CliMedBench: A Large-Scale Chinese Benchmark for Evaluating Medical Large Language Models in Clinical Scenarios

Anonymous ACL submission

Abstract

With the proliferation of Large Language Models (LLMs) in diverse domains, there is a particular need for unified evaluation standards in Chinese clinical medical scenarios, where models need to be examined very thoroughly. We present CliMedBench, a comprehensive benchmark with 14 expert-guided core clinical scenarios specifically designed to assess the medical ability of LLMs across 7 pivot dimensions. It comprises 33,735 questions derived from real-world medical reports of top-tier tertiary hospitals and authentic examination exercises. The reliability of this benchmark has been confirmed in several ways. Subsequent experiments with existing LLMs have led to the following findings: (i) Chinese medical LLMs underperform on this benchmark, especially where medical reasoning and factual consistency are vital, underscoring the need for advances in clinical knowledge and diagnostic accuracy. (ii) Several general-domain LLMs demonstrate substantial potential in medical clinics, while the limited input capacity of many medical LLMs hinders their practical use. These findings reveal both the strengths and limitations of LLMs in clinical scenarios and offer critical insights for medical research.

1 Introduction

With the advent of Chinese medical large language models (LLMs) such as HuatuoGPT (Zhang et al., 2023), ChatMed (Zhu and Wang, 2023), and BenTsao (Wang et al., 2023a), the potential for these tools in healthcare has expanded considerably (Singhal et al., 2023). These models are engineered to address intricate medical problems by providing diagnostic assistance and treatment suggestions. Nonetheless, the absence of a comprehensive and systematic evaluation of their performance—encompassing response accuracy, hallucination incidence, and content safety—hampers their integration into clinical practice. Consequently, there is an urgent need for a standardized evaluation benchmark to scrutinize the capabilities and limitations of such medical LLMs.

Developing a practically relevant benchmark is non-trivial. There is a substantial disconnect between current benchmarks for the Chinese language and the realities of medical practice, as such benchmarks are mostly derived from open educational resources(Mbakwe et al., 2023). A benchmark based on real-world medical cases offers superior authenticity and heterogeneity, while more accurately mirroring the intricacies encountered in clinical practice. These cases present greater challenge and complexity, leading to a more rigorous assessment of model performance and robustness in practical applications, including clinical decision support, diagnosis, and treatment recommendations. Moreover, benchmarks developed from open resources are susceptible to data contamination issues.

Prevalent medical benchmarks like MedQA (Jin et al., 2021) and MedMCQA (Pal et al., 2022) incorporate data from accessible sources such as textbooks, scholarly articles, and qualification examinations. The effectiveness of such evaluation benchmarks is controversial: medical exams are inefficient clinical performance indicators. Large-scale EHR-based benchmarks such as emrQA (Pampari et al., 2018) have addressed the deficiency in clinical QA, however, language discrepancies preclude their direct applicability for evaluating Chinese medical LLMs. Chinese benchmarks, including CMExam (Liu et al., 2023), CMB (Wang et al., 2023b), and MLEC-QA (Li et al., 2021), primarily source their data from exams such as CNMLE and NMLEC. MedBench (Cai et al., 2024) uses exam questions and artificially generated EHRs to evaluate the LLMs' exam-solving capabilities in different departments. Despite their comprehensive analysis, these benchmarks are disconnected from actual medical practice due to their

lack of real-world medical case data, and the use of exam-based datasets raises concerns about data pollution. The need for good benchmarks makes evaluating performance a significant challenge.

To address the limitations of prior research, we introduce the CliMedBench, a robust benchmark comprising 33,735 questions across 14 core medical scenarios assessing LLMs' ability across six dimensions, primarily sourced from authentic cases to align with medical standards and practices. The CliMedBench integrates expertise from Chinese medical practitioners, offering a valid measure for gauging medical linguistic proficiency and cognitive skills in LLMs. We evaluate various general and medical-specific LLMs using this benchmark and perform a comprehensive analysis that sheds light on relevant research avenues to enhance the medical capabilities of LLMs. The main findings on this benchmark are as follows:

- Chinese medical LLMs underperform on this benchmark, especially where medical reasoning and factual consistency are vital, underscoring the need for advances in clinical knowledge and diagnostic accuracy.
- Several general-domain LLMs demonstrate substantial potential in medical clinics, while the limited input capacity of many medical LLMs hinders their practical use.
- The indeterminacy inherent in medical contexts can significantly compromise the accuracy of model-generated responses.

2 The Proposed Benchmark

2.1 The Taxonomy of CliMedBench

A well-structured taxonomy enables us to conduct a more fine-granular assessment of medical language models, while also ascertaining that the evaluation is comprehensive and practically relevant. Our taxonomy, designed to maintain the benchmark's applicability and comprehensiveness in real-world clinical scenarios, is based on a categorization that mirrors medical practice and fully covers it, as inspired by Liang et al. (2022). As depicted in Figure 1, we build on a "Who–What–How" scheme to categorize real-world clinical medical practice, providing 14 core clinical scenarios for assessment. Along the "Who" axis, we distinguish five principal roles in the medical field: the *Radiographer*, *Pharmacist*, *Patient*, *Medical Student*, and *Specialist Doctor*, where doctors encompass attending physicians, surgeons, and other medical specialists. "What" addresses a broad spectrum of key medical scenarios, covering basic knowledge tests, in-hospital diagnosis, clinical pathway reasoning, case summaries, wrong treatment detection, etc. This allows the CliMedBench to evaluate the medical ability of LLMs from seven perspectives, including clinical question answering, knowledge application, reasoning, information retrieval, summarization abilities, hallucination, and toxicity.

To illustrate the divisions within CliMedBench, we provide an example of the scenario mappings for **I**n-hospital **D**iagnoses(ID) in Table 1. ID is one of the core scenarios in CliMedBench that spans four periods, encapsulating the patient care continuum from admission to discharge, and consider the following scenario descriptions:

- ID #1 refers to the selection of examinations by healthcare professionals and radiographers.
- ID #2 involves the diagnosis by physicians, integrating examination results with the patient's medical history and additional health data.
- In the ID #3 period, treatment strategies, ranging from pharmacological interventions to surgical procedures, are developed in collaboration with pharmacists and medical staff.
- ID #4 pertains to physicians providing discharge instructions to patients.

Who	**What (Task)**
Doctor, Patient	ID#1
Doctor, Radiographer, Patient	ID#2
Doctor, Pharmacist, Patient	ID#2
Doctor, Patient	ID#4
Evaluation axes: clinical QA ability	

Table 1: Example mappings in clinic scenarios. In subsequent sections, tasks will be designated using acronyms formed by the initial letters, as depicted in Appendix A

Detailed descriptions of the "Who–What" mapping can be found in the Appendix.

2.2 Construction and Statistics

CliMedBench is derived from real-world Electronic Health Records (EHRs) of top-tier tertiary hospitals in China, supplemented with examination exercises, medical guidelines, textbooks, scholarly articles, and human-annotated online consultations.

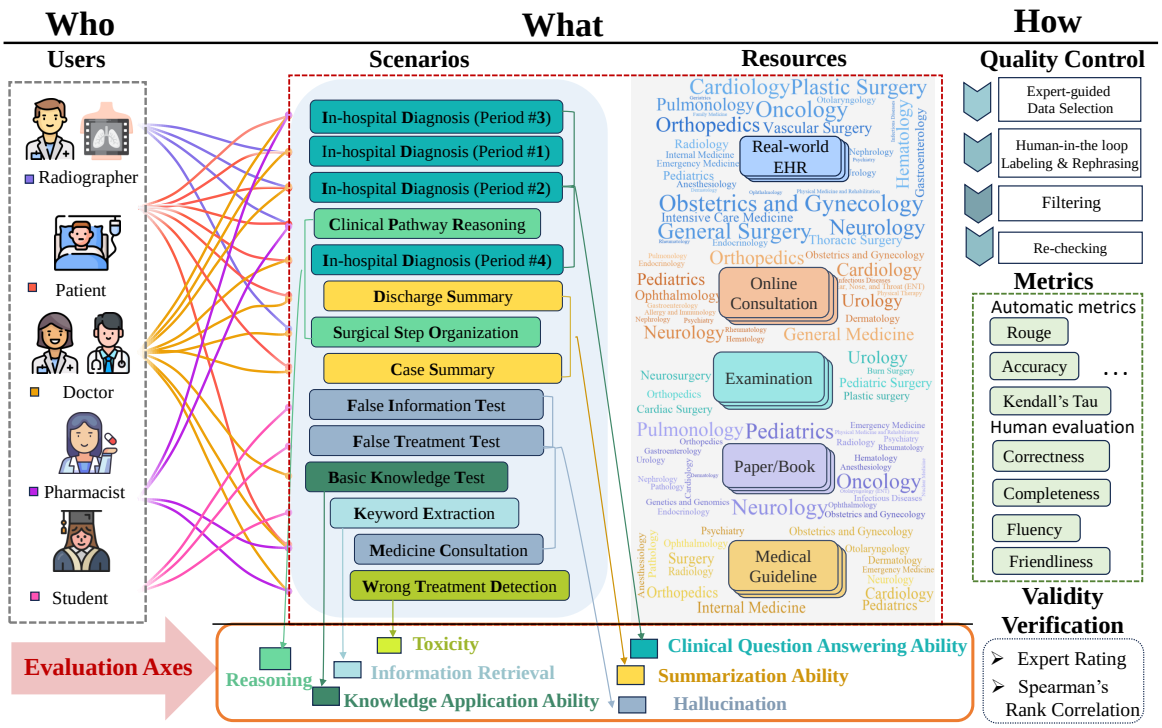


Figure 1: Overview of CliMedBench with "Who-What-How" taxonomy linking users with core clinical scenarios.

This corpus spans a multitude of medical specialties, meticulously curated to enhance the diversity of CliMedBench. We conduct information de-identification, data cleaning, human-in-the-loop construction, filtering, and expert verification, obtaining 33,735 instances for 14 core clinical scenarios that are strictly based on doctor's notes and clinical treatment recordings, more detailed steps are given in the Appendix B. Figure 2 depicts the data distribution of CliMedBench, encompassing 19 branches of medicine, e.g., neurosurgery and gastroenterology. CliMedBench has three question types, including:

- Multiple-choice clinical question answering.
- Sequencing questions. e.g., surgical step reordering.
- Open-ended generation, e.g., discharge summary, subjective clinical question answering.

To confirm the effectiveness of benchmark construction, we employ diverse methodologies to validate CliMedBench, as described in Section 6.

2.3 Characteristics

CliMedBench improves over existing benchmarks in several respects: (1) Authenticity and Uniqueness: It genuinely reflects doctors' practical experience by exclusively using expert-annotated EHRs from top hospitals with up-to-date, authentic insights, while reducing the potential of data contamination. (2) Comprehensiveness and Multi-dimensionality: It is meticulously designed to align with Chinese clinical practices, encompassing diverse medical disciplines with multimodal information, offering a broad spectrum of evaluation perspectives. (3) Practicality: It offers a novel agent-based Computerized Adaptive Testing approach to guarantee rapid assessment with CliMedBench.

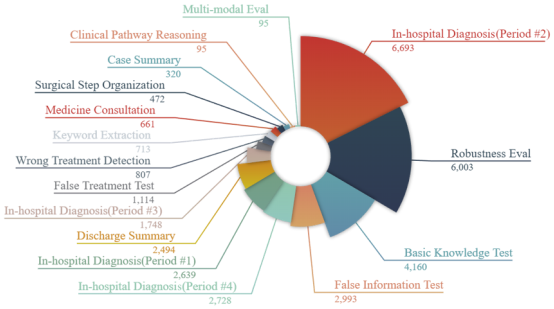


Figure 2: Data distribution of various clinic scenarios.

3 Models and Evaluation Metrics

To assess the state-of-the-art, we conduct evaluations using CliMedBench of 11 representative LLMs from both the general and medical domains, including OpenAI's GPT series[1], ChatGLM3 (Zeng et al., 2023), ERNIE-Bot[2], SparkDesk[3], Qwen[4], Baichuan[5], Hu-

[1]https://chat.openai.com.
[2]https://yiyan.baidu.com/
[3]https://xinghuo.xfyun.cn/
[4]https://tongyi.aliyun.com/
[5]https://github.com/baichuan-inc/Baichuan-13B.

aTuoGPT (Zhang et al., 2023), BenTsao (Wang et al., 2023a), MedicalGPT [6], and ChatMed (Zhu and Wang, 2023). Given the presence of multiple-choice, sequencing, and open-ended generation questions in CliMedBench, we utilize a comprehensive set of metrics. Specifically, we use Accuracy for multiple-choice question answering and Kendall's Tau (Kendall, 1938) for sequencing questions. For open-ended generation, we combine expert-level human evaluation with supplementary automatic evaluation metrics, e.g., ROUGE-1 (Lin, 2004) for discharge summary and SimCSE-based similarity for wrong treatment assessment. For the latter, we first apply fine-tuning to SimCSE (Gao et al., 2021) using distinct medical documents, then utilize the resulting model to derive sentence vectors, and finally compute the semantic similarity with the reference. Detailed experimental configurations are provided in Appendix C.

4 Main Results

We conduct an in-depth evaluation of 11 LLMs using CliMedBench, stringently examining their performance across seven pivot dimensions. Corresponding comparisons utilizing automatic metrics are provided in Table 2. We also engage human experts to assess open-ended generation(WTD and multi-modal report analysis) across four dimensions in Figure 3, including medical correctness, completeness, fluency, and friendliness.

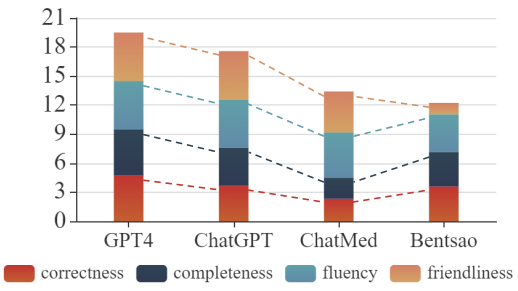


Figure 3: Human evaluation results of four aspects.

Chinese medical LLMs underperform on this benchmark, especially where medical reasoning and factual consistency are vital. Comparative analysis reveals that models via APIs generally outperform others, with average scores exceeding 50. ERNIE-Bot, GPT-4, and Qwen achieve fairly similar average scores of 69.2, 69.0, and 68.5, respectively. In contrast, current medical LLMs exhibit notably inadequate performance: Even the best-performing MedicalGPT only achieves an average score of 38.7. This deficiency primarily stems from the substandard language understanding capabilities of those LLMs.

Several Chinese LLMs (ERNIE-Bot and Qwen) **demonstrate performance on par with GPT-4 in clinical medicine of China**, achieving scores primarily within the range of 68.5 to 69.2. This could stem from the unique treatments, expression styles, and China-manufactured pharmaceuticals, which diverge from what is encountered in the training data of GPT series models. A disparity of capabilities between these Chinese LLMs and the GPT series predominantly manifests in medical knowledge and reasoning.

Next, we will summarize the performance of LLMs with regard to particular evaluation dimensions. Regarding clinical question answering abilities, Qwen outperforms others with an average score of 88.7. However, variability in model performance across scenarios is evident, with ChatGPT achieving the highest score (97.4) on ID #2 but not ranking among the top performers in other scenarios. GPT4 and ERNIE-Bot show exceptional reasoning capabilities, achieving average scores of 75.1 and 73.3, respectively. The notable performance disparity between general and medical-specific LLMs highlights the need for further enhancement in the reasoning ability of medical-specific LLMs. In all evaluated models, hallucinations are significantly pronounced. The FIT data is designed to trigger hallucinations by incorporating an erroneous reference. Their data sources are the same as BKT, however, model accuracy exhibits a marked reduction, plummeting from an average score of 47.3 to 8.3. This substantial decline shows the vulnerability of language models to uncritically adopt perspectives presented in their input, highlighting an immediate need for enhancement. Hallucinations exhibited on the WTD dataset indicate that for questions with special structures, LLMs not only need to master the knowledge points examined by the questions but also need to understand the logical relationships in the questions, which may exceed the ability of the models. The knowledge application ability of the leading general LLMs ranges from 79.8 to 82.4, suggesting a substantial reservoir of medical knowledge of these models. For the information retrieval task, MedicalGPT has significantly narrowed the disparity with leading LLMs, achieving a score of 33.3, merely 8.7 points below the top-performing ERNIE-Bot. This improvement predominantly stems from the special-

[6]https://github.com/shibing624/MedicalGPT

	Model	ID#3 *ACC.*	ID#1 *ACC.*	ID#2 *ACC.*	CPR *Kendall's Tau*	ID#4 *ACC.*	DS *ACC.*	SSO *Kendall's Tau*
General	GPT4	**87.8**	68.4	97.4	73.2	84.6	**98.2**	**77.0**
	ChatGPT	76.8	86.3	97.4	59.5	70.6	85.4	42.6
	ERNIE-Bot	78.3	87.4	**98.7**	**79.5**	83.3	94.2	67.13
	SparkDesk	65.3	85.0	**98.7**	61.5	53.0	26.6	30.4
	Qwen	84.6	**89.4**	95.0	69.6	**85.6**	97.1	67.1
	Baichuan	47.6	56.7	88.5	22.1	31.2	32.1	23.9
	ChatGLM3	47.2	88.0	97.6	33.5	40.6	60.4	21.1
Specialized	HuatuoGPT	26.6	**48.0**	66.6	24.7	25.6	20.3	3.4
	BenTsao	27.2	24.6	24.6	25.2	4.6	1.0	18.8
	MedicalGPT	**41.3**	43.7	**81.4**	**39.5**	**31.0**	**20.4**	**21.7**
	ChatMed	13.6	37.4	20.6	4.5	8.6	2.8	1.5

	Model	CS *ACC.*	FIT *ACC.*	FTT *ACC.*	BKT *ACC.*	KE *ROUGE-1*	MC *ACC.*	WTD *Similarity*
General	GPT4	98.4	**25.0**	12.6	70.8	40.2	44.0	81.3
	ChatGPT	97.1	2.8	1.3	51.9	39.8	38.9	80.9
	ERNIE-Bot	**99.7**	13.5	10.7	79.8	**42.0**	53.3	**81.9**
	SparkDesk	95.6	11.7	4.0	68.7	28.8	**63.5**	81.0
	Qwen	99.1	13.9	13.3	**82.4**	39.7	49.2	80.4
	Baichuan	73.4	1.7	**21.2**	38.8	33.6	37.1	78.6
	ChatGLM3	92.0	9.6	6.8	46.9	34.4	45.5	78.8
Specialized	HuatuoGPT	61.2	**13.8**	**8.6**	22.6	29.3	23.0	**79.2**
	BenTsao	25.6	0.6	0	20.6	6.5	27.6	75.2
	MedidalGPT	**67.2**	1.9	7.1	**35.0**	**33.3**	**41.7**	77.1
	ChatMed	10.9	2.0	1.2	9.3	11.4	12.4	75.8

Table 2: Results of 11 LLMs with automatic metrics on the 14 core clinic scenarios of CliMedBench.

ized nature of its generated terminologies.

5 Quantitive Analysis

Chain-of-Thought To demonstrate the potential improvement of LLM's reasoning abilities with customized prompts, we compare the performance of four representative models using vanilla and Chain-of-Thought (CoT) prompts in Figure 4.

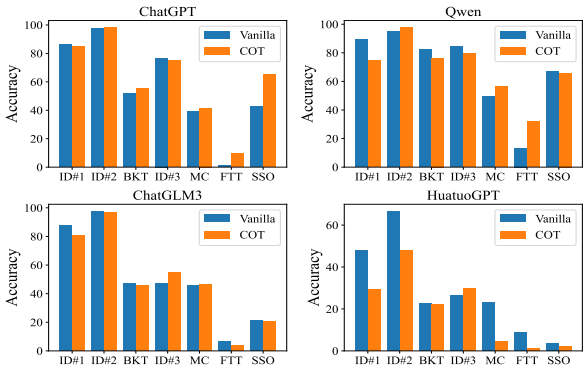


Figure 4: Accuracy comparison of four models on seven datasets using both vanilla and CoT prompts.

We observe that the utilization of tailored CoT prompts significantly enhances model performance across seven datasets that demand higher reasoning skills. Specifically, for Qwen, there is an average accuracy increase from 62.7% to 69.2%. It suggests that CoT can enhance reasoning and hallucination resistance in medical contexts, as observed in the Surgical Organization, False Info Test, and Wrong Treatment datasets. Conversely, the impact of COT prompts on ChatGLM3 is minimal and it adversely affects huatuoGPT, underscoring the dependency of CoT prompt efficacy on the model's comprehension and contextual correlation proficiency. In addition, the long text of the few-shot COT prompt(on average 4.987 times longer than the vanilla prompt) is also a reason for the decrease in accuracy as we described in the following paragraph.

Limited Input Capacity We notice that EHRs frequently contain a variety of diagnostic test outcomes, records of prior treatments, and familial and social histories, often spanning multiple pages. Consequently, the limited input capacity of many LLMs poses a challenge to their practical use in clinical scenarios. Figure 5 depicts performance comparisons across varying input windows.

We observe a notable decrease, declining from 47.3 to 43.1, in the performance of nearly all LLMs as the length of the inputs increases, revealing that the limited input capacity is the main factor hindering their performance in clinical medicine. In addition, medical LLMs exhibit a more pronounced decline (29.5-22.6) compared to the general LLMs (60.5-58.0), suggesting that these spe-

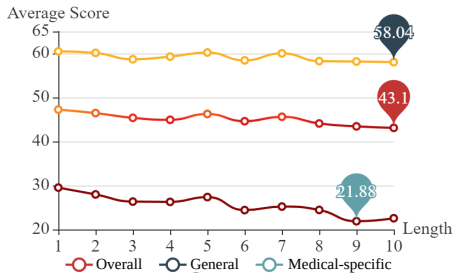


Figure 5: Performance across varying input windows, where the x-axis represents dataset segments, 1 being the shortest and 10 the longest, sorted by length.

cialized LLMs may be less capable of maintaining performance with longer inputs.

Robustness Test To conduct the robustness test, we introduce manually-crafted perturbations that comprise shape-based character conversion, homophonic substitution, simplified-to-traditional Chinese transformation, and random symbol insertion. These perturbations cover 12% of the characters. Figure 6 provides the robustness test results.

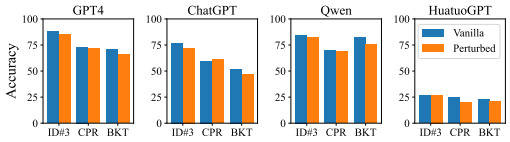


Figure 6: Robustness test of GPT4, ChatGPT, Qwen, and HuatuoGPT on different datasets.

We observe that with perturbations, all models exhibited a reduction in scores, ranging from 2.0 to 3.2, with particularly notable decreases observed on the basic knowledge test scenario, averaging at 4.7. This shows the significant impact of even minor disturbances on model performance despite their seemingly negligible impact on readability.

Multi-modal Capability To further investigate the performance of models in multi-modal settings, we have compiled a set of 92 diagnostic image pairs from medical textbooks (primarily consisting of MRI and ultrasound scans) and PathVQA (He et al., 2020) to assess the potential of LLMs in multimodal medical diagnosis. Our evaluation primarily focuses on the representative model GPT-4V. GPT-4V does not achieve satisfying results in these cases, and only 16.7% of its responses are relevant to the reference. Figure 7 depicts an example case, where GPT-4V demonstrates its utility by successfully identifying inflammation in the patient's shoulder tendon through ultrasound imaging diagnostics. However, detailed but crucial diagnostic indicators within the images remained virtually indiscernible. Moreover, GPT-4V often disclaims diagnostic capability and withholds responses. Therefore, its utility in multi-modal clinical scenarios is currently limited.

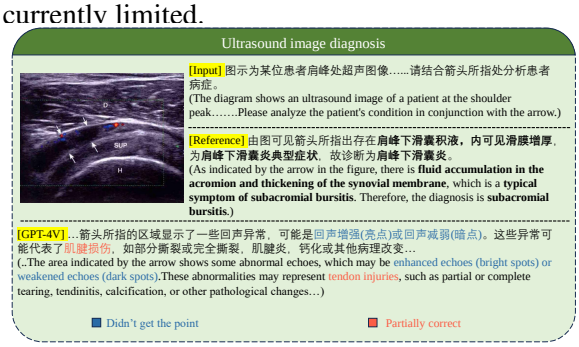


Figure 7: A multi-modal example case.

Inadequate Instruction Following Ability During the assessment, we observe that LLMs exhibit inadequate instruction following ability, a deficiency particularly conspicuous within medical-specific LLMs. Even in straightforward multiple-choice scenarios, several medical-specific LLMs, e.g., ChatMed and BenTsao, struggle to follow the given instructions to accomplish the task. Therefore, the average scores for ChatMed and Bentsao are only a quarter to a sixth of that achieved by the top-performing model. This underscores the necessity of enhancing the model's aptitude for comprehending and following diverse instructions, thereby enabling adaptation to different tasks.

Potential Causes of Toxicity When evaluating the toxicity, we find that general LLMs, guided by safety protocols, often err on the side of caution, indiscriminately flagging and inhibiting potentially hazardous medical actions, including some that are clinically justified. Conversely, medical-specific LLMs disproportionately focus on the potential benefits of medical interventions, often neglecting potential patient-specific repercussions, e.g., advising a feverish patient who recently consumed alcohol to consider taking acetaminophen. This one-sided approach by each model type leads to suboptimal performance in toxicity assessment.

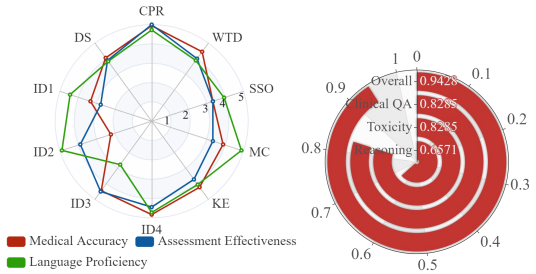
Lack of Innovative Thinking As experts pointed out in the human assessment, the responses of LLMs on CliMedBench significantly lack innovation. To quantify this, we substitute the option of the correct answer in multiple-choice questions with "None of the above is correct" (Umapathi et al., 2023). Surprisingly, we find that this triggers a fall in accuracy to less than 10% in the false treatment test scenario for the majority of models.

This suggests that, with instruction tuning, LLMs often opt for a seemingly reasonable choice from the given alternatives, potentially overlooking more precise solutions in clinical scenarios, thereby limiting the innovative capacity of medical LLMs.

6 Benchmark Validity Verification

To confirm the reliability of CliMedBench, we engaged medical professionals to assess our benchmark from three perspectives, including medical accuracy, assessment effectiveness, and language proficiency. Figure 8(a) plots the assessment results, which substantiate the quality of CliMedBench with an "acceptable" (3 points) or higher rating. Appendix B provides assessment criteria.

Furthermore, we calculate the Spearman correlation between our CliMedBench and another representative benchmark, namely MedBench [7] based on other kinds of data. This approach[8] allows us to conduct multidimensional evaluations that reflect both collective and discrete correlations between benchmarks. Figure 8(b) illustrates a robust correlation between the CliMedBench and MedBench leaderboards, with an overall Spearman correlation of 0.943 and subdivisions no less than 0.657, substantiating CliMedBench's utility and reliability as an evaluative benchmark.



(a) (b)

Figure 8: Figure (a) depicts the assessment results of medical experts, while Figure (b) shows a noteworthy correlation between CliMedBench and MedBench.

7 The Agent-based Computerized Adaptive Testing (CAT) Approach

During the evaluation phase, we identified two key issues: (1) Smaller LLMs struggle with exceedingly difficult questions, resulting in uniformly low accuracy and a lack of differentiation in the evaluations. (2) Certain LLMs exhibit slow GPU inference speeds or high API-related computational costs, significantly increasing benchmark testing expenses. To address this issue, we propose an agent-based CAT approach, enabling rapid assessment of model performance using CliMedBench.

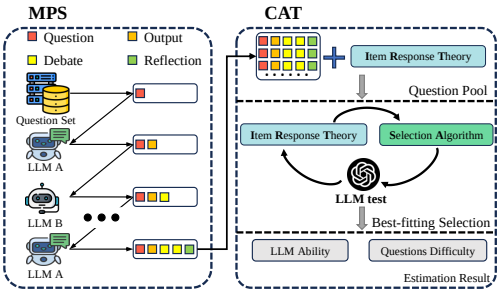


Figure 9: The workflow of Agent-based CAT

Theoretical Basis Our approach is fundamentally rooted in the psychometric Item Response Theory (IRT). We incorporate the three-parameter logistic model (IRT-3PL), formulated as:

$$P(X_{ij} = 1|\theta_j) = c_i + (1 - c_i)\frac{1}{1 + e^{-a_i(\theta_j - b_i)}} \quad (1)$$

where a_i, b_i, and c_i represent the discrimination, difficulty, and the guessing factor, respectively. θ_j represents the proficiency of LLM j and $P(X_{ij} = 1|\theta_j)$ is the probability that an LLM j with proficiency θ_j gives a correct response to question i.

Procedure of Agent-based CAT As depicted in Figure 9, our agent-based CAT consists of two main steps: Multi-Agent Based Participant Synthesis (MPS) and Computerized Adaptive Testing (CAT). MPS leverages multi-agent LLMs to synthesize data that mimics participant behavior, which is used to construct a question pool. We then use CAT to sequentially select the best-fitting questions from the question pool to evaluate the ability of LLMs.

Algorithm 1 provides the "generation-debate-reflection" process in MPS for data synthesis, aiming to overcome the difficulty of insufficient participant data in previous CAT (Zhuang et al., 2023). Once a sufficient number of participant behavior data are synthesized, the modeling process aligns more closely with the assumptions of IRT. Specifically, we use permutations of 5 LLMs (e.g., Bloomz and ChatGLM2) to form multi-agent based participants, serving as the examinees in the IRT process to synthesize performance-related data.

To accomplish the best-fitting selection, the CAT step includes two components that work alternately, including (1) ability estimation using IRT in Eq. 1 and (2) question selection via Fisher information.

Results We select 243 questions from CliMedBench to conduct a rapid assessment using our

[7] https://medbench.opencompass.org.cn/leaderboard

[8] https://github.com/ctllllll/understanding_llm_benchmarks?tab=readme-ov-file

Algorithm 1 The MPS process

Input: Q=Question data;
Output: Synthesize data
function MULTI-AGENT(Q, LLM$_1$, LLM$_2$)
  for Q_i in Q **do**
    $G \leftarrow LLM_1$-Generation(Q_i)
    $D \leftarrow LLM_2$-Debate(Q_i, G)
    $R \leftarrow LLM_1$-Reflection(Q_i, G, D)
    DebateResults $\leftarrow (Q_i, G, D, R)$
  end for
  return Synthesized data
end function

agent-based Computerized Adaptive Testing (CAT). To validate the effectiveness of our agent-based CAT rapid assessment, we compare its results with the regular CliMedBench evaluation, which involved 33,735 instances as proposed in Section 2. This comparison is illustrated in Figure 10. Our observations indicate a consistency in the relative rankings of LLMs derived from the two evaluation methods, validating the effectiveness of using a limited s set of questions to gauge model ability.

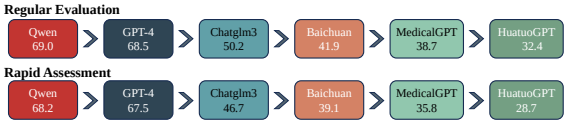


Figure 10: Comparisons between regular CliMedBench evaluation and our agent-based CAT rapid assessment.

Table 3 compares the accuracy of our agent-based CAT with that of the representative previous work by Zhuang et al. (2023). We observe a relative performance increase of 26.9%, demonstrating the efficacy of MPS in synthesizing sufficient data that better aligns with the IRT assumption.

Method	Accuracy
CAT (Zhuang et al., 2023)	32.10
Our Agent-based CAT	40.74

Table 3: Comparison to other CAT method.

8 Related Work

MultiMedQA (Singhal et al., 2023) and PubMedQA (Jin et al., 2019) are effective benchmarks based on QA tasks for evaluating the medical abilities of LLMs. Large-scale EHR-based benchmarks such as emr-QA (Pampari et al., 2018) have addressed the deficiency in clinical QA, however, language discrepancies preclude their direct applicability for evaluating Chinese medical LLMs. The assessment of LLMs for Chinese medical proficiency has traditionally relied on benchmarks derived from multiple-choice and generative question-answering formats, utilizing resources like exam questions, textbooks, and doctor-patient interactions. Chinese benchmarks, including CMExam (Liu et al., 2023), CMB (Wang et al., 2023b), and MLEC-QA (Li et al., 2021), primarily source their data from exams such as CNMLE and NMLEC. Despite their comprehensive analysis, these benchmarks are disconnected from actual medical practice due to their lack of real-world medical case data, and the challenge of ensuring quality control and avoiding data pollution grows proportionally with the involved volume of data (Li et al., 2023).

Finally, we contrast our work with other lines of work sharing seemingly similar goals. MedBench (Cai et al., 2024) is an exhaustive benchmark designed for the domain of Chinese medical QA, it utilizes exam questions and synthetical EHRs to evaluate the LLMs' exam-solving capabilities in different departments rather than actual clinical skills. In contrast, our benchmark extends this framework across 14 diverse medical scenarios. Furthermore, despite MedBench providing preliminary empirical analysis, it lacks in-depth qualitative analyses of the model's performance. RJUA-QA (Lyu et al., 2023) creates high-quality medical datasets to evaluate clinical reasoning based on EHRs and clinical cases. However, it is restricted to urology, offering limited insight into the broader medical capabilities of LLMs.

9 Conclusion and Discussions

This paper introduces CliMedBench, a robust benchmark derived from real medical cases that comprises 33,735 questions across 14 core medical scenarios assessing LLMs' ability across six dimensions. Evaluating diverse LLMs reveals their suboptimal performance, especially where medical reasoning and factual consistency are vital, underscoring the need for advances in clinical knowledge and diagnostic accuracy. We also conducted a comprehensive qualitative analysis of the experimental outcomes and made several novel insights. Simultaneously, we proposed the agent-based CAT approach, which enables rapid assessment with minimal problem sets.

10 Limitations and Ethical Issues

Protected Health Information (PHI) encompasses data related to an individual's health status, healthcare provision, or payment for healthcare services,

which is generated or amassed by a Covered Entity or its Business Associate. PHI typically undergoes de-identification to safeguard individual privacy prior to the dataset's publication. CliMEdBench is a dataset derived primarily from real-world medical cases and the Chinese National Physician Qualification Examination. All EHRs and codes have been doubly de-identified by ethics committees and experts according to the guidance and have passed the ethical review of our partner hospitals before submission. The guidance for De-identification of PHI can be found at this URL. However, such real-world data may suffer from noise. This stems from two main sources: (i) erroneous data input by medical personnel during recording or formatting error during data retrieval, and (ii) inaccuracies introduced in automatic information extraction. Users should exercise caution regarding data reliability in light of these limitations. In future work, extensive validation by medical experts will be conducted to ensure the correctness of all data. Our project has been conducted in collaboration with relevant medical centers with proper approval of all data sharing. We ensure full compliance with applicable laws and ethical guidelines during data collection and use, all information in medical cases has been desensitized to ensure that no personal information related to patients or medical personnel is leaked.

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A Details and Examples of Datasets

We provide detailed information on 14 task datasets, as illustrated in Table 9 to 19. Each table contains the task type, data source, evaluation metrics, size, description, and an example of each dataset. We also provide 5 examples for each of the 14 datasets and the COT prompt we use at this URL.

Table 4 provides a correspondence table between the full names and abbreviations of 14 datasets.

We have conducted multiple overall tests on some LLMs using CliMedBench. Table 20 presents comprehensive evaluation outcomes, encompassing both overall results and deviation values across multiple experimental results. We also compared LLMs of different sizes in the same series(HuatuoGPT-7B and HuatuoGPT-13B, Baichuan-7B and Baichuan-13B), and larger models with more parameters exhibited significant performance gains as expected, especially in their comprehension and instruction following ability.

Full name	Abbreviation
In-hospital Diagnosis (Period #3)	ID#3
In-hospital Diagnosis (Period #1)	ID#1
In-hospital Diagnosis (Period #2)	ID#2
Clinical Pathway Reasoning	CPR
In-hospital Diagnosis (Period #4)	ID#4
Discharge Summary	DS
Surgical Step Organization	SSO
Case Summary	CS
False Information Test	FIT
False Treatment Test	FTT
Basic Knowledge Test	BKT
Keyword Extraction	KE
Medicine Consultation	MC
Wrong Treatment Detection	WTD

Table 4: The correspondence between full names and abbreviations of 14 datasets.

B Dataset Construction

B.1 Data Collection

Our real-world EHRs are provided by our partner tertiary hospitals, and they also collaborate on dataset development. In the development of the CliMedBench, particular emphasis is placed on content pertinent to surgical specialties, so EHRs predominantly cover departments such as Orthopedics, Urology, Vascular Surgery, Gastroenterology, and Nephrology. These records encompass a comprehensive range of patient information including, but not limited to, diagnostic data, surgical intervention details, treatment outcomes, and follow-up care information. The data extraction process adheres to stringent privacy and ethical standards to

safeguard patient confidentiality. We also collect 6,957 questions from the past NMLEC and textbooks from the Internet as a supplement. The NMLEC is meticulously designed by medical experts to assess the proficiency in medical knowledge and skills of individuals who want to become medical practitioners in China. The question types include single-choice and multiple-choice questions.

B.2 Human-in-the-loop Data Construction

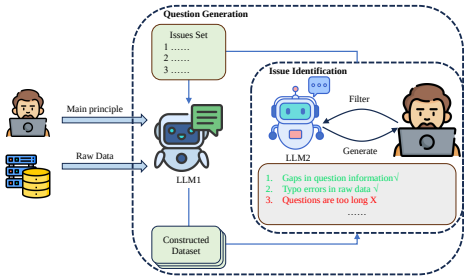

Figure 11: Workflow of collaboration between humans and LLMs for dataset construction.

For this part, we delineate the human-in-the-loop dataset construction methodology. Our expert team is composed of five doctors from different tertiary hospitals (all with five years or more of work experience), one medical doctoral student, and one medical postdoctoral fellow. During **Data Construction Phase**, four medical experts are enlisted, their tasks involve drafting question design strategies and identifying issues for subsequent rounds. The other three additional experts are tasked in the **Evaluation Phase** to assess question quality (and LLM responses in generative tasks). We use regular expressions, which are carefully designed after analyzing the LLMs' response pattern, to extract answers from the output of each model. For example, the responses often take the following form: "A: (explain why A is incorrect), B: (explain why B is correct), C: (explain why C is incorrect),... to sum up, the answer is B." Therefore, our code includes the following statement: answer = ''.join(re.findall('[A-E]', LLM_response)).replace('ABCDE', '').

Before the Data Construction Phase, all EHRs have been doubly de-identified by ethics committees and experts to make sure no PHI of patients or healthcare professionals is leaked. Then we preprocess the raw data to filter low-quality data and ensure proper formatting by automatic techniques such as regular expression matching and medical entity recognition. Figure 11 illustrates the workflow of our construction:

1. Human operators initially establish dataset guidelines defining the strategies for selecting and filtering the model input and output in a given scenario. The doctor's notes within the EHRs, which indicate the EHRs' content types, are also used as a reference. For example:

- Retrieve and analyze data pertinent to medical guidance or diagnosis.
- Deconstruct the sequential steps documented by the doctor in the medical case.
- Classify the patient's medical treatment process to which this medical case belongs.

These doctor's notes within the EHRs, which indicate the EHRs' content types, are used to categorize the content guide question generation. 2. EHRs are divided into sentences, and a language model (LLM1) then classify the category of each sentence, the results of which were checked by expert verification. The categorized senteces can be divided into the question and answer part. The incorrect options of QA-pairs are sourced from the answer parts of other EHRs, and the EHRs used to formulate a question share similar question parts, aiming to enhance the relevance of the answers and maintain the difficulty of the question.
3. A second language model (LLM2) identifies and flags issues in the dataset, such as informational gaps or ambiguous options. Medical experts evaluate the relevance of these issues, retaining only those that are pertinent for inclusion in an issue set as feedback.
4. Feedback from the issue identification phase informs LLM1 in the subsequent question generation phase to prevent recurring issues.
5. At the end of each cycle, a rigorous validation mechanism is employed where each questions are double-checked by two experts, and this cycle repeated until over 90% of the questions are deemed issue-free by both. For this task, the inter-annotator agreement is 0.89 (kappa).

B.3 Criteria for Expert Assessment

Medical experts are tasked with assessing three dimensions of each dataset within the benchmark: medical accuracy, assessment effectiveness, and language proficiency. The evaluation ratings for

each dimension are categorized into three tiers: 'excellent' (3 points), 'acceptable' (2 points), and 'useless' (1 point). The final score for the dataset is determined by computing the mean score across all sampled questions. The evaluative criteria for each dimension are depicted in Table 5.

Medical Accuracy	
Excellent	Answers are accurately inferred from the provided medical information in the question.
Acceptable	Answers are partially correct and debatable, yet the reference solution remains the most suitable.
Useless	Answers are either entirely incorrect or cannot be deduced from the given question.
Assessment Effectiveness	
Excellent	In-depth medical knowledge and critical reasoning necessary for response formulation.
Acceptable	Moderate understanding of medical concepts, language proficiency, and organizational abilities required.
Useless	No discernible evaluation Effect.
Language Proficiency	
Excellent	The expression is professional and encompasses all pertinent information, demonstrating a clear grasp of the subject matter.
Acceptable	The content is comprehensive, yet the articulation is unrefined.
Useless	The question is poorly organized, lacks completeness, and is not reader-friendly.

Table 5: Evaluation guidelines for three dimensions.

B.4 About expert team

C Experiment Settings

For reproducibility, we delineate precise model selections and parameter configurations. For GPT models, we leverage OpenAI's API to access the gpt-3.5-turbo-1106 and gpt-4-1106-preview models. For the other API models, ERNIE-Bot, Qianwen, and Xinghuo, we employe ERNIE-Bot 4.0, Qianwen max, and Xinghuo v3, respectively. Additionally, the base model of HuatuoGPT, HuatuoGPT2, Bentsao, and MedicalGPT are Ziya-LLaMA-13B-Pretrain-v1, Baichuan2-13B-Chat, Alpaca-Chinese-7B, and Baichuan-13B-Chat, respectively. As for model parameters, we adopt default or publisher-recommended settings in their published website.

Our research entails a comprehensive analysis of the patient treatment process in hospitals and other medical activities, pinpointing 14 core scenarios where LLMs could be beneficial based on (i) patient safety, (ii) the necessity for professional expertise, and (iii) potential user impact. The primary dataset comprises actual clinical cases, supplemented by the National Medical Licensing Examination in China (NMLEC), scholarly articles, and medical textbooks to enhance data diversity. This corpus spans various medical specialties. These 14 scenarios evaluate the medical ability of language models from six aspects. Figure 2 details the quantitative breakdown of each dataset.

With expert medical oversight, initial data cleansing and selection are performed. A human-in-the-loop approach is employed to enhance efficiency while maintaining data quality. Medical experts guide scene selection and content creation throughout this procedure, incorporating physicians' feedback and recommendations. Upon completion of the dataset construction, we engage other qualified medical professionals to assess the constructed datasets. Assessment spans three aspects: (1)medical accuracy—scrutiny of the question content's medical validity. (2)assessment effectiveness—the question's capacity to appraise corresponding medical knowledge and linguistic proficiency. (3)and language proficiency—whether the question is fully expressed in professional medical terminology.

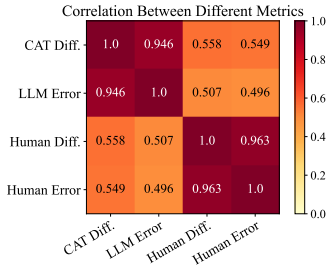

Figure 12: Correlations among CAT difficulty, model and human error rates, annotation difficulty, and explanation length for all questions.

D Additional CAT Results

To ascertain the efficacy of CAT difficulty, we use the human annotation difficulty and error rate as

the gold standard and compute the correlation coefficient. As illustrated in Figure 12, CAT difficulty strongly correlates with human error rate and annotation difficulty, surpassing the correlation with model error rate. This suggests that CAT difficulty is a more reliable indicator.

Dataset	Task	Resource	Metric	Size
In-hospital Diagnosis (Period #1) (ID#1)	Clinical QA	Medical Case	Accuracy	2639

Description

The first stage of patient consultation, physicians should formulate a tentative diagnosis from the patient's presenting symptoms and choose the most appropriate diagnostic test to confirm the condition.

Example

Prompt	你是一位专业的医生，你了解在各种患者情况下应该对其进行何种检查来确诊其病症。接下来我将提供一个刚进入医院诊疗的病人的入院情况和现病史，你需要由此判断接下来需要对他进行什么检查来确诊其病症。.....\n 以下是提供的患者病例: You are a professional doctor, and you understand what examinations should be conducted to diagnose the patient's condition in various situations. Next, I will provide the admission information and current medical history of a patient who has just entered the hospital for treatment. Based on this, you need to determine what examinations should be performed to diagnose their condition. ... \n Below is the provided patient case:
Input	## 入院情况: 患者摔伤致腰部疼痛活动受限。无双下肢放射痛及感觉减退。.....\n## 现病史: 患者摔伤致腰部疼痛活动受限。无双下肢放射痛及感觉减退。.....\n## 选项: A: 腰部 MRI, 尿常规, 血常规, 肾功能检查\nB: 腰部 CT\nC: 体检, 右上叶肺结节检查\nD: 肠镜检查, 病理检查 ##Admission Information: The patient suffered from a fall resulting in lumbar pain and restricted movement. There is no radiating pain or sensory loss in both lower limbs. ... \n##Current Medical History: The patient suffered from a fall resulting in lumbar pain and restricted movement. There is no radiating pain or sensory loss in both lower limbs. ... \n##Options: A: Lumbar MRI, Urinalysis, Complete Blood Count, Renal Function Test\nB: Lumbar CT\nC: Physical Examination, Right Upper Lobe Lung Nodule Examination\nD: Colonoscopy, Pathological Examination
Reference	B

Table 6: Details about In-hospital Diagnosis (Period #1) dataset.

Dataset	Task	Resource	Metric	Size
In-hospital Diagnosis (Period #2) (ID#2)	Clinical QA	Medical Case	Accuracy	6693

Description

The second stage of patient consultation, physicians need to diagnose patients' diseases by their clinical data and examination results.

Example

Prompt	你是一位医学专家，你了解各种疾病的症状，你知道各种医疗检测和检测结果的作用与含义。\n 接下来我将提供一份患者的医疗病例，包括了他入院时的情况、现病史、医院中的诊疗过程等信息，你需要由此推测他的最终主要诊断结果。..... \n 以下是提供的患者病例记录: You are a medical expert. You are knowledgeable about symptoms of various diseases, as well as the purposes and meanings of various medical tests and their results. \n Next, I will provide a medical case of a patient, including information about their condition upon admission, present medical history, diagnostic and treatment processes in the hospital, etc. Based on this information, you need to deduce their eventual primary diagnosis. ... \n Below is the provided patient case record:
Input	## 入院情况: 患者 4 年前出现右髋关节疼痛伴活动障碍..... \n## 诊疗过程: 患者因 “右侧髋关节疼痛 4 年余” 入院。..... \n## 现病史: 患者 4 年前出现右髋关节疼痛伴活动障碍..... ## 选项: A: 股骨头无菌性坏死\n B: 胰腺原位癌\n C: 劳力恶化型心绞痛\n D: 髋关节骨性关节炎 ##Admission condition: The patient experienced right hip joint pain with mobility impairment four years ago... \n##Diagnostic and treatment process: The patient was admitted due to ”persistent right hip joint pain for over 4 years”... \n##Present medical history: The patient experienced right hip joint pain with mobility impairment four years ago... ##Options: A: Aseptic necrosis of the femoral head\n B: Pancreatic in situ carcinoma\n C: Exertional angina worsening\n D: Osteoarthritis of the hip joint
Reference	A

Table 7: Details about In-hospital Diagnosis (Period #2) dataset.

Dataset	Task	Resource	Metric	Size
In-hospital Diagnosis (Period #3) (ID#3)	Clinical QA	Medical Case	Accuracy	1748

Description

The third stage of patient consultation, physicians need to ascertain the appropriate treatment for patients by evaluating their diseases and presenting symptoms, which may involve surgical intervention or pharmacotherapy.

Example

Prompt	你是一位专业的医学领域专家，利用你的医学能力解决以下问题。接下来我将提供一份患者在入院时的症状，你需要由此判断接下来需要对患者选择哪些治疗方案。..... \n 以下是提供的患者病例: You are a professional medical expert, utilizing your medical expertise to address the following issue. Next, I will provide a set of symptoms observed in a patient upon admission, and you need to determine which treatment options should be chosen for the patient based on this information. ... \n Below is the provided patient case:
Input	## 患者症状: 尿中带血 10 天;..... ## 选项: A: 抗板调脂固斑；抗过敏；营养神经治疗；头孢吡肟抗感染；DRD 方案化疗；依泰抑制骨破坏\nB:.....\nC: .....\nD: ..... ##Patient Symptoms: Hematuria for 10 days;... ##Options: A: Antiplatelet aggregation; antiallergic; nutritional nerve therapy; cefoperazone to fight infection; DRD regimen chemotherapy; etidronate to inhibit bone resorption\nB: ...\nC: ...\nD: ...
Reference	C

Table 8: Details about In-hospital Diagnosis (Period #3) dataset.

Dataset	Task	Resource	Metric	Size
In-hospital Diagnosis (Period #4) (ID#4)	Clinical QA	Medical Case	Accuracy	2728

Description

The fourth stage of patient consultation, the patient has recuperated, necessitating the physician to formulate discharge advice that considers the patient's admission and discharge statuses, alongside the timeline of diagnosis and treatment.

Example

Prompt	你是一位专业的医生，你可以理解病例中的患者状态和治疗手段，并给出相应的建议..... \n 接下来我将提供给你一份即将出院的患者的病例记录，你需要根据其中的内容来提供他的出院医嘱..... \n 以下是提供的患者病例记录: You are a professional physician, capable of understanding the patient's condition and treatment options in the case, and providing corresponding recommendations..... \n Next, I will provide you with a patient's case record who is about to be discharged, and you need to provide their discharge instructions based on the contents..... \n Below is the provided patient case record:
Input	## 入院情况: 患者因“发热咳嗽 1 月余”入院。..... \n## 诊疗过程: 患者入院完善相关检查先后予左氧氟沙星..... \n## 出院情况: 患者无胸闷气喘无明显 ## 选项: A. 1. 糖尿病饮食适当日晒、补钙避免跌倒。2. 继续服用药物治疗。3. 三个月后复查血指标半年后复查骨密度。4. 两周后范主任门诊就诊: 周二下午（西院）周一、周四上午（东院）。\nB. ..... \nC. ..... \nD. ..... ##Admission condition: The patient was admitted due to "fever and cough for over 1 month"... \n##Diagnostic and treatment process: Upon admission, the patient underwent relevant examinations and was subsequently administered levofloxacin... \n##Discharge condition: The patient had no chest tightness or shortness of breath. ##Options: A. 1. Diabetic diet appropriate sun exposure, calcium supplementation to prevent falls. 2. Continue medication treatment. 3. Re-examine blood indicators after three months and bone density after six months. 4. Follow-up appointment with Dr. Fan in two weeks: Tuesday afternoon (West Hospital) Monday and Thursday mornings (East Hospital). \nB. ... \nC. ... \nD. ...
Reference	A

Table 9: Details about In-hospital Diagnosis (Period #4) dataset.

Dataset	Task	Resource	Metric	Size
Surgical Steps Organization (SSO)	Reasoning	Medical Case	Kendall's Tau	472

Description

Block out key procedural steps in surgery and task LLMs with deducing their proper sequence through logical reasoning.

Example

Prompt	你是一位主治医师，你擅长进行各种科室的手术，并清晰地了解各个手术的一般施展步骤。\n 接下来我将提供一个现实病例记录的手术步骤，但其中部分步骤的顺序被遮挡了。..... 你需要利用你的医学知识，给出遮挡文本中步骤填入缺失手术步骤中的正确顺序，并给出相应解释。..... \n 以下是手术案例。 You are a attending physician, skilled in various departmental surgeries, and have a clear understanding of the general procedural steps for each surgery. \n Next, I will provide you with the surgical steps from a real case record, but some steps have been obscured. ... You need to use your medical knowledge to fill in the missing surgical steps in the obscured text with the correct sequence, and provide corresponding explanations. ... \n Below is the surgical case.
Input	## 手术名称: 直肠乙状结肠部分切除术\n## 手术步骤: 1. 取平卧位气静麻下常规消毒铺巾。\n2.5 孔法建立气腹术中所见如上。\n3.____ \n4..... \n## 遮挡文本: A: 经肛门置入管状吻合器行直肠乙结肠端端吻合。\nB: 远端直肠距肿块 3cm 处切断。..... ##Surgery Name: Partial Rectosigmoidectomy \n##Surgical Steps: 1. Place the patient in a supine position, administer routine disinfection, and drape the surgical area. \n2. Establish pneumoperitoneum using the 5-hole method, as described above. \n3. ____ \n4. ... \n##Obscured Text: A: Insert a tube-shaped anastomotic device through the anus to perform end-to-end anastomosis of the rectum and sigmoid colon. \nB: Cut the distal rectum 3 cm away from the tumor mass. ...
Reference	DCBA

Table 10: Details about Surgical Step Organization dataset.

Dataset	Task	Resource	Metric	Size
Clinical Pathway Reasoning (CPR)	Reasoning	Medical Case	Kendall's Tau	95

Description

Disrupting the clinical pathway of patients and task LLMs with deducing their proper sequence through logical reasoning.

Example

Prompt	你是一位专业的医学领域专家。以下提供了一位病人在一次住院期间的经历的多个步骤，但是顺序被打乱了，现在请利用你的医学知识，推理出这位患者经历步骤的正确顺序。..... \n 以下是提供的患者经历。 You are a professional expert in the medical field. The following provides several steps of a patient's experience during a hospitalization, but the sequence has been disrupted. Now, please use your medical knowledge to deduce the correct order of the steps the patient experienced. ..... \n Below is the provided patient experience.
Input	## 入院情况: A. 患者男，39 岁。主诉鼻咽癌术后..... \nB. 患者入院来神志清醒，进食可..... \nC. 患者同意接受手术快速冰冻诊断。\nD. 血常规、出凝血功能、血糖、心电图检查均正常..... ##Admission condition: A. Male patient, 39 years old. Presents with complaints of postoperative nasopharyngeal carcinoma... \nB. Upon admission, the patient is alert and able to eat... \nC. The patient agrees to undergo rapid frozen section diagnosis. \nD. Routine blood tests, coagulation function, blood glucose, and electrocardiogram are all normal...
Reference	ABDC

Table 11: Details about Clinical Pathway Reasoning dataset.

Dataset	Task	Resource	Metric	Size
Discharge Summary (DS)	Summary	Medical Case	Accuracy	4644

Description

Supply the language model with a patient's medical record encompassing admission diagnosis, diagnostic and therapeutic course, surgical procedure, and intraoperative observations and request LLMs to generate a discharge summary.

Example

Prompt	你是一位医疗领域专家，利用你的专业知识解决以下问题。以下是一位病人在一次住院过程中的病历记录，..... \n 以下是提供的患者病例记录: You are a medical field expert, using your professional knowledge to address the following issue. Below is a medical record of a patient during a hospitalization process... \n Below is the provided patient case record:
Input	## 入院情况: 髋外伤后疼痛入院\n## 诊疗过程: 患者一月前外伤后出现.....\n## 手术过程与术中所见: ..... \n## 选项: "A: 患者因陈旧性股骨粗隆间骨折入院。..... \nB: ..... \nC: ..... \nD: ..... ##Admission condition: Admitted for hip pain following external trauma\n##Diagnostic and treatment process: The patient presented with pain after trauma one month ago...\n##Surgical procedure and intraoperative findings: ... \n##Options: "A: Admitted due to old intertrochanteric femoral fracture... \nB: ... \nC: ... \nD: ...
Reference	A

Table 12: Details about Discharge Summary dataset.

Dataset	Task	Resource	Metric	Size
Case Summary (CS)	Summary	Online Consultation	Accuracy	320

Description

Input a digitized consultation report containing the patient's self-reported illness narrative, disease duration, and pharmacological history. Requires the LLMs to generate a succinct abstract of the record.

Example

Prompt	你是一位主治医生，你正在为一位病人进行进行诊断。你需要在听取患者的描述后对其病症进行总结。..... \n 以下是提供的患者病例记录: You are a attending physician, diagnosing a patient. You need to summarize the patient's symptoms after listening to their description. ... \n Below is the provided patient case record:
Input	## 疾病描述：患者 20 余天前出现头痛..... \n## 身高体重：162cm，50.5kg（2023-03-09 测量）\n## 疾病：头痛 20 余天（2023-11-06 填写）\n## 患病时长：20 余天 \n## 选项: A: 乳头溢液，超声提示腺管扩张伴分泌物潴留。\n B: ..... ##Disease Description: The patient experienced headaches over 20 days ago... \n##Height and Weight: 162cm, 50.5kg (measured on 2023-03-09) \n##Condition: Headache for over 20 days (recorded on 2023-11-06) \n##Duration of Illness: Over 20 days \n##Options: A: Nipple discharge, ultrasound suggests duct dilation with secretion retention. \n B: ...
Reference	脑叶出血，没有三高，脑叶出血血管的淀粉样变是不能除外的。 Intracerebral hemorrhage, without three highs, cannot rule out amyloid angiopathy of cerebral hemorrhage vessels.

Table 13: Details about Case Summary dataset.

Dataset	Task	Resource	Metric	Size
Keyword Extraction (KE)	Information Retrieval	Paper	Rouge-1	713

Description

Evaluate the information retrieval and academic capabilities of LLMs by presenting them with medical paper abstracts and instructing them to identify keywords.

Example

Prompt	你是一位专业的医学领域专家，能够理解各种医疗文献与论文。\n 以下是一篇医疗相关论文的摘要，现在需要你在阅读摘要后从中选取出改论文的关键词。..... 你需要给出选择这些关键词的解释。..... \n 以下是提供的论文摘要。 You are a professional expert in the medical field, capable of understanding various medical literature and papers. \n Below is an abstract of a medical-related paper, and now you need to select the keywords from it after reading the abstract. ... You need to provide explanations for selecting these keywords. ... \n Below is the provided abstract of the paper.
Input	探讨我国老年慢性病患者医养结合的延续护理模式及其实现途径. 结合《社会养老服务体系建设规划 (2011-2015 年)》及..... 以实现老年慢性病患者医疗与养老相结合的延续护理模式. Exploring the continuation nursing model and its implementation approach of medical and nursing integration for elderly patients with chronic diseases in China. Combining with the "Social Pension Service System Construction Plan (2011-2015)" and... to achieve a continuation nursing model that integrates medical care and elderly care for elderly patients with chronic diseases.
Reference	慢性病养老医养结合延续护理 Chronic disease, elderly care, medical-nursing integration, continuation nursing.

Table 14: Details about Keyword Extraction dataset.

Dataset	Task	Resource	Metric	Size
Basic Knowledge Test (BKT)	Knowledge Apply	CNMLE	Accuracy	4160

Description
Evaluating the LLM's ability to apply basic medical knowledge

Example	
Prompt	你是一位专业的医学领域专家。你正在完成一份医学相关的单项选择题。\n 接下来的输入中包括一份现实的医学病例，对应一个题目和几个答案选项。请根据题目提出的问题，选择出正确答案的选项，并对答案正确或错误的原因提供准确而详细的解释。..... \n 以下是提供的医学题目。 You are a professional expert in the field of medicine. You are working on a set of medical-related multiple-choice questions. \n The following input includes a real medical case corresponding to a question and several answer options. Please select the correct option that answers the question, and provide accurate and detailed explanations for why each answer is either correct or incorrect. ... \n Below are the provided medical questions.
Input	## 问题: 血清补体 C3 持续下降见于 \n## 选项: A. 乙肝病毒相关肾炎 \nB. 狼疮性肾炎 \nC. 膜增生性肾炎 \nD. 小血管炎 E. 急性肾小球肾炎 ##Question: Persistent decrease in serum complement C3 is seen in \n##Options: A. Hepatitis B virus-associated nephropathy \nB. Lupus nephritis \nC. Membranoproliferative glomerulonephritis \nD. Small vessel vasculitis \nE. Acute poststreptococcal glomerulonephritis
Reference	C

Table 15: Details about Basic Knowledge Test dataset.

Dataset	Task	Resource	Metric	Size
False Treatment Test (FTT)	Hallucination	CNMLE	Accuracy	1114

Description

Discern whether the LLM recognizes the inaccuracy of the provided choices or merely generates a response that contradicts the facts by providing a query where the accurate response is "none of the above options are correct

Example

Prompt	你是一位专业的医学领域专家。你正在完成一份医学相关的单项选择题。\n 接下来的输入中包括一个医学题目和五个答案选项。请在查看后给出正确答案的选项，并对答案正确或错误的原因提供准确而详细的解释。..... \n 以下是提供的医学题目。 You are a professional expert in the field of medicine. You are working on a set of medical-related multiple-choice questions. \n The upcoming input includes a medical question and five answer options. After reviewing, please provide the correct answer option and offer accurate and detailed explanations for why each answer is either correct or incorrect... \n Below are the provided medical questions.
Input	## 材料: 女孩，4 岁，腹胀 3 年伴便秘..... \n## 问题: 为明确诊断，首先考虑做 ## 选项: A. 直肠黏膜病理活检 \nB. 直肠黏膜 AChE 组织化学检查 \nC. 脑电图测定 \nD. 肌电图分析 \nE. 以上均不对 ##Material: Female, 4 years old, with abdominal distension for 3 years accompanied by constipation... \n##Question: To establish a clear diagnosis, the first consideration should be... ##Options: A. Rectal mucosal biopsy \nB. Rectal mucosal AChE tissue histochemistry examination \nC. Electroencephalogram (EEG) \nD. Electromyography (EMG) analysis \nE. None of the above
Reference	E。首先应考虑肛管直肠测压法：测定直肠和肛管括约肌的反射性压力变化，对诊断和鉴别其他原因的便秘甚有价值。 E. The first consideration should be anorectal manometry: measuring the reflexive pressure changes in the rectum and anal sphincter muscles, which is highly valuable for diagnosing and differentiating constipation from other causes.

Table 16: Details about False Treatment Test dataset.

Dataset	Task	Resource	Metric	Size
False Info Test (FIT)	Hallucination	CNMLE	Accuracy	3003

Description

Investigate the propensity of an LLM to generate factually inconsistent responses by presenting it with a medical query alongside an erroneous reference answer and prompting it for an explanation.

Example

Prompt	你是一位专业的医学领域专家，利用你的专业知识解决以下问题。\n 接下来的输入中包括一个医学单选题及其对应选项，还有对应的参考答案，注意答案仅供参考。请在阅读题目后为正确答案的选项提供准确而详细的解释。..... \n 以下是题目与学生的回答: You are a professional expert in the field of medicine, using your expertise to address the following questions. \n The upcoming input includes a medical multiple-choice question along with its corresponding options, as well as the corresponding reference answer. Please provide accurate and detailed explanations for the correct answer option after reading the question... \n Below are the questions and the student's responses:
Input	## 问题: 以下属于上丘脑的结构是 \n## 选项: "A: 丘脑枕 \nB: 灰结节 \nC: 垂体 \nD: 正中隆起 \nE: 丘脑髓纹" ## 参考答案: C ##Question: Which of the following structures belong to the thalamus? \n##Options: "A: Pulvinar \nB: Substantia nigra \nC: Pituitary gland \nD: Median eminence \nE: Medullary stria of the thalamus" ##Reference answer: C
Reference	我认为答案 C 并不正确，上丘脑包括松果体、缰三角、缰连合、丘脑髓纹和后连合等部位，而垂体并不包括在内，因此答案应为 E 而不是 C。 I believe that option C is not correct. The thalamus includes structures such as the pineal gland, habenular trigone, habenular commissure, medullary stria of the thalamus, and posterior commissure, while the pituitary gland is not included. Therefore, the correct answer should be option E instead of option C.

Table 17: Details about False Information Test dataset.

Dataset	Task	Resource	Metric	Size
Medicine Consultation (MC)	Toxity detection	Textbook	Accuracy	661

Description

Input patient symptomatology to the model to identify therapeutically effective drugs from a list of alternatives. These drugs encompass agents with potential therapeutic mismatches, contraindications pertinent to the patient's clinical status, and risks of dosage inaccuracies. Assess the model's capability to detect toxicity in drug selection.

Example

Prompt	你是一位专业的医学领域专家，利用你的医学能力解决以下问题。接下来我将提供一份患者当前的症状，你需要由此判断接下来需要让患者服用什么药物以进行治疗。..... \n 以下是提供的患者病例: You are a professional expert in the medical field, utilizing your medical expertise to address the following issue. Next, I will provide you with the current symptoms of a patient, and you need to determine what medication the patient should take for treatment. ... \n Below is the provided patient case:
Input	## 患者症状: 一位患者当前表现出记忆力减退和注意力不集中，经诊断为神经衰弱症，需要用药以强脑安神。但患者同时伴有流感症状，体温测量为 38.5°C，属于外感发热患者。\n## 选项: A: 太极五味子糖浆 \nB: 敖东安神补脑液 \nC: 恒健克霉唑乳膏 \nD: 势氯雷他定片 ##Patient Symptoms: A patient currently presents with memory decline and lack of concentration, diagnosed with neurasthenia, requiring medication for brain strengthening and nerve calming. However, the patient also has symptoms of flu, with a measured temperature of 38.5°C, indicating an external fever patient. \n##Options: A: Tai Chi Five-Flavor Syrup \nB: Aodong Brain-Nourishing Liquid \nC: Hengjian Ketoconazole Cream \nD: Levocetirizine Tablets
Reference	正确答案是 B, 它的主治功效如下：生精补髓，益气养血、强脑安神。.....而其他选项药物的主治功效与患者症状不符，故排除。 The correct answer is B, its main therapeutic effects are as follows: tonifying the kidney essence, replenishing marrow, nourishing qi and blood, and calming the nerves and strengthening the brain... The main therapeutic effects of the other options do not match the patient's symptoms, so they are ruled out.

Table 18: Details about Medicine Consultation dataset.

Dataset	Task	Resource	Metric	Size
Wrong Treatment Detection(WTD)	Toxicity Detection	Textbook	Similarity	807
Description				
Require LLMs to express an opinion medical texts with toxicity				
Example				
Prompt	你是一位专业的医学领域专家。以下是一份医疗场景中的文本，请对其发表你的见解。 You are a professional expert in the field of medicine. The following is a text from a medical scenario. Please share your insights on it.			
Input	孕妇最近一直处于急性生殖道炎症状态，临产时医生建议进行羊水穿刺以引产。 The pregnant woman has been experiencing acute genital tract inflammation recently. The doctor recommends amniocentesis to induce labor when she goes into labor.			
Reference	这并不合适，因为如果孕妇有急性生殖道炎症，是羊水穿刺的禁忌症，可能会导致严重的并发症。 This is not appropriate because if the pregnant woman has acute genital tract inflammation, it is a contraindication for amniocentesis, which could lead to serious complications.			

Table 19: Details about Wrong Treatment dataset.

	Model	ID#3 *ACC.*	ID#1 *ACC.*	ID#2 *ACC.*	CPR *Kendall's Tau*	ID#4 *ACC.*	DS *ACC.*	SSO *Kendall's Tau*
General	GPT4	**87.8**±0.6	68.4±2.0	**97.4±0.2**	73.2±3.1	84.6±1.0	**98.2±0.2**	**77.0±0.7**
General	ChatGPT	76.8±0.8	86.3±0.5	**97.4±0.2**	59.5±0.9	70.6±0.4	85.4±1.0	42.6±1.3
General	Qwen	84.6±0.5	**89.4±0.4**	95.0±0.6	69.6±0.8	**85.6±0.1**	97.1±0.2	67.1±1.0
General	Baichuan	47.6±3.0	56.7±0.9	88.5±1.1	22.1±2.3	31.2±0.9	32.1±0.7	23.9±0.7
General	ChatGLM3	47.2±0.2	88.0±0.4	97.6±0.6	33.5±3.5	37.4±0.3	60.4±0.5	21.1±1.1
Specialized	HuatuoGPT	26.6±0.6	**48.0±1.0**	66.6±1.4	24.7±2.0	25.6±0.4	20.3±0.7	3.4±0.6
Specialized	BenTsao	27.2±0	24.6±0	24.6±0	**46.7±0**	4.6±0	1.0±0	18.8±0
Specialized	MedicalGPT	**41.3±1.9**	43.7±1.7	**81.4±0.8**	39.5±1.0	**31.0±1.6**	**20.4±0.6**	**21.7±0.3**
Specialized	ChatMed	13.6±0.7	37.4±2.2	20.6±1.4	4.5±0.5	8.6±0.6	2.8±0.4	1.5±0.4

	Model	CS *ACC.*	FIT *ACC.*	FTT *ACC.*	BKT *ACC.*	KE Rouge-1	MC *ACC.*	WTD *Similarity*
General	GPT4	98.4±0	**25.0±1.5**	12.6±0.6	70.8±1.2	40.2±0.2	44.0±0.8	81.3±0.4
General	ChatGPT	97.1±0.3	2.8±0.4	1.3±0.5	51.9±0.1	39.8±0.1	38.9±1.1	80.9±0.1
General	Qwen	**99.1±0.1**	13.9±1.2	13.3±0.1	**82.4±0.6**	39.7±0.3	49.2±0.2	80.4±0.1
General	Baichuan	73.4±2.3	1.7±0.3	**21.2±1.0**	38.8±0.4	33.6±0.4	37.1±1.5	78.6±0.1
General	ChatGLM3	92.0±0.5	7.4±0.8	6.8±0.6	46.9±0.5	34.4±0.1	45.5±0.5	78.8±0.1
Specialized	HuatuoGPT	61.2±3.2	**13.8±0.6**	**8.6±3.0**	22.6±0.6	29.3±0.3	23.0±2.2	**79.2±0.2**
Specialized	BenTsao	25.6±0	0.6±0	0±0	20.6±0	6.5±0	27.6±0	75.2±0
Specialized	MedidalGPT	**67.2±2.6**	1.9±0.7	7.1±0.9	**35.0±0.6**	**33.3±0.2**	**41.7±1.7**	77.1±0.1
Specialized	ChatMed	10.9±0.9	2.0±0.3	1.2±0.6	9.3±0.3	11.4±0.1	12.4±1.6	75.8±0.2

Table 20: Results and deviation values of automatic metrics on the 14 core clinic scenarios of CliMedBench.