments, medical disciplines, areas of competency, and question difficulty levels, enabling a thorough understanding of LLM performance from various angles. Additionally, to facilitate objective evaluations, we provide benchmark results from state-of-the-art models on our dataset. By offering a broader scope and richer analysis dimensions, CMExam provides a valuable resource for assessing the medical abilities of LLMs.

Other Benchmark Datasets of Large Language Models The assessment of LLMs has witnessed significant progress, with the introduction of diverse benchmarks that evaluate different dimensions across multiple languages and models. Many datasets focus on assessing natural language understanding and reasoning of LLMs. RACE (Lai et al., 2017) includes English exams for Chinese middle and high school students. TriviaQA (Joshi et al., 2017) consists of question-answer pairs authored by trivia enthusiasts. DROP (Dua et al., 2019) evaluates reading comprehension with discrete reasoning and arithmetic components. GLUE (Wang et al., 2018) encompasses four existing NLU tasks, while SuperGLUE (Wang et al., 2019) extends it with a more challenging benchmark of eight language understanding tasks. Other datasets, such as HellaSwag (Zellers et al., 2019) and WinoGrande (Sakaguchi et al., 2021), focus on commonsense reasoning. TruthfulQA (Lin et al.,

Table 2: Basic statistics of CMExam. Q: questions; E: explanations; Q1/3: the first/ third quantile.

	Train	Dev	Test	Total
Question #	54,497	6,811	6,811	68,119
Vocab	4,545	3,620	3,599	4,629
Max Q tokens	676	500	585	676
Max E tokens	2,999	2,678	2,680	2,999
Avg Q tokens	29.78	30.07	32.63	30.83
Avg E tokens	186.24	188.95	201.44	192.21
Median (Q1, Q3) Q tokens	17 (12, 32)	18 (12, 32)	18 (12, 37)	18 (12, 32)
Median (Q1, Q3) E tokens	146 (69, 246)	143 (65, 247)	158 (80, 263)	146 (69, 247)

2021) includes health, law, finance, and politics, to assess LLMs’ ability to mimic human falsehoods, while MMCU (Zeng, 2023) covers medical, legal, psychology, and education to evaluate multitask Chinese understanding. In addition to language understanding and reasoning, several datasets focus on specific subjects and topics, such as Python coding tasks (Chen et al., 2021) and middle school mathematics questions (Cobbe et al., 2021).

3 The CMExam Dataset

Data Collection and Pre-processing CMExam comprises authentic past licensed physician exams in the Chinese National Medical Licensing Examination (CNMLE) collected from the Internet. The CNMLE, also known as the Physician Qualification Examination, is a standardized exam that assesses applicants’ medical knowledge and skills in China. It includes a written test with multiple-choice questions covering various medical subjects and a clinical skills assessment simulating patient diagnosis and treatment. We excluded questions that rely on non-textual information, including questions with external information such as images and tables, and questions with keywords "graph" and "table". Duplicate questions were removed from the dataset. In total, collected 96,161 questions, 68,119 of which were retained after pre-processing. The dataset was then randomly split into training/development/test sets with a ratio of 8:1:1. Each question in the dataset is associated with an ID, five candidate answers, and a correct answer. 85.24% of questions have brief solution explanations and questions in the test dataset contain additional annotations.

Data Annotation CMExam provides a comprehensive analysis of LLM performance through five additional annotation dimensions. The first dimension involves disease groups based on the 11th revision of the International Classification of Diseases (ICD-11) (World Health Organization (WHO), 2021). ICD-11 is a globally recognized standard classification system for documenting and categorizing health conditions, consisting of 27 major disease groups. The second dimension comprises 36 clinical departments derived from the Directory of Medical Institution Diagnostic and Therapeutic Categories (DMIDTC) ², published by the National Health Commission of China. DMIDTC is an authoritative guide used for categorizing and naming diagnostic and therapeutic subjects within healthcare institutes. In cases where the question cannot be successfully classified by ICD-11 or DMIDTC, the annotation is marked as "N/A". The third dimension refers to medical disciplines, which are categorized based on the List of Graduate Education Disciplinary Majors (2022) published by the Ministry of Education of the People’s Republic of China ³. This dimension encompasses seven categories representing study majors used in universities. The fourth dimension was created by two medical professionals within the team to assess the primary medical competency tested by each associated question. It consists of four categories. The fifth dimension represents the difficulty level of each question, determined by analyzing the correctness rate observed in human performance data collected alongside the questions. It includes five categories: easy, manageable, moderate, difficult, and extra difficult. For detailed information on these additional annotations, please refer to supplementary materials.

Dataset Characteristics The CMExam dataset has several advantages over previous medical QA datasets regarding: 1) *Reliability and Authenticity*: CMExam is sourced exclusively from the CNMLE that undergoes rigorous review and validation processes, ensuring its accuracy and adherence to established medical standards. 2) *Standardization and Comprehensiveness*: CMExam includes both multiple-choice questions that ensure fair and objective evaluations of models’ performance and question-wise open-ended reasoning that allows in-depth analysis and assessment of model reasoning

² <http://www.nhc.gov.cn/fzs/s3576/201808/345269bd570b47e7aef9a60f5d17db97.shtml>

³ http://www.moe.gov.cn/srcsite/A22/moe_833/202209/t20220914_660828.html

abilities and comprehension. CMExam reflects the comprehensive coverage of medical knowledge and reasoning required in clinical practice, as it is sourced from carefully designed national medical exams. The inclusion of five additional annotation dimensions enhances the dataset’s rigor and offers valuable insights for in-depth evaluation and analysis. 3) *Scale*: CMExam consists of over 60K high-quality questions, providing a large and reliable dataset.

Data Statistics The dataset has a total of 68,119 questions, with 65,950 answers being single-choice and 2,169 being multiple-choice, with a maximum of five answer choices. Among all questions, 85.24% have associated solution explanations. Questions in CMExam have a median length of 17 (Q1: 12, Q3: 32). Regarding solution explanations, the median length is 146 tokens (Q1: 69, Q3: 247). Table 2 shows more basic statistics of CMExam, and Figure 2 shows additional statistics visualization. Within the test set, 4,493 questions (65.97%) have corresponding disease group annotations. The most prevalent disease group is Traditional Medicine Disease Patterns (TMDP), followed by Digestive System Diseases, Certain Infectious (Digest) and Parasitic Diseases (InfDis), Endocrine, Nutritional, or Metabolic Diseases (Endo), and Circulatory System Diseases (Circ). For the associated clinical department annotations, 4,965 questions (72.90%) have been assigned values. The two most frequently represented clinical departments are Internal Medicine (IM) and Traditional Chinese Medicine (TCM), with Dentistry (Dent) and Surgery (Surg) following closely. Every question in the test set has been labeled with a discipline, where Clinical Medicine (ClinMed) comprises the largest proportion. Additionally, each question has been categorized into a competency area, with Medical Fundamentals (MedFund) being the predominant category. The difficulty levels of the questions align with common exam patterns, with a greater number of easy questions and a smaller number of hard questions.

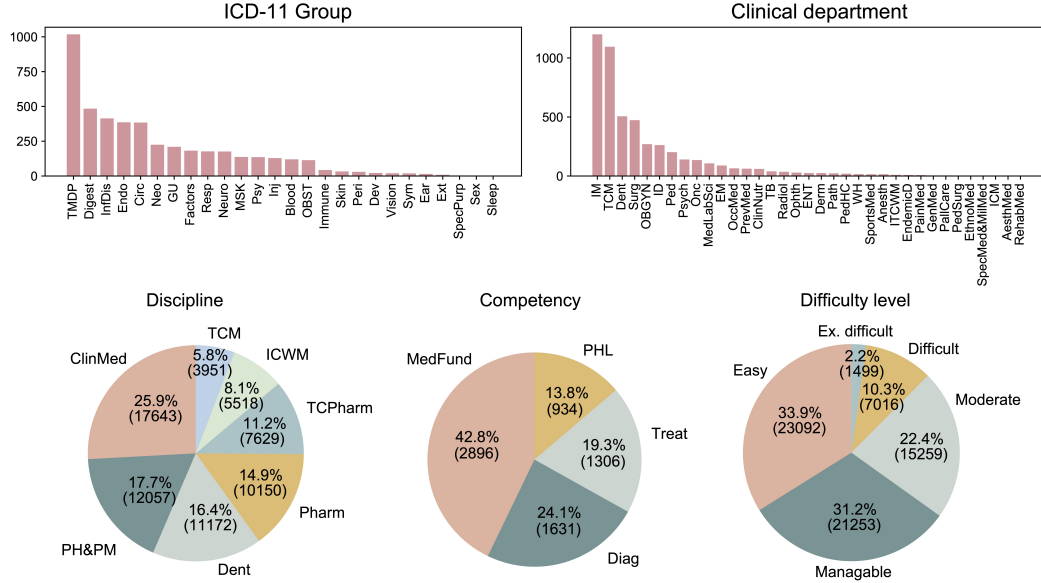


Figure 2: Additional CMExam statistics. For the question length distribution subplot, only the portion within IQR is shown.

4 Benchmarks

4.1 Baselines, Settings, and Metrics

Model selection The LLMs we benchmarked on the CMExam can be divided into two groups based on domains: 1) *General Domain LLMs*: This group comprises GPT3.5/4 (Brown et al., 2020; OpenAI, 2023), ChatGLM (Du et al., 2022; Zeng et al., 2023), LLaMA (Touvron et al., 2023), Alpaca (Taori et al., 2023), and Vicuna (Chiang et al., 2023). These models are general-purpose language models trained on a massive amount of general-purpose corpora; 2) *Medical Domain LLMs*: This group can be further divided into two subgroups. The first subgroup consists of representative LLMs specifically

designed for the medical domain, including DoctorGLM (Xiong et al., 2023) and Huatuo (Wang et al., 2023). DoctorGLM is a healthcare-specific language model initialized with ChatGLM-6B parameters and further fine-tuned on Chinese medical dialogues extracted from ChatGPT. Huatuo, on the other hand, is a knowledge-enhanced model, which builds upon the LLaMA architecture and is additionally supervised-fine-tuned with knowledge-based instruction data harvested from the Chinese medical knowledge graph (CMeKG). The second subgroup comprises medical LLMs that were constructed through supervised fine-tuning of LLMs using the CMExam training set. This subgroup includes models fine-tuned on BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), Huatuo, ChatGLM, LLaMA, Alpaca, and Vicuna.

Human Performance To effectively gauge the medical proficiency of LLMs, incorporating a measure of human performance into the benchmarking process is of paramount importance. Therefore, during data collection, we preserved the accuracy of human responses for each question. Human performance is estimated by computing a weighted average of response accuracy within each dimension, with weights determined by the number of respondents. This design ensures a robust comparison of LLMs’ performance relative to human capabilities, particularly when larger respondent samples contribute to a question’s accuracy.

Experimental Setting For GPT models, we leveraged OPENAI’s API to access the GPT-3.5-turbo and GPT-4-0314 models, given that their open-source variants are currently unavailable. The LLaMA, Alpaca, and Vicuna models were used in their respective 7B versions, while ChatGLM was evaluated using its publicly accessible 6B version. Additionally, we performed fine-tuning on open-source models using the CMExam dataset. We used P-tuning V2 (Liu et al., 2021) for ChatGLM-6B, with the length of prefix tokens set to 128, and the learning rate set to $2e-2$, LoRA (Hu et al., 2021) for LLaMA, Alpaca, Vicuna, and Huatuo models, with the rank set to 8, alpha set to 16, and dropout at 0.05. For BERT models, we followed the fine-tuning methods outlined in (Devlin et al., 2019), with batch size set to 16, learning rate set to $2e-4$, hidden dropout probability set to 0.4, and maximum input length set to 192. The fine-tuning processes for all models except BERT involved a batch size of 64, a maximum input length, and a target length of 256. All fine-tuning was performed using NVIDIA V100 GPUs for 10 epochs.

Metrics We assess model performance on multiple choice questions using accuracy and weighted F1 score. These metrics are commonly employed in information retrieval and question-answering tasks to evaluate model performance. For the open-ended solution explanation part of CMExam, BLUE (Papineni et al., 2002) and ROUGE (Lin and Hovy, 2003) were used to evaluate the discrepancy between model-generated explanations and ground truth.

4.2 Results and Analysis

Overall Comparison We first assessed the performance of general domain LLMs and medical domain LLMs for answer prediction and reasoning tasks. The results are displayed in Table 3. For the answer prediction task, GPT-4 significantly outperforms other methods, demonstrating a zero-shot performance with an accuracy of 61.6% and an F1 score of 0.617. While a performance gap still exists when compared to human performance (which stands at 71.6% accuracy), it’s noteworthy that this gap has been greatly reduced from what was observed with GPT-3.5. Among lightweight, general domain LLMs, ChatGLM outperforms LLaMA, Alpaca, and Vicuna, likely attributable to their limited coverage of the Chinese corpus. This restriction seemingly hampers their ability to provide accurate responses to CMExam queries. Furthermore, a noticeable deficiency in zero-shot performance is evident in lightweight medical domain LLMs such as Huatuo, owing to their restricted medical corpus diversity, which hampers the acquisition of broad medical knowledge and accurate interpretation of CMExam questions. Our findings suggest that finetuning models with CMExam enhance their performance. For instance, with an accuracy of 45.3%, ChatGLM-CMExam is comparable to GPT-3.5’s performance, despite utilizing only about 3% of the parameters employed by GPT-3.5. It is noteworthy that encoder-only LLMs, such as BERT and RoBERTa, remain a robust baseline for answer prediction tasks. Their performance can par with, or even exceed, that of certain decoder-only LLMs, such as LLaMA-CMExam and Alpaca-CMExam, despite having fewer parameters.

For the solution explanation task, we observe that GPT models performed poorly on the BLUE metric, likely due to their tendency of generating short explanations. However, they exhibited an advantage on the ROUGE metric. As DoctorGLM is unable to return answer options according to the prompt,

Table 3: Overall comparison on CMExam dataset. We **bold** the best result and underline the second best result.

Model type	Models	size	Prediction		Reasoning				
			Acc (%)	F1 (%)	BLUE-1	BLUE-4	ROUGE-1	ROUGE-2	ROUGE-L
General Domain	GPT-3.5-turbo	175B	46.4±0.6	46.1±0.7	3.56±0.67	1.49±0.51	33.80±0.19	16.39±0.18	14.83±0.13
	GPT-4	-	61.6±0.1	61.7±0.1	0.17±0.00	0.06±0.00	29.74±0.09	14.84±0.04	11.51±0.03
	ChatGLM	6B	26.3±0.0	25.7±0.1	16.51±0.08	5.00±0.06	35.18±0.11	15.73±0.05	17.09±0.13
	LLaMA	7B	0.4±0.0	0.3±0.0	11.99±0.03	5.70±0.0	27.33±0.06	11.88±0.03	10.78±0.04
	Vicuna	7B	5.0±0.0	4.8±0.1	20.15±0.01	9.26±0.01	38.43±0.02	16.90±0.01	16.33±0.01
	Alpaca	7B	8.5±0.0	8.4±0.0	4.75±0.00	2.50±0.00	22.52±0.00	9.54±0.00	8.40±0.00
Medical Domain	Huatuo	7B	12.9±0.0	7.0±0.0	0.21±0.00	0.12±0.00	25.11±0.08	11.56±0.04	9.73±0.02
	DoctorGLM	6B	-	-	9.43±0.09	2.65±0.03	21.11±0.03	6.86±0.01	9.99±0.06
	BERT-CMExam	0.1B	31.8±0.2	31.2±0.2	-	-	-	-	-
	RoBERTa-CMExam	0.3B	37.1±0.1	36.7±0.4	-	-	-	-	-
	Huatuo-CMExam	7B	28.6±0.5	29.3±0.2	29.04±0.01	16.72±0.03	43.85±0.24	25.36±0.22	21.72±0.24
	ChatGLM-CMExam	6B	45.3±1.4	45.2±1.4	31.10±0.23	18.94±0.12	43.94±0.28	31.48±0.14	29.39±0.14
	LLaMA-CMExam	7B	18.3±0.5	20.6±0.5	29.25±0.23	16.46±0.10	45.88±0.04	26.57±0.04	23.31±0.02
	Alpaca-CMExam	7B	21.1±0.6	24.9±0.4	29.57±0.10	16.40±0.12	<u>45.48±0.12</u>	25.53±0.18	22.97±0.06
	Vicuna-CMExam	7B	27.3±0.5	28.2±0.3	<u>29.82±0.03</u>	<u>17.30±0.01</u>	44.98±0.16	26.25±0.13	22.44±0.09
	Random	Random	-	3.1±0.2	5.1±0.3	-	-	-	-
Human Performance	Human volunteers	-	71.6	-	-	-	-	-	-

Table 4: Comparing disease classifications.

Categories	GPT-4	GPT-3.5	ChatGLM	ChatGLM-CMExam	Average
Neo	74.4±2.2	63.9±1.4	32.4±1.6	51.9±0.2	55.6±0.8
Psy	74.0±0.7	62.0±1.7	33.3±1.3	54.7±0.8	56.0±0.9
Factors	70.0±1.0	57.5±1.4	28.0±1.1	51.1±1.4	51.6±0.5
MSK	65.9±0.8	53.8±0.8	29.2±0.4	53.5±0.0	50.6±0.4
GU	69.2±0.4	52.1±1.1	30.0±0.2	49.5±0.9	50.2±0.3
Inj	65.9±2.3	45.7±1.3	37.2±2.9	49.1±1.8	49.5±1.4
Circ	68.8±0.3	49.3±0.7	30.9±0.7	47.0±0.3	49.0±0.2
Endo	70.6±1.1	49.4±1.1	25.5±0.8	46.1±0.4	47.9±0.2
Digest	67.0±1.0	48.8±1.4	26.2±0.7	49.4±1.1	47.8±0.4
InfDis	66.0±0.5	49.2±0.8	27.5±0.6	48.2±0.8	47.7±0.4
Neuro	64.4±1.2	48.7±3.1	28.6±0.4	45.3±1.3	46.7±1.1
OBST	63.5±0.3	45.0±2.4	25.7±0.9	49.4±0.3	45.9±0.5
BLOOD	69.4±0.3	45.3±1.4	18.9±1.6	43.3±0.7	44.2±0.4
Resp	62.7±0.8	44.3±1.4	24.5±0.3	42.9±0.0	43.6±0.7
N/A	60.0±0.1	46.8±0.3	24.9±0.2	42.5±0.1	43.5±0.1
TCMDP	44.3±0.9	31.0±0.6	24.2±0.4	47.9±0.0	36.9±0.6

Table 5: Comparing clinical department.

Categories	GPT-4	GPT-3.5	ChatGLM	ChatGLM-CMExam	Average
EM	67.4±0.2	49.8±0.7	36.3±0.4	50.2±0.5	50.9±0.1
OBGYN	66.4±1.0	51.7±1.5	28.6±0.5	52.0±0.0	49.7±0.3
IM	70.2±0.6	51.8±0.8	26.0±1.1	47.9±0.9	49.0±1.0
ID	67.4±1.9	49.5±3.3	26.1±1.9	49.6±3.8	48.2±1.2
Surg	63.6±0.8	49.5±1.5	28.8±0.5	47.7±0.9	47.4±1.5
ClinNutr	68.3±2.4	48.3±2.9	23.9±1.1	47.8±0.5	47.1±0.7
MedLabSci	69.2±0.6	48.3±2.0	29.0±1.5	40.8±0.6	46.8±0.2
Ped	64.5±0.0	47.2±1.4	26.7±2.1	41.9±5.5	45.1±1.7
N/A	62.6±0.2	48.6±1.1	24.6±0.4	44.3±0.9	45.0±1.0
Ophth	60.9±0.5	39.1±0.8	21.8±0.8	54.0±0.2	44.0±0.8
OccMed	61.5±4.3	38.5±1.6	31.3±4.3	41.5±3.3	43.2±2.5
DENT	54.9±2.0	41.2±1.6	27.9±0.8	43.5±0.9	41.9±1.0
TCM	43.1±1.3	31.4±1.3	24.5±1.9	45.8±4.4	36.2±0.6
ENT	41.3±0.8	28.0±0.6	29.3±0.1	26.7±0.1	31.3±0.5
ICM	33.3±0.0	11.1±15.7	0.0±0.0	11.1±15.7	13.9±4.8

we only report its performance in the solution explanation task. Through finetuning, LLM was able to generate more reasonable explanations. For instance, ChatGLM-CMExam achieved scores of 31.10 and 18.94 on BLUE-1 and BLUE-4, respectively, and scores of 43.94, 31.48, and 29.39 on the ROUGE metrics.

Results by Disease Groups Drawing upon ICD-11 annotations (26 categories), we conducted an analysis of the performance of several LLMs across various categories. To mitigate the potential impact of random variability resulting from the number of questions, we limited our analysis to categories containing more than 100 questions. According to Table 4, LLMs have uneven performance and significant gaps in knowledge. GPT-4’s accuracy ranges from 74.4% for *Neo* to 44.3% for *TCMDP*, GPT-3.5’s accuracy ranges from 63.9% for *Neo* to 31.0% for *TCMDP* and ChatGLM-CMExam’s accuracy ranges from 54.7% for *Psy* to 42.9% for *RESP*.

Results by Clinical Departments To compare model performance regarding the clinical department dimension (36 categories), we only analyzed categories with more than 50 questions to ensure result representativeness. Results presented in Table 5 highlight that the models show relatively high accuracy on questions associated with commonly encountered departments, such as Emergency Medicine (*EM*), Internal Medicine (*IM*) and Surgery (*Surg*). Their accuracy on questions associated with rarer departments, such as Traditional Chinese Medicine (*TCM*). There is a marked discrepancy in the average accuracy among different departments, with the highest being 50.9% and the lowest being only 13.9%. This observation suggests there are notable variations in medical knowledge and reasoning approaches among different departments. Consequently, it may be necessary to examine specific optimization strategies for different departments.

Results by Medical Disciplines Then, we evaluated LLM performance across seven medical disciplines. As depicted in Table 6, the performance of LLMs across disciplines such as Traditional Chinese Medicine (*TCM*), Traditional Chinese Pharmacy (*TCPharm*), and Pharmacy (*Pharm*) was notably subpar, with all accuracy rates falling below 42%. This pattern suggests a potential deficiency in the exposure of these models to data within these categories. Conversely, disciplines such as *ClinMed* and *Ph&PM* demonstrated higher accuracy rates, likely due to the abundance of relevant data. The observed variability in performance across different disciplines underscores the distinctiveness of data characteristics and complexities inherent to each field, thereby advocating for discipline-specific model optimizations and enhancements.

Table 6: Comparing medical discipline.

Categories	GPT-4	GPT-3.5	ChatGLM	ChatGLM-CMExam	Average
ClinMed	67.9±0.1	51.4±0.4	27.3±0.3	48.9±0.4	48.8±0.7
PH&PM	68.2±0.4	52.7±1.7	26.2±0.3	47.3±1.0	48.6±0.5
ICWM	56.1±0.1	40.0±2.3	29.4±0.8	53.6±0.7	44.8±0.9
Dent	59.5±0.7	43.9±1.9	28.5±1.1	45.3±0.6	44.3±0.3
Pharm	61.1±0.4	46.3±0.5	23.2±0.2	37.0±0.1	41.9±0.3
TCM	53.5±0.4	35.9±0.2	24.1±0.3	49.1±0.0	40.6±1.1
TCPharm	45.4±1.2	35.6±0.1	24.1±1.0	43.1±0.4	37.1±0.5

Table 7: Comparing LLMs’ competencies.

Categories	GPT-4	GPT-3.5	ChatGLM	ChatGLM-CMExam	Average
Diag	70.1±5.5	50.9±2.1	30.9±2.8	51.6±1.0	50.9±1.4
PHL	64.2±0.7	50.0±0.5	26.8±0.3	49.6±0.1	47.6±0.3
Treat	56.5±0.5	43.0±1.1	25.7±0.2	47.4±0.6	43.2±0.8
McFund	58.3±0.3	44.6±0.7	23.9±0.5	41.6±0.4	42.1±0.9
N/A	54.8±0.2	30.4±0.4	23.7±0.1	38.5±0.2	36.9±0.3

Results by Competencies Evaluations based on medical competency areas aimed at a higher-level understanding of model capability in solving medical problems. As indicated in Table 7, the lowest average accuracy across LLMs was observed within the domain of mastering Medical Fundamentals (*MedFund*), with a meager average score of 42.1%. This result demonstrates that these models, predominantly trained on general textual data, have inadequate exposure to medical-specific data. While fine-tuning did provide some improvement, these models could benefit from additional medical scenario data to further augment their performance. It is worth highlighting that the average accuracy in the domain of Public Health Laws and Ethics (*PHL*) was reasonably high, notably achieving an average of 47.6%. In addition, the LLMs showcased their proficiency in accurate disease diagnosis.

Results by Question Difficulty

To evaluate model performance in tackling questions of varying levels of difficulty, we conducted experiments regarding the question difficulty dimension, which was calculated based on human

Table 8: Results by question difficulty.

Categories	GPT-4	GPT-3.5	ChatGLM	ChatGLM-CMExam	Average
Easy	74.6±0.1	58.5±0.6	31.4±0.2	61.5±0.3	56.5±0.4
Manageable	63.9±0.2	47.4±0.7	25.9±0.5	46.1±0.3	45.8±0.6
Moderate	51.3±0.6	36.8±0.8	23.0±0.4	34.5±0.6	36.4±0.7
Difficult	36.4±0.9	26.2±0.7	18.9±0.5	24.3±0.9	26.5±0.6
Extremely difficult	27.2±1.0	21.4±2.2	15.8±1.0	12.2±1.1	19.1±1.1

exam-taker performance. As shown in Table 8, there’s an evident trend where model accuracies decrease as question complexity rises. This pattern suggests that more sophisticated questions demand an extensive knowledge base and complex reasoning, which are challenging for the LLMs, thus reflecting patterns observed in human performance.

Results by Question Length Finally, to investigate if model performance is associated with input lengths, we compared their performance regarding question lengths. Figure 3 illustrates that Large Language Models (LLMs) generally show higher accuracy with problem lengths between 60 and 90. However, their performance seems to falter with problems that are either too short or overly long. Additionally, we noticed that the effect of question length varies across different LLMs. For instance, GPT models tend to incrementally improve as the problem length expands, performing optimally within the 50 to 90 range. Conversely, ChatGLM-CMExam’s performance fluctuates noticeably with varying lengths, and it tends to fall short compared to GPT models when addressing longer problems.

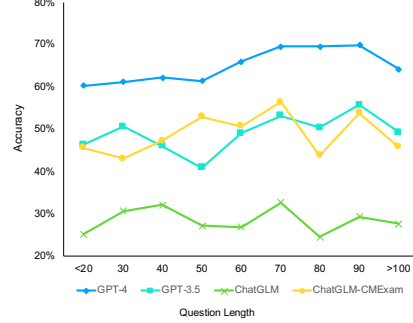


Figure 3: Results stratified by question length.

5 Conclusion and Discussions

In this work, we developed CMExam, a dataset sourced from the stringent Chinese National Medical Licensing Examination, featuring 60,000+ multiple-choice questions, with detailed explanations. CMExam ensures reliability, validity, and adherence to medical standards. It also demonstrates the practicality of employing GPT-4 to automate the annotation process, which strikes a harmonious balance between efficiency and cost-effectiveness while maintaining the desired level of accuracy and reliability of the annotation. Utilizing this large and reliable corpus, we tested several LLMs for answer selection and reasoning tasks. A performance gap was observed between LLMs and human experts, signaling the need for additional LLM research. CMExam’s standardization and comprehensiveness also ensure objective evaluations of models while enabling in-depth analysis of their reasoning capabilities. The questions cover a wide spectrum of medical knowledge, augmented with five additional annotation dimensions for rigorous evaluation. This study aims to spur further exploration of LLMs in medicine by providing a comprehensive benchmark for their evaluation.

We anticipate CMExam to contribute significantly to future advancements of LLMs, particularly in handling medical question-answering tasks.

Limitations Firstly, while CMExam is derived from meticulously designed medical examinations, our process of excluding questions requiring non-textual information may inadvertently affect the balance of the remaining questions, potentially introducing unexpected biases. It is critical to acknowledge this aspect while interpreting any findings or analyses conducted using this dataset. Furthermore, the current BLUE and ROUGE metrics primarily evaluate the explanation task, but these measures are insufficient for assessing the reasonableness of the answer. In future work, we will incorporate human evaluation to provide a more comprehensive assessment of the models.

Ethics CMExam is a dataset derived from the Chinese National Medical Licensing Examination, which aligns with numerous datasets containing similar National Medical Licensing Examinations (Li et al., 2021; Hendrycks et al., 2020; Jin et al., 2021; Pal et al., 2022; Singhal et al., 2022). We have ensured adherence to applicable legal and ethical guidelines during data collection and use. The authenticity and accuracy of the exam questions have been thoroughly verified, providing a reliable basis for evaluating LLMs. Please note that the CMExam dataset is intended for academic and research purposes only. Any commercial use or other misuse that deviates from this purpose is expressly prohibited. We urge all users to respect this stipulation in the interest of maintaining the integrity and ethical use of this valuable resource.

Societal Impacts While CMExam aims to enhance LLM evaluations in the medical field, it should not be misused for assessing individual medical competence or for patient diagnosis. Conclusions drawn from models trained on this dataset should acknowledge its limitations, especially given its single source and the specific context of the CNMLE. The use of this dataset should strictly be limited to research purposes to avoid potential misuse.

References

- Asma Ben Abacha, Eugene Agichtein, Yuval Pinter, and Dina Demner-Fushman. 2017. Overview of the medical question answering task at TREC 2017 LiveQA.. In *TREC*. 1–12.
- Asma Ben Abacha, Yassine Mrabet, Mark Sharp, Travis R Goodwin, Sonya E Shooshan, and Dina Demner-Fushman. 2019a. Bridging the Gap Between Consumers’ Medication Questions and Trusted Answers.. In *MedInfo*. 25–29.
- Asma Ben Abacha, Chaitanya Shivade, and Dina Demner-Fushman. 2019b. Overview of the mediqua 2019 shared task on textual inference, question entailment and question answering. In *Proceedings of the 18th BioNLP Workshop and Shared Task*. 370–379.
- Asma Ben Abacha and Dina Demner-Fushman. 2019. A question-entailment approach to question answering. *BMC bioinformatics* 20, 1 (2019), 1–23.
- Steven Bird. 2020. Decolonising speech and language technology. In *Proceedings of the 28th International Conference on Computational Linguistics*. 3504–3519.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. 2021. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374* (2021).
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%* ChatGPT Quality. <https://lmsys.org/blog/2023-03-30-vicuna/>
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. 2021. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168* (2021).

- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *ArXiv abs/1810.04805* (2019).
- Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. 2022. GLM: General Language Model Pretraining with Autoregressive Blank Infilling. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 320–335.
- Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. *arXiv preprint arXiv:1903.00161* (2019).
- Junqing He, Mingming Fu, and Manshu Tu. 2019. Applying deep matching networks to Chinese medical question answering: a study and a dataset. *BMC medical informatics and decision making* 19, 2 (2019), 91–100.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300* (2020).
- J. Edward Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, and Weizhu Chen. 2021. LoRA: Low-Rank Adaptation of Large Language Models. *ArXiv abs/2106.09685* (2021).
- Di Jin, Eileen Pan, Nassim Oufattole, Wei-Hung Weng, Hanyi Fang, and Peter Szolovits. 2021. What disease does this patient have? a large-scale open domain question answering dataset from medical exams. *Applied Sciences* 11, 14 (2021), 6421.
- Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. 2017. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. *arXiv preprint arXiv:1705.03551* (2017).
- Anastasia Krithara, Anastasios Nentidis, Konstantinos Bougiatiotis, and Georgios Paliouras. 2023. BioASQ-QA: A manually curated corpus for Biomedical Question Answering. *Scientific Data* 10, 1 (2023), 170.
- Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. 2017. Race: Large-scale reading comprehension dataset from examinations. *arXiv preprint arXiv:1704.04683* (2017).
- Jianquan Li, Xidong Wang, Xiangbo Wu, Zhiyi Zhang, Xiaolong Xu, Jie Fu, Prayag Tiwari, Xiang Wan, and Benyou Wang. 2023. Huatuo-26M, a Large-scale Chinese Medical QA Dataset. *arXiv preprint arXiv:2305.01526* (2023).
- Jing Li, Shangping Zhong, and Kaizhi Chen. 2021. MLEC-QA: A Chinese Multi-Choice Biomedical Question Answering Dataset. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 8862–8874.
- Chin-Yew Lin and Eduard H. Hovy. 2003. Automatic Evaluation of Summaries Using N-gram Co-occurrence Statistics. In *North American Chapter of the Association for Computational Linguistics*.
- Stephanie Lin, Jacob Hilton, and Owain Evans. 2021. Truthfulqa: Measuring how models mimic human falsehoods. *arXiv preprint arXiv:2109.07958* (2021).
- Xiao Liu, Kaixuan Ji, Yicheng Fu, Zhengxiao Du, Zhilin Yang, and Jie Tang. 2021. P-Tuning v2: Prompt Tuning Can Be Comparable to Fine-tuning Universally Across Scales and Tasks. *ArXiv abs/2110.07602* (2021).
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. *CoRR abs/1907.11692* (2019). [arXiv:1907.11692](http://arxiv.org/abs/1907.11692) <http://arxiv.org/abs/1907.11692>
- OpenAI. 2023. GPT-4 Technical Report. *ArXiv abs/2303.08774* (2023).

- Ankit Pal, Logesh Kumar Umapathi, and Malaikannan Sankarasubbu. 2022. MedMCQA: A large-scale multi-subject multi-choice dataset for medical domain question answering. In *Conference on Health, Inference, and Learning*. PMLR, 248–260.
- Anusri Pampari, Preethi Raghavan, Jennifer Liang, and Jian Peng. 2018. emrqa: A large corpus for question answering on electronic medical records. *arXiv preprint arXiv:1809.00732* (2018).
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a Method for Automatic Evaluation of Machine Translation. In *Annual Meeting of the Association for Computational Linguistics*.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research* 21, 1 (2020), 5485–5551.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2021. Winogrande: An adversarial winograd schema challenge at scale. *Commun. ACM* 64, 9 (2021), 99–106.
- Max Savery, Asma Ben Abacha, Soumya Gayen, and Dina Demner-Fushman. 2020. Question-driven summarization of answers to consumer health questions. *Scientific Data* 7, 1 (2020), 322.
- Karan Singhal, Shekoofeh Azizi, Tao Tu, S Sara Mahdavi, Jason Wei, Hyung Won Chung, Nathan Scales, Ajay Tanwani, Heather Cole-Lewis, Stephen Pfohl, et al. 2022. Large Language Models Encode Clinical Knowledge. *arXiv preprint arXiv:2212.13138* (2022).
- Simon Šuster and Walter Daelemans. 2018. CliCR: a dataset of clinical case reports for machine reading comprehension. *arXiv preprint arXiv:1803.09720* (2018).
- Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023. Stanford Alpaca: An Instruction-following LLaMA model. https://github.com/tatsu-lab/stanford_alpaca.
- Yuanhe Tian, Weicheng Ma, Fei Xia, and Yan Song. 2019. ChiMed: A Chinese medical corpus for question answering. In *Proceedings of the 18th BioNLP Workshop and Shared Task*. 250–260.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurélien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. LLaMA: Open and Efficient Foundation Language Models. *ArXiv abs/2302.13971* (2023).
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019. SuperGlue: A stickier benchmark for general-purpose language understanding systems. *Advances in neural information processing systems* 32 (2019).
- Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461* (2018).
- Haochun Wang, Chi Liu, Nuwa Xi, Zewen Qiang, Sendong Zhao, Bing Qin, and Ting Liu. 2023. HuaTuo: Tuning LLaMA Model with Chinese Medical Knowledge. *arXiv:2304.06975 [cs.CL]*
- World Health Organization (WHO). 2019/2021. International Classification of Diseases, Eleventh Revision (ICD-11). <https://icd.who.int/browse11>. Licensed under Creative Commons Attribution-NoDerivatives 3.0 IGO licence (CC BY-ND 3.0 IGO).
- Honglin Xiong, Sheng Wang, Yitao Zhu, Zihao Zhao, Yuxiao Liu, Linlin Huang, Qian Wang, and Dinggang Shen. 2023. DoctorGLM: Fine-tuning your Chinese Doctor is not a Herculean Task. *ArXiv abs/2304.01097* (2023).
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. HellaSwag: Can a machine really finish your sentence? *arXiv preprint arXiv:1905.07830* (2019).

- Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Zhiyuan Liu, Peng Zhang, Yuxiao Dong, and Jie Tang. 2023. GLM-130B: An Open Bilingual Pre-trained Model. In *The Eleventh International Conference on Learning Representations (ICLR)*. <https://openreview.net/forum?id=-Aw0rrrPUF>
- Hui Zeng. 2023. Measuring Massive Multitask Chinese Understanding. *arXiv preprint arXiv:2304.12986* (2023).
- Qingcheng Zeng, Lucas Garay, Peilin Zhou, Dading Chong, Yining Hua, Jiageng Wu, Yikang Pan, Han Zhou, and Jie Yang. 2022. GreenPLM: Cross-lingual pre-trained language model conversion with (almost) no cost. *arXiv preprint arXiv:2211.06993* (2022).
- Sheng Zhang, Xin Zhang, Hui Wang, Jiajun Cheng, Pei Li, and Zhaoyun Ding. 2017. Chinese medical question answer matching using end-to-end character-level multi-scale CNNs. *Applied Sciences* 7, 8 (2017), 767.
- Sheng Zhang, Xin Zhang, Hui Wang, Lixiang Guo, and Shanshan Liu. 2018. Multi-scale attentive interaction networks for chinese medical question answer selection. *IEEE Access* 6 (2018), 74061–74071.
- Ming Zhu, Aman Ahuja, Da-Cheng Juan, Wei Wei, and Chandan K Reddy. 2020. Question answering with long multiple-span answers. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. 3840–3849.
- Ming Zhu, Aman Ahuja, Wei Wei, and Chandan K Reddy. 2019. A hierarchical attention retrieval model for healthcare question answering. In *The World Wide Web Conference*. 2472–2482.

Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to **[Yes]**, **[No]**, or **[N/A]**. You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? **[Yes]** See Section ??.
- Did you include the license to the code and datasets? **[No]** The code and the data are proprietary.
- Did you include the license to the code and datasets? **[N/A]**

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? **[Yes]**
 - (b) Did you describe the limitations of your work? **[Yes]** See Section 5
 - (c) Did you discuss any potential negative societal impacts of your work? **[Yes]** See Section 5
 - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? **[Yes]**
2. If you are including theoretical results...
 - (a) Did you state the full set of assumptions of all theoretical results? **[N/A]**
 - (b) Did you include complete proofs of all theoretical results? **[N/A]**
3. If you ran experiments (e.g. for benchmarks)...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **[Yes]** All the datasets, benchmarks and code are available at <https://github.com/williamliujl/CMExam>
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **[Yes]** Those details were listed in Section 3 and Section 4.1.
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **[Yes]**
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **[Yes]** We report the type of resources in Section 4.1.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
 - (a) If your work uses existing assets, did you cite the creators? **[Yes]** We used code from several models in our benchmarks, all the sources were properly cited in this paper.
 - (b) Did you mention the license of the assets? **[No]** The code we used are all open available, they were used to evaluate model performance in our new dataset. We do not claim any copyright from the code.
 - (c) Did you include any new assets either in the supplemental material or as a URL? **[No]**
 - (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? **[Yes]** This work was conducted on public available data, so this study is waived from the participant’s consent.
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **[No]** This work did not contain any personally identifiable information or offensive content.
5. If you used crowdsourcing or conducted research with human subjects...

- (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] This work was conducted on public available data, it doesn't have participants.
- (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A] This dataset is based on authentic past licensed physician exams in the Chinese National Medical Licensing Examination (CNMLE) collected from the Internet, it doesn't have potential participant risks.
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [No] This dataset was voluntarily annotated by the authors and two medical professionals.

A Appendix

A.1 Abbreviations, Full Names, and Translations of Additional Annotations

This section presents four tables of additional annotations that contain translation. It showcases abbreviations, full English names, and Chinese names for each group in each annotation dimension. Table 9 showcases all disease groups included in the 11th revision of the International Classification of Diseases (ICD-11). We present the disease group in the same order found on the official website. Table 10 offers a classification of 36 clinical departments derived from the Directory of Medical Institution Diagnostic and Therapeutic Categories. Table 11 presents a breakdown of medical disciplines based on the List of Graduate Education Disciplinary Majors published by the Ministry of Education of the People’s Republic of China. This categorization comprises seven study majors used in universities. Table 12 provides all groups of areas of medical competency assessed in Chinese medical licensing exams.

Table 9: ICD-11 Groups

Abbreviation	Full English Name	Chinese Name
InfDis	Certain infectious or parasitic diseases	某些感染性疾病或寄生虫病
Neo	Neoplasms	肿瘤
Blood	Diseases of the blood or blood-forming organs	血液或造血器官疾病
Immune	Diseases of the immune system	免疫系统疾病
Endo	Endocrine, nutritional or metabolic diseases	内分泌、营养或代谢疾病
Psy	Mental, behavioural or neurodevelopmental disorders	精神、行为或神经发育障碍
Sleep	Sleep-wake disorders	睡眠-觉醒障碍
Neuro	Diseases of the nervous system	神经系统疾病
Vision	Diseases of the visual system	视觉系统疾病
Ear	Diseases of the ear or mastoid process	耳或乳突疾病
Circ	Diseases of the circulatory system	循环系统疾病
Resp	Diseases of the respiratory system	呼吸系统疾病
Digest	Diseases of the digestive system	消化系统疾病
Skin	Diseases of the skin	皮肤疾病
MSK	Diseases of the musculoskeletal system or connective tissue	肌肉骨骼系统或结缔组织疾病
GU	Diseases of the genitourinary system	泌尿生殖系统疾病
Sex	Conditions related to sexual health	性健康相关情况
OBST	Pregnancy, childbirth or the puerperium	妊娠、分娩或产褥期
Peri	Certain conditions originating in the perinatal period	起源于围生期的某些情况
Dev	Developmental anomalies	发育异常
Sym	Symptoms, signs or clinical findings, not elsewhere classified	症状、体征或临床所见，不可归类在他处者
Inj	Injury, poisoning or certain other consequences of external causes	损伤、中毒或外因的某些其他后果
Ext	External causes of morbidity or mortality	疾病或死亡的外因
Factors	Factors influencing health status or contact with health services	影响健康状态或与
SpecPurp	Codes for special purposes	用于特殊目的的编码
TCMDP	Supplementary Chapter Traditional Medicine Conditions - Module I	补充章传统医学病证-模块1
FuncAssess	Supplementary section for functioning assessment	功能评定补充部分
ExtCodes	Extension Codes	扩展码
N/A	Not Applicable	不符合

A.2 Instructions for pre-annotation

In this section, we present instructions used to pre-annotate CMExam test set data using GPT4. As shown in Figure 4, we first constrained the output from GPT4 to return only specific categories. We then annotated each of the five additional annotation dimensions relevant to this study with all the category information for each dimension. Next, we provided specific prompt information and finally, we performed filtering on the GPT4 output to improve the effectiveness of pre-annotation. During the actual annotation process, specific categories and prompt information should be filled in the grey background areas.

Table 10: Clinical Departments

Abbreviation	Full English Name	Chinese Name
AesthMed	Aesthetic Medicine	医疗美容科
Anesth	Anesthesiology	麻醉科
ClinNutr	Clinical Nutrition	临床营养科
Dent	Dentistry	口腔科
Derm	Dermatology	皮肤科
EM	Emergency Medicine	急诊医学科
EndemicD	Endemic Disease	地方病科
ENT	Otolaryngology	耳鼻咽喉科
EthnoMed	Ethnic Medicine	民族医学科
GenMed	General Medicine	全科医疗
ICM	Intensive Care Medicine	重症医学科
ID	Infectious Diseases	传染科
IM	Internal Medicine	内科
ITCWM	Integrated Traditional Chinese and Western Medicine	中西医结合科
MedLabSci	Medical Laboratory Science	医学检验科
N/A	Not Applicable	不符合
OBGYN	Obstetrics and Gynecology	妇产科
OccMed	Occupational Medicine	职业病科
Onc	Oncology	肿瘤科
Ophth	Ophthalmology	眼科
PainMed	Pain Medicine	疼痛科
PallCare	Palliative Care	临终关怀科
Path	Pathology	病理科
Ped	Pediatrics	儿科
PedHC	Pediatric Health Care	儿童保健科
PedSurg	Pediatric Surgery	儿童外科
PrevMed	Preventive Medicine	预防保健科
Psych	Psychiatry	精神科
PT	Physical Therapy	理疗科
Radiol	Radiology	医学影像科
RehabMed	Rehabilitation Medicine	康复医学科
SpecMed&MilMed	Special Medical and Military Medicine	特种医学与军事医学科
SportsMed	Sports Medicine	运动医学科
Surg	Surgery	外科
TB	Tuberculosis	结核病科
TCM	Traditional Chinese Medicine	中医科
WH	Women's Health	妇女保健

Table 11: Medical Disciplines

Abbreviation	Full English Name	Chinese Name
ClinMed	Clinical Medicine	临床医学
Dent	Dentistry	口腔医学
ICWM	Integrated Chinese and Western Medicine	中西医结合
PH&PM	Public Health and Preventive Medicine	公卫预防
Pharm	Pharmacy	药学
TCM	Traditional Chinese Medicine	中医学
TCPharm	Traditional Chinese Pharmacy	中药学

Table 12: Medical Specialties

Abbreviation	Full English Name	Chinese Name
Diag	Disease Diagnosis and Differential Diagnosis	疾病诊断和鉴别诊断
MedFund	Medical Fundamentals	医学基础知识
N/A	Not Applicable	不符合
PHL	Public Health Law and Ethics	公共卫生法律伦理
Treat	Disease Treatment	疾病治疗

ZH:返回格式限制为某个具体类目的名称即可。
EN:The return format is limited to the name of a specific category.

ZH:共有4个类别: 医学基础知识、疾病诊断和鉴别诊断、疾病治疗、公共卫生法律伦理。
假设你是一位医疗行业专家, 请判断下面这个题目属于哪个类别, 若都不符合, 则只返回"不符合"这个标签。
EN:There are four categories: Basic Medical Knowledge, Disease Diagnosis and Differential Diagnosis, Disease Treatment, and Public Health Law and Ethics.

ZH:题目信息为"女34岁。月经量进行性减少, 现闭经半年, 泌乳3个月, 首选检查项目应是: A 孕激素试验, B 血HCG测定, C 血PRL测定, D 性激素测定, E 诊断性刮宫"。
EN:The question is "A 34-year-old woman has experienced progressive reduction in menstrual flow and has been amenorrheic for 6 months. She has been lactating for 3 months. Which of the following is the preferred test to perform? A. Progesterone test B. Blood HCG test C. Blood PRL test D. Sex hormone test E. Diagnostic curettage".

ZH:注意, 不需要回答问题本身, 只需要返回这个题目与上述4个类目中的哪个类目最相关, 返回4个类目中的一个, 不需要其他文字。
EN:Note that you do not need to answer the question itself, just return which of the four categories listed above is most relevant to this question. Return only one of the four categories, no additional words necessary.

Figure 4: Instruction of Pre-annotation.